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Demographic Factors as Predictors of AI Use: A Focus on Postgraduate Teachers

Joseph Baidoo[*1] & Nixon Saba Adzifome[1]

***Corresponding author**
E-mail: algyasare5@yahoo.com

1. Department of Basic Education, School of Education and Lifelong Learning, University of Education, Winneba, Ghana.

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ABSTRACT

Artificial Intelligence (AI) is increasingly transforming education by providing teachers with innovative tools to improve teaching and learning. However, the extent to which teachers adopt AI varies, raising questions about whether background characteristics influence these differences. This study investigated the role of teacher demographic factors in the adoption of AI tools for academic purposes among in-service teachers receiving postgraduate education in a Ghanaian university. Drawing on the Technology Acceptance Model (TAM) and Diffusion of Innovation (DOI) theory, the study examined gender, age, teaching experience, and level of study as potential predictors of AI use. A quantitative cross-sectional survey design was adopted, with data collected from 104 conveniently sampled postgraduate teachers through a structured questionnaire. Data analysis employed t-test, Pearson correlation, and multiple linear regression. Findings showed that level of study was the strongest positive predictor of AI adoption, while teaching experience negatively influenced adoption. Gender, professional rank and age exhibited no significant associations with AI use. The study concludes that advanced academic demands promote AI uptake, whereas reliance on traditional practices may hinder experienced teachers. It recommends leveraging postgraduate programmes as centers of innovation while offering inclusive professional development that supports all teachers regardless of gender or age.

KEYWORDS

Artificial Intelligence (AI); AI use in education; teachers; predictors; gender; age; teaching experience; level of study.

INTRODUCTION

AI, an abbreviation for Artificial Intelligence, refers to computer systems that possess the ability to perform tasks typically associated with intelligent beings (Tuomi, 2018). Gocen and Aydemir (2021) define AI as the capacity of machines or computers to think and act like humans. It encompasses systems or machines that mimic human intelligence and adapt based on accumulated data (Angelov et al., 2021). Wartman and Combs (2018) elaborate on efforts to create computerized systems capable of imitating human thinking and actions. Similarly, Mohammed and Watson (2019) define AI as the skillful imitation of human behavior or cognition by tools or programmes. Dörfler (2022) defines AI as machines that can perform tasks that humans typically carry out using their cognitive abilities. Due to its pervasive influence on contemporary society, Ng (2017) likens AI to the "new electricity" of our age. Consequently, countries such as China have made substantial investments in AI, with $40 billion allocated in 2017 (Mou, 2019), leading to an expected 26% increase in the country's gross domestic product (GDP) amounting to $7 trillion by 2030. Similarly, North America is projected to experience a 14.5% increase, equivalent to $3.7 trillion, during the same period (PwC, 2017). These statistics underscore the global impact of AI on future economic growth and workforce development across nations. The integration of Artificial Intelligence (AI) in education has become a growing area of interest in recent years, with AI-powered tools increasingly being adopted to support teaching, learning, and assessment. AI applications such as intelligent tutoring systems, automated grading, adaptive learning platforms, and chatbots are gradually reshaping classroom practices worldwide. Scholars argue that AI has the potential to personalize learning, enhance instructional delivery, and reduce teachers' workload (Abbas, Khan, & Jam, 2025). In Ghana and across sub-Saharan Africa, however, the use of AI in schools is still emerging, and its effective integration depends largely on teachers' willingness, readiness, and capacity to adapt.

In Ghana, teacher education is offered through both pre-service and in-service (postgraduate) programmes (NORC, 2019). Pre-service teacher training for basic and secondary schools traditionally occurred in Colleges of Education, which provided a three-year Diploma in Basic Education (DBE) (NORC, 2019). More recently, many Colleges of Education have been upgraded and now offer degree-level teacher education, including a four-year Bachelor of Education (B.Ed) as the minimum qualification for teaching in basic schools (Oxford Business Group, 2020). For individuals who already hold a bachelor's degree but lack pedagogical training, the pathway to becoming a professional teacher often involves enrolling in a Postgraduate Diploma in Education (PGDE), such as the one offered by the University of Education, Winneba (UEW, n.d.). Additionally, for those teaching at the tertiary (higher-education) level without formal higher-education teaching credentials, UEW provides a Postgraduate Diploma in Teaching & Learning in Higher Education (PGDTLHE), designed to give lecturers the pedagogical training required for tertiary institutions (UEW, n.d.) Consequently, the "postgraduate teachers" sampled in this study are actively engaged teaching professionals, either at the primary school level upgrading their qualifications or at the high school level obtaining pedagogical credentials, rather than typical university students. This ensures that participants are well-positioned to provide meaningful insights on AI use, as they are already involved in teaching, learning, and research activities where AI integration is relevant.

Research has shown that teachers' background characteristics such as gender, age, academic qualification, teaching experience, and digital competence often shape their willingness and ability to adopt new technologies (Kwaah et al., 2022; Nyakoe et al., 2021). Several studies have investigated gender differences in AI use (Ofosu-Ampong, 2023; Iddrisu et al., 2025; Russo et al., 2025; Asio & Sardina, 2025; Tin et al., 2025; Dringó-Horváth et al., 2025; Rajki et al., 2025; Akbar, 2025; Fakuade et al., 2025). Findings are mixed. Some studies reported that men use AI tools more often, across more devices, and for advanced purposes such as data analysis and research planning (Stöhr et al., 2024; Russo et al., 2025; Rajki et al., 2025; Akbar, 2025). Others, however, found no significant gender differences in AI adoption (Iddrisu et al., 2025; Asio & Sardina, 2025; Tin et al., 2025; Fakuade et al., 2025). Dringó-Horváth et al. (2025) added that gender disparities were most pronounced in technology-related fields, with male teachers showing greater engagement than females. Research on age and AI use has yielded contrasting findings (Tin et al., 2025; Dringó-Horváth et al., 2025; Kubovics, 2025; Hamrin Reinhed & Blomgren, 2024). Some studies showed that younger people are more digitally adaptable, making them better at recognizing AI-generated content and more engaged with digital tools (Kubovics, 2025; Hamrin Reinhed & Blomgren, 2024). Ting et al. (2025), however, found a positive correlation between age and AI use, suggesting that older individuals also engage actively with AI. In contrast, Dringó-Horváth et al. (2025) found no significant relationship between age and AI adoption in higher education.

The role of teaching experience in AI adoption has been widely explored (Daly et al., 2025; Cui, 2025; Thomas et al., 2025; Hamrin Reinhed & Blomgren, 2024). Findings suggest that greater exposure to AI fosters positive attitudes, enjoyment, and stronger intentions to use (Daly et al., 2025; Cui, 2025). However, Thomas et al. (2025) discovered that less-experienced lecturers reported higher AI use than their more senior colleagues, suggesting that early-career teachers may be more open to adopting new technologies. Hamrin Reinhed and Blomgren (2024) further noted that professional experience may weaken the relationship between AI familiarity and actual engagement The influence of education level on AI use has been confirmed in several studies (Arowosegbe et al., 2024; Strzelecki & ElArabawy, 2024; Pang et al., 2024; Rajki et al., 2025; Wang et al., 2023; Akbar, 2025; Biswas & Murray, 2024). Graduate and postgraduate students tend to use AI more than undergraduates, particularly for research-related tasks such as coding, data analysis, and academic writing (Arowosegbe et al., 2024; Strzelecki & ElArabawy, 2024; Pang et al., 2024; Rajki et al., 2025; Akbar, 2025). Undergraduates, by contrast, mainly use AI to support coursework and basic learning. Biswas and Murray (2024) further found that individuals with higher education levels rely significantly more on AI-powered recommendations.

While international studies consistently highlight how demographic and professional characteristics influence AI adoption, there is little empirical evidence in Ghana. Most local studies have focused on general ICT integration rather than AI-specific adoption (Kwaah et al., 2022; Ofosu-Ampong, 2023). Some studies have examined postgraduate students' research competencies (Baidoo & Tetteh, 2024; Baidoo, 2025) and their general use of AI tools (Baidoo & Bondzie, 2025). This gap raises questions about whether global findings on the role of teacher characteristics in predicting AI use can be generalized to Ghana's unique educational context. Without Ghana-specific evidence, policymakers and stakeholders may struggle to design effective teacher training programmes, allocate resources fairly, or support AI-driven teaching and learning. Thus, this study investigates how teachers' background characteristics including gender, age, teaching experience, and level of study, predict their adoption of AI in academic work.

Theoretical Lens

This study is underpinned by the Technology Acceptance Model (TAM) and the Diffusion of Innovation (DOI) theory, which together provide a useful lens for understanding how teacher background characteristics influence AI use in academic work. The TAM, developed by Davis (1989), posits that perceived usefulness and perceived ease of use determine an individual's intention and actual use of technology. In this study, characteristics such as gender, age, teaching experience, and level of study are expected to shape teachers' perceptions of the usefulness and ease of AI tools, thereby influencing their adoption. Complementing this, Rogers' (2003) DOI theory explains how innovations spread across social systems, categorizing individuals as innovators, early adopters, early majority, late majority, or laggards depending on their readiness to adopt (Rogers et al., 2014). Teacher characteristics often determine where they fall within these categories, with younger or digitally trained teachers more likely to adopt early, while less exposed or traditionally oriented teachers may adopt later. Together, TAM and DOI allow the study to examine both the perceptual and sociological dimensions of AI use, making it possible to predict how background characteristics shape teachers' adoption and integration of AI in academic work.

Conceptual Framework

The conceptual framework in Figure 1 posits that teacher background characteristics influence the use of Artificial Intelligence (AI) in academic work, both directly and indirectly through mediating factors. The independent variables in this study are teacher background characteristics, including gender, age, professional rank, teaching experience, and level of course study. These characteristics are expected to shape teachers' perceptions and readiness toward AI adoption, which serve as mediating variables, specifically perceived usefulness, perceived ease of use, and readiness to adopt AI tools, drawing on the Technology Acceptance Model (TAM) and the Diffusion of Innovation (DOI) theory. The dependent variable is the use of AI in academic work, including applications in lesson planning, instructional delivery, assessment, and research support. The framework assumes that while teacher characteristics can directly influence AI use, their effects are also mediated by perceptual and contextual factors, providing a structured approach to understanding the predictors and patterns of AI adoption among teachers.

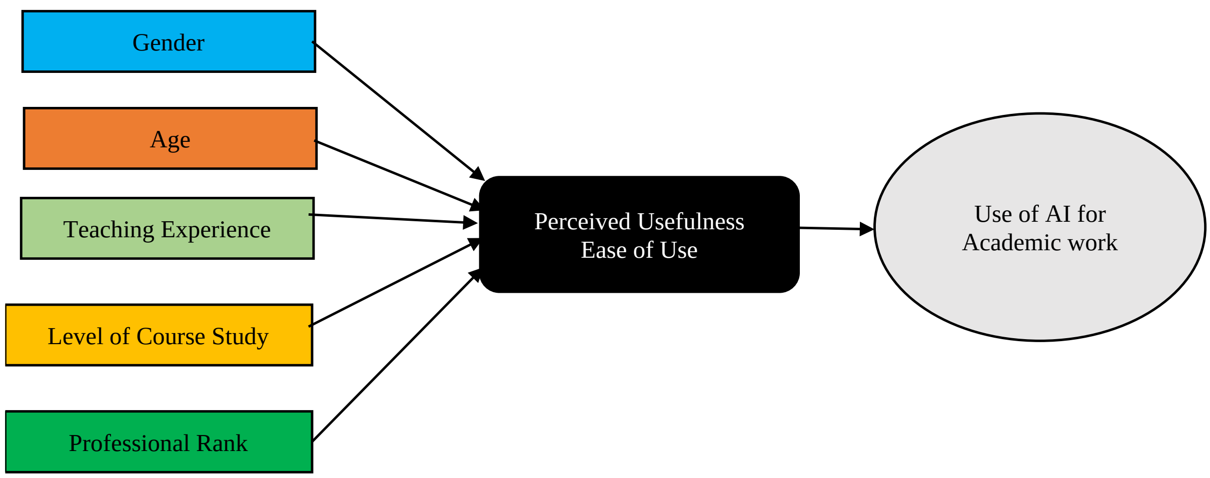

Figure 1: *Conceptual framework for Teacher Background Characteristics as Predictors of AI usage.*

RESEARCH METHODOLOGY

This study was a survey. Survey is one of the quantitative research designs. The use of survey was considered appropriate because it enables researchers to collect data from a relatively large group within a short time and to make inferences about the relationships among variables (Creswell & Creswell, 2018).

The target population comprised all postgraduate teachers at the University of Education, Winneba (UEW). In this study, postgraduate teachers refer to classroom teachers who are pursuing postgraduate-level education (master's) to enhance their teaching skills, research competencies, and professional qualifications. These teachers are actively engaged in teaching, learning, and research activities, making them particularly relevant for examining AI use in academic and instructional contexts (Bryman, 2016). A total of 104 postgraduate teachers were sampled using the convenience sampling technique, which allowed the researcher to reach participants who were readily available and willing to take part in the study (Etikan et al., 2016).

Data were gathered through a structured questionnaire, a widely used survey tool that ensures standardized responses and easy quantification of data (Fraenkel et al., 2019). The instrument consisted of two sections: demographic characteristics (gender, age, professional rank, study level and years of teaching experience), and AI use in academic work. There were nine (9) items on the uses of AI in the section B. Items were measured on a 4-point Likert scale ranging from 1 (Rarely), 2 (Sometimes), 3 (Often) to 4 (Almost Always). The questionnaire was piloted using 30 undergraduate students. After the pretesting, the reliability coefficient was computed using SPSS, yielding a Cronbach's alpha of $0.764 \geq 0.70$. This coefficient obtained met the acceptable threshold for internal consistency. According to Kensinger (2017), coefficients values above 0.7 are regarded as satisfactory, and those yielding above 0.8 as very good. Hence, the obtained coefficients of 0.764 proved that the instrument was satisfactory in collecting reliable data from the respondents. Informed consent was obtained from the postgraduate teachers before administering the questionnaire both in print and electronically via Google Forms, and participants were informed of the purpose of the study, assured of confidentiality, and reminded that participation was voluntary (Cohen, Manion, & Morrison, 2018).

The data collected were coded and analyzed using SPSS, with analysis conducted at three levels: descriptive statistics (means and standard deviations) to summarize background characteristics and AI use, correlation analysis to examine the relationships between teacher characteristics and AI use, and t-test, correlation and multiple regression analysis to determine the predictive power of teacher background characteristics on AI use. Table 1 summarizes how mean scores were interpretated. Finally, the study adhered to ethical guidelines for educational research, with respondents providing informed consent, their anonymity preserved, and their responses used solely for academic purposes (BERA, 2018).

Table 1: *Interpretation of Mean Scores*

Score Range	Remarks
1.0 – 1.4	Rarely Used
1.5 – 2.4	Sometimes Used
2.5 – 3.4	Often Used
3.5 – 4.0	Almost Always Used

RESULTS

General Characteristics of the Participants

The general characteristics of the participants included gender, age, years of teaching experience, course study level and professional rank. The results are provided on Table 2.

Table 2: *General Characteristics of the Participants*

Characteristics	Category	Number	Percentage (%)
Gender	Male	56	53.8
	Female	48	46.2
	Total	**104**	**100%**
Age	20-30 years	46	44.2
	31-40 years	41	39.4
	41-50 years	17	16.4
	Total	**104**	**100%**
Teaching Experience	Less than a year	19	18.3
	1-5 years	48	46.2
	6-10 years	30	28.8
	11-15 years	7	6.7
	Total	**104**	**100%**
Course Study Level	First year	64	61.5
	Final year	40	38.5
	Total	**104**	**100%**
Professional Rank	Snr. Sup II	38	36.5
	Snr. Sup II	11	10.6
	Principal Sup	31	29.8
	Ass. Director II	16	15.4
	Ass. Director II	8	7.7
	Total	**104**	**100%**

The data in Table 2 shows a near balance between males (53.8%) and females (46.2%), suggesting that AI adoption is unlikely to be influenced by gender differences. Most participants are between 20–40 years (83.6%), indicating a young and active teaching workforce likely to be open to innovation and ready to use AI tools. With the majority having 1–5 years of experience (46.2%), the group is predominantly early-career and more willing to experiment with AI. Most participants are first-year students (61.5%), implying that many are still in the early stages of professional training and may use AI more for exploratory learning than advanced classroom tasks. The dominance of Senior Superintendent II (36.5%) and Principal Superintendent (29.8%) shows that most hold mid-level ranks and are active classroom practitioners well-positioned to integrate AI into academic and professional work.

Assumptions Test

Before conducting the inferential test of analysis, all assumptions were checked to ensure the validity of results. Normality was first examined using the Kolmogorov-Smirnov and Shapiro-Wilk tests. The results of the Kolmogorov-Smirnov test ($D = .129$, $p = .292$) and the Shapiro-Wilk test ($W = .971$, p = .204) for the overall use of AI indicate that the data were not significantly different from a normal distribution ($p > .05$). This shows that the assumption of normality was met as shown in Table 3.

Table 3: *Tests of Normality*

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Overall use of AI	.129	104	.292	.971	104	.204

a. Lilliefors Significance Correction

Similarly, the histogram of the scores displayed a roughly bell-shaped curve, which further confirmed that the assumption of normality was met. (Figure 2) and the normal Q–Q plot (Figure 3), where the points closely followed the diagonal line.

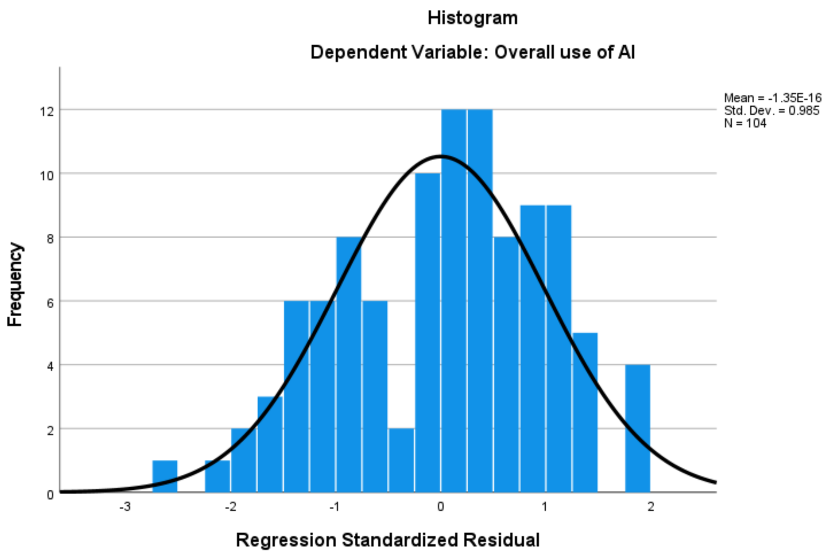

Figure 2: *Histogram*

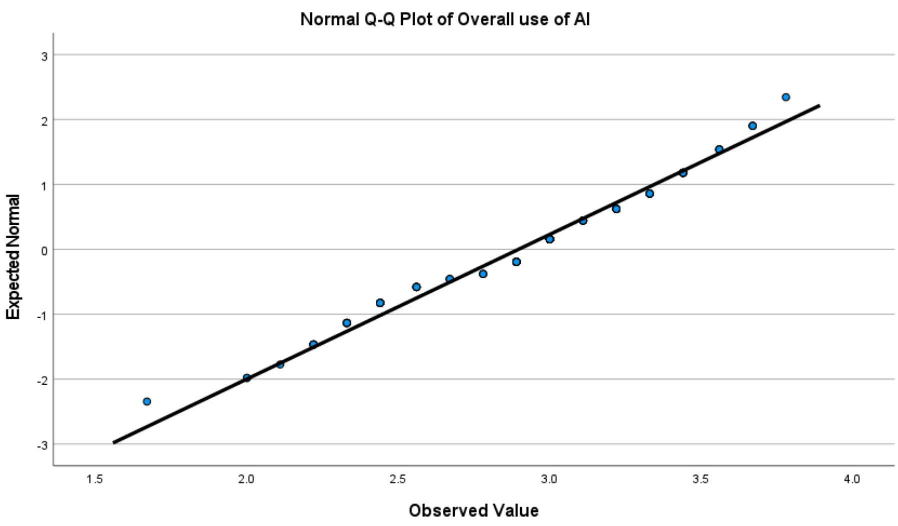

Figure 3: *Normal Q-Q Plot*

Again, linearity was assessed using scatterplots (Figure 4 and 5) of the independent variables against the dependent variable. The scatterplots showed reasonably straight-line relationships, indicating that the assumption of linearity was met.

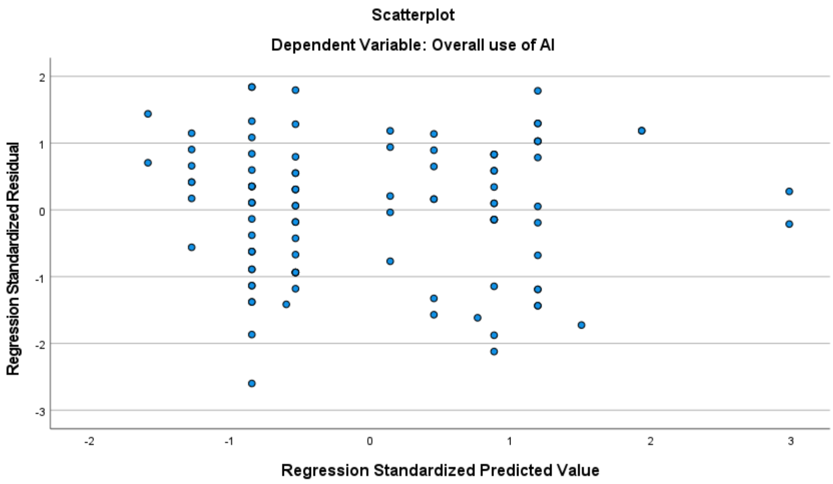

Figure 4: *Scatter Plot*

Also, homoscedasticity was checked using the scatterplot of standardized residuals against standardized predicted values (Figure 5), which showed that the residuals were spread evenly across all levels of predicted values, confirming homoscedasticity.

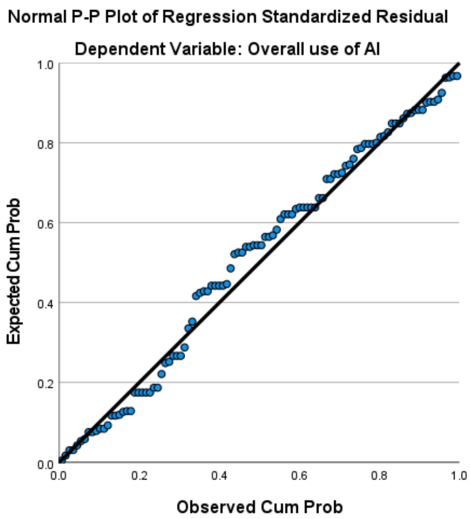

Figure 5: *Standardized Residual Q Plot*

In addition, outliers were examined using boxplots. Figure 6 showed that the data points were within acceptable ranges, with no extreme values that could unduly influence the results. This indicates that the assumption of absence of significant outliers was met.

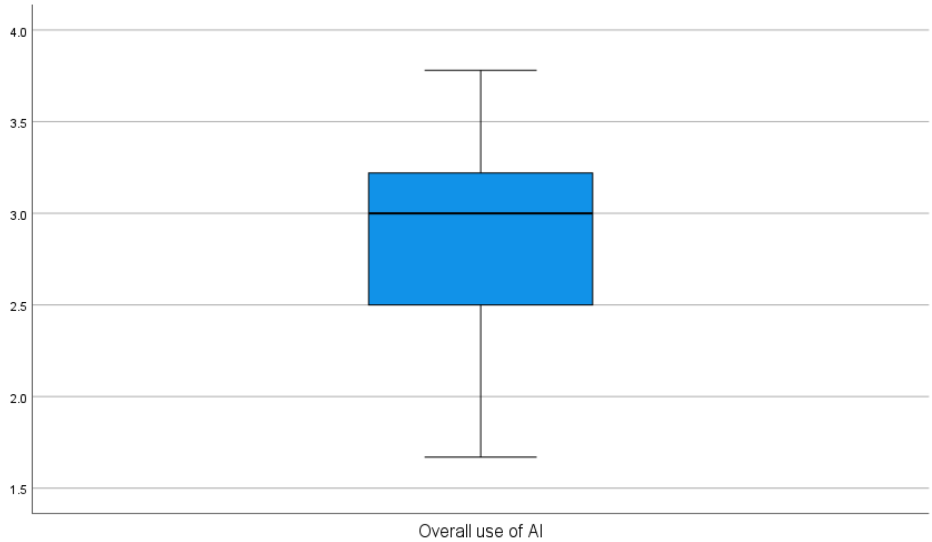

Figure 6: *Box Plot*

Furthermore, the collinearity statistics in Table 16 show that all VIF values ranged from 1.051 to 1.146, and Tolerance values were all above .87. According to common thresholds (VIF < 10 and Tolerance > .10; Field, 2018), these results indicate that multicollinearity was not a concern in the model. Therefore, each predictor variable contributed unique variance to the explanation of AI use.

Lastly, the assumption of independence of errors was tested using the Durbin-Watson statistic in Table 14. The obtained value was 1.844, which falls within the acceptable range of 1.5 to 2.5, indicating that the residuals were independent.

Research Question 1: What relationship exist between postgraduate teachers' gender and their use of AI?

This research question sought to examine whether postgraduate teachers' use of AI tools differed significantly based on gender. An independent samples t-test was conducted to compare the mean scores of male and female teachers. Table 4 presents the descriptive statistics.

Table 4: *Descriptive statistics on Gender*

Gender	Mean (M)	St. Dev (SD)	Extent of Use
Male	2.84	0.42	Often
Female	2.96	0.47	Often

The data in Table 4 shows that both male (M = 2.84, SD = 0.42) and female teachers (M = 2.96, SD = 0.47) reported using AI tools often, with females showing a slightly higher mean.

The results of the t-test analysis based on gender is presented in Table 5.

Table 5: *T-test Results Based on Gender*

Gender	N	t	df	Sig. (2-tailed	Effect Size (Cohen's d)
Males	56	-1.327	102	0.187	.447
Females	48				

The data in Table 5 showed that males (M = 2.84, SD = 0.42, *n* = 56) and females (M = 2.96, SD = 0.47, *n* = 48) did not differ significantly in their AI use, $t(102) = –1.33$, $p = .187$, Cohen's $d = 0.45$. Although the negative *t*-value indicates that females reported slightly lower use than males, the difference was small and not statistically significant. This suggests that gender is not a meaningful factor in predicting postgraduate teachers' AI use. The implication is that gender does not significantly influence the extent to which postgraduate teachers use AI tools in their academic work.

Research Question 2: To what extent does postgraduate teachers' age influence their use of AI?

The aim of this research question was to examine whether postgraduate teachers' age had any influence on their use of AI tools. Pearson correlation was used. Descriptive statistics are presented in Table 6.

Table 6: Descriptive statistics on Age

Age	N	Mean (M)	St. Dev (SD)	Extent of Use
20-30 years	46	2.87	.471	Often
31-40 years	41	2.95	.429	Often
41-50 years	17	2.88	.430	Often

Source: Field data (2025)

The data in Table 6 shows that teachers across all age groups reported using AI often, with mean scores ranging from 2.87 to 2.95. The highest average use was observed among teachers aged 31–40 years (M = 2.95, SD = 0.429).

Furthermore, the Pearson correlation analysis (Table 7) confirmed the absence of a significant relationship between age and AI use.

Table 7: *Pearson correlation analysis based on Age*

	Use of AI	
Age	Pearson Correlation	-.007
	Sig (2-tailed)	.944
	N	104

As shown in Table 7, the Pearson correlation between age and AI use was not statistically significant ($r = –.007$, $p = .944$). The *p*-value (.944) is far above the .05 threshold, confirming that age does not significantly influence postgraduate teachers' use of AI. This implies that postgraduate teachers across all age groups use AI to a similar extent, with no statistically significant differences.

Research Question 3: What influence does postgraduate teachers' experience in teaching have on their use of AI?

This research question examined whether postgraduate teachers' teaching experience influenced their use of AI tools. To address this, descriptive statistics and Pearson correlation analysis were employed. Descriptive statistics are presented in Table 8.

Table 8: *Descriptive statistics on Teaching Experience*

Teaching Experience	N	Mean (M)	St. Dev (SD)	Extent of Use
Less than a year	19	3.12	0.33	Often
1-5 years	48	2.85	0.43	Often
6-10 years	30	2.91	0.51	Often
11-15 years	7	2.54	0.34	Often

The data in Table 8 shows that Teachers with less than one year of experience reported the highest AI use (M = 3.12, SD = 0.33), while those with 11–15 years of experience reported the lowest (M = 2.54, SD = 0.34). Teachers all the categories however reported using AI often.

The results of the Pearson correlation analysis based on teaching experience is presented in Table 9.

Table 9: *Pearson correlation analysis based on teaching experience*

	Use of AI	
Teaching experience	Pearson Correlation	-.231
	Sig (2-tailed)	.018
	N	104

The results in Table 9 revealed a significant negative relationship between teaching experience and AI use, $r = -.231$, $p = .018$. The p-value (.018) is less than the .05 threshold, confirming that the relationship between teaching experience and AI use is statistically significant. The negative correlation indicates that as teaching experience increases, teachers' use of AI tends to decrease. Although all groups reported using AI often, the correlation suggests that less experienced teachers tend to use AI tools more frequently than those with longer years of teaching experience. This implies that AI adoption may be higher among younger or less experienced teachers, while more experienced teachers are less likely to integrate AI into their academic work.

Research Question 4: What is the influence of postgraduate teachers' level of study on their use of AI?

This research question investigated whether postgraduate teachers' level of study (first year or final year) influenced their use of AI tools. To address this, descriptive statistics and Pearson correlation analysis were used. Table 10 presents the descriptive results.

Table 10: *Descriptive statistics on course study level*

Course Study Level	Mean (M)	St. Dev (SD)	Extent of Use
First year	2.83	0.47	Often
Final year	3.01	0.39	Often

The data in Table 10 shows that both first-year (M = 2.83, SD = 0.47) and final-year (M = 3.01, SD = 0.39) postgraduate teachers reported using AI often. However, the mean score for final-year students was higher, suggesting greater AI use compared to first-year students.

Table 11 shows the results of the Pearson correlation analysis.

Table 11: *Pearson correlation analysis based on course study level*

	Use of AI	
Course Study Level	Pearson Correlation	.201
	Sig (2-tailed)	.040
	N	104

The results in Table 11 indicated a statistically significant positive relationship between course study level and AI use, $r = .201$, $p = .040$. The significant p-value (.040) indicates that level of study is a predictor of AI use. The positive correlation suggests that final-year students are more likely to use AI tools compared to first-year students. This finding implies that as postgraduate teachers advance in their studies, their engagement with AI tools tends to increase, possibly due to greater academic demands or familiarity with technology.

Research Question 5: What influence does professional rank have on postgraduate teachers use of AI?

This research question aimed to find out whether postgraduate teachers' professional rank influence their use of AI tools. To address this, descriptive statistics and Pearson correlation analysis were used. Table 12 presents the descriptive results.

Table 12: *Descriptive statistics on professional rank*

Professional rank	Mean (M)	St. Dev (SD)	Extent of Use
Snr Sup II	2.96	0.41	Often
Snr Sup I	2.83	0.59	Often
Principal Sup	2.86	0.42	Often
Assist Director II	2.88	0.45	Often
Assist Director I	2.89	0.51	Often

The data in Table 12 shows that Senior Superintendent II (M = 2.96, SD = 0.42) reported the highest use of AI, while Senior Superintendent I (M = 2.83, SD = 0.59) reported the lowest. However, the mean scores for all ranks (M=2.5 to 3.4) suggest that they use AI tools often.

Table 13 shows the results of the Pearson correlation analysis.

Table 13: *Pearson correlation analysis based on professional rank*

	Use of AI	
Professional rank	Pearson Correlation	-.066
	Sig (2-tailed)	. 507
	N	104

The results in Table 13 shows no significant association between teachers' rank and overall use of A, r(102) = –.07, p = .507. This indicates a very weak and negative relationship, meaning higher or lower postgraduate rank has virtually no association with how much AI is used. The p-value exceeds the .05 threshold, showing that the relationship is not statistically significant. In practical terms, this means postgraduate rank does not meaningfully influence participants' use of AI.

Research Question 6: Which background characteristics of postgraduate teachers is the most significant predictor of their use of AI tools?

This question was addressed using multiple regression analysis to determine which teacher background characteristics (age, gender, teaching experience, professional rank, and level of study) best predict AI use. Table 14 shows the model summary results.

Table 14: *Model Summary*

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	.360[a]	.130	.085	.429	.130	2.924	5	98	.017	1.844

a. Predictors: (Constant), Teaching experience, Age Category, Study level, Rank, Gender
b. Dependent Variable: Overall use of AI

The model summary in Table 14 shows that the predictors together explained 13.0% of the variance in teachers' use of AI ($R^2 = .130$, Adjusted $R^2 = .085$). The overall regression model was statistically significant, $F(5, 98) = 2.92$, p = .017, indicating that the set of predictors reliably explained variations in AI use.

Table 15: *ANOVA*

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2.694	5	.539	2.924	.017[b]
	Residual	18.057	98	.184		
	Total	20.751	103			

a. Dependent Variable: Overall use of AI
b. Predictors: (Constant), Teaching experience, Age Category, Study level, Rank, Gender

The ANOVA results in Table 15 confirm that the model as a whole was significant ($p = .017$). The individual contribution of each predictor is presented in Table 16.

Table 16: *Coefficients*

Model		Unstandardized Coefficients		Standardized Coefficients			Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Tolerance	VIF
1	(Constant)	2.635	.261		10.105	<.001		
	Study level	.236	.090	.257	2.614	.010	.922	1.084
	Rank	-.020	.031	-.064	-.640	.523	.896	1.116
	Gender	.171	.090	.191	1.893	.061	.873	1.146
	Age Category	-.004	.058	-.006	-.063	.950	.941	1.062
	Teaching experience	-.115	.052	-.212	-2.197	.030	.951	1.051

The coefficients in Table 16 indicate that level of study ($\beta = .257$, $p = .010$) and teaching experience ($\beta = -.212$, $p = .030$) were significant predictors of AI use. Specifically, higher levels of study positively predicted AI use, whereas more teaching experience negatively predicted AI use. Gender ($p = .061$), professional rank ($p = .523$), and age ($p = .950$) were not significant predictors. The analysis shows that postgraduate teachers' level of study is the strongest positive predictor of AI use, while teaching experience is a significant negative predictor. This suggests that final-year students are more inclined to use AI tools compared to first-year students, possibly due to greater academic workload and exposure. On the other hand, teachers with more years of teaching experience tend to rely less on AI, which may reflect stronger dependence on traditional methods or less openness to technological change. Other characteristics such as gender, professional rank, and age did not significantly predict AI use.

DISCUSSION

Gender and AI Use

This study found that gender is not a meaningful factor in predicting postgraduate teachers' AI use. From the perspective of the Technology Acceptance Model (TAM), this suggests that both male and female teachers perceive AI tools as equally useful and easy to use, which minimizes gender-based differences in adoption. Since TAM emphasizes perceived usefulness and perceived ease of use (Davis, 1989), the absence of gender effects implies that these perceptions are more strongly shaped by professional and academic needs rather than by gender. Similarly, the Diffusion of Innovation (DOI) theory (Rogers, 2003) highlights that adoption depends on perceived relative advantage, compatibility, complexity, trialability, and observability. In this case, the decision to use AI tools among postgraduate teachers appears driven by professional innovation needs rather than gender identity, indicating that AI adoption is normalizing across genders within academic contexts. When aligned with the literature, the finding that gender does not significantly predict AI use resonates with studies by Iddrisu et al. (2025), Asio and Sardina (2025), Tin et al. (2025), and Fakuade et al. (2025), all of which reported no meaningful gender differences in AI adoption. However, it contrasts with findings from Stöhr et al. (2024), Ofosu-Ampong (2023), Fihris et al. (2024), Russo et al. (2025), Rajki et al. (2025), and Akbar (2025), who observed that men are more frequent and diverse users of AI, particularly for advanced academic tasks such as research planning and data analysis. Dringó-Horváth et al. (2025) also noted that gender disparities were most visible in technology-oriented fields, where male teachers demonstrated greater engagement. The inconsistency across contexts suggests that gender may be a less stable predictor of AI use and that contextual variables, such as academic level, professional roles, and access to training, may play stronger roles in shaping adoption patterns. Taken together, these insights suggest that in the Ghanaian context, postgraduate teachers' adoption of AI is likely shaped more by academic and professional imperatives than by gender. Both TAM and DOI help explain why teachers across genders converge in their use of AI: they recognize its usefulness, find it manageable within their professional routines, and perceive its adoption as compatible with the demands of contemporary academic work. This finding emphasizes the need for policymakers and educational leaders to shift attention from gender-based assumptions toward structural and institutional factors, such as training, infrastructure, and digital literacy support, that may more strongly predict AI adoption among teachers.

Age and AI Use

The study found that age does not significantly influence postgraduate teachers' use of AI. From the perspective of the Technology Acceptance Model (TAM), this suggests that regardless of age, teachers evaluate AI primarily through perceived usefulness and ease of use, rather than through demographic characteristics. Similarly, the Diffusion of Innovation (DOI) theory highlights that innovation adoption is shaped more by perceived compatibility, trialability, and observability than by chronological age. Thus, while older and younger teachers may differ in exposure to digital tools, their decision to adopt AI is mediated more by its practical relevance and accessibility than by their age group. This finding aligns with Dringó-Horváth et al. (2025), who reported that age was not a determining factor in teachers' engagement with AI in Hungarian higher education. Likewise, it supports the general argument that functional benefits of AI can outweigh demographic boundaries in adoption. However, contrasting evidence exists. Ting et al. (2025) reported a positive correlation between age and AI use, suggesting that older individuals might engage with AI more strategically in academic settings. In contrast, Kubovics (2025) found that younger groups were more engaged with digital tools, reflecting higher technological literacy and comfort. Further, Hamrin Reinhed and Blomgren (2024) found a negative correlation between age and accuracy in detecting AI-generated images, showing that younger participants exhibited stronger AI-related literacy and adaptability. These mixed results underscore the need to contextualize AI use within institutional, cultural, and technological environments, as the role of age in shaping AI engagement may be more nuanced than a simple direct relationship.

Teaching Experience and AI Use

The study found a significant negative relationship between teaching experience and AI use, indicating that less-experienced postgraduate teachers are more inclined to integrate AI into their academic work than their senior counterparts. Within the Technology Acceptance Model (TAM), this can be understood as younger or less-experienced teachers perceiving AI as easier to use and more useful for enhancing productivity, while more experienced teachers may rely on established routines and feel less compelled to adopt new technologies. Similarly, the Diffusion of Innovation (DOI) theory suggests that adopters differ in their readiness for innovation; less-experienced teachers may fall into the category of early adopters or early majority, showing higher willingness to experiment with AI tools, whereas senior teachers may represent the late majority or laggards, adopting innovations only when they become unavoidable or institutionally enforced. This finding supports Thomas et al. (2025), who reported that less-experienced lecturers showed higher AI use compared to senior colleagues. It also aligns with Hamrin Reinhed and Blomgren (2024), who observed that teaching experience moderated AI adoption, with the relationship being weaker among more experienced teachers. However, contrasting results exist. Daly et al. (2025) found that the more experience individuals have with AI, the more likely they are to develop positive and trusting attitudes toward it. Similarly, Cui (2025) reported that greater experience with AI tools enhanced perceived enjoyment and intention to use, suggesting that familiarity fosters confidence. These differences highlight the dual role of experience: while professional teaching experience may reduce experimentation with AI, direct experience with AI tools themselves may strengthen positive attitudes and eventual adoption. Thus, the divergence may lie not in teaching tenure alone, but in the kind and depth of exposure to AI technologies across professional trajectories.

Level of Study and AI Use

The study found a statistically significant positive relationship between course study level and AI use, indicating that students at higher levels of study are more likely to engage with AI tools than their lower-level counterparts. Within the Technology Acceptance Model (TAM), this can be explained by the higher perceived usefulness of AI among advanced students, who often face complex research tasks and require tools for efficiency and accuracy. The Diffusion of Innovation (DOI) theory also helps to explain this pattern, as postgraduate students, driven by academic and research demands, are more likely to act as early adopters of AI innovations, recognizing their relative advantage and compatibility with scholarly work. This finding is consistent with several studies. Arowosegbe et al. (2024) and Strzelecki and ElArabawy (2024) observed that graduate students (MA and PhD) engage more with AI tools than undergraduates due to the advanced nature of their academic work. Similarly, Pang et al. (2024) and Rajki et al. (2025) reported that postgraduate students demonstrate broader awareness and greater tool use compared to those at lower levels. Akbar (2025) reinforced this by showing that postgraduate students rely heavily on AI for research-related tasks such as data analysis, coding, and writing, whereas undergraduates mainly use AI for coursework support. Wang et al. (2023) further found that seniors who perceived supportive environments and held stronger expectancy–value beliefs had higher intentions to engage with AI. Likewise, Biswas and Murray (2024) demonstrated that individuals with higher education levels exhibit greater reliance on AI-powered recommendations. Taken together, these findings suggest that study level significantly shapes AI adoption, with postgraduate students integrating AI more deeply into their academic practices, not only out of necessity but also because the technology aligns closely with the demands of advanced scholarship.

Professional Rank and AI Use

The study found no significant association between teachers' professional rank and overall use of AI, suggesting that professional rank does not meaningfully influence AI adoption among postgraduate teachers. This is consistent with research highlighting the importance of educational qualifications rather than hierarchical position. For instance, Strzelecki and ElArabawy (2024) reported that higher-level students demonstrated greater engagement with AI-driven platforms, while Pang et al. (2024) and Rajki et al. (2025) observed that individuals with advanced qualifications relied more heavily on AI for academic and professional tasks. Biswas and Murray (2024) further emphasized that those with graduate-level education showed significantly higher adoption of AI-powered recommendations. Given that the participants in this study are postgraduate teachers, their high educational qualifications likely facilitate AI adoption across ranks, making professional rank less relevant. This suggests that qualifications and academic training may have a greater influence on AI engagement than hierarchical position, consistent with the literature emphasizing the role of education level in shaping AI use.

CONCLUSION, RECOMMENDATIONS, AND FUTURE RESEARCH DIRECTIONS

The findings of this study carry several implications for AI adoption in academic work. First, the absence of gender differences in AI use implies that adoption is not shaped by gender identity. This suggests that professional development efforts of the University of Education, Winneba should be gender-inclusive, ensuring equal opportunities for all teachers without designing interventions based on gender assumptions. Similarly, the non-significant role of age indicates that generational gaps do not naturally hinder AI adoption. Instead, engagement with AI depends more on the support structures available to teachers. As such, training programmes organized by Departments and University of Education, Winneba should be open to all age groups, emphasizing practical competencies rather than relying on age-related stereotypes. Teaching experience, however, showed a negative relationship with AI use, implying that long-serving teachers may be less inclined to integrate new technologies because of reliance on established pedagogical routines. This calls for UEW to bring on board sensitization seminars that focus on experienced teachers, helping them to see AI not as a replacement but as a complementary tool that enhances existing practices.

Finally, the strong positive effect of level of study implies that advanced academic demands drive greater AI adoption, positioning postgraduate teachers as early adopters. This reflects the way complex research tasks and advanced scholarship create a natural pull towards AI use. The University of Education, Winneba and other institutions can therefore leverage postgraduate programmes as hubs for AI innovation and diffusion. At the same time, they should extend deliberate support to teachers at lower levels of study, ensuring that disparities in AI engagement are minimized and that all teachers are empowered to integrate AI meaningfully into their academic work.

Future studies could investigate how the constructs in the Technology Acceptance Model (TAM) and the Diffusion of Innovation (DOI) theory interact with teacher background characteristics to shape adoption, offering richer theoretical explanations for the patterns observed.

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