PSYCHOSOCIAL PREDICTORS OF UNDERGRADUATE STUDENTS' USE OF ARTIFICIAL INTELLIGENCE TOOLS FOR LEARNING

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Abstract

Artificial intelligence (AI) has emerged as another sthece of influence on the educational landscape, with the potential to revolutionize teaching and learning. Despite the fact that effective use of technologies is largely dependent on the user's readiness and belief on the ability to use the particular technology, little is known about how undergraduate students' online technology self-efficacy, attitude towards AI, gender and place of residence influence their use of AI for their learning particularly in developing contexts. The study employed a cross-sectional correlational research design to understand the predictive influence of these variables on the use of AI for their learning. The participants consisted of 206 (male = 12.6%; female = 87.4%) undergraduate students randomly sampled from a Federal university in Anambra State, Nigeria. Using the hierarchical regression analysis, major findings revealed that online technology self-efficacy and attitude towards the use of AI are significant predictors of students' use of AI for their learning with gender and place of primary residence having no substantial relationship with AI use for learning. Based on the findings of the study, the study concluded that undergraduate use of AI for learning could depend on the internal perceptions and beliefs of the users. Implications of the findings were highlighted.

Keywords: Artificial intelligence, attitude, learning, self-efficacy, technology

Introduction

One interesting advancements in new technologies is the development of artificial intelligence (AI) that mimics the human behavithe and reasoning. Though it could be said to be at its nascent stage, its revolutionary impact is irresistible across all known facets of the modern society. Shiohira (2021) has noted that the 'era of artificial intelligence is young but advanced in impact' (pp 3). One area of great influence of AI is on higher education. Its application in the higher education has revealed its potentiality to revolutionize teaching and learning (Tomat, 2023). For example, researchers have highlighted that the shared understanding of the merits of the adoption of AI include increasing the learning experiences and learning motivation of students and the provision of customized, adaptable and flexible learning pathways to support the learning process (Begum, 2024; Pedró, 2020). Similarly, AI has been noted to play crucial roles in equipping graduates with new skills, positively impacting teaching and learning and assessment and classification process (Slimi, 2023; Chacón, Pedró & Inzolia, 2023). Review studies have indicated that most areas of AI used in higher education include assessment/evaluation, forecasting trends in data, AI assistantship, intelligent tutoring systems, and management of students' learning (Crompton & Burke, 2023). Tomat (2023) revealed that the clusters that emerged from the review of studies conducted in the use of AI in higher institution include AI organizational research cluster, AI technology cluster and AI content related clusters. Also, it has been demonstrated that most undergraduate students adopt AI tools in learning particularly in areas that they know that they are going to be assessed (Enebechi et al., 2025).

The potentials of AI in optimizing the skillset of undergraduate students makes it crucial that factors that can either hinder or foster their engagement with AI is investigated. It appears that studies have focused on AI use and adoption by higher education institutions, with little emphasis on students, who are crucial to the diffusion of AI due to their imminent entry into the workforce as well as their prospective inventor status. AI comes with the demands of acquiring new skillsets for effective navigation of the AI landscape by students. A number of concerns, especially ethical concerns and the fact that AI has the potential of taking away available jobs from human beings, have been raised (Chacón et al., 2023; Slimi, 2023). Undoubtedly, the perceived merits and demerits of AI can potentially influence students' engagements with AI. However, given its significance on education practice, factors that unravel students' readiness and willingness to use AI for their learning must be investigated. One important area of research that has been significant in the use of and engagement with new technologies is technology self-efficacy which has been pointed out to influence perceived usefulness (PU) and ease of use of technology related platforms for effective learning (Rahman et al., 2023). Wang et al (2021) have noted that self-efficacy is related to willingness and ability to perform a particular task. Technology/computer self-efficacy is a psychological construct that is based on Bandura's social cognitive theory that emphasized that expectations about the future have consequences for the processing of new information and how individuals are likely to behave (Nabavi & Bijandi, 2011). Within the context of technology use, self-efficacy refers to one's evaluation of one's capacity to use and operate computer related technologies (Nwosu et al., 2015). Similarly, Masry-Herzallah and Watted (2024) technology self-efficacy 'reflects users' confidence in using online platforms, systems, and content' (pp.3). Technology/computer self-efficacy has been variously linked to a number of variables. Researchers have found that it is positively related to actual use of computer (Chibisa et al., 2021; Hasan, 2006); future computer skills acquisition of students (Karsten & Roth, 1998); performance expectancy (Mshali, & Al-Azawei, 2022); perceived cognitive effort and personal innovation in technology usage (Agarwal et al., 2000). Computer self-efficacy has been found to be a significant mediator in the relationship between computer anxiety and perceived ease of use (Saadé & Sira, 2009). The researchers stated that computer self-efficacy was able to reduce the strength of computer anxiety. It has demonstrated significant negative effects on computer anxiety (Azizi et al., 2022). These indicate that lower technology self-efficacy could portend a negative consequence in students' use of new technologies whereas higher technology self-efficacy could foster engagement with these technologies.

Another important research area in the use of new technologies is students' attitude to technology. This is particularly important to the use of AI due to the fact that research on public acceptance of AI indicates that people, irrespective of their social demographic characteristics, are apprehensive of the potentialities of AI (Stein et al., 2024). Similarly, Novozhilova et al (2024) found that the American populace are very uncomfortable with AI management across domains. These public perceptions are likely to impact the use of AI among undergraduate students in as much as the fact that individuals could differ in their evaluations of the benefits and demerits of AI (Stein et al., 2024). Though studies on attitude towards AI are emerging from different perspectives, Koenig (2024) has noted that a combination of perspectives/models is paramount in understanding the perceptions of AI and its use. This particularly is important considering that understanding AI attitude will enable end-users' opinions to be integrated in the development of solutions that utilize AI (Bergdahl et al., 2023). Importantly, positive attitude to AI is likely to influence the productive engagement of undergraduate students with it. Furthermore, the employment of artificial intelligence has prompted concerns about exclusivity, particularly in terms of gender and urban-rural inequality. There are worries that gender bias and disparities in restheces available to urban and rural inhabitants may exacerbate disparities in AI use. According to Olawale (2022), gender disparity has remained in the technological workforce, with women accounting for only a small percentage of the workforce. Franken et al. (2020) found that women are less interested and proficient in the use of AI. Based on the fact that female students lag behind male students in Science, Technology, Engineering and Mathematics (STEM) and the erroneous belief that STEM is more or less male cthese, researchers have also looked at gender differences in AI. For example, Ofosu-Ampong (2023) has found that gender is a determining factor in the use of AI, and that there exists significant disparity in the overall levels of perceived innovation characteristics of AI based gender. Similarly, Armutat et al. (2024) found that female students reported gender inequality and discrimination as obstacles to their use of AI. Another socio-demographic factor being currently considered in AI research is the impact it could have on urban-rural parity. AI is currently viewed as having the potentials to significantly address the educational gaps between students from rural areas and those from urban areas (Roy & Swargiary, 2024). AI is found to improve rural students' learning confidence, school enrolment and retention (Darda et al., 2024). However, little is known about how rural-urban dichotomy could predict AI use of undergraduate students especially in a developing context.

Despite the significant impact of students' psychosocial factors on AI use, there is limited research on how online technology self-efficacy, attitude towards AI, gender and primary place of residence (rural/urban residence) could individually and collectively predict undergraduate students' use of AI tools for their learning, particularly in the context of a developing country. The findings are relevant since most studies in AI are undertaken in advanced countries, with a major focus in the areas of language learning and computer engineering, and educators are not sharing their research in AI and pedagogy (Crompton & Burke, 2023). Also, Africa, for example, has been noted to be slow in adopting modern technologies (Ade-Ibijola & Okonkwo, 2023). The study, undertaken in a developing context, will help to bridge this gap by focusing on psychosocial factors that could impact on undergraduate students' use of AI for learning.

Research Questions

The following research questions guided the study:

1. Is undergraduate students' online technology self-efficacy a significant predictor of their use of AI tools for their learning?
2. Is undergraduate students' attitude towards AI a significant predictor of their use of AI tools for their learning?
3. Do undergraduate students' gender and primary place of residence individually and collectively predict their use of AI tools for learning?
4. Do the undergraduate students' psychosocial factors combine to predict their use of AI tools for learning?

Methods

The study adopted a cross-sectional research design of the quantitative paradigm. This is aimed at investigating the behavioral characteristics that were prominent in a population by sampling a cross- Delete the whole line from research to technique. 'Methods' has taken care of all that section of the population at a specific period in time (Fraenkel & Wallen, 2000; Stockemer, 2019). This enabled us to have an overall sense of the behavitheal characteristics of undergraduate students in the use of AI for their learning. The study sample consisted of 206 (male = 12.6%; female = 87.4%; mean age =21.38±15.94) undergraduate students from the Faculty of Education Nnamdi Azikiwe University, Anambra State, Nigeria. The students were randomly sampled in three classes.The socio-demographic variables of the students are presented in Table 1. Three instruments were used for data collection. The first questionnaire is the Online Technologies Self-Efficacy Scale (OTSES) developed by Miltiadou and Yu (2000). This scale was developed to measure specially perceived abilities on online environment. The psychometric properties of the scale were ascertained. Though the items could be summed together, it consists of the Internet competence (9 items focusing on the "use of application (such as Netscape or Explorer) that enabled participants to use the Internet", pp. 7), the synchronous interaction (4 items which consist of items about the use of a synchronous chat system that enable online present participants to communicate simultaneously with each other), asynchronous interaction I (9 items which comprise the "use of an electronic mail system such as Pine, Netscape Mail, or Outlook that enabled participants who were not online at the same time to communicate with other people", pp.8), and asynchronous interaction II (7 items consisting of the 'use of a newsgroup, a bulletin board, or the discussion board of a conferencing system such as CtheseInfo or FirstClass that enabled participants who were not online at the same time to post messages or reply to messages", pp. 8-9) subscales. It contains a total of 29 items. In the present study, the items were structured on the fthe-point scale of strongly agree (SA), agree (A), disagree (D) and strongly disagree (SD). The reliability indexes for this study using Cronbach Alpha coefficients are: .62, .50; .74; .80 whereas the overall coefficient is .84. The second questionnaire is the AI Attitude Scale (AIAS-4) which is a brief measure of general attitude towards AI. It was developed by Grassini (2023). It is a one-dimensional scale and confirmatory factor analysis conducted on it revealed that it demonstrated adequate fit with different samples. In the present study, it was structured based on the fthe-point scale of strongly agree (SA), agree (A), disagree (D) and strongly disagree (SD). In the current, the internal consistency reliability index using Cronbach reliability statistic is .773. The third scale is a 24-item researcher-developed questionnaire based on review literature. The questionnaire was structured based on the fthe-point scale of strongly agree (SA), agree (A), disagree (D) and strongly disagree (SD). Items targeted at understanding what students use AI tools to do in their learning activities. The responses on the items were summed together to get a score indicating the use of AI tools for the students. Higher scores indicate higher use of AI tools for learning. The internal reliability index using Cronbach Alpha statistics is .895. Section A is comprised of the socio-demographic variables of the students which is presented in table 1. The study employed the IBM Statistical Package for Social Sciences version 25 for the data analysis. Data were analyzed using bivariate analysis and hierarchical regression analysis to understand the complex data relationship. Because we hypothesized that the nature and strength of the relationship between the dependent variables and the multiple independent variables may change as we entered one variable or the other, the hierarchical regression model becomes important. This nested model enabled us have insights into the relative importance of the variables and help unpack the complex interactions therein. The basic statistical assumptions were checked. They are normality, independence of observations using the Durbin-Watson statistic; assumption of linearity using scatter plots and partial regression plots; assumption of homoscedasticity, multicollinearity through an inspection of correlation coefficients and Tolerance/VIF value. The normality test was ascertained by the inspection of the histogram and Normal P-P Plot of Standard Residuals indicating that the errors contained in the data were approximately distributed. The Normal P-P Plot of Standard Residuals showed that the points were very close to the regression line (Jeong & Jung, 2016). These are presented in Figures 1 and 2, respectively. The assumption of independent errors was also met given that the Durbin Watson test revealed a value of 2.15 which is within the acceptable range (Ho, 2013). Furthermore, multicollinearity was determined indicating that independent variables represented distinct constructs which enabled the identification of which variable influences the dependent variable. We entered the independent variables simultaneously. Tolerance values ranged from 0.665 to 0.839 while those of the VIF ranged from 1.54 to 1.197. Daoud (2017) and Senaviratna & Cooray (2019) have noted that VIF should be < 10 whereas Tolerance values should be > 0.1. Inspection of the scatter plot showed that the assumptions of linearity and homoscedasticity were met in the sense that the "residuals are randomly scattered around the zero point on the horizontal line" (Jeong & Jung, 2016, pp. 338). After testing for the relevant assumptions, bivariate and hierarchical multiple regression were adopted in the analysis. The online technology self-efficacy was decomposed according to the established sub-components (Miltiadou & Yu, 2000). The study first entered the socio-demographic variables to represent social variables, then the psychological factors consisting of the online technology self-efficacy components and attitude to AI were entered in models two and three respectively.

Results

Presented are the figures for the assumption indicating multivariate normality. Results showed that data did not violate the normality assumption.

Figure 1: *Histogram for Normality Testing*

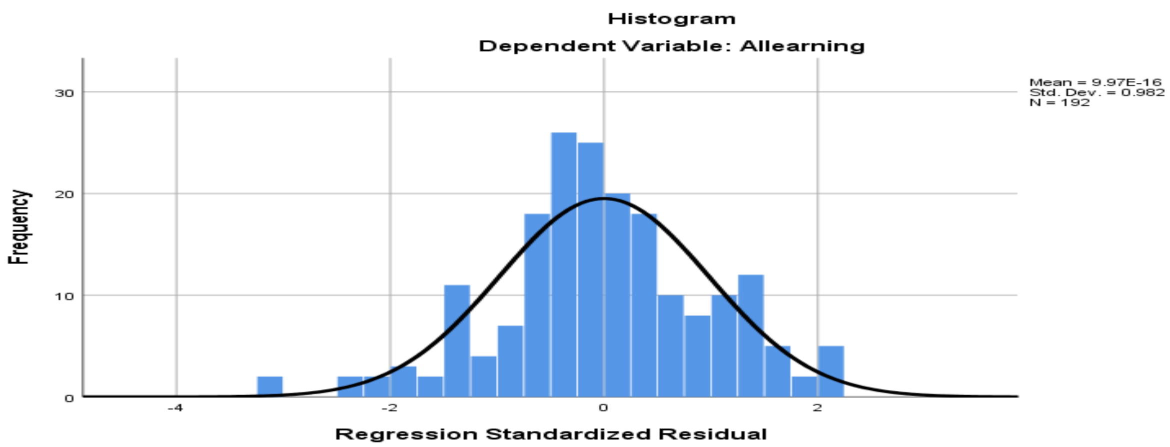

Figure 2

Normal P-P Plot of Standard Residuals for Normality Testing

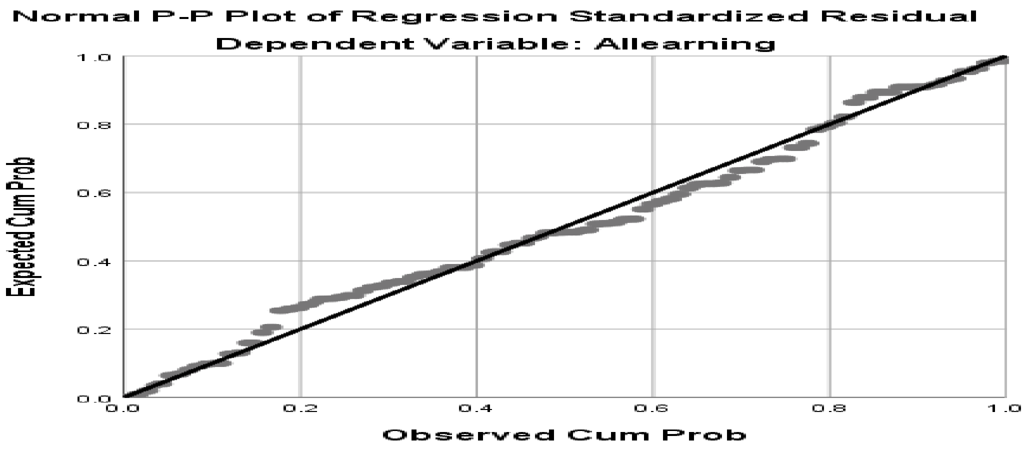

Table 1 : Socio-demographic Variables of the Respondents

S/N	Variable	Frequencies	Percentages	Mean	*SD*
1	Gender				
	Male	26	12.6		
	Female	180	87.4		
	Total	206	100.0		
2	Age Range				
3	Primary Place of Residence			21.38	15.94
	Rural	86	44.3		
	Urban	108	55.7		
	Total	194	100.0		
	Missing	12			
4	Internet Use				
	Not All	8	4.0		
	Once a Week	5	2.5		
	About Twice a Week	6	3.0		
	Almost Everyday	180	90.5		
	Total	199	100.0		
	Missing Value	7			

Table 1 revealed the socio-demographic variables of undergraduate students recruited in the study. The majority of the respondents is made up of female students with average mean age of 21.38, about 55.7% of the students have their primary place of their residence in urban areas. Regarding their internet use, the finding revealed that the majority of undergraduate students (90.5%) use the internet every day.

Table 2: Bivariate Relationships among the Predictors and the Criterion Variable

S/N	Variable	1	2	3	4	5	6	7	8	9
1	Gender	-	.136	-.209**	-.250**	-.032	.029	-.135	-.035	-.093
2	Primary Place of Residence		-	.158*	.089	-.068	-.183*	-.017	-.048	-.153*

		1	2	3	4	5	6	7	8	9
3	Internet competence sub-component			-	.339**	.367**	.342**	.744**	.294**	.274**
4	Synchronous sub-component				-	.338**	.231**	.567**	.278**	.411**
5	Asynchronous1 sub-component					-	.346**	.770**	.302**	.321**
6	Asynchronous11 sub-component						-	.705**	.221**	.398**
7	Total online Technology self-efficacy							-	.383**	.478**
8	Ai attitude								-	.573**
9	AI learning									-
	Skewness	-	-	-.11	.10	-.38	.05	.23	-77	.02
	Kurtosis	-	-	.16	-.20	.09	-.57	.10	.45	-.32
	Mean	-	-	26.28	11.74	26.156	20.07	84.24	13.41	72.23
	SD	-	-	4.11	2.16	4.53	3.99	10.58	2.26	11.62

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

Table 2 shows the relationships among the variables. Students' primary place of residence, internet competence, synchronous interaction, asynchronous interaction I, asynchronous interaction II, total online technology self-efficacy and attitude towards AI had significant relationships with their use of AI for learning. Only students' gender did not show significant relationship with the use of AI for learning, r = -.093, p > .05.

Table 3
Predictive Values of the Predictors on Students' Use of AI for Learning

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant) R^2 = .032; F = 3.121; p = .046	82.792	5.082		16.290	.000
	Gender	-2.939	2.480	-.086	-1.185	.237
	Primary Place of Residence	-3.450	1.706	-.146	-2.022	.045
2	(Constant) R^2 = .283, ΔR^2 = .251; F = 12.179, p = .000	32.433	8.020		4.044	.000
	Gender	.283	2.335	.008	.121	.904
	Primary Place of Residence	-3.471	1.605	-.147	-2.163	.032
	Internet competence	.200	.211	.071	.948	.344
	Synchronous Interaction	1.606	.377	.302	4.260	.000
	Asynchronous Interaction 1	.283	.184	.111	1.540	.125

	Asynchronous Interaction 11	.648	.215	.220	3.012	.003
3	(Constant) R^2 = .456, ΔR^2 = .172; F = 21.994, p = .000	18.583	7.239		2.567	.011
	Gender	-.507	2.043	-.015	-.248	.804
	Primary Place of Residence	-2.663	1.406	-.113	-1.894	.060
	Internet competence	-.034	.187	-.012	-.179	.858
	Synchronous Interaction	1.212	.333	.228	3.634	.000
	Asynchronous Interaction 1	.109	.162	.043	.674	.501
	Asynchronous Interaction 11	.561	.188	.190	2.976	.003
	Ai Attitude	2.330	.305	.453	7.633	.000

a. Dependent Variable: AI Use for Learning
b. Predictors in the Model: (Constant), Primary Place of Residence, Gender
c. Predictors in the Model: (Constant), Primary Place of Residence, Gender, Asynchronous Interaction 1, Asynchronous Interaction 11, Synchronous Interaction, Internet Competence
d. Predictors in the Model: (Constant), Primary Place of Residence, Gender, Asynchronous Interaction 1, Asynchronous Interaction 11, Synchronous Interaction, Internet Competence, AI Attitude

Table 3 showed that undergraduate students' online technology self-efficacy and attitude had positive significant associations with their use of AI for learning. We first entered students' gender and primary place of residence representing the social factors as predictors in model 1. This model was statistically significant, F (2, 191) = 3.121; $P < 0.05$. Gender did not make significant individual contribution to the model (β = -.086; p = .237) whereas students' place of primary residence made significant individual contribution to the model (β = -.146; p = .045). This accounted for 14.6% of the variances in students' use of AI for their learning. Also, model 2 was statistically significant, F (6, 191) = 12.179; $P < 0.05$ after entering the dimensions of their online technology self-efficacy in the model as a predictor. While gender remained a non-significant predictor, students' primary place of residence also remained a significant predictor of students' use of AI for their learning.

Model 2 revealed the individual contributions of the dimensions of online technology self-efficacy. Internet competence and asynchronous interaction I sub-dimensions of the online technology self-efficacy did not make significant individual contributions to the model, (β = .071; p = .344; β = .111; p = .125) respectively. On the other hand, the synchronous interaction and asynchronous interaction II of the sub-dimensions the online technology self-efficacy made individual contributions to the model (β = .302; p = .000; β = .220; p = .003) respectively. These accounted, respectively, 30.2% and 22% variances in students' responses to the use of AI tools for learning, and the synchronous interaction as a best predictor in the model. The addition of the online technology self-efficacy factor explained additional 25.1% variance in the use of AI for the learning (ΔR^2 = .251; F = 12.179, p = .000). However, the total online technology self-efficacy which is the composite score for all the dimensions was automatically excluded by the SPSS algorithm indicating possible co-linearity with the dimensions in the model. Table 4 shows evidence of this exclusion.

Finally, entering attitude towards AI in model 3, the total variance explained by the model was 45.6% (F (7, 191) = 21.994; P = .000). It explained additional 17.2% of variance in the use of AI for their learning, after controlling for socio-demographic variables and the online technology self-efficacy (ΔR2 = .172; *F* (7, 191) = 21.994, *p* = .000). In the final adjusted model only students' synchronous (β = .228; *p* = .000), asynchronous interaction II (β = .190; *p* = .000), and attitude towards the use of AI (β = .453; *p* = .000) was statistically associated with their use of AI in their learning, and accounted for about 22.8%, 19% and 45.3% respectively of the variances. It also revealed that students' attitude towards of AI is the best predictor of AI use for learning in the model.

Table 4: *Excluded Variable in Models 2 and 3*

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics Tolerance
1	Internet competence	.296[b]	4.132	.000	.289	.918
	Synchronous Interaction	.425[b]	6.218	.000	.413	.916
	Asynchronous Interaction 1	.319[b]	4.692	.000	.324	.994
	Asynchronous Interaction 11	.374[b]	5.502	.000	.372	.961
	Total online technology self-efficacy	.463[b]	7.210	.000	.465	.978
	AI Attitude	.568[b]	9.654	.000	.576	.996
2	Total online technology self-efficacy	.[c]	.	.	.	.000
	Ai Attitude	.453[c]	7.633	.000	.490	.839
3	Total online technology self-efficacy	.[d]	.	.	.	.000

Table 4 revealed a potential co-linearity between total online technology self-efficacy and its components indicating that it contributed absolutely no new information to the model that wasn't already in the model. Hence, it was automatically removed from the models by SPSS algorithm. The tolerance value showed that it is > 0.1. This was undetected in the earlier general multiple regression analysis in which all predictor variables were added in one model.

Discussion

The study aimed to understand how undergraduate students' psychosocial factors –gender, primary place of residence, online technology self-efficacy and attitude towards AI - could predict their use of AI for their learning. This was informed by the fact that, notwithstanding the concerns regarding the use of AI, its impact is rapidly being felt across all facets of human endeavor and demands that university students who are to be future innovators are trained with requisite skills that will ensure productivity especially in developing contexts. The findings showed that students' primary place of residence, internet competence, synchronous interaction, asynchronous interaction I, asynchronous interaction II, total online technology self-efficacy and attitude towards AI had significant relationships with their use of AI for learning. Only students' gender did not show significant relationship with the use of AI for learning using Pearson Product Moment

Correlation. Model 1 in the regression analysis showed that gender and students' place of primary residence combined to make significant contributions to the variances in the use of AI for learning. Examined individually, gender was not a predictor of students' use of AI for learning whereas their place of primary residence was a significant predictor of AI use for learning. This indicates that among the respondents, there is no significant variances in responses accounted for by gender. This contradicts similar studies that have found gender a significant determinant to students' use of AI in higher education (Ofosu-Ampong, 2023; Stöhr et al., 2024). These studies demonstrated that male students were more likely to use AI than their female counterparts. Consistently, literature have pointed out significant gender differences in all facets of technology use in both developing and developed countries (Hossain et al, 2023; Ofosu-Ampong 2023). This is due to the fact that male students may be more skilled at using technology than female students, which could have a substantial impact on the use of artificial intelligence for learning. However, the findings were contrary to this, demonstrating that if male and female students have almost equal online technology self-efficacy and attitudes toward AI, there may be no difference in their use of AI for learning. The findings also demonstrated a strong negative correlation between undergraduate students' primary place of residence and their use of AI. The primary place of residence included both urban and rural areas. Urban areas were coded as 2, and rural areas as 1. Based on this result, students from rural areas use AI for learning more than their counterparts from rural areas. Though little is known about the comparative use of AI by rural and urban students, what has been severally documented in literature is the possibility of AI in enhancing the education of students in rural and urban areas (Darda et al., 2024, Roy & Swargiary, 2024). The findings, while contradicting the fact that technological tools are typically more prevalent in urban areas, which may influence their use and competence, could imply that when rural students are given equal opportunities, they are more likely to outperform those from rural areas in the use of AI for learning.

The addition of the online technology self-efficacy in model 2 improved the model significantly. These factors explained additional 25.1% variance in the use of AI for the learning confirming the critical role students' online technology self-efficacy could play in students' use of AI tools for their learning. Researchers have emphasized the importance of self-efficacy in different technological landscapes (Author et al., 2015; Downey & Kher, 2015) noting that technology-related self-efficacy could influence self-directed learning with technology (Sumuer, 2018). The use of AI tools could be driven by students' capacities to see new opportunities which could be enhanced by the beliefs on the capabilities to navigate the online environments. There is the possibility that those who see themselves as having the capacity to navigate the online technology environment could be audacious to explore the plethora of AI tools and their uses for learning. Examining the dimensions of online technology self-efficacy in the model revealed that Internet competence and asynchronous interaction I sub-dimensions of the online technology self-efficacy did not make significant individual contributions to the model even though they had significant relationships with AI use for learning in the bivariate analysis whereas the synchronous interaction and asynchronous interaction II of the sub-dimensions the online technology self-efficacy made individual contributions to the model. This finding has shown that components of online technology self-efficacy could have differential impacts on AI use for learning among undergraduate students. It does appear that beliefs on more complex abilities as seen in the synchronous interaction sub-component and the asynchronous interaction II could be more related to AI use than beliefs on their capabilities to handle more familiar technology environments. This finding could be explained in the light of studies that have found that individuals who use such real-time and asynchronous communication platforms as Twitter have been found to have positive attitude to AI tools such as ChatGPT (Li et al., 2023). Similarly, among teachers, high digital competence has been found to be related to high willingness to use AI (Galindo-Domínguez et al., 2024).

The final model revealed that the addition of attitude towards AI explained additional 17.2% in the model indicating that attitude towards AI is significantly and positively related to students' AI use for learning. Because studies are few demonstrating how attitude towards AI could relate to undergraduate students' use of AI for their learning, we found it difficult to relate these findings to previous literature. However, recent studies have demonstrated the importance of AI attitude to AI use particularly with regards to concerns on AI (Bergdahl et al., 2023, Novozhilova et al., 2024, Stein et al., 2024). Currently, studies show that students' attitude towards AI is increasingly becoming positive (Ajlouni, et al., 2023), and consequently, similar studies show that use of AI is related to acceptance of AI (Acosta-Enriquez et al., 2024; Kashive et al., 2021). The impact of attitude toward AI on its use for learning may have emerged from students' recognition of the benefits of AI technologies in their learning. AI technologies are presently employed for a variety of learning goals, including resthece sthecing, language editing, mathematical problem solving, and so on. Moreover, the final model indicated that synchronous interactions, asynchronous interaction II and attitude towards AI were the only significant predictors of undergraduate students' AI use for learning with attitude being the best predictor. This shows that when attitude was entered into the model, students' primary place of residence became non-significant indicating a possible interaction. It could mean that irrespective of place of residence, the higher the students' attitude towards AI, the higher their use of AI for learning.

The study have made significant theoretical and practical contributions to the field of AI and learning in the study. Theoretically, we have looked at how students' psychosocial factors could influence their use of AI tools for learning. The study is the first to explore how students' gender, place of primary residence, online technology self-efficacy and attitude towards AI are associated with their use of AI tools for learning. This is imperative given that there is the concern that AI could exacerbate inequality when it is not well managed especially among genders and rural-urban populations. On the other hand, use of technologies are dependent on users' beliefs and convictions, undergraduate students' attitude and online technology self-efficacy become significant to understand their use of AI. The findings demonstrated further, the likely differential impact of the dimensions of online technology self-efficacy on students' use of AI for learning implying that some dimensions may not necessarily be important factors influencing students' use of AI. Also, the adoption of hierarchical regression showed the factors that may be more important in influencing students' use of AI for learning as well as the interactions that exist among them. For example, when attitude was entered in the model, students' primary place of residence that was initially significant the models 1 and 2 became non-significant.

Practically, the study indicates that for the improvement of students' use of AI for their learning, intervention programmes could be mounted for undergraduate students targeted at improving their attitudes and their technology self-efficacy. Regarding attitude, the concerns about AI could be objectively handled and students taught the best way to use AI tools and ways to make the best out of them. There are a number of concerns about AI including taking away people's job (Li et al., 2023) and other conspiracy theories. These must be targeted and students told that AI could make their works easier and a new dimension of skillset would arise from the emergence of AI. More so, for the fact that technology self-efficacy is positively and significantly related to AI use for learning, students' technology skills and competence must be a target of improvement given that advanced skills in digital technology could be a sthece of their self-efficacy (Ibrahim & Aldawsari, 2023). Emphasis should be laid on improving students' digital competencies so as to enhance their confidence in exploring the AI technological landscape. More importantly, is the finding that shows that relative importance of these factors. This indicates that equal importance may not be accorded to these factors in intervention programmes that could facilitate students' use of AI in their learning endeavor. Stakeholders should first address students' attitude and then their beliefs on their capabilities in exploring the digital world through improving their digital competences.

Conclusion

The study findings have demonstrated that students' attitude and their online technology self-efficacy are critical factors in determining the use of AI for learning. We decomposed the online technology self-efficacy into its factors, and findings revealed that they have differential impacts on students' use of AI. Besides, the significant association between students' place of primary residence and their use of AI became non-existent once attitude of students was entered into the model indicating that irrespective of place of residence, the higher students' attitude towards AI, the higher their use of AI for learning. Hence, we concluded that undergraduate students' use of AI for learning could depend on the internal perceptions and beliefs of the users, and intervention programmes to advance undergraduate students' AI use must be tailored to address their attitude and beliefs on the abilities to navigate online technological landscapes especially in synchronous interactions.

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