International Journal of Learning, Teaching and Educational Research
Vol. 24, No. 6, pp. 251-272, June 2025
https://doi.org/10.26803/ijlter.24.6.12
Received Apr 21, 2025; Revised May 22, 2025; Accepted May 28, 2025

Assessment of Artificial Intelligence (AI) Proficiency and its Demographic Dynamics among Open Distance Learning (ODL) Students in Nigeria

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Abstract. This study assessed AI proficiency vis-à-vis AI literacy, self-efficacy, and self-competency, and its demographic dynamics among ODL students in Nigeria. Social Cognitive Theory served as the conceptual foundation for the study. The study adopted a quantitative approach, and the participants of the study consisted of students chosen from a purposively selected ODL institution (University of Ibadan Distance Learning Centre). The rationale is because they have similar characteristics to other ODL institutions in the country. 301 students selected using a convenience sampling technique participated in the study. A structured questionnaire consisting of demographic information and 29 items adapted to measure AI Proficiency indicators served as the data collection instrument for the study. The items were anchored on a 4 point Likert scale from not at all =1, to a great extent =4. Participation in the study was through an online survey. The data generated from the study were analysed using descriptive statistics (frequency counts, percentages, mean, and standard deviation) and inferential statistics (multiple linear regression analysis, Pearson correlation, T-test, ANOVA, and MANOVA). Results of the study revealed that while the majority of ODL students exhibited high AI literacy, slightly above half of them had low AI self-efficacy. However, most ODL students reported a high level

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of AI self-competence. Similarly, the study found AI literacy and AI self-efficacy jointly predict ODL students’ AI self-competency. However, AI self-efficacy is the prominent factor. Further, the result revealed that males exhibited significantly higher AI literacy than females. Moreover, the study established that ODL students’ AI proficiency is shaped by intersectional demographic factors. Combined factors (age and programme level; marital status and employment status; and employment status and programme level) influence the AI proficiency of ODL students more than single demographics. It is recommended, amongst others, that ODL institutions and policymakers implement targeted interventions based on the identified factors to prepare ODL students for AI-driven learning in the country.

Keywords: Artificial Intelligence Proficiency; AI Literacy; AI self-efficacy; AI self-competency; Demographic Factors in AI Education; Nigerian ODL Students' AI Proficiency.

1. Introduction

In the fast-evolving world of technology, artificial intelligence (AI) has become a revolutionary force, influencing diverse sectors profoundly (Asio, 2024). AI was first defined as the science and engineering of making intelligent machines (McCarthy, 2007). Its definition was broadened to include machines that can perform cognitive tasks especially, learning and problem-solving (Wang, 2019). In whatever way AI is seen, it is an intelligent machine that can mimic human intelligence by reasoning and adapting based on rules and environments (McCarthy, 2007). It affects many facets of human life and has spread across industries (Ng et al., 2021). Its impact on education cannot be overemphasized. AI has reshaped how learning is delivered, accessed, and experienced (Onesi-Ozigagun et al., 2024).

According to Chen et al. (2020), the integration of AI in educational systems worldwide has enhanced learners’ experience and overall quality by automating administrative functions, customizing curriculum, and enhancing their learning outcomes. With AI playing an ever-growing role in daily activities, individuals, particularly open and distance learning students, must gain a thorough understanding of its effects and possibilities (Asio, 2024). However, the extent to which students can harness these benefits depends largely on their proficiency in AI, encompassing their literacy, self-efficacy, and self-competence (Ng et al., 2021; Chiu, 2024).

The concept of AI literacy goes beyond familiarity with AI terminology or comprehension of AI systems (Asio, 2024). It is the ability to recognize, grasp, use, and critically assess AI technologies and their impacts (Jones, 2024). According to Lindauer (2024), AI literacy encompasses the knowledge and skills required to effectively and ethically evaluate, interpret, and apply AI tools, fostering informed participation in a technology-driven world. Since everyday living now includes an array of AI-related activities, AI literacy becomes important for individuals as they navigate the real-world impact of AI (Gomstyn & Jonker, 2025). According to Almatrafi et al. (2024), AI literacy enables people to make better decisions for themselves and their communities. For individuals, AI literacy provides the necessary knowledge and skills to engage with AI systems; enables them to evaluate AI technologies and information they provide critically, and fosters the ability to communicate and collaborate effectively with AI.

For communities, a more AI-literate population can contribute to informed discussions and decision-making regarding the societal implications of AI (Almatrafi et al., 2024). Essentially, AI literacy serves as a fundamental skill for the 21st Century. It prepares students for a future where AI is ubiquitous in personal and professional lives (Walter, 2024). Nevertheless, Du et al. (2024) indicated that people lack AI literacy, thus, preventing them from fully utilizing AI in educational settings. Similarly, Ng et al. (2021) suggested that acquiring AI literacy does not necessarily translate to having the confidence (self-efficacy) to apply it in practical scenarios.

However, Bewersdorff et al. (2024) found AI literacy to influence students' AI self-efficacy.AI self-efficacy refers to an individual's belief in their ability to effectively interact with and use AI technologies and products (Wang & Chuang, 2023). It encompasses individual's confidence in their competence to utilize AI to achieve specific tasks and goals (Morales-García et al., 2025). This includes not only the technical handling of AI-based tools but also the capacity to integrate these tools for problem-solving, adapting to changes, and overcoming difficulties through innovative AI use (Morales-García et al., 2024). Several factors influence AI self-efficacy, particularly among students. These factors include prior experience with technology and perceptions of its usefulness, AI literacy, technical skills, social influence, and levels of anxiety and concerns related to AI's impact (Wang, 2019; Zhang & Xu, 2024; Asio & Suero, 2024).

AI self-competency on the other hand, encompasses a broader set of skills, including problem-solving, decision-making, and adaptability in AI-driven environments (Asio, 2024). According to Asio and Suero (2024), AI self-competency refers to individuals' view of their overall capabilities and performance in various disciplines. It reflects how people perceive their general proficiency in using AI effectively (Asio & Suero, 2024). While AI self-efficacy is task-specific, AI self-competency emphasizes working with AI across different areas. Carolus et al. (2023) suggested that individuals with a stronger belief in their specific AI task abilities have a higher view of their overall AI competency.

Despite the growing body of research on AI in education, there exists a critical gap in understanding the AI proficiency levels among higher education students in Nigeria, particularly in the ODL context. ODL plays a critical role in expanding access to higher education in the country (Itasanmi, 2022). However, there is a persistence of digital divides and infrastructural challenges (Igboeli & Bisallah, 2021). Existing research (Mansoor et al., 2024; Bergdahl & Sjöberg, 2025) highlights disparities in AI literacy and self-efficacy, with studies indicating that possessing AI literacy does not always translate into confidence in using AI (Ng et al., 2021). Equally, demographic factors (age, gender, marital status, employment status, and programme level) may shape AI proficiency. However, findings remain inconsistent across different contexts. For instance, while studies (Mai et al., 2024; Favorito et al., 2024; Zhong and Liu, 2025) reported gender differences in AI literacy, Samngamjan et al. (2024) found no gender difference.

Furthermore, employed students may have greater exposure to AI applications, potentially enhancing their AI self-competence. Whereas, married or older learners might face time constraints or technological anxiety (Mariano et al., 2021). Moreover, intersectional identities, such as being married, employed students, or older learners at higher levels of the educational programme, may further complicate the demographic dynamics. This, thus, highlights the need for empirical research that will examine how these dynamics manifest especially in resource-constrained settings.

This study aims to bridge this gap by assessing AI Proficiency vis-à-vis AI literacy, self-efficacy, and self-competence and its demographic dynamics among ODL students in Nigeria. This is done to gain insight and provide evidence on AI proficiency level and the relationship among the AI proficiency indicators as well as how demographic factors influence them. This can guide policymakers and educators in developing targeted interventions to enhance AI proficiency among ODL students and ensure equitable access to AI-driven educational opportunities.

Specifically, this study aims to examine the impact of AI literacy and AI self-efficacy on AI self-competency and identify if differences exist in AI proficiency indicators based on five demographic characteristics (age, gender, marital status, employment status, and programme level). Equally, the study answers the question: do age, gender, marital status, employment status, and programme level interactively influence AI proficiency indicators? By answering these questions, this study will add to the discourse on AI proficiency and other associated factors, and serve as a reference point for future studies.

1.1 Theoretical Framework: Social Cognitive Theory (SCT)

The Social Cognitive Theory (SCT) evolved from the Social Learning Theory (SLT), which was initially developed by Albert Bandura in the 1960s (LaMorte, 2022). Bandura further refined and introduced SCT in 1986, emphasizing that learning occurs within a social context through a dynamic and reciprocal interaction between the individual, their environment, and their behaviour (Bandura, 1986; Schunk & DiBenedetto, 2020).

A distinctive aspect of SCT is its emphasis on social influence, encompassing both external and internal social reinforcement (Bandura, 1988). The theory explores how individuals acquire and maintain behaviours, taking into account the social environment in which these behaviours occur (Bandura, 2001). Additionally, SCT incorporates the role of past experiences, which influence an individual's expectations, beliefs about outcomes, and the likelihood of performing a behaviour. These experiences shape the reinforcements and motivations behind engaging in specific actions (LaMorte, 2022).

SCT seeks to explain how individuals regulate their actions through self-control and reinforcement, fostering sustained, goal-oriented behaviours (Schunk & DiBenedetto, 2020). According to Krcmar (2019), SCT is built on six key components that collectively explain how people learn and manage their behaviour within a social context.

1. Reciprocal Determinism: This foundational concept of SCT highlights the continuous, bidirectional interaction between the individual (with their learned experiences), the environment (social and external context), and behaviour (responses to stimuli aimed at achieving goals) (Phipps et al., 2013).
2. Behavioural Capability: This refers to an individual's knowledge and skills required to perform a specific behaviour. Successful execution depends on understanding what to do and how to do it. Additionally, learning from the consequences of one's actions can influence and shape their environment (Boston University, 2019).
3. Observational Learning: This principle suggests that individuals can learn by observing and imitating the behaviours of others, a process often referred to as modelling. When people witness others successfully performing a behaviour, they are more likely to believe in their ability to replicate it (Krcmar, 2019).
4. Reinforcements: These are internal or external responses that follow a behaviour and determine the likelihood of its repetition. Reinforcements can originate from within the individual or from the environment and may be positive or negative. This concept underscores the reciprocal relationship between behaviour and the environment.
5. Expectations: This component involves the anticipated outcomes of a behaviour, which may or may not be related to health. Individuals weigh the potential consequences of their actions before engaging in them. These expectations (often shaped by past experiences) play a critical role in determining whether the behaviour is performed (Schunk & Usher, 2012).
6. Self-Efficacy: This is a unique and central concept in SCT, and refers to an individual’s confidence in their ability to successfully perform a behaviour. While other theories have adopted this idea, SCT emphasizes that self-efficacy is influenced by personal abilities, specific characteristics, and environmental factors (Islam et al., 2023).

SCT has been used as a theoretical framework in different fields, contexts, and populations (Ratten & Ratten, 2007; Middleton et al., 2018; Graf et al., 2020; Almogren & Aljammaz, 2022). It has also helped researchers to determine the drivers of AI adoption (Kim & Lee, 2024; Lin et al., 2024; Bognár et al., 2024; Shata & Hartley, 2025). SCT is particularly relevant to this study because it provides a robust framework to understand ODL students’ AI proficiency based on the exploration of the triadic relationship between AI literacy, AI self-efficacy, and AI self-competency and how they are influenced by the students’ demographic factors. This aligns with reciprocal determinism, a core concept of SCT that emphasizes bidirectional interaction between behaviour, as well as personal and environmental factors. For instance, ODL students with high AI literacy can have their AI self-efficacy boosted which can enhance their AI self-competence. These triadic interactions can be further shaped by age, gender, marital status, programme level, and employment status of the students.

Specifically, assessing the AI literacy of the students which reflects their knowledge and skills required to understand and use AI aligns with the behavioural capability construct of the SCT. Similarly, assessing the AI self-efficacy and AI self-competency of the students aligns with the self-efficacy components of SCT. It is believed that how students will perceive their AI self-efficacy and AI self-competency may be influenced by mastery experiences, vicarious experiences, and social persuasion as emphasized by SCT (Lee & Bong, 2023).

2. Methodology

Research design

This study adopted a quantitative approach to provide insights into ODL students' AI proficiency levels and demographic dynamics. This method is considered appropriate as it provides the opportunity to collect numerical data that allow for the systematic quantification of the variables under consideration. This can generalize the research findings easily to a broader population.

Population and sampling technique

The population of the study consisted of students who enrolled in ODL mode of educational delivery in Nigeria. However, the target population of the study comprises students enrolled in programmes offered by the University of Ibadan Distance Learning Centre (UI-DLC). UI-DLC was purposively selected for the study based on having similar characteristics to other ODL institutions in the country. This is aside from the fact that UI-DLC is one of the oldest distance-learning institutions in Nigeria. Findings from UI-DLC could have significant policy implications for ODL in the country. The study participants were selected using a convenience sampling technique.

Instrument

The study utilized a structured questionnaire consisting of demographic information (age, sex, marital status, employment status, and programme level) and items adapted from Carolus et al. (2023) to measure AI Proficiency indicators (AI literacy (18 items), AI self-efficacy (6 items), and AI self-competence (5 items). The questionnaire was anchored on a 4 point Likert scale of not at all =1, to a great extent =4. It was pilot-tested among twenty (20) students from the National Open University of Nigeria (NOUN) Ibadan Study Centre. Cronbach's alpha values of 0.97, 0.94, and 0.91 were obtained for AI literacy, AI self-efficacy, and AI self-competence, respectively. This indicates that the items within each dimension consistently measure the intended constructs. The excellent internal consistency across dimensions shows that the questionnaire is a reliable tool for evaluating AI proficiency indicators among respondents.

Data collection

Approval to conduct the study was obtained from the Department of Adult Education, University of Ibadan, and the management of UI-DLC before the study was conducted. Participants participated in the study through the online questionnaire designed on ArcGIS Survey123. The questionnaire link was sent to the student's institutional mail by a staff of UI-DLC. In the mail containing the link to the online questionnaire, the researchers provided clear information about the study, its objectives, their rights, and the confidentiality of the information provided to the students. Data collection spans six weeks, running from 23 February to 5 April 2024.A total of 301 ODL students participated in the study.

Data analysis
The data generated from the study were analysed using descriptive statistics (frequency counts, percentages, mean, and standard deviation) and inferential statistics (multiple linear regression analysis, Pearson correlation, T-test, One-Way Analysis of Variance (ANOVA), and Multivariate Analysis of Variance (MANOVA)). The level of AI proficiency indicators (AI literacy, AI self-efficacy, and AI self-competency) of the students was determined using the sum of the scores of the items in each section divided by the maximum score obtained and multiplied by 100. A score <60% is taken to be low while a score of ¬60% is taken as high. A p-value of <0.05 was considered statistically significant.

3. Result

Socio-demographic characteristics

The respondents' socio-demographic characteristics are presented in Table 1. The age distribution of the respondents shows that most students (52.8%) are between 16 and25 years old. The sample is gender-balanced, with 49.8% males and 50.2% females. Regarding marital status, most students (66.4%) are single. A relatively small percentage of the students (1.3%) are divorced, separated, or widowed. The employment status of students shows that 42.9% are self-employed, 34.9% are employed, and 22.3% are unemployed. The programme level distribution for students indicates that 30.2% are in 100L, 15.6% in 200L, 13.6% in 300L, 11.9% in 400L, 28.6% in 500L, and 3.3% in other programs.

In summary, the population sample is predominantly young, evenly distributed by sex, mostly single, and engaged in various employment statuses and programme levels.

Table 1: Socio-demographic characteristics of the respondents

Age	16-20	82	27.2
	21-25	77	25.6
	26-30	31	10.3
	31-35	2	0.7
	36-40	50	16.6
	41-45	23	7.6

	46-50	4	1.3
	51-55	21	7.0
	56-60	10	3.3
	60 & above	1	0.3
Sex	Male	150	49.8
	Female	151	50.2
Marital Status	Single	200	66.4
	Married	97	32.2
	Divorced/Separated/Widowed	4	1.3
Employment Status	Employed	105	34.9
	Unemployed	67	22.3
	Self-Employed	129	42.9
Programme Level	100L	91	30.2
	200L	47	15.6
	300L	41	13.6
	400L	36	11.9
	500L	86	28.6

AI proficiency level

Table 2 shows that the majority of the ODL students (60.1%) have a high level of AI literacy while 39.9% have low AI literacy. It was also indicated that slightly above half of the ODL students (50.8%) have low AI self-efficacy levels while 49.2% have high AI self-efficacy levels. Results revealed that the majority (60.5%) of the ODL students have high AI self-competency levels while 39.5% of them have low AI self-competency levels.

Table 2: AI Proficiency Indicators Levels (AI Literacy, AI Self-Efficacy, And AI self-competency)

Variables	Subcategory	Frequency	Percentage (%)
AI Literacy	Low Level	120	39.9
	High Level	181	60.1
AI Self Efficacy	Low Level	153	50.8
	High Level	148	49.2
AI Self-Competency	Low Level	119	39.5
	High Level	182	60.5

Impact of AI literacy and AI self-efficacy on AI self-competency
Table 3 shows the individual and joint impact of AI literacy and AI self-efficacy on ODL students' AI competency skills. The regression model explained approximately 46.8% of the variance in AI Self-Competency scores, as indicated by an R^2 value of 0.468, with an adjusted R^2 of 0.465. The overall regression model was statistically significant, with an F-statistic of 131.141 and a p-value of 0.000. This indicates that both independent variables significantly predict AI Self-Competency scores.

Furthermore, AI Self-Efficacy was found to be a significant predictor, with a coefficient of 0.466 ($p = 0.000$), indicating that higher levels of AI Self-Efficacy are associated with increased AI Self-Competency scores. Similarly, AI Literacy also emerged as a significant predictor, with a coefficient of 0.220 ($p = 0.007$), suggesting that higher levels of AI Literacy contribute to higher AI Self-Competency skills among the students.

Table 3: Regression Analysis Result

Variables	β	Std. Error	p-value
(Constant)	20.675	2.697	0.000
AI Self-Efficacy	0.466	0.084	0.000
AI Self-Competence	0.220	0.081	0.007
R^2= 0.468, F(2,298)=131.141, P-value = 0.000			

Relationships among the AI proficiency indicators
Table 4 shows the relationships among the AI proficiency indicators (AI Literacy, AI Self-Efficacy, and AI Self-Competence). The results show a statistically significant positive association among AI proficiency indicators. It was revealed that there exists a strong positive association between AI Literacy and AI Self-Efficacy ($r = 0.868$, $p < 0.01$). Moreover, a positive association was identified between AI Literacy and AI Self-Competence ($r = 0.642$, $p < 0.01$). In addition, a significant positive association was established between AI Self-Efficacy and AI Self-Competence ($r = 0.675$, $p < 0.01$).

Table 4: Bivariate correlation

Variables	1	2	3
AI Literacy	1		
AI Self-Efficacy	0.868**	1	
AI Self-Competence	0.642**	0.675**	1

Demographic factors influencing AI proficiency indicators

Table 5 presents the influence of the socio-demographic factors on AI proficiency indicators (AI Literacy, AI Self-Efficacy, and AI Self-Competence). Significant differences were observed in AI Literacy (t = 2.847, p = 0.045), where males (mean = 2.81) exhibited higher AI literacy compared to females (mean = 2.57). This indicates that gender influences AI literacy among ODL students. While males have higher AI self-efficacy and AI self-competency mean scores than females, the difference is however not significant. Using One-Way ANOVA, the age group of the students does not significantly influence their AI literacy level, AI self-efficacy, and AI self-competence. Also, marital status, employment status, and the programme level of students do not significantly influence their AI proficiency indicators.

The MANOVA Pillai's Trace test results shown in Table 6 indicate that there exist no significant effects of age (Pillai's Trace = 0.193, F = 1.289, p = 0.152), gender (Pillai's Trace = 0.024, F = 1.380, p = 0.251), marital status (Pillai's Trace = 0.033, F = 0.938, p = 0.468), employment status (Pillai's Trace = 0.055, F = 1.589, p = 0.149), and programme level (Pillai's Trace = 0.100, F = 1.166, p = 0.295) on overall AI proficiency of the ODL students.

However, the interaction between age and programme level (Pillai's Trace = 0.381, F = 1.366, p = 0.048), interaction between marital status and employment status, (Pillai's Trace = 0.048, F = 2.798, p = 0.042), and interaction between employment status and programme level (Pillai's Trace = 0.261, F = 2.013, p = 0.003) significantly influence overall AI proficiency. These results suggest that a combined influence of demographic factors predicts ODL students' overall AI proficiency. A follow-up univariate ANOVA was further computed and the results are presented in Table 7.

Table 7 reveals that while age, sex, marital status, and programme level do not individually influence AI literacy, the interaction between age and level (F = 1.864, p = 0.022), the interaction between employment status and programme level (F = 2.960, p = 0.004) and the three-way interaction between age, sex and employment status significantly influence ODL students' AI literacy. Also, Table 7 reveals that while age, sex, marital status, and programme level do not individually influence AI self-efficacy, the interaction between age, sex, and employment status significantly influences AI self-efficacy. Lastly, out of the demographic factors, only employment status has a significant main influence on ODL students' AI self-competence (F = 3.413, p = 0.035). Also, the interaction between marital status and employment status significantly influences students' AI self-competence.

Table 5: AI proficiency indicators based on socio-demographic factors

	AI Literacy			AI Self-Efficacy			AI Self-Competence		
Variables	**Mean (SD)**	**t**	**P-value**	**Mean (SD)**	**t**	**P-value**	**Mean (SD)**	**t**	**P-value**
Gender									
Male	2.81 (0.70)	2.847	0.045	2.71 (0.79)	1.983	0.478	2.92 (0.77)	0.459	0.061
Female	2.57 (0.79)			2.52 (0.82)			2.87 (0.86)		
		F	**P-value**		**F**	**P-value**		**F**	**P-value**
Age (Years)									
16-20	2.72 (0.76)	1.278	0.248	2.60 (0.77)	0.875	0.548	2.93 (0.76)	1.205	0.292
21-25	2.78 (0.75)			2.73 (0.84)			2.91 (0.88)		
26-30	2.90 (0.73)			2.81 (0.82)			3.14 (0.68)		
31-35	1.72 (0.39)			2.25 (0.35)			2.90 (0.71)		
36-40	2.58 (0.81)			2.52 (0.88)			2.75 (0.92)		
41-45	2.56 (0.67)			2.33 (0.70)			2.68 (0.79)		
46-50	2.25 (0.63)			2.46 (0.52)			3.45 (0.55)		
51-55	2.70 (0.73)			2.66 (0.80)			2.81 (0.65)		
56-60	2.40 (0.78)			2.45 (0.76)			2.70 (0.88)		
60 & above	2.44 (0.00)			2.50 (0.00)			4.00 (0.00)		
Marital Status									
Single	2.73 (0.75)	1.062	0.347	2.64 (0.79)	0.571	0.566	2.92 (0.80)	0.904	0.406
Married	2.60 (0.76)			2.55 (0.85)			2.82 (0.86)		
Divorced/Separated/Widowed	2.81 (0.86)			2.83 (0.85)			3.25 (0.53)		
Employment Status									
Employed	2.73 (0.75)	1.111	0.330	2.65 (0.80)	1.296	0.275	2.96 (0.75)	2.855	0.059
Unemployed	2.57 (0.87)			2.48 (0.91)			2.69 (0.85)		
Self-Employed	2.72 (0.69)			2.66 (0.75)			2.95 (0.83)		
Programme Level									
100L	2.72 (0.74)	0.299	0.913	2.65 (0.81)	0.264	0.933	3.04 (0.74)	1.519	1.184
200L	2.63 (0.80)			2.55 (0.87)			2.90 (0.82)		
300L	2.73 (0.70)			2.68 (0.72)			2.91 (0.75)		
400L	2.74 (0.81)			2.65 (0.74)			2.93 (0.80)		
500L	2.64 (0.76)			2.56 (0.84)			2.71 (0.89)		
Others	2.84 (0.83)			2.72 (0.82)			2.98 (0.88)		

Table 6: Multivariate Effect of Demographic Factors on Overall AI Proficiency Indicators

Effect	Pillai's Trace	F	df	Error df	Sig.
Age	0.193	1.289	27	507	0.152
Sex	0.024	1.380	3	167	0.251
Marital Status	0.033	0.938	6	336	0.468
Employment Status	0.055	1.589	6	336	0.149
Programme Level	0.100	1.166	15	507	0.295
Age * Sex	0.116	1.132	18	507	0.316
Age * Employment Status	0.120	0.879	24	507	0.632
Age * Level	0.381	1.366	54	507	0.048
Marital Status * Employment	0.048	2.798	3	167	0.042
Employment Status * Level	0.261	2.013	24	507	0.003
Age * Sex * Employment Status	0.081	1.567	9	507	0.122

Table 7: Univariate effect of Age, Sex, Marital Status, and Level

Source	Dependent Variable	Type III Sum of Squares	Df	Mean Square	F	Sig.
Age	AI Literacy	3001.417	9	333.491	1.378	0.202
	AI Self Efficacy	1194.014	9	132.668	.516	0.862
	AI Self Competency	2162.366	9	240.263	.905	0.522
Sex	AI Literacy	455.272	1	455.272	1.881	0.172
	AI Self Efficacy	37.181	1	37.181	.145	0.704
	AI Self Competency	71.553	1	71.553	.270	0.604
Marital Status	AI Literacy	812.156	2	406.078	1.677	0.190
	AI Self Efficacy	1188.852	2	594.426	2.312	0.102
	AI Self Competency	972.594	2	486.297	1.832	0.163
Employment Status	AI Literacy	1399.136	2	699.568	2.890	0.058
	AI Self Efficacy	748.908	2	374.454	1.457	0.236
	AI Self Competency	1812.391	2	906.196	3.413	0.035
Level	AI Literacy	1188.163	5	237.633	.982	0.431
	AI Self Efficacy	693.405	5	138.681	.540	0.746
	AI Self Competency	1557.065	5	311.413	1.173	0.325
Age * Sex	AI Literacy	1804.486	6	300.748	1.242	0.287
	AI Self Efficacy	1605.008	6	267.501	1.041	0.401
	AI Self Competency	1694.699	6	282.450	1.064	0.386

Age * Marital Status	AI Literacy	1410.725	4	352.681	1.457	0.218
	AI Self Efficacy	1128.505	4	282.126	1.098	0.360
	AI Self Competency	1822.684	4	455.671	1.716	0.149
Age * Employment Status	AI Literacy	2163.162	8	270.395	1.117	0.354
	AI Self Efficacy	2792.086	8	349.011	1.358	0.219
	AI Self Competency	1190.956	8	148.870	.561	0.809
Age * Level	AI Literacy	8122.717	18	451.262	1.864	0.022
	AI Self Efficacy	6230.799	18	346.156	1.347	0.165
	AI Self Competency	6486.129	18	360.341	1.357	0.159
Sex * Marital Status	AI Literacy	209.750	1	209.750	.866	0.353
	AI Self Efficacy	606.492	1	606.492	2.359	0.126
	AI Self Competency	56.231	1	56.231	.212	0.646
Sex * Employment Status	AI Literacy	1045.685	2	522.843	2.160	0.119
	AI Self Efficacy	974.141	2	487.071	1.895	0.154
	AI Self Competency	651.808	2	325.904	1.228	0.296
Sex * Level	AI Literacy	813.312	4	203.328	.840	0.502
	AI Self Efficacy	881.213	4	220.303	.857	0.491
	AI Self Competency	973.566	4	243.392	.917	0.456
Marital Status * Employment Status	AI Literacy	98.605	1	98.605	.407	0.524
	AI Self Efficacy	779.711	1	779.711	3.033	0.083
	AI Self Competency	1231.868	1	1231.868	4.640	0.033
Marital Status * Level	AI Literacy	2517.040	5	503.408	2.079	0.070
	AI Self Efficacy	2637.702	5	527.540	2.052	0.074
	AI Self Competency	823.541	5	164.708	.620	0.684
Employment Status * Level	AI Literacy	5732.309	8	716.539	2.960	0.004
	AI Self Efficacy	1848.928	8	231.116	.899	0.519
	AI Self Competency	3467.532	8	433.441	1.633	0.119
Age * Sex * Marital Status	AI Literacy	.000	0	.	.	.
	AI Self Efficacy	.000	0	.	.	.
	AI Self Competency	.000	0	.	.	.
Age * Sex * Employment Status	AI Literacy	2963.891	3	987.964	4.081	.008
	AI Self Efficacy	2137.798	3	712.599	2.772	.043
	AI Self Competency	1472.314	3	490.771	1.849	.140
Age * Sex * Level	AI Literacy	1368.344	3	456.115	1.884	.134
	AI Self Efficacy	1361.549	3	453.850	1.766	.156
	AI Self Competency	1794.185	3	598.062	2.253	.084
Age * Marital Status * Employment Status	AI Literacy	11.160	1	11.160	.046	.830
	AI Self Efficacy	136.544	1	136.544	.531	.467
	AI Self Competency	21.412	1	21.412	.081	.777
Age * Marital Status * Level	AI Literacy	47.297	1	47.297	.195	.659
	AI Self Efficacy	3.304	1	3.304	.013	.910
	AI Self Competency	176.595	1	176.595	.665	.416
Age * Employment Status * Level	AI Literacy	983.817	4	245.954	1.016	.401
	AI Self Efficacy	1081.619	4	270.405	1.052	.382
	AI Self Competency	1117.177	4	279.294	1.052	.382
Sex * Marital Status * Employment Status	AI Literacy	117.251	1	117.251	.484	.487
	AI Self Efficacy	92.392	1	92.392	.359	.550
	AI Self Competency	74.123	1	74.123	.279	.598
Sex * Marital Status * Level	AI Literacy	358.117	1	358.117	1.479	.226
	AI Self Efficacy	68.299	1	68.299	.266	.607
	AI Self Competency	265.126	1	265.126	.999	.319

Sex * Employment Status * Level	AI Literacy	823.230	3	274.410	1.133	.337
	AI Self Efficacy	415.712	3	138.571	.539	.656
	AI Self Competency	399.135	3	133.045	.501	.682
Marital Status * Employment Status * Level	AI Literacy	239.760	1	239.760	.990	.321
	AI Self Efficacy	16.381	1	16.381	.064	.801
	AI Self Competency	9.759	1	9.759	.037	.848
Error	AI Literacy	40913.729	169	242.093		
	AI Self Efficacy	43442.131	169	257.054		
	AI Self Competency	44867.785	169	265.490		
Total	AI Literacy	1332673.641	301			
	AI Self Efficacy	1053408.083	301			
	AI Self Competency	1214252.000	301			

4. Discussion

The main objective of this study was to assess ODL students' AI proficiency based on their AI literacy, AI self-efficacy, and AI self-competency and how these are influenced by demographic factors. The results of this study indicate that while the majority of ODL students exhibited high AI literacy, slightly above half of them have low AI self-efficacy. This result suggests that there exists a gap between ODL students' knowledge of AI and their confidence to effectively use it.

This result reechoes the assertion made by Ng et al. (2021), that possessing technical knowledge of AI does not always translate to confidence in using it. AI self-efficacy may be undermined by the fear of complexity or ethical concerns regarding AI (Ng et al., 2021). Since self-efficacy stems from mastery experiences, vicarious learning, and emotional state (Lee & Bong, 2023), low AI self-efficacy among ODL students despite high AI literacy might not be unconnected from their lack of hands-on AI practice or peer role models due to low integration of AI in ODL delivery in Nigeria (Olojede & Olakulehin, 2024).

Studies (Bewersdorff et al., 2024; Canonigo, 2024; Guo et al., 2024) have suggested that practical use of AI and peers serving as role models have the potential to enhance students' confidence in using AI effectively. The results also revealed that most ODL students reported a high level of AI self-competence. This result contradicts the findings of a similar study (Sadykova & Kayumova, 2025) that found the majority of educators to have average AI competency skills.

However, the difference in findings might be due to the measurement scale and different contexts in which the study was conducted. The study demonstrates that AI literacy and AI self-efficacy jointly predict ODL students' AI self-competency. This result is consistent with similar research findings (Chen et al., 2022; Chen et al., 2024; Chiu et al., 2024). According to Ng et al. (2021), individuals with a better understanding of AI and confidence in their AI abilities will have a greater belief in their capacity to perform AI-related tasks. This result lends credence to SCT which emphasizes that competency is shaped by knowledge (literacy) and confidence (self-efficacy).

However, the result indicates that between AI literacy and AI self-efficacy, AI self-efficacy is a stronger predictor of ODL students' AI self-competency skills. In other words, AI self-competency among ODL students is more closely tied to confidence than knowledge. This result implies that while AI literacy is important, possessing it alone is not sufficient for students to feel competent in engaging in AI-related tasks. AI literacy must therefore be paired with applied practice to translate into self-competency (Ng et al., 2021; Chiu, 2024). This aligns with the United Nations Educational, Scientific, and Cultural Organization (UNESCO) advocacy for human-centric AI education that prioritizes empowerment alongside literacy (UNESCO, 2021).

The results also revealed strong, statistically significant positive associations among the three AI proficiency indicators (AI literacy, AI self-efficacy, and AI self-competency). This result aligns with the SCT's reciprocal determinism where knowledge (AI literacy), beliefs (AI self-efficacy), and perceived ability (AI competence) dynamically influence each other (Bautista, 2012). Firstly, it was established that a very high correlation exists between AI literacy and AI self-efficacy. This suggests that ODL students who possess high AI literacy also tend to have greater self-efficacy in using AI. This result supports the SCT assumption that knowledge acquisition influences self-efficacy through mastery experiences.

That is, skill development and confidence grow in tandem (Ng et al., 2021; Lee & Bong, 2023). Secondly, a positive association exists between AI literacy and AI self-competence. This result suggests that ODL students with higher AI literacy report greater perceived AI competence. However, this association is weaker than with self-efficacy. This indicates that while AI literacy provides foundation knowledge, competence in AI-related tasks requires applied practice (UNESCO, 2021). Further, it was indicated that a positive, significant association exists between AI self-efficacy and AI self-competence. This suggests that ODL students' AI self-efficacy strongly influences their perceived AI competence. According to Khan and Iqbal (2015), when students feel efficacious, they see themselves as more capable of handling difficult tasks and succeeding. Thus, the higher the students' AI self-efficacy, the greater their perceived ability to engage in AI-related tasks.

On the demographic factors influencing AI proficiency indicators among ODL students, the result revealed that males exhibited significantly higher AI literacy than females. This result is consistent with the findings of Mai et al. (2024), Favorito et al. (2024), and Zhong and Liu, (2025). However, the result is inconsistent with the findings of Samngamjan et al. (2024), who found no gender difference in AI literacy among students. This study found no gender differences in ODL students' AI self-efficacy and AI self-competence. This suggests that once female ODL students acquire AI literacy, their confidence and perceived AI competency 'level up'. This result contrasts with the study of Young et al. (2023), that have consistently indicated gender gaps in AI self-efficacy and competence.

Also, the study found no significant individual effects of age, marital status, employment status, and programme level on AI proficiency indicators. This result contradicts the traditional stereotype often associated with new technology usage. It is usually believed that older learners, working or married students struggle with new technologies, especially AI (Mariano et al., 2021; Hampel & Kunze, 2023). The researchers believe that due to the flexible nature of ODL that allows self-paced learning through technology, demographic disparities in AI proficiency may have been mitigated.

Results further revealed a combined interaction effect of age and programme level on ODL students' AI proficiency. This result suggests that the effect of age on the overall AI proficiency of ODL students varies based on the student's programme level. Similarly, there exists an interaction effect of marital status and employment status on students' AI proficiency indicators. This result indicates that the combined interaction effects of marital status and employment status influence ODL students' overall AI proficiency. Likewise, the interaction between employment status and programme level was significant. This implies that employment status and programme level jointly influence overall AI proficiency among ODL students.

It could be deduced from these results that ODL students' AI proficiency is largely determined by intersectional identities (Keyes et al., 2021). Employed students in an advanced stage of the ODL programme may leverage workplace AI exposure while married employed students may face time constraints but also have applied AI needs. Thus, understanding students' AI proficiency based on demographic factors should go beyond considering individual factors. Rather, the interplay between multiple demographic factors should be considered to gain insight into how they influence overall AI proficiency.

Lastly, the results found employment status as the only main predictor of AI self-competence among the ODL students. This result lends credence to the practical exposure hypothesis that emphasizes individuals develop greater confidence in their abilities when they have more hands-on, real-world experiences with a particular skill or technology (Bandura, 1997; Kolb, 2015). The researchers believe that employed ODL students are more likely to have regular exposure to AI tools and workplace training which might reinforce their AI perceived competency. Unlike unemployed or self-employed students who may have less structured exposure to AI applications, leading to lower self-assessed AI competency. This result is consistent with studies (Van Dijk, 2017; Lee et al., 2024) that observe a close association between employment status and better technology access.

4.1 Implications of the study

As Education 5.0 gains traction and AI integration in education become more prevalent (Osiesi & Blignaut, 2025), understanding students' AI proficiency and demographic factors that influence it is crucial for ODL institutions, policymakers, educators, and stakeholders. This study's findings have the potential to inform policy actions that can effectively harness and integrate AI into course delivery to enhance learning outcomes among ODL students. Specifically, the study highlights the multidimensionality of AI proficiency among ODL students and how AI literacy does not guarantee confidence or true competency in AI-related tasks.

This, therefore, underscores the need for pedagogical strategies that are grounded in SCT to bridge the gap. Additionally, insight from the demographic factors influencing AI proficiency among the students offers perspectives for enhancing inclusive digital education that prioritizes equity in the AI era. ODL institutions can provide targeted support that addresses individual and intersectional AI needs of students, especially women and married employed students.

5. Conclusion and recommendations

This study assessed ODL AI proficiency vis-à-vis AI literacy, AI self-efficacy, and AI self-competence and how these are influenced by their demographic factors. The findings of the study revealed that while the majority of ODL students exhibited high AI literacy, slightly above half of them had low AI self-efficacy. However, most ODL students reported a high level of AI self-competence. It is recommended that targeted interventions should be given to the students. For example, for students with low AI literacy, foundational AI modules should be incorporated into their learning courses and scaffolding AI tasks should be given to those with low AI self-efficacy. This will close the AI knowledge gap and build AI confidence in the ODL students.

Similarly, the study found AI literacy and AI self-efficacy to jointly predict ODL students' AI self-competency. However, AI self-efficacy is the prominent factor. ODL institutions must adopt dual-focused strategies (enhancing students' technical skills and psychological readiness) to prepare students for AI-driven learning. Also, the study established a positive association among the AI proficiency indicators (AI literacy, AI self-efficacy, and AI self-competence). To foster true AI competence in ODL students, the institution must go beyond AI training that emphasizes skills acquisition only. ODL institutions must adopt holistic pedagogies that build students' AI knowledge, confidence, and real-world application.

Further, the result revealed that males exhibited significantly higher AI literacy than females. However, the study found no gender differences in ODL students' AI self-efficacy and AI self-competence. The ODL institution must provide targeted support for female learners. This could come in the form of gender-inclusive pedagogy that could mitigate stereotype threat.

Moreover, the study established that ODL students' AI proficiency is shaped by intersectional demographical factors. Combined factors (age and programme level; marital status and employment status; and employment status and programme level) influence the AI proficiency of ODL students more than single demographics. It is recommended that ODL institutions should adopt differentiated strategies that account for learners' multifaceted identities.

This could help move beyond the 'one-size-fits-all' AI education approach that pays less attention to equity in the AI era. Lastly, employment status significantly predicts ODL students' AI self-competency. Therefore, ODL institutions should strategically harness this to enhance AI learning among the students. This can be done through work-integrated learning partnerships with key players in the industry, peer knowledge sharing, or using employed students as peer mentors.

5.1 Limitations of the study

This study may not have accurately captured the subjective and contextual experiences of the sampled ODL students due to its cross-sectional and descriptive nature. Also, the sampled population may not be representative of the total population. Equally, self-report bias and deliberate purposive selection of an ODL institution among Nigeria's numerous ODL institutions may have affected the study's results, conclusions, and applicability to other ODL contexts. Further, the researchers believe that the data collection method (online questionnaire) and time constraints may have influenced the study's results and conclusions.

6. Suggestions for further studies

The researchers advise that further studies use different research methodologies, such as mixed methods or qualitative approaches to explore the study's subject matter in greater detail to obtain deeper insights. Also, the researchers propose that future studies should use performance-based instruments, and the study should involve a larger population cutting across different ODL institutions in the country. Further, research in the future might explore moderators like prior AI exposure or course delivery mode on the relationships among the AI proficiency indicators. Moreover, future studies should employ longitudinal analysis to track how AI literacy and efficacy interact over time. Lastly, intersectional frameworks explaining how combined demographics influence AI adoption could also be explored by future studies.

7. Acknowledgments

The authors appreciate Mrs. Elizabeth Mojisola Ogunmoye and Dr. Bamidele Stephen Omoyajowo for their assistance during the data collection phase of this study.

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