Discover Computing

RESEARCH

Open Access

Evidence from West Africa on the interplay of affective behavioral cognitive and ethical dimensions of AI literacy in Ghanaian and Nigerian Universities

Muhammad Zaheer Asghar[1*], Kwasi Agyemang Duah[1], Javed Iqbal[2] and Hanna Järvenoja[1]

*Correspondence:
Muhammad Zaheer Asghar
Muhammad.asghar@oulu.fi
[1]Learning and Educational Technology Research Lab (LET), Learning and Learning Processes Research Unit, Faculty of Education and Psychology, University of Oulu, P.O. BOX 8000, 90014 Oulu, Finland
[2]School of English Studies, Zhejiang International Studies University, Hangzhou 310023, Zhejiang, China

Abstract
This study addresses the need for context-specific Artificial Intelligence (AI) literacy research in West Africa, confronting challenges such as interrelation of AI literacy dimensions, ethical concerns, and a scarcity of localized studies. It investigates AI literacy among university students in Ghana and Nigeria through a quantitative cross-sectional survey of 427 participants (n = 206 Ghana, n = 221 Nigeria). The investigation focuses on four interconnected dimensions from the ABCE framework: Affective (motivation, self-efficacy), representing emotional engagement with AI; Behavioral (collaboration, intentional use), reflecting active participation in AI-related tasks; Cognitive (knowledge, critical thinking), encompassing understanding and application of AI concepts; and Ethical, pertaining to awareness and commitment to AI's societal implications. Using partial least squares structural equation modeling (PLS-SEM), findings confirm that affective factors positively influence cognitive outcomes, mediated by behavioral engagement and ethical understanding. Notably, country differences do not significantly affect these relationships, thereby justifying the analysis of the combined dataset and highlighting shared patterns in AI literacy development across the two contexts. This consistency validates a common underlying mechanism for AI literacy development in these West African contexts. The study shows the importance of integrating technical AI skills with ethical principles, collaborative learning, and culturally appropriate strategies. Specifically, it offers actionable strategies for strengthening affective learning, designing collaborative behavioral interventions, embedding ethical reasoning into curricula, and contextualizing pedagogies for regional realities, thereby informing stakeholders on effective AI education in West Africa.

Keywords Affective, Africa, Artificial intelligence, Behavioral, Cognitive, Ethical literacy, Higher education students

1 Introduction

The integration of Artificial Intelligence (AI) into education has emerged as a transformative force globally, offering solutions to systemic challenges such as personalized learning, equitable access, and pedagogical efficiency. In West Africa, where education emphasizes communal values, practical learning, and cultural relevance, AI presents unique opportunities to address socioeconomic disparities and bridge urban–rural divides [13, 14, 68]. Ghanaian and Nigerian universities in Western Africa are pioneering AI-driven tools—such as adaptive learning platforms, multilingual chatbots, and virtual teaching assistants—to enhance educational outcomes. For instance, KNUSTbot and SuaCode's bilingual assistant have demonstrated improved student engagement and critical thinking in Ghana and Nigeria, respectively [19, 36].

However, while AI holds promise, its implementation in Africa is hindered by infrastructural constraints, ethical concerns, and a paucity of context-specific research on AI literacy [72, 79]. Quantifying the extent of these challenges, such as limited infrastructure and insufficient localized research, is crucial for effective policy intervention. Understanding how students engage with AI—affectively, behaviourally, cognitively, and ethically—is critical to unlocking its potential in culturally resonant ways. West African education systems prioritize empirical, community-oriented learning, contrasting with Western theoretical paradigms [68]. The West African Examinations Council (WAEC), serving Ghana and Nigeria reinforces this approach through a standardized curriculum that emphasizes practical knowledge and collective problem-solving. This approach aligns with AI's capacity to deliver tailored, experiential learning, yet infrastructure gaps and uneven resource distribution limit its reach. Both countries Nigeria and Ghana shares same level of global AI index [90]. Educators express concerns about AI's ethical implications, including data privacy and algorithmic bias, underscoring the need for frameworks that integrate local values like Ubuntu [8, 40]. Globally, AI literacy research focuses on technical and cognitive competencies, often neglecting affective and ethical dimensions critical to Africa's sociocultural context [73, 92]. Existing frameworks, largely developed in Western contexts, inadequately address Africa's unique educational ethos and challenges, such as linguistic diversity and communal learning practices [52, 84].

Several scholars have proposed frameworks for understanding AI literacy. Long & Magerko [62] defined it as a collection of skills that empower individuals to critically assess AI technologies and utilize them to enhance communication and collaboration. Similarly, Ng et al., [73] outlined four key dimensions of AI literacy: (1) knowledge and comprehension of AI, (2) practical application of AI, (3) evaluation and development of AI systems, and (4) ethical considerations in AI. Touretzky et al., [91] introduced five core concepts for AI education—perception, representation and reasoning, machine learning, natural interaction, and AI's societal impact. Meanwhile, Zhang et al., [28] designed a curriculum focusing on three pillars: foundational AI concepts, ethical and social consequences, and AI-related careers—though their approach lacks emphasis on AI creation. Additionally, a UNESCO [92] report highlighted that AI literacy should equip students with an understanding of data processing in AI systems, including collection, cleaning, and analysis, as well as algorithm literacy—the ability to comprehend how AI algorithms detect patterns in data for human–machine interactions.

The effective development of AI literacy among university students is essential for successful AI integration in education. Existing AI literacy frameworks delineate key dimensions, including Affective, Behavioral, Cognitive, and Ethical aspects [12, 74]. However, these frameworks often lack a detailed examination of the interrelationships among these dimensions, which is crucial for understanding how they collectively contribute to AI literacy. Furthermore, the majority of AI literacy research is conducted in Western contexts [7], leaving a significant gap in studies that address the unique sociocultural and educational environments of West Africa, specifically Ghana and Nigeria [93]. While these countries share educational similarities and AI readiness level, they also possess distinct contextual nuances that necessitate focused research. Consequently, there is a need to investigate how the interplay of the Affective, Behavioral, Cognitive, and Ethical dimensions of AI literacy manifests within West African higher education. Therefore, this study aims to explore and validate a comprehensive model of AI literacy that reflects the specific context of Ghanaian and Nigerian university students, thereby providing empirical evidence to inform the development of culturally relevant and effective AI education strategies in the region.

The study has objectives to: (1) validate the AI Literacy Questionnaire (AILQ) within West African higher education contexts; (2) analyze how affective factors influence cognitive outcomes through behavioral and ethical mediators; and (3) assess whether national demographics moderate these relationships. By employing the ABCE framework [74, 75], the research provides a multidimensional perspective on AI engagement, bridging theoretical and practical gaps in non-Western settings. Hence the research questions (RQs) are:

RQ 1. How ethical and behavioral dimension mediate between affective and cognitive dimension of AI literacy?

RQ2. To what extent does country of origin (Ghana or Nigeria) moderate the relationships among the affective, behavioral, cognitive, and ethical dimensions of AI literacy among university students?

This study contributes to the global AI literacy discourse by foregrounding West African perspectives, where cultural values and infrastructural realities shape technology adoption. Findings will inform policymakers and educators in designing curricula that balance technical proficiency with ethical awareness, fostering responsible AI usage. For instance, insights into self-efficacy and collaboration can enhance pedagogical strategies, while ethical considerations aligned with Ubuntu philosophy can promote inclusive AI systems. By comparing Ghana and Nigeria—countries with shared educational frameworks but distinct cultural-institutional nuances—the study offers actionable recommendations for regional AI integration, advancing Sustainable Development Goals (SDGs) in education and digital equity. Specifically, this research aligns with SDG 4 (Quality Education) by promoting accessible and relevant AI education, and SDG 10 (Reduced Inequalities) by addressing disparities in digital literacy and ensuring equitable technological progress in Africa. Ultimately, this work underscores the urgency of context-driven AI literacy research to ensure equitable technological progress in Africa.

The novelty of this study lies in its empirical examination of the interrelationships among the Affective, Behavioral, Cognitive, and Ethical (ABCE) dimensions of AI literacy within the specific socio-cultural and educational contexts of West African university students, particularly in Ghana and Nigeria. While prior research has conceptualized AI literacy and explored some of its dimensions, few studies have holistically investigated how these dimensions interact in a non-Western setting. Furthermore, our finding that country demographics do not significantly moderate these core relationships offers a novel insight into the shared patterns of AI literacy development in this region, suggesting a unifying backdrop that transcends minor contextual variations. This contributes to a more nuanced understanding of AI literacy beyond Western-centric models and provides practical, context-specific recommendations for educators and policymakers in West Africa.

The rest of the paper is structured as follows: Sect. 2 explores the conceptual background and establishes the theoretical framework. Section 3 formulates the hypotheses, while Sect. 4 details the methodology. Section 5 presents the findings from the data analysis. Finally, Sects. 6 and 7 conclude the study, discussing its theoretical and practical implications and offering suggestions for future research.

2 Literature review and theoretical framework

AI literacy has evolved from a narrow focus on technical proficiency to a multidimensional construct encompassing cognitive, affective, behavioral, and ethical competencies. Defined as the ability to understand, critically evaluate, and ethically engage with AI technologies [62, 73], AI literacy is particularly significant in Africa, where education systems emphasize communal values, practical learning, and cultural relevance [68]. In this context, AI literacy must transcend Western-centric models to address localized challenges, such as linguistic diversity, infrastructural gaps, and ethical concerns rooted in indigenous philosophies like Ubuntu [13, 14, 40]. A scoping review of AI literacy in higher education across the Global South highlights this gap, noting a pronounced lack of research centered on Africa despite the increasing relevance of AI in education [93]. A search of the ERIC database for studies on AI literacy published since 2021 found 300 relevant works globally, but only 1.67% studies focused on Africa (ERIC—Education Resources Information Center, [34]). This shows that AI literacy research in African contexts is currently greatly underrepresented in the literature. While bibliometric analyses show a rise in AI-related publications from Africa—particularly with South Africa emerging as a leader in AI development [54]—this growth has not been matched by studies that examine AI literacy within the continent's specific contexts. The absence of an AI readiness index tailored to African needs further complicates efforts to measure and enhance AI preparedness in educational systems and beyond [15]. Moreover, the lack of contextualized educational resources and culturally relevant pedagogical strategies poses significant barriers to effective AI literacy (Onyebuchi Nneamaka [77]). Additionally, expanding the use of AI in African scientific research could not only strengthen local innovation ecosystems but also diversify and enrich global research agendas, benefiting civil society at large [32]. A more inclusive and culturally sensitive framework for AI governance that incorporates African perspectives is essential to ensuring ethical development and equitable access to AI technologies [38].

Globally, AI literacy research underscores its role in fostering critical thinking, collaboration, and responsible innovation. However, African studies remain limited and fragmented. For instance, Ghanaian medical students exhibit moderate AI awareness but lack structured training opportunities [9], while Nigerian pre-service teachers demonstrate strong ethical knowledge but struggle with emotion regulation in AI contexts [13, 14]. Transnational surveys further reveal disparities, with African students lagging behind Asian counterparts in AI literacy due to systemic inequities in access and infrastructure [65]. These challenges are compounded by cultural hesitations, such as concerns about AI replacing human interaction in Ghanaian education system [67]. Addressing the existing research gap will require collaborative efforts among governments, academic institutions, private sector actors, and technology developers. These partnerships are vital for developing context-specific strategies that align AI integration with the continent's ethical values, educational priorities, and socio-economic goals. By doing so, Africa can fully harness the transformative power of AI to address its unique challenges and actively contribute to the global AI discourse.

Existing AI literacy frameworks, such as UNESCO's competency model [70], multidimensional approach [17] and Ng et al., [73] taxonomy, prioritize cognitive and technical skills but overlook the interrelation of its affective, behavioral, and ethical dimensions critical to Africa's communal learning environments. For example, [42] highlights the need to decolonize AI ethics in African healthcare to reflect communal values, while [85] discusses how corporate AI adoption risks undermining values like Afro-communitarianism and human dignity. As another example, Ubuntu philosophy—which emphasizes relationality, collective welfare, and ethical responsibility [40]—demands frameworks that integrate socio-emotional engagement and community-oriented practices. Western models often neglect these cultural nuances, creating a gap between theoretical constructs and Africa's educational realities. This study addresses this gap by empirically validating a comprehensive model of AI literacy within the West African context, by exploring the interplay of these dimensions, which is crucial for effective learning outcomes and technology adoption.

The ABCE framework addresses these limitations by offering a holistic, culturally resonant approach to AI literacy [74, 75]. Developed through rigorous pilot studies, this framework aligns with Africa's educational ethos, where learning is deeply intertwined with communal values and moral accountability. The ABCE framework comprises four interconnected dimensions.

Affective Learning encompasses emotional and motivational engagement with AI, comprising intrinsic motivation and self-efficacy. Intrinsic motivation reflects learners' genuine interest in AI's societal impact, while self-efficacy denotes confidence in mastering AI tools. In Ghana, educators recognize AI's potential for personalized learning but express concerns about its impact on human interaction [67], highlighting the need to nurture motivation and confidence. Nigerian studies similarly link self-efficacy to positive AI attitudes among students, suggesting that affective factors are pivotal for sustained engagement [13, 14]. This dimension is crucial for understanding technology adoption in Africa, as motivation and self-efficacy significantly influence individuals' willingness to engage with AI tools [5, 48].

Behavioral Learning focuses on actions and participatory engagement in AI-related tasks, including collaboration and intentionality. Collaboration emphasizes peer and community-driven problem-solving, while intentionality reflects a commitment to applying AI skills ethically. Ghana's KNUSTbot, a virtual teaching assistant, exemplifies this dimension by fostering collaborative learning in programming courses [36]. Similarly, Nigerian AI curricula prioritize hands-on activities, encouraging students to co-create solutions with peers [84], aligning with Africa's emphasis on collective knowledge-building. The importance of this dimension is underscored by frameworks like the Technology Acceptance Model (TAM) and the Theory of Planned Behavior (TPB), which highlight perceived usefulness, ease of use, subjective norms, and perceived behavioral control as key determinants of technology adoption and behavioral intention [48, 71].

Cognitive Learning involves the acquisition and application of AI knowledge, spanning foundational understanding (e.g., basic AI concepts) and critical thinking (e.g., evaluating risks and benefits). While Ghanaian students using VoiceBots demonstrate improved programming comprehension [35], gaps persist in advanced AI skills, such as algorithm design [9]. This underscores the need for curricula that balance technical mastery with analytical rigor.

2.1 Ethical learning

Centers on awareness of AI's societal implications, including privacy, bias, and fairness, as well as a commitment to equitable use. In Ghana, frameworks inspired by Ubuntu philosophy stress communal accountability and inclusive design [8], while Nigerian initiatives leverage AI to decolonize education through indigenous language preservation [86]. These efforts highlight Africa's unique contribution to global AI ethics discourse. The integration of ethical concepts into AI education is crucial for developing responsible AI in Africa, emphasizing local values in training developers and users [55]. Furthermore, addressing ethical concerns like bias, exploitation, and cultural diversity in generative AI systems is vital for robust AI governance in the region [94].

The ABCE framework is uniquely suited to African contexts for three reasons. First, it integrates Ubuntu values, such as relationality and collective welfare, ensuring cultural relevance. Second, it moves beyond technical skills to address affective and behavioral factors, which are critical in resource-constrained environments were motivation and collaboration drive innovation. Third, its empirical validation across diverse educational settings ensures reliability in measuring AI literacy holistically [74, 75]. By adopting this framework, the study bridges global theories with Africa's socio-cultural realities, offering a roadmap for equitable, context-driven AI education that prioritizes both competence and conscience.

2.2 Conceptual framework

The conceptual framework of this study outlines the interplay between core dimensions shaping AI literacy. We discussed in theoretical framework [74, 75], the basic dimensions of AI literacy based on bloom taxonomy. However, the intricate relationships and dynamic interplay among these dimensions, and their collective influence on, remain underexplored. This study, therefore, presents a novel conceptual framework (Fig. 1) to bridge this critical gap in Western African context. The *affective dimension*—comprising intrinsic motivation and self-efficacy. It serves as the foundational influence. It directly connects to the *cognitive dimension*, which encompasses knowledge & understanding and critical thinking. Two mediating pathways bridge the affective and cognitive dimensions: the *behavioral dimension* (with sub factors collaboration and intentions) and *ethical dimension*. Additionally, demographic factor country moderate how the cognitive dimension manifests, shaping outcomes based on individual or contextual differences.

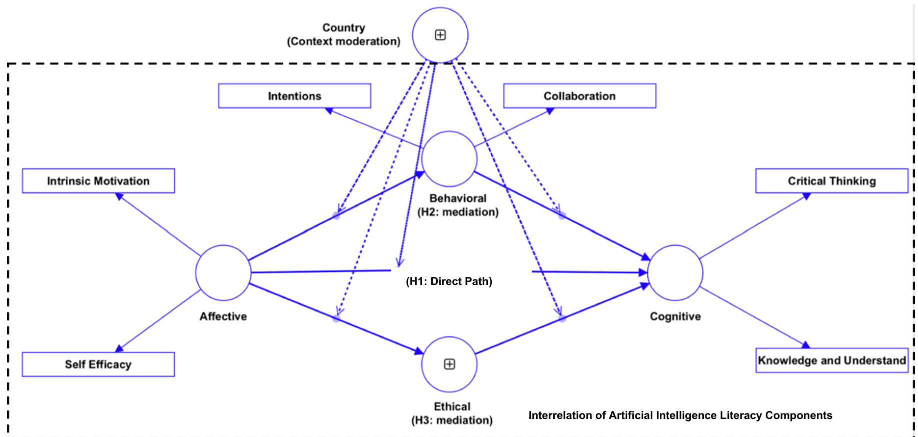

Fig. 1 An Interrelational Framework of AI Literacy in West Africa

Arrows in the Fig. 1 depict direct relationships, mediated pathways, and moderating effects, with sub-factors nested within their respective dimensions to reflect hierarchical structure. The model emphasizes how affective factors, mediated by behavior and ethics, alongside demographic influences, collectively shape cognitive AI literacy.

2.2.1 Hypothesis development

Research suggests that the *affective dimensions* of AI literacy—specifically intrinsic motivation (a personal drive to learn) and self-efficacy (confidence in one's ability)—help strengthen the *cognitive dimensions* of AI literacy, such as knowledge understanding (grasping AI concepts) and critical thinking (analyzing AI's risks and benefits). For instance, intrinsic motivation pushes learners to engage deeply with AI topics, especially in interactive settings like gamified lessons, which improves their grasp of technical ideas [56, 74, 75]. Similarly, self-efficacy—built through supportive feedback and practice—helps learners persist through challenges, boosting their ability to think critically about AI applications [26]. Studies also show that when learners feel motivated *and* confident, they retain AI knowledge better and ask sharper questions about ethics or biases [49, 96]. However, while affective factors like motivation and confidence are key, they work best alongside hands-on practice and structured lessons. Based on this, the hypothesis is proposed**:**

Hypothesis 1. Affective dimension of AI literacy positively influences the cognitive dimension of AI literacy.

AI literacy development is shaped by the interplay of affective, behavioral, and cognitive dimensions. The *affective dimension*—comprising intrinsic motivation and self-efficacy—drives learners to engage with AI tasks and persist through challenges, fostering enthusiasm and confidence in collaborative settings [17, 74, 75]. These affective factors catalyze the *behavioral dimension* (collaboration and intentions), where learners actively participate in peer or human-AI interactions, utilize tools like GenAI Teachable Machine for hands-on projects, and align their goals with ethical AI practices [7, 47, 61]. This aligns with theories such as the Theory of Planned Behavior (TPB) and Technology Acceptance Model (TAM), where attitudes (affective) influence behavioral intentions and actual behavior, which in turn impact skill acquisition and learning outcomes [6, 10, 11]. Such behavioral engagement mediates the *cognitive dimension* by enhancing knowledge retention, conceptual understanding, and critical thinking through context-rich, collaborative experiences [51, 76]. However, over-reliance on AI tools risks automation bias and inequitable access, necessitating balanced, human-centered design [12, 53].

Hypothesis 2. Behavioral dimension mediates between affective and cognitive dimension of the AI literacy.

A growing body of research underscores the importance of affective factors—such as intrinsic motivation and self-efficacy—in shaping learners' engagement with ethical issues in AI. These affective components do not act in isolation; rather, they interact meaningfully with the ethical dimension to guide learners' understanding and application of AI concepts. For instance, motivated learners are more inclined to explore the societal impacts of AI, including algorithmic bias and fairness [33, 59]. Similarly, high self-efficacy empowers individuals to navigate ethical dilemmas with confidence [21, 87].

This ethical engagement, in turn, serves as a bridge to cognitive development. Ethical literacy—nurtured through structured instruction, frameworks like ALiF, and tools such as the AI Literacy Questionnaire (AILQ)—stimulates critical thinking, conceptual understanding, and knowledge integration by embedding moral reasoning into technical learning [12, 22, 76]. For example, analyzing biases in machine learning algorithms or debating ethical dilemmas fosters deeper cognitive processing by requiring learners to synthesize information and evaluate socio-technical consequences. The ethical dimension thus plays a mediating role: it translates affective engagement into cognitive outcomes by providing a moral and evaluative lens through which learners interpret AI content. Research shows [17, 23], ethics balances knowledge and emotions, fostering a holistic AI literacy that is both informed and empathetic. This literature leads to the formulation of:

Hypothesis 3. The ethical dimension mediates the relationship between affective and cognitive dimensions of AI literacy.

3 Research methodology

This study employed a quantitative cross-sectional survey research design. The survey method was selected to efficiently gather insights from a large sample, enabling the analysis of patterns and relationships between variables.

3.1 Population and sampling

The study targeted higher education students in Nigeria and Ghana, collecting data from 427 participants via email. An online sample size calculator [31]. We anticipated effect size of 0.5, 80% statistical power, 4 latent variables, and a 0.05 significance level determined a sample size of 241 to ensure robust model structural validity [29, 95]. The collected sample (N = 427) comfortably exceeds the recommended minimum (241), ensuring adequate power to test the hypothesized relationships while accounting for the model's complexity. This justifies the sample's suitability for structural equation modeling (SEM) analyses. Moreover, data distribution were 206 participants from Ghana comprising 48% and 221 participants were from Nigeria comprising 52% of the sample size.

The focus on Ghana and Nigeria is justified by their shared educational systems (e.g., the West African Examinations Council—WAEC curriculum) and similar AI readiness indices [90], which provide a comparable context for examining AI literacy development in West Africa. This allows for a robust comparative analysis of the relationships between the ABCE dimensions without significant confounding factors related to fundamental educational structures or technological exposure.

This study involved an anonymous, minimal-risk survey. Ethical approval was obtained from the Ethics Review Committee of the host research university. All procedures were conducted in accordance with the ethical principles outlined in the Declaration of Helsinki and relevant institutional guidelines. Informed consent was implied through voluntary participation, with respondents assured of anonymity, confidentiality, and the right to withdraw at any time.

3.2 Measurement of constructs

The study measured four constructs—affective**,** behavioral**,** cognitive, and ethical learning—using validated scales adapted from Ng et al., [74]. Each construct and its sub-factors were assessed with a 5-point Likert scale (1 = *Strongly Disagree* to 5 = *Strongly Agree*). Cronbach's alpha values (α) for the constructs and sub-factors are reported to demonstrate reliability. The original questionnaire by Ng et al. [74] underwent rigorous pre-testing procedures, including pilot studies and expert reviews, to ensure its validity and reliability before its application in this study.

Affective learning (α = 0.885) evaluates learners' emotional and motivational engagement with AI. It comprises two sub-factors: *motivation* (α = 0.879; 4 items), which measures intrinsic interest in AI (e.g., "Learning AI makes my everyday life more meaningful"), and *self-efficacy* (α = 0.959; 4 items), which assesses confidence in mastering AI skills (e.g., "I believe I can master AI knowledge and skills").

Behavioral learning (α = 0.822) captures learners' actions and commitments toward AI engagement. This construct includes two sub-factors: *collaboration* (α = 0.892; 3 items), focusing on teamwork in AI tasks (e.g., "I try to work with classmates to complete AI learning projects"), and *intentions* (α = 0.923; 5 items), measuring dedication to future AI use (e.g., "I will keep myself updated with the latest AI technologies").

Cognitive learning (α = 0.800) evaluates knowledge acquisition and application of AI concepts. It consists of two sub-factors: *know and understand* (α = 0.741; 3 items), which assesses basic AI knowledge (e.g., "I know how to use AI applications such as chatbots"), and *critical thinking* (α = 0.823; 3 items), which measures analytical use of AI (e.g., "I can evaluate AI applications for different situations").

Ethical learning, adapted from [74, 75], assesses awareness of AI ethics and societal implications. This construct includes 8 items without sub-factors (e.g., "I think AI systems should benefit everyone, regardless of physical abilities or gender").

All constructs and sub-factors demonstrated acceptable reliability (α ≥ 0.70), indicating strong internal consistency. Ethical learning items were retained as validated by Ng et al., [74], ensuring alignment with the original scale's integrity.

4 Data analysis

The current study used the partial least square structural equation modelling (PLS-SEM) in SmartPLS. The choice of PLS-SEM over covariance-based SEM (CB-SEM) is justified due to its suitability for complex models with formative constructs, as well as for exploratory research aimed at developing new theoretical frameworks, which aligns with the objectives of this study in a relatively underexplored context [44, 80, 83]. PLS-SEM is also robust with non-normal data and smaller sample sizes, although our sample size comfortably exceeds the minimum required. Hence, the PLS-SEM was used to evaluate both the measurement and structural models, focusing on the constructs affective, behavioral, cognitive, and ethical (ABCE) dimensions of AI literacy. We also used consistent multi-group analysis (cMGA) for comparison between Ghana and Nigeria. The analysis included an assessment of reliability and viability, path analysis, hypothesis testing, and model fit evaluation.

4.1 Outer model assessment

The outer model (measurement model) was evaluated for reliability and validity. For first-order constructs, all Cronbach's alpha (α) values exceeded the threshold of 0.7 [44], ranging from 0.736 (Knowledge and understanding) to 0.920 (Self-efficacy), indicating strong internal consistency. Composite reliability (rho) values were also above 0.7, further confirming reliability. Average Variance Extracted (AVE) for all constructs surpassed the 0.5 cut-off [37], confirming convergent validity (e.g., Ethical: 0.642). For second-order constructs, Cronbach's alpha (Affective: 0.909, Behavioral: 0.907; Cognitive: 0.803) and AVE values (all > 0.5) met thresholds, demonstrating robust reliability and convergent validity as given in Table 1.

4.1.1 Heterotrait-Monotrait (HTMT)

To assess discriminant validity using the Heterotrait-Monotrait (HTMT) ratio, we compare the calculated HTMT values for each pair of constructs against a cut-point of 0.90 [44]. The HTMT ratio between Behavioral and Affective is 0.891, between Cognitive and Affective is 0.723, between Cognitive and Behavioral is 0.819, between Ethics and Affective is 0.577, between Ethics and Behavioral is 0.547, and between Ethics and Cognitive is 0.593. All of these values are below the commonly recommended threshold of 0.90, suggesting adequate discriminant validity between these constructs.

Table 1 Reliability and Validity

	sub-factor	Sub factor loading	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Affective			0.885	0.885	0.946	0.897
	Motivation	0.946	0.879	0.883	0.917	0.734
	self-Efficacy	0.948	0.959	0.96	0.967	0.83
Behavioral			0.822	0.841	0.917	0.848
	Collaboration	0.906	0.892	0.896	0.933	0.822
	Intentions	0.935	0.923	0.927	0.938	0.656
Cognitive			0.8	0.8	0.909	0.833
	Know and Understand	0.911	0.741	0.749	0.852	0.658
	Critical Thinking	0.914	0.823	0.858	0.892	0.733

4.2 Inner model assessment

The structural (inner) model was evaluated for collinearity, predictive power, and model fit. Variance Inflation Factor (VIF) values for all constructs were below 3.5 (Affective: 3.479; Behavioral: 3.295), well under the critical threshold of 5 [45], indicating no multicollinearity concerns.

4.2.1 Model fit

Based on the SmartPLS output, the Estimated model demonstrates acceptable fit with an SRMR of 0.072 below the common cutoff of 0.08 [46], a d_ULS of 0.146, and a d_G of 0.211. While the Chi-square is significant (279.404), this is often influenced by sample size. The NFI of 0.746 suggests a reasonable improvement over the baseline model. Overall, considering these parameters and their typical cut points, the Estimated model provides a reasonably good fit to the data.

4.2.2 R-square and f-square value

The R-square value shows the proportion of variance in the endogenous variable that is predicted by the exogenous variables. In the view of [43], the critical threshold for the R-square value should exceed 0.1. The R-square values for endogenous constructs were moderate: Behavioral (0.68), Cognitive (0.665), and Ethics (0.339), indicating that 68%, 66.5%, and 33.9% of their variances, respectively, were explained by the model. Adjusted R-square values aligned closely, suggesting minimal overfitting. Effect sizes (f-square) revealed that Affective had a large influence on Behavioral ($f^2 = 2.125$) and Ethics ($f^2 = 0.512$).

4.3 Findings related to RQ 1

The results of the direct and indirect path analyses provided evidence to test Hypotheses 1, 2, and 3 in relation to Research Question 1. *How ethical and behavioral dimension mediate between affective and cognitive dimension of AI literacy?*

4.3.1 Direct path analysis

Direct path coefficients were evaluated using bootstrapping (5,000 subsamples). Affective dimension had a strong, significant positive effect on Cognitive dimension ($\beta = 0.169$, $p = 0.022$), hence supported hypothesis 1 as given in Fig. 2.

4.3.2 Indirect path analysis

Mediation analysis revealed significant indirect effects. The path Affective→Behavioral→Cognitive was significant ($\beta = 0.432$, $p < 0.001$), indicating Behavioral mediates Affective's impact on Cognitive supporting the hypothesis 2. Similarly, Affective→Ethical→Cognitive showed a significant indirect effect ($\beta = 0.119$, $p = 0.003$), confirming the hypothesis 3, Ethics as a mediator. These results underscore the cascading influence of Affective on Cognitive through both Behavioral and Ethics as given in Table 2.

4.4 Findings related to RQ 2

Multi-group analysis to examine the generalizability of the proposed model and justify pooling data from Ghana and Nigeria for the main hypothesis tests related to research question 2: *To what extent does country of origin (Ghana or Nigeria) moderate the*

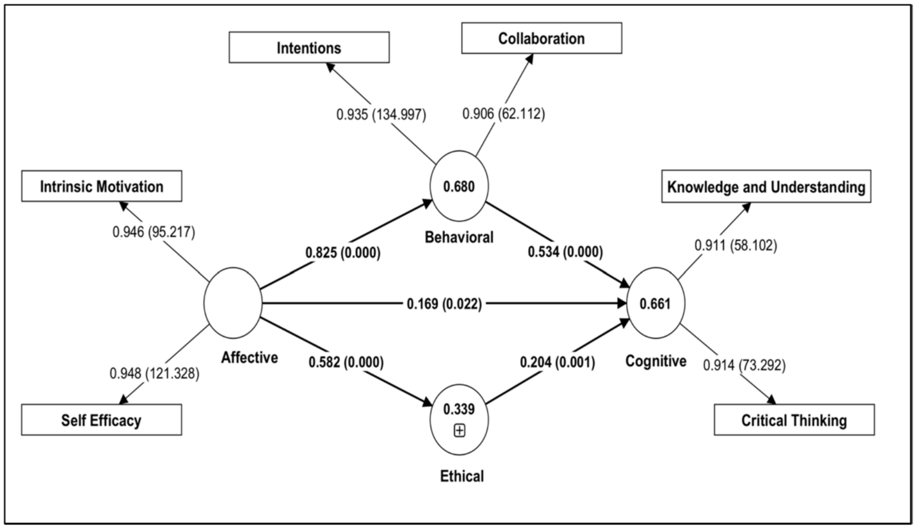

Fig. 2 Path analysis

Table 2 Indirect Paths

	Original sample (O)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Hypothesis
Affective → Behavioral → Cognitive	0.432	0.073	5.953	0.000	Accepted
Affective → Ethics → Cognitive	0.119	0.04	2.994	0.003	Accepted

relationships among the affective, behavioral, cognitive, and ethical dimensions of AI literacy among university students? A bootstrapped consistent multi-group analysis (MGA) in SmartPLS was conducted.

4.4.1 Multi-group analysis

Multi-group analysis to examine the generalizability of the proposed model and justify pooling data from Ghana and Nigeria for the main hypothesis tests, a bootstrapped consistent multi-group analysis (MGA) in SmartPLS was conducted. The bootstrapped consistent multi-group analysis (MGA) in SmartPLS was conducted to compare path coefficients between Ghana (Group 1) and Nigeria (Group 2). In the initial analysis, construct reliability and validity were assessed, confirming the measurement model's adequacy. Therefore, MICOM was not required for consistent MGA, as it is not applicable when using reflective indicators. The results show that the difference in the path coefficient for affective to cognitive is 0.246, with a 1-tailed p-value of 0.117 and a 2-tailed p-value of 0.233, indicating no significant difference. The indirect effect of affective on cognitive through behavior has a path difference of − 0.266, with a 1-tailed p-value of 0.898 and a 2-tailed p-value of 0.203, also showing no significant variation. Similarly, the relationship between affective and cognitive through ethical has a path difference of − 0.129, with a 1-tailed p-value of 0.965 and a 2-tailed p-value of 0.070, which, despite a relatively lower 2-tailed p-value, is not statistically significant. Overall, the results indicate that structural relationships in the model remain stable across Ghana and Nigeria, suggesting no significant moderation by cultural or contextual factors confirming the hypothesis 4a as shown in Table 3. This non-significant moderation supports the decision to analyze the entire dataset (Ghana and Nigeria combined) for testing Hypotheses

Table 3 Multi-group analysis

	Difference (Group_1 -Group_2)	2-tailed (Group_1 vs Group_2) p value
Affective → Cognitive	0.246	0.233
Affective → Behavior → Cognitive	− 0.266	0.203
Affective → Ethical → Cognitive	− 0.129	0.07

1, 2, and 3, thereby enhancing the statistical power and generalizability of the findings to the broader West African university student population.

5 Discussion

This study set out to investigate the intricate relationships between the Affective, Behavioral, Cognitive, and Ethical dimensions of AI literacy among university students in West Africa, specifically within the distinct educational and socio-cultural contexts of Ghana and Nigeria. Claiming its place among the pioneer studies in this burgeoning field within the African continent, this research contributes novel insights by empirically examining the interplay of these crucial dimensions in shaping AI literacy. We have discussed the theoretical and practical implications of the findings in this section.

5.1 Theoretical implications

This section discusses the theoretical implications of the findings in relation to the tested hypotheses and research questions.

5.1.1 Mediation of ethical and behavioral dimensions

For Research Question 1—*How ethical and behavioral dimensions mediate between affective and cognitive dimensions of AI literacy?* —we present the findings relevant to Hypotheses 1, 2, and 3**.** First, this study found that affective learning (which includes intrinsic motivation and self-efficacy) strongly and positively influences cognitive learning (such as knowledge, understanding and critical thinking) in AI education. The results showed a significant direct effect ($\beta = 0.168$, $p = 0.024$; Path Coefficient = 0.183, $p = 0.013$), supporting Hypothesis 1. These findings align with earlier studies [25, 58, 74, 75], which suggest that positive emotions, motivation, and confidence help students engage more deeply, persist longer, and better grasp AI concepts. For example, students with higher intrinsic motivation were more likely to move beyond memorization to actively apply AI principles [74]. Gamified learning tools boosted motivation and basic cognitive skills, but they were less effective for advanced skills like evaluating AI systems [74, 75]. Self-efficacy also mattered: students who believed in their abilities engaged more confidently with AI tasks, interacted better with online learning tools, and collaborated more effectively with peers, all of which improved their understanding (C. [25, 58, 81]). Together, these results highlight that affective factors like motivation and confidence are vital for cognitive growth in AI literacy, but they work best when combined with teaching methods that directly build skills. These findings advance global AI literacy research by underscoring the universal importance of fostering positive affective states to enhance cognitive engagement, even within diverse educational contexts.

Second, the findings indicate that behavioral aspects of AI literacy—specifically collaboration and learning intentions—act as a bridge between affective factors (self-efficacy and intrinsic motivation) and cognitive outcomes (knowledge and understanding, and critical thinking). Mediation analysis confirmed that the pathway from affective → behavioral → cognitive dimensions was significant (β = 0.432, $p < 0.001$), supporting hypothesis 2. This aligns with prior research highlighting how affective states, such as confidence and motivation, influence learning behaviors and persistence, particularly in complex domains like AI [25]. For instance, self-efficacy reduces anxiety and strengthens motivation, encouraging students to engage with challenging tasks [20]. Supportive learning environments further amplify this relationship by fostering autonomy and confidence [58]. Behavioral engagement, such as collaboration, enhances cognitive learning by promoting knowledge exchange and critical analysis of AI systems [7, 82], with structured collaboration being a key predictor of competency development [66]. Behavioral intention, driven by self-efficacy and goal-oriented expectations, also motivates active participation and deeper cognitive engagement [97], a dynamic supported by theoretical frameworks like the Theory of Planned Behavior [24]. These relationships are reflected in AI literacy frameworks such as the AILQ, which integrates behavioral learning as central to cognitive outcomes, and pedagogical strategies like game-based learning, where collaboration and motivation synergistically enhance understanding [74]. Together, these results underscore the interconnected roles of affective, behavioral, and cognitive dimensions in AI literacy development. These findings are consistent with recent studies by [6, 88], which also highlight the importance of behavioral intentions and user engagement for continuous adoption of AI tools in educational settings, further substantiating the mediating role of behavior observed in this study.

Third, the empirical findings support Hypothesis 3, confirming that the ethical dimension of AI literacy significantly and positively mediates the relationship between affective factors (intrinsic motivation, self-efficacy) and cognitive outcomes (knowledge, critical thinking, and conceptual understanding). Mediation analysis revealed a statistically significant indirect effect along the Affective → Ethics → Cognitive path (β = 0.119, p = 0.003), indicating that affective engagement positively influences cognitive development through ethical learning.

This result aligns with prior theoretical and empirical work. Ng et al., [74], argue that emotionally invested learners are more likely to internalize ethical principles, which in turn enhance their capacity to think critically about AI. Affective strategies—such as classroom debates, role-playing, and reflection on ethical dilemmas—boost ethical sensitivity and cognitive activation [25]. Self-efficacy also reinforces ethical engagement by giving learners the confidence to confront morally complex scenarios, facilitating the transfer of ethical insights into technical understanding [58].

Moreover, ethical engagement has been consistently linked to improvements in higher-order cognitive skills. Studies show that grappling with ethical trade-offs requires learners to analyze assumptions, evaluate social impacts, and synthesize interdisciplinary knowledge [28]. These processes directly foster critical thinking and problem-solving abilities [16, 27]. Previous literature further substantiates this mediating role. The ethical dimension integrates cognitive and affective learning by shaping attitudes toward AI while deepening conceptual understanding of its implications (Dabbagh et al., [30], Ng, Wu, et al., [75]). Research [17] emphasizes that the balance between emotional and rational engagement is central to developing a comprehensive and socially responsible AI literacy. Finally, from an educational and policy standpoint, these findings highlight the need for AI curricula that deliberately embed ethical frameworks and scenarios to foster both motivation and understanding (Dabbagh et al., 23). Programs that ignore the mediating role of ethics risk producing learners who are technically competent but ethically uninformed, thereby undermining the goal of responsible AI engagement.

5.1.2 Moderating role of country of origin

This addresses Research Question 2: *To what extent does country of origin (Ghana or Nigeria) moderate the relationships among the affective, behavioral, cognitive, and ethical dimensions of AI literacy among university students?* The multi-group analysis indicated that country demographics do not significantly influence the interconnectedness of affective, behavioral, cognitive, and ethical dimensions of AI literacy among university students in Ghana and Nigeria. The survey findings reveal that the interplay between these dimensions remains consistent across both countries, likely due to shared systemic challenges and educational contexts within the African region. The non-significant differences observed in the multi-group analysis (as shown in Table 3) imply that the fundamental relationships between affective, behavioral, cognitive, and ethical dimensions of AI literacy are robust and not significantly altered by country-specific factors within this West African context. Both nations face comparable infrastructural constraints, such as limited access to advanced technologies and AI-specific educational resources [2–4, 64], which shape similar pedagogical approaches and student experiences in AI literacy development. The foundational emphasis on information literacy in both educational systems [2, 4] further supports the alignment of affective (e.g., attitudes toward AI), behavioral (e.g., engagement with AI tools), cognitive (e.g., conceptual understanding), and ethical (e.g., critical evaluation of AI's societal impacts) competencies. For instance, the integration of AI literacy frameworks like ALiF [22], which prioritizes adaptable, context-sensitive learning, and courses emphasizing conceptual over technical mastery [57], appears to foster comparable developmental trajectories across these dimensions in both countries. While minor contextual variations in policy or technological adoption rates may exist, the structural and resource-related commonalities between Ghana and Nigeria create a unifying backdrop that diminishes the role of national demographics in shaping the nexus between these AI literacy components.

5.2 Practical implications

This study provides actionable strategies for enhancing AI literacy in West African universities, focusing on Ghana and Nigeria, by aligning interventions with the interconnected affective, behavioral, cognitive, and ethical dimensions identified in the findings.

5.2.1 Strengthen affective learning to drive cognitive growth

Curriculum designers should prioritize fostering intrinsic motivation and self-efficacy through pedagogical strategies that emphasize AI's relevance to students' personal and professional aspirations. Gamified learning modules [74] and real-world problem-solving tasks can sustain engagement, while scaffolded projects that build incremental mastery (e.g., guided AI tool development) can enhance confidence in technical competencies. Training programs should also emphasize autonomy, allowing students to explore AI applications aligned with their interests, thereby reinforcing self-efficacy and persistence in complex tasks. These recommendations are directly informed by the finding that affective factors positively influence cognitive outcomes, highlighting the need for pedagogical interventions that address students' motivation and confidence as foundational elements for AI literacy development.

5.2.2 Design collaborative behavioral interventions

Institutions should institutionalize structured peer collaboration and project-based learning to translate motivation into tangible cognitive outcomes. Group activities, such as co-developing AI solutions for local challenges (e.g., agriculture or healthcare), can channel behavioral commitment into knowledge-sharing and critical analysis. Encouraging goal-setting frameworks, such as personalized AI learning plans, can also sustain long-term engagement with emerging technologies, ensuring students proactively update their skills and apply theoretical knowledge [60, 66]. This aligns with our findings demonstrating the significant mediating role of behavioral engagement (collaboration, intentional use) in linking affective and cognitive dimensions, suggesting that active and collaborative learning environments are crucial for translating motivation into concrete learning outcomes.

5.2.3 Embed ethical reasoning across AI curricula

Ethical frameworks should be integrated into technical AI courses to mediate the link between motivation and cognitive mastery. Case studies on AI biases, privacy dilemmas, and equitable design principles can cultivate ethical sensitivity while deepening critical thinking. For instance, debates on AI's role in job displacement or algorithmic discrimination can challenge students to reconcile technical proficiency with societal responsibility, fostering dual competencies in innovation and ethical accountability [39]. Faculty training on facilitating ethical discussions is critical to ensure these topics are not treated as ancillary but as core to AI literacy. This is crucial given our finding that the ethical dimension significantly mediates the relationship between affective and cognitive learning, emphasizing that ethical awareness not only enhances moral reasoning but also deepens conceptual understanding and critical thinking about AI's broader implications.

5.2.4 Contextualize pedagogies for regional realities

Given shared infrastructural constraints in Ghana and Nigeria, institutions should adopt low-resource, high-impact strategies. Mobile-friendly AI learning platforms and offline tools can address connectivity gaps, while prioritizing foundational conceptual understanding over advanced technical skills aligns with regional educational priorities [69]. Partnerships with local industries and NGOs can provide context-specific AI projects, bridging theory and practice while addressing perceptions of AI's irrelevance to African contexts.

5.2.5 Address perceptions and risks proactively

Skepticism about AI's educational value and risks (e.g., plagiarism, bias) must be mitigated through transparency and skill-building. Workshops on critically evaluating AI outputs for accuracy and fairness can reduce over-reliance on tools like ChatGPT. Showcasing AI's potential to solve local challenges—such as improving agricultural yields or healthcare or educational access—can shift perceptions from viewing AI as a foreign technology to a tool for grassroots innovation (Mohamed et al., [1]).

A holistic approach that synergizes motivation, collaboration, ethics, and contextual relevance is essential for advancing AI literacy in Ghana and Nigeria. By prioritizing affective engagement as a catalyst for cognitive growth, embedding ethics into technical training, and adapting strategies to regional constraints, educators can empower students to harness AI as both a technical skill and a force for equitable development.

6 Conclusion

This study examined the relationships between affective, behavioral, cognitive, and ethical dimensions of AI literacy among university students in Ghana and Nigeria. The results confirmed that affective learning—characterized by intrinsic motivation and self-efficacy—directly strengthens cognitive outcomes, such as knowledge, understanding, and critical thinking, by fostering deeper engagement and persistence in AI education. Behavioral learning, including collaboration and intentional practice, further bridges affective and cognitive dimensions, enabling students to translate motivation and confidence into active problem-solving and knowledge-sharing. Ethical learning emerged as a critical mediator, as students with higher self-efficacy and motivation demonstrated greater ethical sensitivity, which in turn deepened their cognitive understanding of AI's societal implications. Notably, the interconnectedness of these dimensions remained consistent across Ghana and Nigeria, suggesting that shared regional challenges, such as infrastructural limitations and pedagogical priorities, shape AI literacy development similarly in both contexts. These findings highlight the interdependence of motivation, collaboration, ethical reasoning, and cognitive skills in fostering well-rounded AI literacy, reinforcing the importance of educational approaches that holistically integrate these dimensions.

6.1 Limitations and future research

This study's focus on two countries limits generalizability across West Africa's diverse contexts, while its cross-sectional design restricts causal inferences. The research used a one-time survey, which restricts the ability to establish causal relationships or track how AI literacy evolves over time among students. Again, Responses were based on participants' self-perceptions, which may be influenced by social desirability or inaccurate self-assessment, particularly in measuring affective (motivation, self-efficacy) and cognitive (knowledge, critical thinking) dimensions. To mitigate potential biases from self-reported data, the study utilized a rigorously validated questionnaire [74] and employed statistical controls within the PLS-SEM framework to ensure the robustness of the relationships identified.

Future research should expand to multi-country comparisons, longitudinal designs, and mixed-methods approaches to capture temporal and cultural depth. Developing locally adapted tools and inclusive sampling (e.g., rural communities, educators) will enhance relevance. Investigating AI literacy's ties to career readiness, entrepreneurship, and Ubuntu-inspired ethics can align strategies with Africa's socio-cultural and developmental goals.

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1007/s10791-025-09691-2.

Updated: Table 1 Reliability and Validity

Acknowledgements
Not applicable.

Author contributions
MZA: Conceptualization, Methodology, Investigation, Writing—review and editing, Supervision, Project administration. KAD: Conceptualization, Methodology, Investigation, Formal analysis, Writing—original draft, Supervision, Project administration. JI: Data curation, Formal analysis, Writing—review and editing, Validation. HJ: Conceptualization, Methodology, Investigation, Writing—review and editing, Supervision, Project administration.

Funding
Open Access funding provided by University of Oulu (including Oulu University Hospital). No funding was received for conducting this study.

Data availability
The data and materials used in this study are available from corresponding author upon request.

Declarations

Ethics approval
This study did not involve experiments on humans or the use of human tissue samples. Ethical approval for the survey was granted by the Institutional Ethical Review Board of Zhejiang International Studies University (IERBZISU: 26042024) on April 26, 2024. The study adhered to the Declaration of Helsinki and relevant national guidelines to ensure participants' rights and welfare were protected. All procedures complied with ethical standards for research involving human data. The online questionnaire ensured participant confidentiality and anonymity.

Consent to participate
Informed consent was obtained in two steps. First, participants received an information sheet outlining the study's purpose, procedures, rights, and data protection measures. They were informed that participation was voluntary, and they could withdraw at any time without penalty. Participants then electronically signed a consent form, confirming their understanding and agreement to participate. No personal identifiers were collected, and responses were stored securely. The data was anonymized before analysis, and access was restricted to authorized researchers. Verbal informed consent was also obtained. The online questionnaire was distributed with approval from relevant school authorities.

Consent for publication
The authors confirm that they have read and approved the final version of the manuscript and agree to its publication in this journal.

Competing interests
The authors declare no competing interests.

Received: 31 March 2025 / Accepted: 21 July 2025
Published online: 09 August 2025

References

1. Abdelgadir Mohamed Y, Mohamed AHHM, Khanan A, Bashir M, Adiel MAE, Elsadig MA. Navigating the ethical terrain of AI-generated text tools: a review. IEEE Access. 2024;12:197061–120. https://doi.org/10.1109/ACCESS.2024.3521945.
2. Agbo AD, Igwebuike EU. Inculcating information literacy skills in Nigerian university students: the foundation for independent lifelong learning. J Educ Pract. 2014;5(39):19–24.
3. Aiyedun TGO. Artificial intelligence (AI) in education: integration of AI into science education curriculum in Nigerian universities. Int J Artif Intell Digit Market. 2024;1(1):1–14. https://doi.org/10.61796/ijaifd.v1i1.13.
4. Akakpo MG. Skilled for the future: Information literacy for AI use by university students in Africa and the role of librarians. Internet Ref Serv Q. 2024;28(1):19–26. https://doi.org/10.1080/10875301.2023.2280566.
5. Al-Abdullatif AM. Modeling teachers' acceptance of generative artificial intelligence use in higher education: the role of AI literacy, intelligent TPACK, and perceived trust. Educ Sci. 2024;14(11):1209. https://doi.org/10.3390/educsci14111209.
6. Ali RA, Soliman M, Weahama MR, Assalihee M, Mahmud I. Investigating continuous intention to use metaverse in higher education institutions: a dual-staged structural equation modeling-artificial neural network approach. Smart Learn Environ. 2025;12(1):3. https://doi.org/10.1186/s40561-024-00357-y.
7. Allen LK, Kendeou P. ED-AI Lit: An interdisciplinary framework for AI literacy in education. Policy Insights Behav Brain Sci. 2024;11(1):3–10. https://doi.org/10.1177/23727322231220339.
8. Ammah LNA, Lütge C, Kriebitz A, Ramkissoon L. AI4people – an ethical framework for a good AI society: the Ghana (Ga) perspective. J Inf Commun Ethics Soc. 2024;22(4):453–65. https://doi.org/10.1108/JICES-06-2024-0072.
9. Ankamah S, Gyesi K, Amponsah V. Awareness, knowledge, and attitude towards artificial intelligence: perspective of medical students in Ghana. Inform Dev. 2024. https://doi.org/10.1177/02666669241283790.
10. Asghar MZ, Barbera E, Rasool SF, Seitamaa-Hakkarainen P, Mohelská H. Adoption of social media-based knowledge-sharing behaviour and authentic leadership development: evidence from the educational sector of Pakistan during COVID-19. J Knowl Manag. 2022. https://doi.org/10.1108/JKM-11-2021-0892.
11. Asghar MZ, Erdoğmuş YK, Seitamaa-Hakkarainen P. Cultural levels and pre-service teachers' behaviour towards the use of open educational resources. J Interact Media Educ. 2021;2021(1):1–21. https://doi.org/10.5334/jime.674.
12. Asrifan A, Said UMR, Jakob JC, Wanci R. AI literacy. Hershey: IGI Global; 2024. p. 17–48. https://doi.org/10.4018/979-8-3693-8252-3.ch002.

13. Ayanwale MA, Adelana OP, Molefi RR, Adeeko O, Ishola AM. Examining artificial intelligence literacy among pre-service teachers for future classrooms. Comput Educ Open. 2024;6: 100179. https://doi.org/10.1016/j.caeo.2024.100179.
14. Ayanwale MA, Molefi RR, Liapeng S. Unlocking educational frontiers: exploring higher educators' adoption of Google Workspace technology tools for teaching and assessment in Lesotho dynamic landscape. Heliyon. 2024;10(9): e30049. https://doi.org/10.1016/j.heliyon.2024.e30049.
15. Baguma R, Mkoba E, Nahabwe M, Mubangizi MG, Amutorine M, Wanyama D. Towards an artificial intelligence readiness index for Africa. In: Mubangizi MG, editor. Artificial intelligence, blockchain and cybersecurity in Africa. Berlin: Springer; 2023. p. 285–303. https://doi.org/10.1007/978-3-031-28472-4_18.
16. Bellemo V, Lim ZW, Lim G, Nguyen QD, Xie Y, Yip MYT, Hamzah H, Ho J, Lee XQ, Hsu W, Lee ML, Musonda L, Chandran M, Chipalo-Mutati G, Muma M, Tan GSW, Sivaprasad S, Menon G, Wong TY, Ting DSW. Artificial intelligence using deep learning to screen for referable and vision-threatening diabetic retinopathy in Africa: a clinical validation study. Lancet Digit Health. 2019;1(1):e35–44. https://doi.org/10.1016/S2589-7500(19)30004-4.
17. Biagini G. Assessing the assessments: toward a multidimensional approach to AI literacy. Media Education. 2024;15(1):91–101. https://doi.org/10.36253/me-15831.
18. Bickley SJ, Torgler B. Cognitive architectures for artificial intelligence ethics. AI & Soc. 2023;38(2):501–19. https://doi.org/10.1007/s00146-022-01452-9.
19. Boateng G. Kwame: a bilingual AI teaching assistant for online SuaCode courses. In: Bialik M, Fadel C, Wayne H, editors. Artificial intelligence in education. AI in education, artificial intelligence, and society. Berlin: Springer; 2021. p. 93–7. https://doi.org/10.1007/978-3-030-78270-2_16.
20. Bolkan S. Intellectually stimulating students' intrinsic motivation: the mediating influence of affective learning and student engagement. Commun Rep. 2015;28(2):80–91. https://doi.org/10.1080/08934215.2014.962752.
21. Butler-Ulrich T, Hughes J. Going over the wall: supporting critical artificial intelligence literacy using narrative design fiction. J Digit Life Learn. 2025;4(1):86–115. https://doi.org/10.51357/jdll.v4i1.273.
22. Zary, N. (2024). *AI literacy framework (ALiF): A progressive competency development protocol for higher education v1*. protocols.io. https://doi.org/10.17504/protocols.io.bp2l6dbpzvqe/v1
23. Černý, M. (2024). University Students' Conceptualisation of AI Literacy: Theory and Empirical Evidence. Social Sciences, 13(3), 129. https://doi.org/10.3390/socsci13030129
24. Chai CS, Chiu TKF, Wang X, Jiang F, Lin X-F. Modeling Chinese secondary school students' behavioral intentions to learn artificial intelligence with the theory of planned behavior and self-determination theory. Sustainability. 2022;15(1):605. https://doi.org/10.3390/su15010605.
25. Chen C, Hu W, Wei X. From anxiety to action: exploring the impact of artificial intelligence anxiety and artificial intelligence self-efficacy on motivated learning of undergraduate students. Interact Learn Environ. 2024. https://doi.org/10.1080/10494820.2024.2440877.
26. Chen Z, Sukying A. The relationship between intrinsic motivation, self-efficacy, self-regulated learning, and English learning achievement in Chinese high school students. J Engl Lang Linguist. 2024;5(3):261–76. https://doi.org/10.62819/jel.2024.578.
27. Chowning JT, Griswold JC, Kovarik DN, Collins LJ. Fostering critical thinking, reasoning, and argumentation skills through bioethics education. PLoS ONE. 2012;7(5): e36791. https://doi.org/10.1371/journal.pone.0036791.
28. Zhang H, Lee I, Ali S, DiPaola D, Cheng Y, Breazeal C. Integrating ethics and career futures with technical learning to promote AI literacy for middle school students: an exploratory study. Int J Artif Intell Educ. 2023;33(2):290–324. https://doi.org/10.1007/s40593-022-00293-3.
29. Cohen J. Statistical power analysis for the behavioral sciences. New Jersey: Lawrence Erlbaum Associates; 1988.
30. Dabbagh, H., Earp, B.D., Mann, S.P. et al. AI ethics should be mandatory for schoolchildren. AI Ethics 5, 87–92 (2025). https://doi.org/10.1007/s43681-024-00462-1
31. Daniel Soper. (2025, March 25). *A-priori sample size calculator for structural equation models*. https://www.danielsoper.com/statcalc/calculator.aspx?id=89
32. Deewar. Artificial intelligence for science in Africa. Paris: OECD; 2023. https://doi.org/10.1787/399730cc-en.
33. du Boulay B. Artificial intelligence in education and ethics. In: Zawacki-Richter O, Jung T, Stachowiak A, editors. Handbook of open, distance and digital education. Singapore: Springer Nature Singapore; 2022. p. 1–16. https://doi.org/10.1007/978-981-19-0351-9_6-2.
34. ERIC. (2025). *Search results for "AI literacy"*. ERIC - Education Resources Information Center. Retrieved June 23, 2025, from https://eric.ed.gov/?q=AI+literacy
35. Essel HB, Vlachopoulos D, Nunoo-Mensah H, Amankwa JO. Exploring the impact of VoiceBots on multimedia programming education among Ghanaian university students. Br J Educ Technol. 2025;56(1):276–95. https://doi.org/10.1111/bjet.13504.
36. Essel HB, Vlachopoulos D, Tachie-Menson A, Johnson EE, Baah PK. The impact of a virtual teaching assistant (chatbot) on students' learning in Ghanaian higher education. Int J Educ Technol High Educ. 2022;19(1):57. https://doi.org/10.1186/s41239-022-00362-6.
37. Fornell C, Larcker DF. Evaluating structural equation models with unobservable variables and measurement error. J Mark Res. 1981;18(1):39–50. https://doi.org/10.1177/002224378101800104.
38. Frimpong, V. (2024). *Cultural and regional influences on global AI apprehension* [Preprint]. https://doi.org/10.32388/YRDGEX
39. Garrett, N., Beard, N., & Fiesler, C. (2020). More than "if time allows." *Proceedings of the AAAI/ACM Conference on AI, Ethics, and Society*, 272–278. https://doi.org/10.1145/3375627.3375868
40. Gondwe G. Artificial intelligence, journalism, and the Ubuntu robot in sub-Saharan Africa: towards a normative framework. Dig J. 2024. https://doi.org/10.1080/21670811.2024.2311258.
41. Gonsalves C. Generative AI's impact on critical thinking: revisiting bloom's taxonomy. J Market Educ. 2024. https://doi.org/10.1177/02734753241305980.
42. Grancia MK. Decolonizing AI ethics in Africa's healthcare: an ethical perspective. AI Ethics. 2025;5(3):3129–42. https://doi.org/10.1007/s43681-024-00650-z.
43. Hair JF, Ringle CM, Sarstedt M. PLS-SEM: indeed a silver bullet. J Mark Theory Pract. 2011;19(2):139–52. https://doi.org/10.2753/MTP1069-6679190202.

44. Hair JF, Risher JJ, Sarstedt M, Ringle CM. When to use and how to report the results of PLS-SEM. Eur Bus Rev. 2019;31(1):2–24. https://doi.org/10.1108/EBR-11-2018-0203.
45. Hair JF Jr, Matthews LM, Matthews RL, Sarstedt M. PLS-SEM or CB-SEM: Updated guidelines on which method to use. Int J Multivar Data Anal. 2017;1(2):107–23.
46. Hu L, Bentler PM. Cutoff criteria for fit indexes in covariance structure analysis: conventional criteria versus new alternatives. Struct Equ Model. 1999;6(1):1–55.
47. Ibrahim M. AI as a collaborative partner. In: Ismail IA, editor. AI-powered learning environments for adult students. Hershey: IGI Global; 2024. p. 117–49. https://doi.org/10.4018/979-8-3693-1054-0.ch006.
48. Iqbal J, Hashmi ZF, Asghar MZ, Abid MN. Generative AI tool use enhances academic achievement in sustainable education through shared metacognition and cognitive offloading among preservice teachers. Sci Rep. 2025;15(1):16610. https://doi.org/10.1038/s41598-025-01676-x.
49. Ismail IA, Aljabr FS. The interplay of emotion and cognition in adult learning. In: Ismail IA, editor. AI-powered learning environments for adult students. Hershey: IGI Global; 2024. p. 17–44. https://doi.org/10.4018/979-8-3693-2663-3.ch002.
50. Jagger S. Affective learning and the classroom debate. Innov Educ Teach Int. 2013;50(1):38–50. https://doi.org/10.1080/14703297.2012.746515.
51. Yoo Y, Cho YH, Choi J. A systematic review on the competences of human-AI collaboration. Int Conf Comput Educ. 2023. https://doi.org/10.5845/icce.2023.4788.
52. Jatileni CN, Sanusi IT, Olaleye SA, Ayanwale MA, Agbo FJ, Oyelere PB. Artificial intelligence in compulsory level of education: perspectives from Namibian in-service teachers. Educ Inf Technol. 2024;29(10):12569–96. https://doi.org/10.1007/s10639-023-12341-z.
53. Kakina A. Artificial intelligence for functional literacy development. Eurasian Sci Rev Int Peer-Rev Multidiscip J. 2025. https://doi.org/10.6303/esr-301.
54. Kondo, T.S., Diwani, S.A. Artificial intelligence in Africa: a bibliometric analysis from 2013 to 2022. Discov Artif Intell 3, 34 (2023). https://doi.org/10.1007/s44163-023-00084-2
55. Kiemde SMA, Kora AD. Towards an ethics of AI in Africa: rule of education. AI Ethics. 2022;2(1):35–40. https://doi.org/10.1007/s43681-021-00106-8.
56. Kit Ng DT, Wu W, Lok Leung JK, Wah Chu SK. Artificial intelligence (AI) literacy questionnaire with confirmatory factor analysis. IEEE Int Conf Adv Learn Technol (ICALT). 2023;2023:233–5. https://doi.org/10.1109/ICALT58122.2023.00074.
57. Kong S-C, Cheung WM-Y, Zhang G. Evaluating artificial intelligence literacy courses for fostering conceptual learning, literacy and empowerment in university students: refocusing to conceptual building. Comput Human Behav Rep. 2022;7:100223. https://doi.org/10.1016/j.chbr.2022.100223.
58. Kong S-C, Yang Y. Developing and validating an artificial intelligent empowerment instrument: evaluating the impact of an artificial intelligent literacy programme for secondary school and university students. Res Pract Technol Enhanced Learn. 2024;20: 024. https://doi.org/10.58459/rptel.2025.20024.
59. Kwon J. Enhancing ethical awareness through generative AI literacy: a study on user engagement and competence. Edelweiss Appl Sci Technol. 2024;8(6):4136–45. https://doi.org/10.5521/25768484.v8i6.2904.
60. Zhang W, Guan Y, Hu Z. The efficacy of project-based learning in enhancing computational thinking among students: a meta-analysis of 31 experiments and quasi-experiments. Educ Inf Technol. 2024;29(11):14513–45. https://doi.org/10.1007/s10639-023-12392-2.
61. Laru J, Celik I, Kivioja I, Mäkitalo K. Learning AI literacy in collaborative projects with an AI education tool by making machine learning-driven apps: a case study from Finnish pre-service teacher education. OSF. 2024. https://doi.org/10.35542/osf.io/3qx2h.
62. Long, D., & Magerko, B. (2020). What is AI literacy? Competencies and design considerations. *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, 1–16. https://doi.org/10.1145/3313831.3376727
63. Maher D, Young K. Artificial intelligence and literacy development in K–12 schools. In: Keengwe J, editor. Handbook of research on transforming curriculum through digital literacy. Hershey: IGI Global; 2023. p. 80–98. https://doi.org/10.4018/979-8-3693-0205-7.ch004.
64. Maina, AM, Kuria J. "Building an AI Future: Research and Policy Directions for Africa's Higher Education," 2024 IST-Africa Conference (IST-Africa), Dublin, Ireland, 2024, pp. 01-09, doi: https://doi.org/10.23919/IST-Africa63983.2024.10569692.
65. Mansoor HMH, Bawazir A, Alsabri MA, Alharbi A, Okela AH. Artificial intelligence literacy among university students—a comparative transnational survey. Front Commun. 2024. https://doi.org/10.3389/fcomm.2024.1478476.
66. Mena-Guacas AF, Urueña Rodríguez JA, Santana Trujillo DM, Gómez-Galán J, López-Meneses E. Collaborative learning and skill development for educational growth of artificial intelligence: a systematic review. Contemp Educ Technol. 2023;15(3):ep428. https://doi.org/10.30935/cedtech/13123.
67. Mohammed AS. Examining the implementation of artificial intelligence in early childhood education settings in Ghana: educators' attitudes and perceptions towards its long-term viability. Am J Educ Technol. 2023;2(4):36–49. https://doi.org/10.54536/ajet.v2i4.2201.
68. Mosweunyane D. The African educational evolution: from traditional training to formal education. High Educ Stud. 2013. https://doi.org/10.5539/hes.v3n4p50.
69. Moya S, Camacho M. Leveraging AI-powered mobile learning: a pedagogically informed framework. Comput Educ: Artif Intell. 2024;7:100276. https://doi.org/10.1016/j.caeai.2024.100276.
70. Mutawa AM, Sruthi S. UNESCO's AI competency framework. In: Mutawa MA, Sruthi S, editors. Artificial intelligence, ethics, and society. Hershey: IGI Global; 2024. p. 75–96. https://doi.org/10.4018/979-8-3693-0884-4.ch004.
71. Nasni Naseri RN, Abdullah MS. Understanding AI technology adoption in educational settings: a review of theoretical frameworks and their applications. Inform Manag Bus Rev. 2024;16(3I):174–81. https://doi.org/10.2261/imbr.v16i3(I).3963.
72. Nedungadi P, Tang K-Y, Raman R. The transformative power of generative artificial intelligence for achieving the sustainable development goal of quality education. Sustainability. 2024;16(22):9779. https://doi.org/10.3390/su16229779.
73. Ng DTK, Leung JKL, Chu SKW, Qiao MS. Conceptualizing AI literacy: an exploratory review. Comput Educ: Artif Intell. 2021;2:100041. https://doi.org/10.1016/j.caeai.2021.100041.
74. Ng DTK, Wu W, Leung JKL, Chiu TKF, Chu SKW. Design and validation of the AI literacy questionnaire: the affective, behavioural, cognitive and ethical approach. Br J Educ Technol. 2024;55(3):1082–104. https://doi.org/10.1111/bjet.13411.

75. Ng DTK, Xinyu C, Leung JKL, Chu SKW. Fostering students' AI literacy development through educational games: AI knowledge, affective and cognitive engagement. J Comput Assist Learn. 2024;40(5):2049–64. https://doi.org/10.1111/jcal.13009.
76. Nong Y, Cui J, He Y, Zhang P, Zhang T. Development and validation of an AI literacy scale. J Artif Intell Res. 2024;1(1):17–26. https://doi.org/10.70891/JAIR.2024.100029.
77. Chisom ON, Unachukwu CC, Osawaru B. Review of AI in education: transforming learning environments in Africa. Int J Appl Res Soc Sci. 2024;5(10):637–54. https://doi.org/10.5159/ijarss.v5i10.725.
78. Ottonicar SLC, Manhique ILE, Mosconi E. Ethical aspects of information literacy in artificial intelligence. Hershey: IGI Global; 2021. p. 179–201. https://doi.org/10.4018/978-1-7998-4285-9.ch010.
79. Oyelere SS, Sanusi IT, Agbo FJ, Oyelere AS, Omidiora JO, Adewumi AE, Ogbebor C. Artificial intelligence in African schools: Towards a contextualized approach. IEEE Glob Eng Educ Conf (EDUCON). 2022;2022:1577–82. https://doi.org/10.1109/EDUCON52537.2022.9766550.
80. Peng DX, Lai F. Using partial least squares in operations management research: a practical guideline and summary of past research. J Oper Manag. 2012;30(6):467–80. https://doi.org/10.1016/j.jom.2012.06.002.
81. Prior DD, Mazanov J, Meacheam D, Heaslip G, Hanson J. Attitude, digital literacy and self efficacy: flow-on effects for online learning behavior. Internet High Educ. 2016;29:91–7. https://doi.org/10.1016/j.iheduc.2016.01.001.
82. Puzio K, Colby GT. Cooperative learning and literacy: a meta-analytic review. J Res Educ Eff. 2013;6(4):339–60. https://doi.org/10.1080/19345747.2013.775683.
83. Ringle CM, Sarstedt M, Mitchell R, Gudergan SP. Partial least squares structural equation modeling in HRM research. Int J Hum Resour Manage. 2020;31(12):1617–43. https://doi.org/10.1080/09585192.2017.1416655.
84. Sanusi IT, Olaleye SA, Agbo FJ, Chiu TKF. The role of learners' competencies in artificial intelligence education. Comput Educ: Artif Intell. 2022;3: 100098. https://doi.org/10.1016/j.caeai.2022.100098.
85. Segun S. Are certain African ethical values at risk from artificial intelligence? Data Policy. 2024;6: e68. https://doi.org/10.1017/dap.2024.64.
86. Senekal B, Brokensha S. The potential of artificial intelligence (AI) for decolonising education in South Africa through the development of indigenous languages. S Afr J Afr Lang. 2023;43(3):208–15. https://doi.org/10.1080/02572117.2023.2294405.
87. Shao C, Nah S, Makady H, McNealy J. Understanding user attitudes towards AI-enabled technologies: an integrated model of self-efficacy, TAM, and AI ethics. Int J Human-Comput Interact. 2024. https://doi.org/10.1080/10447318.2024.2331858.
88. Soliman M, Ali RA, Khalid J, Mahmud I, Ali WB. Modelling continuous intention to use generative artificial intelligence as an educational tool among university students: findings from PLS-SEM and ANN. J Comput Educ. 2024. https://doi.org/10.1007/s40692-024-00333-y.
89. Stark L. Breaking up (with) AI ethics. Am Lit. 2023;95(2):365–79. https://doi.org/10.1215/00029831-10575148.
90. Tortoise. (2024). *The global AI index*. https://www.tortoisemedia.com/data/global-ai#rankings
91. Touretzky D, Gardner-McCune C, Martin F, Seehorn D. Envisioning AI for K-12: what should every child know about AI? Proc AAAI Conf Artif Intell. 2019;33(01):9795–9. https://doi.org/10.1609/aaai.v33i01.33019795.
92. UNESCO. (2022). *AI curricula: A mapping of government-endorsed AI curricula*. UNESCO.
93. Van Wyk B. Exploring the philosophy and practice of AI literacy in higher education in the Global South: a scoping review. Cybrarians J. 2024;73:1–21. https://doi.org/10.7000/cj.2024.73.601.
94. Wakunuma K, Eke D. Africa, ChatGPT, and generative AI systems: ethical benefits, concerns, and the need for governance. Philosophies. 2024;9(3):80. https://doi.org/10.3390/philosophies9030080.
95. Westland JC. Erratum: lower bounds on sample size in structural equation modelling. Electron Commerce Res Appl. 2012. https://doi.org/10.1016/j.elerap.2012.06.001.
96. Wijoyo H, Santamoko R, Muliansyah D, Yonata H, Handoko AL. The development of affective learning model to improve student's emotional quotient. J Crit Rev. 2020;7(19):1034–9. https://doi.org/10.3183/jcr.07.19.1034.
97. Wu R, Gao L, Li J, Huang Q, Pan Y. Key factors influencing design learners' behavioral intention in human-AI collaboration within the educational metaverse. Sustainability. 2024;16(22):9942. https://doi.org/10.3390/su16229942.

Publisher's Note