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The role of learners' competencies in artificial intelligence education

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ABSTRACT

As society deals with the advances and disruptions owing to artificial intelligence, children must understand how it works. Especially that children grow up with these technologies will help them develop into informed citizens and better understand the world around them. While artificial intelligence education has been considered relevant, there is a growing global trend to teach artificial intelligence across K-12 levels. This development has necessitated designing and implementing artificial intelligence curriculum and related resources in schools. Notwithstanding that the developed curriculum may be adopted in another context, unique needs exist that suggest contextual and cultural values be considered. Besides, the current curriculum and resources designed to promote artificial intelligence education literacy are eastern and western-centric, which indicates a clear gap in artificial intelligence education in Africa. Therefore, this study examines the competencies required to be artificial intelligence literate, utilizing Nigerian secondary school students' data considering gender variation and school ownership type. A total of 605 students provided valuable responses for the analysis done with WarpLS software. We performed structural equation modelling to understand the relationship among the adopted variables utilized in the study. This study reveals the importance of teamwork and the significance of human-tool collaboration in artificial intelligence literacy through course content. This finding emphasizes the significance of teamwork among students to keep up with the pace of emerging technologies. The multigroup analysis also reveals no significant differences across gender and school type. We conclude the study with the implication of the findings and proposed future research agenda.

1. Introduction

Introducing artificial intelligence (AI) education to the K-12 population is a global initiative. This initiative addresses the demand for AI and AI-related future workforce and equips our students with lifelong skills to live and work in the AI-infused world (Cope et al., 2020). As today's children grow up with AI, the need to engage students from kindergarten through high school has been heightened to introduce the basics of AI and inspire early consideration of AI-related careers. As use of AI in education (AIEd) advances due to its enablement of learning support, content delivery and real-time assessment (Chen et al., 2020, 2022), AI education is geared toward teaching students to understand AI concepts. The need to prepare the future creators, designers and shapers of future AI technologies that currently permeate every facet of human lives is connected to the call for AI education inclusion in K-12. As a new subject in the K-12 context, there is, however, the need to uncover teaching approaches and tools (Sanusi et al., 2021; Sanusi & Oyelere, 2020) and conduct more research to understand how to implement AI education in schools effectively. Many AI education activities, including curriculum and resources, have been developed for K-12 (Chiu et al., 2021; Touretzky et al., 2019). In these studies, they focus on designing and developing AI content. The importance of curriculum design in competency, which includes knowledge and skill development, cannot be overemphasized. This development has been established by the growing research on the intersection of AI education, content, and curriculum in K-12. Such as shown in the study of Chai et al. (2020) that examined Chinese secondary school students' intention to learn AI. Relatedly, Chai et al. (2021) investigated the factors affecting

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behavioural intention toward learning AI. Chiu et al. (2021) also presented a co-creation process of developing, implementing, and evaluating a new pre-tertiary AI curriculum.

While curriculum and initiatives have been designed to introduce the AI concept and promote AI literacy in pre-K and Kindergarten (Williams et al., 2019), elementary (Kim et al., 2021), middle (Huang, 2021, ; Sabuncuoglu, 2020) and secondary (Chiu et al., 2021) school, they mainly emanated from Asia, America, and Europe. This situation indicates a clear gap in AI education in Africa, among other developing contexts (Sanusi et al., 2021). Earlier studies (Chiu & Chai, 2020) have explored the views of teachers with and without AI teaching experience on key considerations for preparing, implementing, and refining a formal AI curriculum for K-12 schools. Lin and Van Brummelen (2021) also investigated how AI education can be designed to be more accessible to all learners and organized co-design workshops with K-12 teachers to develop a curriculum that leverages learners' interests. To the best of our knowledge, no prior studies considered the views of the beneficiary of the contents in the curriculum development phase. Though Huang (2021) describes how AI courses cultivate students' key competencies, their perception gathers after exposing the students to AI courses. Notwithstanding that another context can adopt the developed curriculum, others suggest contextual and cultural values be considered. Research in the IS and education domain has shown that contextual factors influence IT resource arrangements and the core and peripheral elements in achieving incremental and radical process innovation capabilities (Akinbola et al., 2020; Mikalef & Krogstie, 2020; Park et al., 2017).

While AI literacy makes students more willing and able to engage with new technologies and less fearful of an AI-powered world (Chai et al., 2021), AI competencies are necessary to achieve AI literacy (Kim et al., 2021). Based on recent empirical work (Huang, 2021), we anticipate that learners' key competencies are vital to AI literacy and understanding of AI concepts in the African context. We also forecast that discerning the key competencies of learners will assist the designers of an AI curriculum in ensuring an "appropriate level of difficulty" and "ample illustrations with meaningful examples", as asserted by Chai et al. (2021, p.90). This forecast is expected to encourage the participation of students in AI education as they contribute to what they learn. What is more, to support student learning, curriculum and instruction should be designed in a thoughtful sequence through the inclusion of authentic tasks and understandable representations that build on students' prior knowledge and capture the key aspects of the content to be learned (Darling-Hammond et al., 2020). An earlier study has explored how AI courses cultivate students' key competencies: knowledge, team, and learning competence (Huang, 2021).

Recent authors acknowledge ethical concerns and Competencies required for students to participate actively and thrive in artificial intelligence education in K-12 (Sanusi et al., 2022). The present study extends the earlier study by considering gender differences and school types in learners' competencies for AI education in Nigerian secondary schools. The paper contributes to the ongoing effort to integrate AI education into the K-12 curriculum taking cognizance of the peculiarity of the African community in the competencies required to learn AI.

Fig. 1 depicts the argued interplay of the competencies required to equip learners with AI literacy and visualize the interactions among the competencies employed in the study. The figure illustrates the simultaneous interactions between all the elements and suggests that specific causal recipes will produce required AI literacy and skills. The rest of the paper is structured thus. First, we introduce the central concepts of this research, followed by the definition of the key competencies as conceptualized in this paper in Section 2. In the same section, this study drew the hypotheses from relevant literature. Section 3 outlines the methodology employed in the study detailing the data collection process, the measuring items, the participants, ethical considerations, and the data analysis techniques. Section 4 presents the results of the structural equation modelling (SEM) analyses, including the multigroup analysis of gender and school types. Finally, we discussed and drew on the implications of this study in Section 5 while outlining some limitations and proposed future research.

2. Conceptual framework and hypotheses development

This section describes the conceptual framework and hypotheses development. As shown in Fig. 1, the operational definition of learners' competencies in the context of AI education has been based on a previous study that investigated several competencies for AI education (Sanusi et al., 2022). Guenole et al. (2018), in their IBM's competencies in the AI era report also taxonomized knowledge, cognitive abilities, experience, and other attributes as key competencies for contemporary AI learners. In this study, the key competencies are categorized under three headings of Learning, Knowledge, and Team competencies. Each of these competencies is further sub-divided into two. Learning competence includes cognitive and self-learning competence, Knowledge competence includes skill and cultural competencies, and Team competence consists of teamwork and human-tool collaboration competence. We hypothesized that the relationship among these adopted constructs is essential in grooming AI literates. This study reckoned with cognitive, self-learning, teamwork, and human-tool collaboration

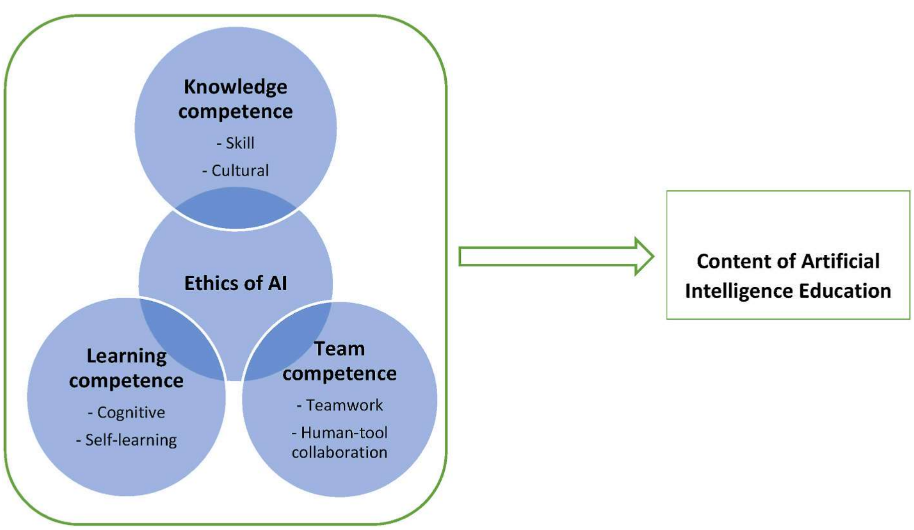

Fig. 1. Proposed framework of competencies for AI education (Sanusi, Olaleye, et al., 2022).

competence about AI course content. While it is inappropriate to think that these learners' competencies may be AI-specific, this study contextualizes them to understand the investigated phenomenon. The research model is shown in Fig. 2, which employed paths based on existing studies (Sanusi et al., 2022).

2.1. Cognitive competence

Educating citizens about AI has become necessary since its application in daily situations has become unavoidable (Sijing and Lan., 2018). We live in an era where computers and other intelligent devices influence how things are done. Understanding the concepts behind AI algorithms can be difficult, especially for novices and students in K-12 settings (Wong et al., 2020). Hence, it is essential to investigate how human characteristics such as cognitive competence and its relationship with other critical factors may influence how children learn AI concepts. The general belief about an individual competence is her/his abilities and skills to complete tasks by applying different strategies that are often unconventional but also proficient (Chong & Shahrill, 2016). According to Blomhøj (2011), cognitive competence is "a person's mental capacity to cope with a certain type of challenge in a knowledgeable and reflective way." This definition suggests that possessing good cognitive competence would require 21st-century learning skills such as critical thinking (Biasi et al., 2020), creative thinking (Kassymova et al., 2020), and problem-solving (Tsankov, 2018). From Geary (2002)'s viewpoint, cognitive competence, also called cognitive ability, is intellectual capacity but also planning communication and interpersonal characteristics for problem-solving that help to cope with social risks of antisocial behaviour. Individuals with good cognitive competence may not only avoid aggression in concrete situations but also exhibit more positive reactions in a different social context (Geary, 2002).

Increasingly huge studies demonstrate how to improve learners' cognitive competence in diverse contexts (Arce et al., 2014; Kassymova et al., 2019; Sik-Lanyi et al., 2017). For example, Resnick et al. (2016) investigated the mediating role of number-related numeracy in the developmental relationship between cognitive competencies of young learners and their later fraction knowledge using structural equation modelling (SEM). Their study shows that some cognitive competency pathway indicators, such as magnitude reasoning ability and calculation ability, affect learners' fraction knowledge.

Additionally, Sik-Lanyi et al. (2017) examined how to develop serious games to facilitate the social and cognitive competence of children with learning disabilities. Their study leveraged 3D simulation games to attract these young learners for inclusive education and to achieve their primary goal of integration and improvement in cognitive competence. Recently, a study investigated the role of infrastructure and cognitive competence of learners in distance learning situations during the Covid-19 Pandemic (Garad et al., 2021). According to these authors, cognitive competence, among other indicators, positively influence distance learning, specifically in a pandemic era. Although other similar studies exist, there is still a considerable need to conduct a study investigating the relationships between cognitive competence and other constructs within the context of AI in K-12 education. Moreover, this study is vital to demonstrate the dynamics of cognitive competence in teaching and learning AI concepts in a highly sophisticated era of technological advancement powered by AI, the Internet of Things (IoT), and human-computer interactions. Thus, this section presents the relationship between cognitive competence and other associated constructs investigated in this study.

2.2. Teamwork competence

Nowadays, different societal groups, including business organizations and educational institutions, are increasingly realigning their operational process to foster the adoption of teamwork theory (Lerís et al., 2014) that can enhance participation, streamline turnaround time, and improve efficiency and performance (Baker et al., 2005; Nadal et al., 2015). In a dynamic society where different stakeholders often expect more specific, technical, and methodological competencies, including organizations, educators, and other professionals, the role of teamwork on achievement cannot be underestimated (Nadal et al., 2015). Consequently, individuals contributing to the success of any organization are required to possess teamwork competence to drive collaborative work. One way to create a social environment that facilitates collaborations is through teamwork. From a broader perspective, teamwork comprises three components: team inputs, processes, and outputs (Baker et al., 2005). Team inputs refer to the nature of tasks to be performed, attitudes each team member brings, and the contextual situation of the teamwork. The team process delineates intricate communications and interactions among the team members toward completing the task. Team outputs

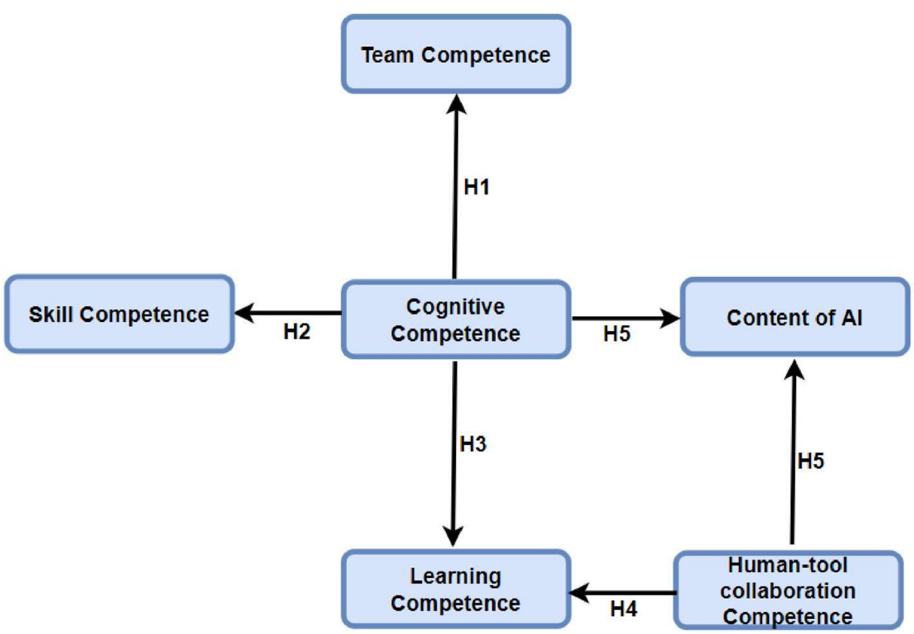

Fig. 2. Research model.

refer to concrete products that emanate from teamwork.

According to Cannon-Bowers and Salas (1998), team competencies are defined as a "learned capacity to interact with other team members at some minimal proficiency level "In the context of education, teaching and learning strategy that adopts teamwork is being exploited in a different context and learner's competence is a major concern that scholars are investigating (Hebles et al., 2019; Herrera et al., 2017; Necchi et al., 2020). According to Inceoglu and Ciloglugil (2020), the Teamwork approach in teaching computer engineering courses facilitates students' co-regulation skills. Therefore, this study hypothesizes that in acquiring AI literacy, learners' cognitive competence can influence their teamwork competence.

H1. Cognitive competence influence Teamwork competence

2.3. Skill competence

Skill, that can be used interchangeably with competency Putman (2017), refers to the capability to carry out a job function or a task through the application of acquired knowledge systematically and deliberately with sustained efforts (Salmela & Parnisto, 2005). According to Djoub (2021), skill can be domain-general or domain-specific. For instance, domain-general skills in the workplace could include teamwork, leadership, or efficient time management, whereas domain-specific skills could be required to perform a specific task such as designing a file sharing protocol within an organization (Djoub, 2021). Skill competence, therefore, can be understood as mastery of specific learned sets of abilities needed to specialize and complete tasks. Perceived cognitive competence is an important factor for learners of AI concepts that are already complex to comprehend. Therefore, this study hypothesizes that increasing learners' cognitive competence may affect their skill competence to demonstrate AI education. *H2: Cognitive competence influences Skill competence*.

2.4. Self-learning competence

Simply put, self-learning is a situation whereby learners learn on their own without the interference or intervention of others. In other words, learners independently take control of what they learn, when they learn, and how they learn (McKain, 2019). Therefore, they determine the scope of learning, aims, and learning sources (Liu, 2015). Self-learning allows the learner to be involved in creating their knowledge and improving their cognitive skills. In education and at the workplace, self-learning is required as a necessary skill (Liu, 2015). Studies have shown that students who can conveniently learn on their own outperform those who do not have this competence (Broadbent & Poon, 2015; Oyelere et al., 2021). In addition, a study by Yingxue et al. (2013) shows that self-efficacy positively impacts self-learning expectancies. Based on the perceived role that self-learning plays by allowing students' involvement to create and control their learning situation, this study investigates the impact of cognitive competence of k-12 students who are learning AI on their self-learning competence. In other words, this study hypothesizes that the cognitive competence of learners trying to gain AI literacy can influence their competence in self-learning.

H3. Cognitive competence influences self-learning competence

2.5. Human-tool collaboration competence

Human beings have been collaborating for a long time to learn at school or solve tasks at the workplace. With technological advances, humans and tools can collaborate through a computer agent technology powered by AI (Rosen, 2015; Rosen & Tager, 2013). In this era human-tool interaction and collaboration are topics that have been explored as a pedagogical approach to foster student engagement for an enhanced learning experience (Cho et al., 2009; Moallem, 2015; Nuci et al., 2021). For example, Rosen and Tager (2013) conducted a study to investigate the dichotomy between the human-to-agent versus the human-to-human approach to assessing collaborative problem-solving skills. According to Rosen and colleagues, the human-to-agent approach applied more attempts to solve given problems compared to the human-to-human approach. Similarly, studies have demonstrated how human-robot collaboration can foster learning and task completion in an efficient manner (Knauer et al., 2017; Shu, Sziebig, & Pieskä, 2018). Thus, this study seeks to examine how the human-tool collaboration approach in teaching AI to K-12 students can affect their self-learning competence by hypothesizing that.

H4. Human-tool collaboration competence influences self-learning competence

2.6. Content of AI

Learning content remains a critical element playing a vital role in students' achievements (Wegner et al., 2013). Students' ability to process information, comprehend and retain knowledge largely depends on the learning material, among other factors (Oyelere et al., 2021). Therefore, for students in K-12 settings to develop an interest in learning AI concepts, the content must be carefully planned to motivate and arouse their curiosity towards uncovering how AI perform intelligently behind the scenes. Therefore, this study examines how students' cognitive competence can influence the content of AI and whether human-tool collaboration competence impacts AI content. Hence, the following hypothesis was formulated.

H5. Human-tool collaboration competence influences the understanding of the content of AI

H6. Cognitive competence influences the understanding of the content of AI

3. Methodology

3.1. Context and instrument

A survey instrument was adapted and administered to 605 secondary school students to explore the key constructs of competencies concerning the content of AI education.

For this study, the survey was adapted from Huang (2021, pp. 1–21), which sampled K-12 students in China after teaching AI courses. The survey targets their K-12 counterpart in Nigeria to understand the competencies required to be AI literate in schools owing to contextual and cultural differences. It is important to note that AI education has not been introduced to K-12 in Africa and Nigeria, but the survey was carried out after an experimental teaching session, as detailed in 3.3. The hardcopy questionnaire contained questions about competencies required to learn new and emerging technology concepts such as AI courses. Since the variables utilized were based on previously published latent variables, the instrument used with psychometric properties supports their validity. A 7-point Likert scale was utilized for all constructs and their corresponding items. This scale is adopted because it provides more options, increasing the probability of meeting the objective reality of people (Joshi et al., 2015). It was further stressed that a 7-point scale reveals more description of the motif and thus appeals practically to the "faculty of reason" of the participants. Mikalef and Krogstie (2020) also asserts that it is a well-established practice in large-scale empirical research settings where no standardized measures exist for quantifying notions such as resources and capabilities.

Below are the adapted items:

CAI refers to content related to AI. The items were "Acquiring programming knowledge is beneficial to me; Intelligent robots are useful in my life; Knowledge of AI is crucial in understanding AI". SKC measures basic knowledge and basic applicable methods the student possesses. The items used were "My logical thinking is strong; My critical thinking is strong; I am good at observing".

TWC measures the students' ability to deal with interpersonal relationships and to communicate with students in a team. The items were "I would like to collaborate with another student; I would like to shoulder responsibility in the collaborative projects in my school; I would like to discuss and solve problems together with other students in cooperative projects". HTC emphasizes students' ability to recognize technological tools and use them properly. The items were "I can use technological tools to help me solve problems; I am dependent on technological tools; I can select suitable technological tools; Technological tools help improve my abilities."

CC refers to the perception of students' ability to feel, perceive and represent things and the ability to judge, reason, analyze and draw conclusions. The items were "I would like to perceive things; I would like to represent things; I would like to judge concepts". SLC refers to students acquiring knowledge through independent analysis, exploration, practice, questioning, and creation. The measures were "I would like to analyze problems independently; I would like to explore independently; I would like to practice independently; I would like to ask myself questions; I would like to create independently."

3.2. Participants

Data were retrieved from the students based on the adapted survey. A total of 614 students started to complete the survey, with 605 providing complete responses. Since the survey was introduced after the teaching session, it served as an effective way to reduce incomplete responses. The final set of responses came from students of different age groups and class grades, as depicted in Table 1. Regarding the participation by gender, female (50.2%) is slightly more than male (49.8%). The number of both sexes involved in the study is almost the same, which constitutes a gender balance.

Regarding their age, the student's age range falls mostly within 16–20 years (58%). As expected, because of the age range, the students are majorly in grade 12 (51%) while Grade 9 students are the least at 1%. To further explore students' course orientation, an attempt has been made to classify them whether they are active in science, art or commercial. 71% of students were in the science department, while only a few (8%) were in the commercial class. While almost the same number of the students involved represent both government-owned and privately-owned schools, 81% of the students are from schools located in urban areas. Almost 80% of the students possess either a phone or laptop device.

Table 1
Sample characteristics of the K-12 participants.

Factors	Sample (N = 605)	Proportion (%)
Gender		
Female	307	50.2
Male	298	49.8
Age		
10–15	244	40
16–20	352	58
20 and above	9	1
Grade		
Grade 9	8	1
Grade 10	161	27
Grade 11	125	21
Grade 12	311	51
Group		
Science	429	71
Art	126	21
Commercial	50	8
School type		
Public	299	49
Private	306	51
School Location		
Urban	489	81
Rural	116	19
Types Mobile device owned		
Phone	334	55
Laptop	19	3
Phone and Laptop	120	20
None	132	22

3.3. Research procedure

Respondents in this study are six hundred and five secondary school students recruited across five different schools across different locations, school types, and classes. The schools' authorities were approached individually and discussed the possibility of conducting an experimental teaching session on AI education. Out of the ten schools approached, five of the school consented and allocated an hour each scheduled for their extra curriculum activities for the proposed session on separate days. The teaching session was designed as a 45-min intensive session introducing AI education concepts. The researcher(s) developed a teaching guide specifically for the session based on the seven main categories set by (Huang, 2021), which include knowledge of programming, image processing knowledge, natural language processing knowledge, knowledge of robots, the course of AI development, ethics of artificial intelligence and machine learning.

The teaching session starts with short videos describing Artificial Intelligence, Machine Learning and Programming with illustrations and their examples as utilized in day-to-day activities. The session specifically utilizes a 4-minutes video of CSER MOOC on Teaching Artificial Intelligence as a point of departure. A 3-minutes short video on machine learning from the Australian Institute of Machine Learning was shown afterwards. Programming and robotics about AI were briefly discussed with illustrations and their examples as utilized in day-to-day activities. The specific short videos were introduced due to the simplification of their contents, providing practical examples that allow even novices to grasp AI. The videos describe AI, ML, and related concepts with illustrations and everyday examples.

After showing the videos and in-between interjections from the teacher for emphasis and clarity of the concept, the session continued as student-led discussions. Previous literature (Brisbin, 2015; Burgess, 2009; Rugutt & Chemosit, 2009) have emphasized the effectiveness of student-led discussions teaching strategy. Brisbin (2015) reported that students majorly feel much more motivated to complete the task at hand when allowed to freely discuss the ideas of the class about the content being taught. Burgess (2009) further stressed that the format of the conversation does not matter regarding the effect of the increased motivation but what is most important is that students have the freedom to take the discussion to places that they see fit. As a result of the discussions, we noticed that students were able to give examples of AI applications. After the end of the inclusive discussion, hardcopy questionnaires were distributed to gauge the students' perception of AI education based on the lesson taught as well as the ratings of their competencies.

3.4. Data analysis

This study utilized WarpPLS for reliability test (Cronbach's alpha α), factor loadings, average variance extracted (AVE), and composite reliability (CR) and model fit shown in Table 2, 3, 4 and 5. The factor loadings results show a reliable loading and range between 0.63 and 0.80, while the factor loading values are higher than the required 0.5. The composite reliability values are also equal to and greater than the boundary of 0.7. The results show a minimum of 0.74 and a maximum of 0.87. also, the average variance extracted (AVE) with a minimum of 0.50 and a maximum of 0.61. All the values are equal to or higher than the threshold of 0.5. The Variance Inflation Factor (VIF) results also show that the measurement's multicollinearity is not outrageous, and the data is free from collinearity issues. The correlations among the latent variables with the square root of AVEs are shown in Table 4, while

Table 2
Model fit and quality indices.

No	Model fit and quality indices	Criterion	Result	Interpretation
1	Average path coefficient (APC)	P value ≤ α (5%)	P < 0.001	Acceptable
2	Average R-squared (ARS)	P value ≤ α (5%)	P < 0.001	Acceptable
3	Average adjusted R-squared (AARS)	P value ≤ α (5%)	P < 0.001	Acceptable
4	Average block VIF (AVIF)	Acceptable if ≤ 5, ideally ≤ 3.3	1.157	Acceptable
5	Average full collinearity VIF (AFVIF)	Acceptable if ≤ 5, ideally ≤ 3.3	1.340	Acceptable
6	Tenenhaus GoF (FoF)	Small ≥ 0.1, Medium ≥ 0.25, Large ≥ 0.36	0.264	Large
7	Sympson's paradox ratio (SPR)	Acceptable if ≥ 0.7, ideally = 1	1.000	Acceptable
8	R-squared contribution ratio (RSCR)	Acceptable if ≥ 0.9, ideally = 1	1.000	Acceptable
9	Statistical suppression ratio (SSR)	Acceptable if ≥ 0.7	1.000	Acceptable
10	NLBCDR	Acceptable if ≥ 0.7	1.000	Acceptable

NLBCDR=Nonlinear bivariate causality direction ratio.

all the indices meet the established thresholds in the model fits and quality indices in Table 2.

4. Result

4.1. General structural model

Table 5 shows the path coefficients and variation of the paths for the general structural model. In the overall model, cognitive competence is the highest predictor of teamwork competence, while human collaboration tool competence is the most impactful in relation to the contents of AI. All the hypotheses are supported. WarpPLS software was used to test the hypotheses of partial least square (PLS) path modelling in this study. A structural equation modelling (SEM) approach aids in analyzing the research models comprising multiple constructs with multiple items. The tested hypotheses are shown in Fig. 3, which includes path coefficients and variance descriptions. As revealed in Fig. 3, cognitive competence predicts teamwork competence, with CC → TWC $\beta = 0.31$ and t = 7.90, cognitive competence is associated with skill competence, with CC → SKC $\beta = 0.24$ and t = 6.15, and Cognitive competence is associated self-learning competence, CC → SLC $\beta = 0.26$ and t = 6.49. Human collaboration tool competence will positively affect self-learning competence; HTC → SLC $\beta = 0.30$ and t = 7.53 and human collaboration tool competence and contents of AI, HTC → Content $\beta = 0.29$ and t =

Table 4
Correlations among latent variables with AVEs.

	TWC	CAI	SKC	CC	SLC	HTC
TWC	0.778					
CAI	0.239	**0.704**				
SKC	0.432	0.294	**0.755**			
CC	0.31	0.241	0.243	**0.777**		
SLC	0.369	0.298	0.361	0.366	**0.757**	
HTC	0.355	0.336	0.344	0.368	0.391	**0.73**

Note: Square roots of average variances extracted (AVEs) shown on diagonal.

Table 5
Standardized path coefficients for general model.

Hypotheses	Path Links	β	T Ratio	P-value	Result
H1	CC → TWC	0.31	7.90	<0.001	Significant
H2	CC → SKC	0.24	6.15	<0.001	Significant
H3	CC → SLC	0.26	6.49	<0.001	Significant
H4	HTC → SLC	0.30	7.53	<0.001	Significant
H5	HTC → CAI	0.29	7.28	<0.001	Significant
H6	CC → CAI	0.14	3.37	<0.001	Significant

Table 3
Standardized loading and construct reliability.

Items	TWC	CAI	SKC	CC	SLC	HTC	*f*	CR	AVE
TWC							0.096	0.821	0.61
TW1	0.805								
TW2	0.757								
TW4	0.77								
CAI							0.032	0.746	0.50
CAI1		0.639							
CAI4		0.736							
CAI5		0.732							
SKC							0.059	0.798	0.57
SKC1			0.806						
SKC2			0.772						
SKC4			0.682						
CC							0.094	0.820	0.60
CC1				0.767					
CC2				0.795					
CC3				0.769					
SLC							0.116	0.870	0.57
SLC1					0.732				
SLC2					0.783				
SLC3					0.809				
SLC4					0.695				
SLC5					0.759				
HTC							0.096	0.820	0.53
HTC1						0.706			
HTC2						0.718			
HTC3						0.791			
HTC4						0.701			

Notes: Loadings are unrotated and cross-loadings are oblique-rotated. SEs and P values are for loadings. P values < 0.05 are desirable for reflective indicators. TWC = Teamwork competence, CAI = Content of Artificial Intelligence, SKC = Skill competence, CC = Cognitive competence, SLC = Self-learning competence, HTC = Human-tool collaboration competence, CR = Composite reliability, AVE = Average Variance Extraction.

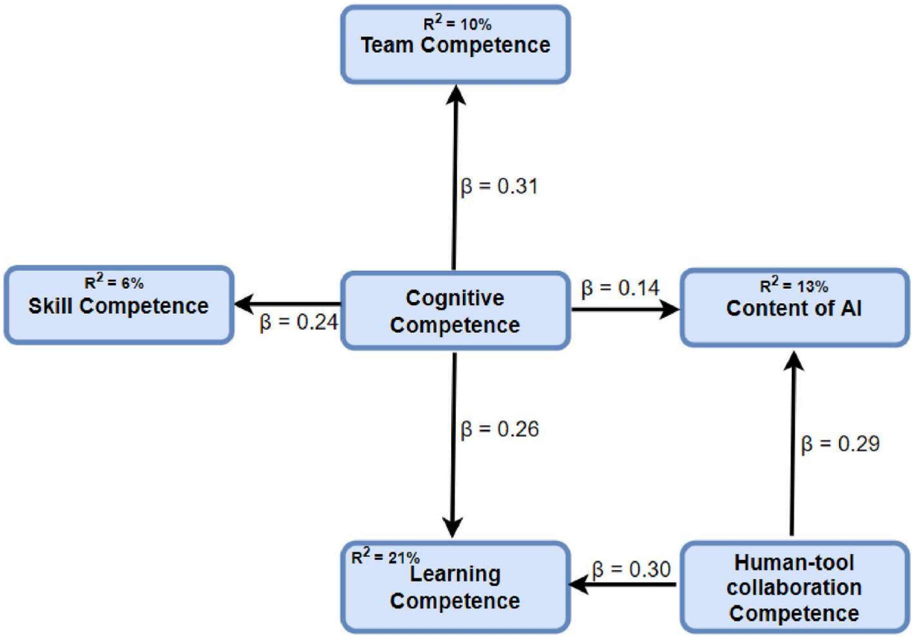

Fig. 3. Tested hypotheses result.

7.28. The relationship between cognitive competence and contents of AI, CC → Content $\beta = .14$ and t = 3.37 was also found to be significant in this study. In the proposed model, Cognitive Competence is the highest predictor of Team Competence. Also, Skill Competence had the lowest coefficient of determination (6%), followed by Team Competence (10%), the Contents of AI (13%), and the highest R^2 is Learning competence (21%). All the variances that the model explained fall below the threshold of weak.

4.2. Gender and school type multigroup model assessment

We embarked on multigroup analysis with WarpPLS Bootstrapping to confirm the gender and school-type differences in their key competencies to learn AI in an African context. The beta coefficient indicates the degree of change in the dependent variable for every 1-unit change in the independent variable, and this study reported the beta coefficient of the multigroup variables. The multigroup path coefficient in this study reveals the difference in the perception of males and females. The perception that cognitive competence and teamwork competence beta coefficient (β) influences AI literacy is higher among males than females (β = 0.35/β = 0.27), while the students' perception of cognition and skill competencies required to learn AI is higher among females than males (β = 0.26/β = 0.21). Cognitive competence and self-learning competence are higher among males than females (0.20/0.33), while human collaboration tool competence and self-learning competence beta coefficient (β) is higher among females than males (β = 0.32/β = 0.27). The association between human collaboration tool competence and contents of AI is higher among females than males (β = 0.35/β = 0.16). The relationship between cognitive competence and contents of AI is higher in males than females (β = 0.09/β = 0.17). All the paths are significant across gender except for cognitive competence contents of AI for females. The cognitive competence exhibited by the female students does not predict literacy in AI course content.

The school-type assessment goes; thus, the perception that cognitive competence and teamwork competence influences AI literacy is higher in private schools than in public schools with a beta coefficient (β = 0.38/β = 0.25), while the students' perception of cognitive and self-learning competencies required to learn AI is higher among public schools than private schools (β = 0.28/β = 0.24). Cognitive competence and skill competence is higher among private school students than public school students (β = 0.33/β = 0.17), while human collaboration tool competence and self-learning competence is higher among students in public school than in private schools (β = 0.32/β = 0.27). The association between human collaboration tool competence and contents of AI is slightly higher among students in private schools than in public schools (β = 0.29/β = 0.28). The relationship between cognitive competence and contents of AI is higher in public than private school students (β = 0.16/β = 0.10). All the paths are significant across school types except for cognitive competence contents of AI for private schools. Cognitive competence is not a predictor of literacy of AI course content among students in privately-owned schools.

This study tested if the proposed model differs between male vs female and private vs public school groups for the measured variables. In summary, all the structural model paths (CC to TWC, CC to SKC, CC to SLC, HTC to SLC, HTC to CAI) are significant for Males, Females, and Private and Public Schools. However, the path from (CC to CAI) was only significant for Males and Public Schools based on two-tailed hypotheses adopted. The *t*-test value for Females and Private Schools are 1.65 and 1.75, which are lower than the critical limit of 1.96 (SeeTable 6 for details).

Table 6
Gender and School type multigroup path coefficients and corresponding hypothesis results.

Path	Male	Female	Private	Public	Different	Remark
CC → TWC	6.29***	4.98***	6.93***	4.57***	YES	S
CC → SKC	3.77***	4.75***	5.92***	2.97**	YES	S
CC → SLC	6.00***	3.53***	4.27***	5.12***	YES	S
HTC → SLC	4.84***	5.84***	4.96***	5.79***	YES	S
HTC → CAI	2.84**	6.45***	5.16***	5.12***	YES	S
CC → CAI	2.99**	1.65	1.75	2.95**	YES	S/NS/NS/S

Note: Table 6 shows two-tailed hypothesis. *** specifies significance of the multigroup path-coefficients at the 0.1% p-value level, ** indicates significance at the p-value level 1% level, * indicates significance at the 5% p-value level. S: Significant; NS: Not Significant.

5. Discussion and implication

Research has begun to examine how AI courses cultivate students' key competencies to promote AI literacy among K-12 students (Huang, 2021). Especially about specific competencies of knowledge, team and learning competencies, little is known about the core competencies that help drive the development of AI literacy, and even less regarding the gender and school-type factors in influencing the understanding of AI education. While it may be useful to consider the requisite competencies for effectively learning AI, taking cognizance of gender and school differences, it is also important to research into a context, in this case, Africa, since there is a dearth of study in the context on AI/ML education for K-12 (Sanusi, 2021a; 2021b). These results reveal the contextual patterns and inform about creating, designing, or adopting appropriate resources/approaches for teaching ML in the region. This study contributes to understanding the ingredients and preconditions of successful implementation of AI education by elaborating on the interrelation between the key competencies and the course content. The study focuses on examining the competencies required to be AI literate, utilizing Nigerian secondary school students to understand better the competencies that will impact the effective learning of AI in an African setting, particularly Nigeria. We anticipate that our initial findings will contribute to the development of AI education, including African schools in the global democratization plan of integrating AI education into K-12. The competencies considered in the study include cognitive, teamwork, skill, self-learning and Human-tool collaboration competence about course contents of AI.

Compared with the work of Huang (2021), which shows teamwork competence and human-tool collaboration competence has negative associations with AI course contents, this study reveals the importance of teamwork and the significance of human-tool collaboration in AI literacy through AI literacy course content. This finding emphasizes the significance of teamwork among students to keep up with the pace of emerging technologies. According to Yang et al. (2011), teamwork encourages the innovative spirit and creative ability to generate new knowledge, think productively and increase the motivation of students and enthusiasm to learn and solve problems together. Plotnikova and Strukov (2019) reiterate that building students' teamwork competencies promotes the formation of critical thinking and creativity. There is a deficiency in skills and attitude to work collaboratively as a team among students and teachers, especially in Africa (Nudelman, 2020; Petker & Petersen, 2017; Pitsoe & Isingoma, 2014); the emphasis should be placed on finding innovative ways of encouraging teamwork. Especially, teamwork competence indirectly influences AI literacy through the course content of AI. This study also confirms the influence of Human-tool collaboration as highlighted in earlier literature. According to Beach et al. (2015), the ability to utilize digital literacy tools allows students to display competence, enhancing their engagement with learning and confidence in exploring new fields. Besides, through students' interaction with digital tools, they began to experience an increased sense of agency which is relevant for succeeding in the world of AI.

This study further indicates that cognitive skills and self-learning competence influence their understanding of AI intelligence through the course content. These findings are in tandem with the study of Huang (2021), which found that these three adopted variables show a positive linear correlation with the contents of AI courses. However, it means in Huang's study that students highly regarded the role of AI course content in the cultivation of the three sub-competencies, whereas our findings signal that developing these competencies is vital for breeding AI literate right from K-12. This result implies that elements of these highlighted competencies should be a factor in the resources to be designed or adapted for students, especially in the context of Africa, to be well equipped with AI education basics. Cognitive competence is the highest predictor of teamwork competence, followed by human-tool collaboration as a predictor of self-learning competence, while human-tool collaboration has the highest and most direct impact on learning AI through course content.

While the disparate learning of AI between rural and urban students has been explored (Sanusi & Olaleye, 2022), extant studies have not paid attention to gender variation as well as school ownership type (Private/public) in learning AI and the relationship between knowledge, team, and learning competence, this study addresses this gap. In contrast to the general model that shows all the tested hypotheses are significant, the multigroup analysis evinces that the relationship between cognitive competence and the course contents is not significant in female students. It further reveals that cognitive competence, and the course contents are not significant among students in private-owned schools. Some of the findings stand out because there are no significant differences across gender and school type. Such those include the obvious differences in how cognitive competence predicts teamwork competence in male students than their female counterparts in private versus public schools. Also, the association of human collaboration tool competence and contents of AI is higher among females than males. Findings further show that cognitive and skill competence is higher among private school students than public school students. The variation in the perceived competencies about course content and AI literacy across schools contributes to discussions around the quality of private versus public schools (Pesando et al., 2020). United Nations Educational Scientific and Cultural Organisation (UNESCO) speculated that the worth of AI in education to be 6 billion dollars by 2024 (UNESCO, 2021). This study generates insightful managerial implications concerning future development. First, the educators and practising managers of AI should focus on gender, public and private school differences when considering how AI can support students' development, well-being, data, privacy, and safety based on identified competencies in this study. Second, the educators and practising managers should create an enabling environment for the student-centered AI to interplay teamwork, skill, cognitive, learning, and human-tool collaboration competencies in a direct and indirect relationship with the AI contents.

Based on our findings from this study, we offer some suggestions for instructors. First, teachers should be provided with pedagogic competency training to utilize novel pedagogies and approaches. Such teacher training will enable them to introduce AI with more engaging approaches and initiatives effectively. Another suggestion is to use intuitive activities to introduce AI concepts to their students. With this, students will access AI lessons designed with simple bite-sized examples they are familiar with (Oyelere et al., 2022). Utilizing such an approach will the relevance of what the students are learning and increase engagement in learning AI. Professional development (PD) is essential in upgrading and updating teachers to improve student learning. Providing PD will prepare teachers with the content, pedagogy and knowledge (Sanusi, Oyelere, & Omidiora, 2022; Ayanwale et al., 2022) to implement AI concepts in classrooms.

6. Conclusion

This study contributes to knowledge by highlighting the important role of learners' competencies in teaching and learning, specifically regarding AI education. Since competence is beyond cognitive elements and encompasses skills and interpersonal attributes appropriate to the context, the role of learner's competencies must be examined to effectively develop content suitable for them. This paper reveals the importance of teamwork and the significance of human-tool collaboration in artificial intelligence literacy through course content. This finding emphasizes the significance of teamwork among students to keep up with the pace of emerging technologies. The multigroup analysis also reveals no significant differences across gender and school type. Currently, limited studies have investigated gender differences in AI learning (e.g., Xia et al., 2022). This study adds to the literature on AI learning differences between boys and girls and school types (private vs government-owned schools).

While the results of this study shed some light on the relationship between some key competencies concerning understanding the content of AI and AI literacy, this work unavoidably has some limitations. First, our sample comprises a few secondary school students from five selected Nigerian schools. Students from other schools or regions may exhibit different perspectives other than the conclusion from the findings. While it may be useful to consider different contexts and gather their views based on their settings and peculiarities, it is also important to conduct research across contexts (comparison within and outside Africa), taking cognizance of heterogeneity to derive contextual patterns with meaningful insights than a country/context study that would be in isolation. Future studies should consider involving more schools and students across the country and African countries. In addition, future studies could validate findings from this study, for example, by conducting activities that support teamwork for AI literacy among students. Second, the quantitative approach may limit our understanding of the students' key competencies in learning AI. As a result, a complementary study adopting a qualitative approach would likely reveal more insight on how to further develop competencies for AI literacy. Finally, one of the study's limitations concerns the duration of the teaching session. Ideally, it would have been preferable that the introduction of the AI content lasted for a school term or session.

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