



Vol.7 No.2 (2024)

Journal of Applied Learning & Teaching

ISSN : 2591-801X

Content Available at : <http://journals.sfu.ca/jalt/index.php/jalt/index>

Curriculum factors and sustainable artificial intelligence-driven classroom assessment. The mediating role of computer self-efficacy and digital literacy

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Keywords

AI;
artificial intelligence;
assessment;
computer self-efficacy;
curriculum innovations;
curriculum quality;
digital literacy;
exploratory and confirmatory factor analysis;
generative artificial intelligence;
sustainability.

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Article Info

Received 29 April 2024
Received in revised form 30 June 2024
Accepted 18 July 2024
Available online 18 July 2024

DOI: <https://doi.org/10.37074/jalt.2024.7.2.10>

Abstract

The impact of artificial intelligence in education has been well documented. However, the sustainability of artificial intelligence-driven classroom assessment has not been the focus of much literature. This study sought to cover this research gap by examining the role of curriculum innovation, quality, and viability when mediated by computer self-efficacy and digital literacy in sustainable AI-driven classroom assessment. A total of 1607 respondents were used for the study. A questionnaire that was validated by experts and the psychometric properties of exploratory and confirmatory factor analysis were used to determine the structure and dimensionality of the scale. The findings of the study revealed that curriculum innovation directly affects curriculum viability, curriculum quality, digital literacy, computer self-efficacy, and sustainable AI-driven classroom assessment. At the same time, curriculum quality and viability also affect digital literacy, computer self-efficacy, and sustainable AI-driven classroom assessment. The mediation of digital literacy and computer self-efficacy in the nexus between curriculum innovation and sustainable AI-driven classroom assessment was significant. However, these mediators were insignificant in the nexus between curriculum quality and sustainable AI-driven classroom assessment. The implications of the findings were discussed, especially for policy developments.

Introduction

Artificial intelligence (AI) is one of the current digital technologies that has permeated the educational sector so deeply that teachers and students currently utilize it for diverse purposes. AI tools are currently engineered to perform human-like functions with accuracy and speed (Chai et al., 2020; Kuleto et al., 2021). Like other groundbreaking technologies: virtual and augmented reality, robotic technology, 3D printing, and advanced networking, AI today can comfortably perform functions like content generation (Qu et al., 2022), automated assessment grading (Gardner et al., 2021), supervision of examinations (Braiki et al., 2020), personalized learning (Zhai et al., 2021), intelligent tutoring (Kubsch et al., 2022; Li et al., 2023) and provision of answers to diverse questions (Ouyang et al., 2023) among others. The sophisticated characteristics of AI tools that have over time advanced from machine learning (ML) through deep learning (DL) and are now applied have led to the performance of other tasks such as language translation, visual perception, speech recognition, and decision-making with virtual tools (Zehner & Hahnel, 2023). Hence, in classroom circles, these advanced tools have, over time, played a significant role in reshaping the traditional mode of assessment with more sophisticated technologies that align with global demands and the dynamic nature of the educational ecosystem (Joosten & Cusatis, 2020).

Artificial Intelligence (AI) has also been revolutionary in assessment. AI is increasingly finding its place in classroom assessment, revolutionizing traditional methods by offering personalized learning experiences and real-time feedback. AI algorithms can analyze student data, such as test results and learning behaviors, to tailor educational content to individual needs (Blikstein, 2018). Moreover, AI-powered assessment tools can assess student performance more accurately and efficiently than manual grading, allowing educators to focus more on teaching (Akinola et al., 2020). For instance, AI can detect patterns in student responses and provide adaptive assessments that challenge students at appropriate levels (Popenici et al., 2023). This integration of AI enhances assessment practices by promoting fairness, efficiency, and personalization in educational settings. For example, language processing systems and AI algorithms can generate responses to students' essay tests and provide immediate feedback to questions raised by the learner (Luckin et al., 2024).

Furthermore, the use of AI has certain implications, given the fact that there are identified dangers associated with the use of AI. The integration of AI in classroom assessment within higher institutions brings forth several potential dangers and challenges. Firstly, concerns arise regarding the reliability and validity of AI algorithms in accurately assessing complex student work, such as essays or creative projects (Williamson et al., 2019). There is a risk that AI may not fully capture the nuances of student learning and could potentially misinterpret or penalize unconventional but valid responses (Williamson et al., 2019). Moreover, there are ethical implications surrounding data privacy and security, as AI systems require access to substantial amounts of student data, raising concerns about confidentiality and misuse (van Dijck, 2014). Furthermore, the reliance on AI for

assessment may lead to a reduction in human interaction and personalized feedback, potentially diminishing the quality of the learning experience (Williamson et al., 2019). Educators may also face challenges in understanding and interpreting AI-generated assessments, impacting their ability to effectively support student learning and development (Selwyn, 2019). These dangers underscore the importance of careful implementation and ongoing evaluation of AI technologies to mitigate risks and maximize their beneficial impact in educational settings.

However, the key question raised over time is basically the sustainability of AI-driven classroom assessment. Sustainable AI-driven classroom assessment describes the assessment practices that integrate AI tools in assessment to enhance educational outcomes while minimizing environmental impact and promoting long-term viability. This helps educators create a flexible assessment method that can foster learning, adjust to the needs and experiences of the students, and reduce resource consumption. According to Baker and Inventado (2019), using adaptive learning platforms is one notable example of sustainable AI-driven assessment because it utilizes AI algorithms to analyse students' data and provide real-time feedback that helps provide curative measures on time. Similarly, the use of AI reduces paper-pencil tests, which sometimes litter materials around the environment, thereby leading to environmental hazards. In an era where traditional methods do not promote inclusivity in testing, sustainable AI-driven assessment accommodates learners with diverse learning abilities and styles using tools like speech recognition technology, which can enable students with disabilities to participate in oral assessments on an equal footing with their peers (Peng et al., 2020).

In the Nigerian context, given the existing inequalities and the lack of access to AI tools by staff and students, there are growing concerns that this integration should not widen the existing gap (UNESCO, 2022). Similarly, the environmental impact of deploying digital infrastructures, such as increased energy consumption, must be addressed, ensuring that AI solutions align with the national agenda for sustainable development. However, despite the potential benefits, efforts by researchers to examine AI-driven assessment sustainability in Nigeria have remained few. There is limited research on how AI tools can be used today and tomorrow without compromising environmental quality, as well as how to integrate them into the curriculum so as to foster innovation and quality education (Jones & Brown, 2021). In fact, several reasons have been adduced for these disparities, which include infrastructure limitations (Oyelami & Badejo, 2020), digital divides (Ogunbodede & Iahad, 2020), financial constraints (Adedaja & Akinola, 2018), data privacy and security concerns (Ojo & Oluwatayo, 2019), curriculum alignment (Okwundu & Olugbara, 2020), and capacity building (Ezekiel et al., 2020). This emerges as a critical issue, with a shortage of expertise and technical skills among educators and administrators impeding the effective deployment and utilization of AI-driven assessment technologies.

Previous studies have attempted to examine the impact of AI on assessment (Adarkwah et al., 2023; Ifelebuegu et al., 2023; Ouyang et al., 2022). For example, the study of Owan et al. (2023) found that AI is essential in educational measurement in that it can be used in the development process of a test. Ofem et al. (2024) found that AI is beneficial for academic research in higher institutions. Rasul et al. (2023) noted that AI has proven to be beneficial to higher education students because it has been used in research support, personalized learning, data collection, and assessment practices. These studies focused more on how AI affects the educational system. It was not focused on the impact of AI on assessment or the sustainability of an AI-driven classroom. Over the years, the rise in the application of AI has raised a lot of attention and even divided schools into those that support and oppose the new technology. Adeleke and Ayo's (2020) study on the use of AI in educational assessment in Nigeria found that AI has improved grading efficiency and provides timely feedback to students. Oyelami and Aderonmu's (2018) study revealed that AI techniques impact students learning in a positive way in secondary schools, especially through personalized learning experiences and improved knowledge of the subject matter. Other studies in Nigeria have also shown that AI has effectively improved assessment practices (Ogunbodede & Iahad, 2020; Olufemi & Akinwale, 2019). Beyond Nigeria, Mbarika et al. (2019) found that AI has been able to enhance inclusivity and equity in assessment practices. Ogundele and Oyediren's (2021) study on data-driven machine learning approaches for managing sustainable development goals in Africa: A Focus on Educational Assessment. AI has been able to maximize sustainable assessment practices at the descriptive level. Huang and Rust (2018) found that AI has opportunities in sustainability practices in assessment and challenges in AI in service industries in Europe, including its potential applications in educational assessment. With their insights, these studies have not examined the impact of curriculum design in the form of curriculum innovation, curriculum quality, and viability on sustainable AI-driven assessment when mediated by computer self-efficacy and digital literacy.

Curriculum design, which in this context is conceptualized as innovation, quality, and viability, are essential educational practices that must align the needs of learners and society with global trends. The flexibility of the curriculum will help new ideas and technologies be incorporated into the system and inculcated in the learners for maximum productivity and usefulness (Adeleke & Ayo, 2020). Other researchers have noted that curriculum innovation in the era of AI-driven assessment ensures that there is educational efficacy because teachers and educators can create more personalized learning experiences that maximize individuals' needs and interests (Oyelami & Aderonmu, 2018). Moreover, a focus on quality assurance ensures that AI-driven assessment methods meet rigorous standards of validity, reliability, and fairness. This is crucial for maintaining the integrity and credibility of assessment results, thus providing reliable feedback to both students and educators. Quality assurance mechanisms, such as validation studies and psychometric analyses, help identify and address potential biases and inaccuracies inherent in AI algorithms (Olufemi & Akinwale, 2019). Additionally, assessing the viability of sustainable

AI-driven assessment involves considerations of scalability, cost-effectiveness, and long-term implementation strategies. Sustainable integration of AI technologies into the curriculum requires careful planning and investment in infrastructure, teacher training, and ongoing support systems (Ogunbodede & Iahad, 2020). Understanding the resource implications and potential challenges associated with AI adoption is essential for educational institutions seeking to maximize the benefits of these technologies while minimizing risks (Fotouhi-Ghazvini & Puteh, 2020).

The study has both theoretical and practical contributions. First, the study may help in the development of sustainable AI-driven assessment tools that can not only be efficient in the classroom but also become adaptive to environmentally and socially sustainable practices. These tools may have the capacity to provide real-time feedback as well as provide more engaging learning experiences, which can inversely improve students' learning outcomes. Secondly, the study may inform policy development based on data-driven evidence that will support sustainable AI integration in schools. These policies could be on data protection, fairness, and equity in access to technology. Educators can benefit from the practical applications of this research through enhanced professional development programmes that include training on the use of sustainable AI in classroom assessments. Additionally, curriculum designers can integrate the findings into curriculum frameworks to prepare students for an increasingly digital and AI-driven world, ensuring that sustainability concepts are embedded within core educational content. Theoretically, the findings of the study can help us understand how AI can be integrated into educational settings in a manner that promotes sustainability. This study can also promote the development of interdisciplinary theories that provide more insights from ethics, sustainability science, educational technology, and cognitive psychology, which will provide a nuanced understanding of the complex interaction between the human learning process and technology. The study, therefore sought to answer the following questions:

1. What is the direct effect of curriculum innovation on curriculum viability, curriculum quality, computer self-efficacy, digital literacy, and sustainable AI-driven assessment?
2. What is the direct effect of curriculum viability on curriculum quality, digital literacy, computer self-efficacy and sustainable AI-driven assessment?
3. How does curriculum quality directly affect digital literacy, computer self-efficacy and sustainable AI-driven assessment?
4. What is the mediating effect of computer self-efficacy and digital literacy in the linkage between curriculum designs (curriculum innovation, curriculum quality and viability) on sustainable AI-driven assessment?

Literature review

Studies of artificial intelligence in assessment

In the rapidly expanding field of educational technology, Artificial Intelligence (AI) in education represents a transformative opportunity, showcasing a wide array of tools and applications at an unprecedented level (Rudolph et al., 2023; Chaka, 2024). AI technologies can automate and enhance various facets of assessment including design, delivery, and grading (Ifelebuegu, 2023). For instance, AI can generate diverse and complex questions that assess higher-order cognitive skills, thereby reducing the manual workload for educators (Bridgeman & Liu, 2023; Gierl & Lai, 2013). Additionally, AI can personalize assessments based on individual student's needs and progress, facilitating differentiated instruction and personalized learning (Vandewaetere et al., 2011; Stahl et al., 2023). AI also plays a pivotal role in supporting collaborative assessments. AI-based analytics can track and analyze individual contributions to group tasks, simplifying the evaluation of each student's performance (Ferguson, 2012). Furthermore, AI can monitor and guide online discussions, ensuring equitable participation among students and fostering critical thinking and effective collaboration (Chan & Tsi, 2023).

However, the use of AI in authentic assessments poses challenges, including potential errors, the difficulty in programming AI to grasp nuances in human responses, and the risk of over-reliance on technology (Sevnarayan & Potter, 2024). Indeed, researchers have documented long-term effects where students may utilize AI to achieve high scores and pass exams, potentially diminishing critical thinking, research skills, and creativity (Mohammad Karimi, 2023; Rudolph et al., 2023; Sison et al., 2023). Such impacts raise questions about students' capacity to develop essential intellectual and analytical skills crucial for personal and professional growth. Moreover, implementing AI necessitates significant investments in technology and training, potentially widening the digital divide and exacerbating educational inequalities (Reich & Ruipérez-Valiente, 2019). However, there remains a scarcity of literature addressing sustainable assessments that utilize AI tools while promoting environmental sustainability, economic feasibility, and social responsibility.

Existing studies on sustainable assessment practices highlight various implications. For example, Smith et al. (2021) emphasized how AI systems can offer timely, personalized feedback to students, thereby fostering continuous learning and reducing the environmental impact associated with traditional paper-based assessments. Johnson and Lee (2020) underscored how adaptive assessments can optimize resource allocation in education, potentially minimizing the environmental footprint by reducing paper usage and energy consumption. Other studies explore sustainable implications of classroom assessment in AI environments (Chen et al., 2019; Jones & Brown, 2022; Garcia et al., 2023). However, these studies do not address how curriculum redesign, particularly in countries like Nigeria where AI integration in curricula remains limited, could further these insights. Therefore, conducting empirical research on how AI-enabled assessment practices can promote sustainable

educational outcomes in diverse contexts, including Nigeria, is essential for informing policy development and educational practice.

Studies on curriculum design

The sustainability of AI-driven assessment cannot go without some factors like curriculum innovation, quality, and viability. Curriculum development provides the learner and teachers with the experiences required to function in society (Kelly, 2009). What we know and do could be a function of the quality of the curriculum content that learners could have been exposed to. In 2018, China officially announced the integration of AI into the curricula of higher institutions (Chen & Wang, 2020). The purpose of this curriculum innovation was to ensure that opportunities are provided to both students and teachers to acquire the right skills required of a technologically driven era, which led to groups like the Advancement of Artificial Intelligence (AAAI) and the Computer Science Teachers Association (CSTA) being formed to provide the right focus (Pedró et al., 2019).

This curriculum development policy will not only help teachers function well in school but will also inspire future research into areas of ethical design that will help bridge the gaps that have already been created by most AI algorithms (Kopcha et al., 2020). It is thus true that in Nigeria, this official policy has not been made. School teachers have a routine timetable that, to an extent, is very inflexible, and the resources to advance this schedule are limited. Most of the teachers are not trained, which makes the integration of AI problematic. Improvements in this area account for innovations in the curriculum so that teachers can understand the value-driven content of AI and where it can fit into their classroom activities (Van Haneghan et al., 2015). There are three related factors, though independent but interacting significantly, that are presumed to help drive the process for sustainable AI-driven assessment. These are curriculum innovation, curriculum planning, and curriculum viability. This is what is referred to as a curriculum design in this study. There are different measures of curriculum quality determination. According to MacCarrick et al. (2010), programme evaluation, educational resources, students, faculty condition, educational programme assessment, mission objectives of the school, as well as governance and administration, are measures for determining curriculum quality. Similarly, comparing the current status of the national curriculum with global standards can also help determine the quality of the curriculum (Rezaeian et al., 2013).

Curriculum viability looks at the present state of the curriculum, determined by the degree to which the standards, inputs, and processes of the elements of the curriculum have or have not been met, and then identifies the inhibitors that affect the achievement of those standards. Curriculum viability focuses on the workability and functionality of the curriculum in delivering the standard that is met for the institution. This is why Khan (2021) quickly concludes that when schools develop standards and incorporate all inputs into the curriculum without determining its viability, they face the problem of implementation crises, which may result in student or teacher dissatisfaction and possibly curriculum

failure. Curriculum innovation, in another sense, is the frequent insertion of new programmes and policies that will keep the standards high as well as provide opportunities to meet global standards. These three factors form the nexus of curriculum design as they work collectively to ensure that the educational ecosystem is alive. The sustainability of AI-driven assessment could rest on these three measures. This is because human and societal needs are complex and ever-changing. The state-of-the-art for today may change in the future, especially as new technologies are evolving and their impacts on education are very visible. There must be a circle of inputs in the curriculum (standards), ensuring the workability of the curriculum in line with the set standards (viability) and the insertion of emerging development (innovation) so as to achieve a set of objectives (Alexander & Flutter, 2009; Haug, 2003; Niederhauser et al., 2018).

Previous studies have examined the nexus between curriculum design and the integration of AI in higher institutions. For example, the Chiu and Chai (2020) study revealed that genuine curriculum creation should encompass all four forms of curriculum design approaches coordinated by teachers' self-determination to orchestrate student learning experiences. Educational content and strategies were mostly the elements of standard but students, faculty, work environment, and technology innovation were quality inhibitors to AI integration. Basically, studies have been carried out in relation to curriculum innovation, quality, and viability with respect to different phenomena (Liu & Zhang, 2021; Chen & Wang, 2020; Brown & Smith, 2021). However, these studies have not looked at the impact of these curriculum designs on sustainable AI-driven assessment. This is a serious problem for policymaking as evidence that will guide their decision is absent or inadequate. Available studies are rather focused on the impact of AI on education as a whole. Efforts to look at curriculum quality, viability, and innovation have not been adequate. In fact, it is not to the knowledge of the researchers if such studies have been carried out in Nigeria and Africa at large.

Thus, as machine learning becomes more efficient, AI performs diverse functions in the assessment industry, which could have more effect on ethical practices because of the inherent bias that most AI tools are programmed with. Future developments will have more effect on the system due to automation and computerization of all that people need to do in the womb of assessment. These practices may also have an effect on the environment, as the resources and technology involved may be impactful. There is a need for teachers and students' knowledge of these AI technologies to increase so that what is done will help the students and the educational system at large in the present and provide measures for the future satisfaction of the system without compromising issues of data privacy, ethical consideration, security, or the standard of the educational sector. This whole effect is dependent on curriculum design (Wang et al., 2019; Piniel & Csizér et al., 2015).

Studies of online digital literacy

Digital literacy and computer self-efficacy are two vital terms that are used to refer to individuals' ability to manipulate the complex technological world that is driving all sectors of society. Digital literacy is different from technical skill, as the latter may be more focused on the management of hardware and software, but for one to be digitally literate, one must have the ability to deal with information online, understand ethical issues, copyright, and use the right digital tool for the right purpose and time for the purpose of collaboration and communication, among others (Udeogalanya, 2022).

Digital literacy is a conglomerate of skills, knowledge, and attitudes that are used to navigate the complex landscape of the digital world and are useful in everyday life. It is all-encompassing in that it ranges from functional skills to more sophisticated attributes, such as creating digital content as well as developing apps that can be used in one's profession. However, for sustainable AI-driven assessment, digital literacy is not just a function of basic functional skills like surfing the internet, typing, or editing, but strategic skills that will help one understand how an AI complex system works: interpreting generated data as well as taking decisions based on data. Since sustainable assessment is based on ensuring that the assessment that is carried out is environmentally sustainable, ethically sound, and socially responsible, digital literacy ensures that the use of AI in assessment minimizes bias, promotes equity, and supports a long-term view that benefits all stakeholders in the educational web (Mailizar et al., 2021).

Several studies have noted that to improve assessment standards that can benefit both present and future needs, digital literacy development is seen as a sine qua non to address this (Hanell, 2018; Porat et al., 2018). This is because ICT is seen as an essential factor for learning and an ingredient to cope with the demands of globalization. More so, with the positive ravaging effect of AI in the educational system, digital literacy is indispensable to the achievement of the Fourth Industrial Revolution (Williamson et al., 2019). Studies that directly explain the link between digital literacy and assessment driven by AI are limited or not available. Over time, different studies have described different aspects of digital literacy, with some focusing on the extent of the respondent's exposure to the digital environment, which may vary depending on the facility's availability and awareness of the importance of digital tools (Wu et al., 2022). Thus, the research field is heterogeneous in its measurement tools, making it difficult to compare different studies. (Alexander et al., 2017; Law et al., 2018; Vuorikari et al., 2022; Wu et al., 2022). In a recent study by Patrik (2024), the findings of the study revealed that digital literacy is fundamental to academic success. However, there are differences based on discipline in considering digital skills among participants.

Boma (2021) revealed that digital literacy is not a significant factor in determining the utilization of online platforms for instructional purposes. This was attributed to factors such as the educators' lack of skills, among others. The Łukasz (2020) study provided a description of issues related to the self-evaluation of digital literacy in using text editors, spreadsheets, and presentation and graphic software. They

also presented the respondents' experiences with e-learning and their participation in online classes while searching for information on the Internet. Mailizar et al.'s (2022) findings revealed that digital literacy and social presence significantly affected teachers' acceptance of online professional development. Yoshija (2024) revealed that AI literacy is identified as crucial, encompassing an understanding of AI technologies and their broader societal impacts.

Prompt engineering is highlighted as a key skill for eliciting specific responses from AI systems, thereby enriching educational experiences, and promoting critical thinking. Ng et al.'s (2023) study on teachers' AI digital competencies and 21st-century skills in the post-pandemic world revealed that many teachers are bereft of the skills required for effective assessment. The review of the literature has shown that extensive work has been done on digital literacy in relation to online teaching and the skills required for teachers to function well in this landscape. However, these studies, as rich as they appeared in the literature, have not focused on how these online competencies can facilitate the sustainability of assessment in the era of AI. Similarly, the studies examined have not looked at the perspective of measures acting as mediator variables in the nexus between curriculum design and sustainable AI-driven assessment. It will, therefore, be imperative to examine this nexus so as to develop appropriate interventions that can also facilitate policymaking in educational technology.

Studies on computer self-efficacy

The concept of self-efficacy stems from the works of Albert Bandura (1977), and it is used to describe a belief in one's ability to perform a particular task. Though a multi-dimensional construct, it is conceptualized here as the ability to handle tasks that are computer-related. Definitions of self-efficacy have centred on an individual's conscious conviction and confidence in his or her abilities to perform a particular task (Lunenburg, 2011; Hong et al., 2012; Su & Duo, 2012) and specifically defined situations. This judgement influences people's decisions, goals, the amount of effort expended in conducting a task, and the length of time they would persevere through obstacles and difficulties (Sam et al., 2005). The concept of computer self-efficacy has been extensively studied in the literature (Esfijani & Zamani, 2020; Graham et al., 2020). The study by Zhao et al. (2021) reported that individuals with strong computer self-efficacy show resilience during adversity.

Mailizar et al.'s (2022) study found that computer self-efficacy and social presence are two factors that predict online engagement among teachers. Nurhikmah et al. (2023) study found that students with high self-efficacy in computer skills improve better on blended learning than students with other students in higher education. Mariefe's (2022) study also found that teachers' computer self-efficacy is associated with their teaching performance in online courses. Other studies have also found that computer self-efficacy is a strong predictor of online programme sustainability and learning outcomes (Idris, 2015; Müller & Mildemberger, 2021; Zhao et al., 2021). Interestingly, these studies were mostly in relation to online learning and performance. These

variables have not been used as mediators in other studies or in the context in which they are used in this study. It is imperative, given the fact that AI is a new technology that most teachers and students may not be fully integrated into, probably due to diverse factors. The researchers are presuming that computer self-efficacy, which is more or less the ability to believe in oneself to operate the computer, may constitute a factor in the attempt to achieve sustainable AI-driven assessment. Thus, the reason for this research is to cover this gap.

Conceptual framework and hypothesis development

The researcher's framework is that sustainable AI-driven assessment is a product of not just one related factor but a set of connections with different measures that may help to achieve that objective. In this study, curriculum design, which is conceptualized in three dimensions: curriculum quality (CQ), curriculum viability (CV), and curriculum innovation (CI), are essential drivers of this phenomenon. However, other factors too could mediate this relationship, and this accounts for why digital literacy (DL) and computer self-efficacy (CE) are considered mediators to the nexus between curriculum design and sustainable AI-driven assessments (SAA). The conceptual idea is shown in Figure 1.

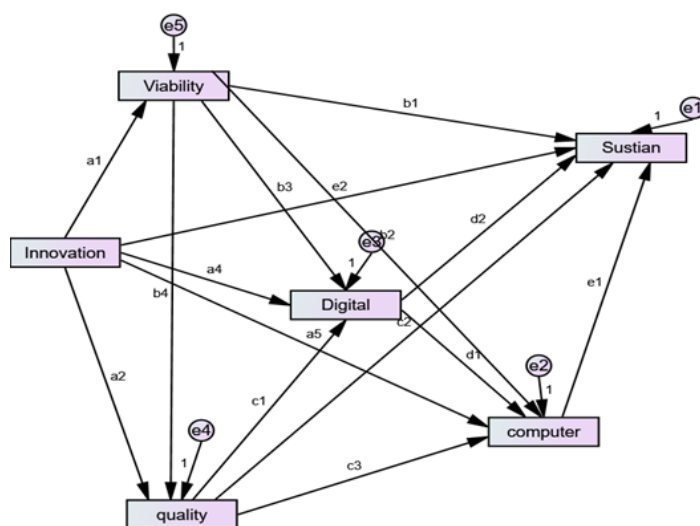


Figure 1. Conceptual framework of the linkage between curriculum design factors and sustainable AI driven assessment through computer self-efficacy and digital literacy.

Methodology

The study is a cross-sectional one since it involves a large pool of respondents that will provide information concerning the phenomenon of interest at the same time. The participants in the study are 149 higher education administrators (23 faculty deans and 126 HODs) and 1458 academic staff in the Faculty of Education across five public universities. The selection of the respondents is because these individuals are vested with the administrative position of the institutions and are knowledgeable of the type of curriculum that is engaged in teaching and learning in schools. The researchers do not consider the sampling of these units of information to collect holistic information that can influence policymaking.

Thus, a total of 1607 participants were engaged in the study.

Measures and instruments

The study involved six measures, which were three independent variables (curriculum quality, curriculum viability, and curriculum innovation) and two mediating variables (digital literacy and computer self-efficacy), while the dependent variable was sustainable AI-driven assessment. Curriculum viability refers to the effectiveness and sustainability of an educational curriculum that ensures that its content meets the needs of the learner in terms of engagement and the flexibility to adapt to diverse learning styles and evolving educational priorities. Curriculum quality refers to the standard with which the content, experiences, and designs align to stimulate students' engagement, deep understanding, and meaningfulness in achieving any objective. Curriculum innovation involves the development and implementation of new approaches, methods, or content within educational curricula to enhance learning outcomes, adapt to changing educational needs, and prepare students for the challenges of the future. Computer self-efficacy is the belief in oneself to handle computers and other related technologies effectively to complete a task. Digital literacy "refers to the ability to find, evaluate, use, and create digital information effectively, efficiently, and ethically in a digital environment. Sustainable AI-driven classroom assessment refers to the integration of artificial intelligence (AI) technology in educational assessment practices in a manner that is enduring, equitable, and beneficial for students, educators, and the learning environment.

A questionnaire that was structured by the researchers after an extensive review of the literature was used for data collection. The instrument was made up of three parts. Part A was designed to collect demographic data from the respondents. Part B, labelled "Curriculum design, computer self-efficacy, and digital literacy (CDCSDL)", was divided into five sections according to the number of sub-variables that made up the independent and mediating variables. Each of the variables was measured with five items on a four-point Likert scale of strongly agree to strongly disagree. The items were developed because of the unavailability of existing scales that would appeal to the context of the study. Sample items of curriculum viability include: "The current curriculum is relevant to the needs of the educational system". Similarly, for curriculum quality, a sample item includes: "Instructional materials and resources are relevant for the achievement of current educational needs". For curriculum innovation, the sample item includes "The current curriculum integrates emerging technologies to enhance learning experiences". More so, items for computer self-efficacy have a sample item as "I feel confident in my ability to use computer hardware and applications", while for digital literacy, a sample item includes, "I understand how to protect my data from external attacks while using digital technologies". Part 3 of the instrument labelled "sustainable artificial intelligence-driven classroom assessment (SADCA)" deals with the measurement of sustainable AI-driven assessment using ten items that were also measured on a four-point Likert-type scale. A sample item for the scale includes "The implementation of AI-driven assessment aligns with long-

term educational goals and priorities".

Validation of the instrument

The first validation of the instrument was done using three experts in curriculum and instruction and two psychometricians to assess the draft of the instrument for content validity. The assessment was based on three criteria which were clarity, suitability, and precision. The universal agreement for the scale content validity index (S-CVI) is 0.96, while the item content validity index (I-CVI) ranges from 0.89 to 0.99 based on the average ratio procedure. Thus, from the expert's assessment and quantitative analysis performed, the S-CVI for the scale was 0.97, while the I-CVI was 0.86–0.98. These values, as obtained, were within the range acceptable to experts (Zamanzadeh et al., 2015). However, some items were deleted following the recommendation of the experts, as they were adjudged to be irrelevant and unclear. Thus, the initial scale of 35 items was reduced to 33 because of the two items that were removed from the scale.

A pilot study was then carried out using a total of 200 lecturers from the computer department and curriculum and instructions from non-participating universities. Since there are 33 items in the instrument, a pilot study of 200 respondents was considered appropriate since the ratio of 1 item to 5 respondents could, according to the golden rule, be seen as adequate (Boateng et al., 2018). The responses of the respondents were used for dimensionality, factor structure checks, and convergent and divergent validities using exploratory and confirmatory factor analysis.

Ethical consideration and data collection

The study was conducted as a survey research that ordinarily meant no harm to the participants. According to the Federal Ministry of Health (2007), ethical clearance can be waived in such studies. However, the researchers, in line with best global practices, ensured that participants provided their consent before the data was collected. The researchers first explained the purpose of the study to the participants and what the data they were providing would be used for. This was to ensure that the participants had knowledge of what the study sought to achieve. Thus, there was no space for name, phone number, or email to anonymize the participants. Similarly, the instruments that were provided and responded to were locked in fireproof closets that only the lead researcher could have access to. Finally, the respondents were informed that their information would be used for publication in reputable journals. Hence, after seeking their consent and interacting with the participants, only 192 participants provided consent for this study. The copies of the questionnaire were distributed to the participants who provided consent. They were allowed to read the questions one by one to make objective responses. After that, all the answers were retrieved from the respondents and arranged for data analysis.

Results

Preliminary analysis

The preliminary analysis of the results was focused on the dimensionality, factor structure, and reliability of the study. This was done in two phases. First, the exploratory factor analysis was carried out using principal component analysis (PCA) with varimax rotation as an option. The results, as presented in Table 1, showed that for automated classroom assessment, a KMO value of 0.811 was obtained with Bartlett's test of sphericity, producing a result of $\chi^2(167) = 2321.11$, $p < .001$, which is an indication that the sample size was adequate for exploratory factor analysis to be carried out. A further inspection showed that eight items in all were deleted due to cross-loading or factor loading less than 0.5 (Costello & Osborne, 2005; Hair et al., 2019). The total variance explained for the six variables of the study was 75.55%, with sustainable AI-driven assessment contributing 22.44%, curriculum viability contributing 15.12%, curriculum quality contributing 13.67%, curriculum innovation contributing 10.77%, computer self-efficacy contributing 8.55%, and digital literacy contributing 6.00%. The reliability of each measure was established using Cronbach's alpha, and the result in Table 2 further proved that there was internal consistency in the scale.

Convergent and discriminant validity

To assess the convergent and discriminant validity of the measures, the Fornell-Larcker criterion, which uses the average variance extracted (AVE) per factor, was used (Fornell & Larcker, 1981). The basic line is that if the AVE of a factor is greater than 0.50, then convergent validity is achieved (see Eriksson et al., 2019; Lee et al., 2019). For the independent, mediating, and dependent factors, the AVE value was greater than 0.50, which is an indication that the items retained in these factors are theoretically related to their latent factors. However, Table 2 shows that the discriminant validity of the six subscales of the instruments was also based on the Fornell-Larcker criterion. According to this criterion, the subscale is diverse theoretically if the square root of the AVE for each factor is greater than their correlation with other factors (Ab Hamid et al., 2017; Hilkenmeier et al., 2020). Thus, as shown in Table 2, the bolded values in the principal diagonal of the six latent factors are greater than their correlation with other factors. Therefore, the factors are theoretically different in measuring automated assessment in the presence of technological acceptance vectors.

Confirmatory factor analysis

The confirmatory factor analysis was carried out using maximum likelihood estimation statistics. As could be seen in Table 1, Figures 2, and 3, there were not many disparities between the factor's loadings of items in the EFA and CFA. This indicates that the dimensionalities obtained and the factor loadings from the EFA are valid measures of the constructs, and the instrument is psychometrically sound. The fit indices of the confirmatory factor analysis were examined. Each of the fit indices has its strengths and

Table 1. Exploratory factor analysis.

Items	N	M	Error	SD	Skew	Kurt	λ	CFA	λ^2
CV1	250	2.17	.010	.52	2.49	2.93	0.88	0.78	.79
CV3	250	2.21	.010	.54	2.513	1.98	0.79	0.75	.63
CV4	250	2.21	.010	.53	2.437	2.79	0.80	0.78	.64
Curriculum Viability	250	8.72	.03	1.67	2.367	.38	2.48	2.32	2.06
CQ1	250	3.12	.013	.70	-.358	-.35	.81	.79	.66
CQ3	250	3.15	.012	.63	-.206	-.27	.77	.70	.60
CQ4	250	3.05	.01	.70	-.131	-.84	.77	.73	.54
CQ5	250	3.04	.01	.64	-.040	-.61	.88	.88	.77
Curriculum Quality	250	15.49	.05	2.97	.174	-.61	3.26	3.12	2.58
CI2	250	2.93	.00	.37	-.263	1.89	.80	.76	.64
CI3	250	2.89	.00	.49	-.187	.06	.99	.96	.99
CI4	250	2.78	.01	.52	-.444	.40	.67	.59	.45
CI5	250	2.89	.00	.49	-.187	1.06	.74	.69	.55
Curriculum Innovation	250	11.56	.03	1.62	-.181	1.04	3.21	3.01	2.64
CSE2	250	2.37	.01	.65	1.48	.88	.789	.65	.62
CSE3	250	2.43	.013	.72	1.34	.23	.788	.73	.62
CSE4	250	2.24	.000	.49	1.88	.74	.670	.58	.44
CSE5	250	2.14	.00751	.39	2.59	1.29	.543	.43	.29
Computer self-efficacy	250	11.36	.04057	2.11	1.13	-.29	2.790	2.397	1.98
DL1	250	2.29	.00	.45	.91	-1.16	.699	.612	.48
DL2	250	2.66	.013	.72	.60	-.892	.612	.570	.37
DL3	250	2.84	.01	.83	.30	-1.49	.902	.863	.81
DL4	250	2.45	.01	.59	.90	-.172	.700	.620	.50
Digital literacy	250	12.56	.04	2.30	.12	-1.43	2.91	2.66	2.17
SAA1	250	2.77	.01	.89	-.22	-.747	.645	.535	.41
SAA3	250	2.53	.01	.85	-.01	-.62	.59	.524	.35
SAA4	250	2.76	.01	.86	-.23	-.62	.89	.80	.80
SAA5	250	2.58	.01	.92	-.07	-.85	.75	.63	.57
SAA6	250	2.57	.01	.90	-.04	-.77	.620	.51	.38
SAA8	250	2.53	.01	.91	-.04	-.81	.68	.52	.47
Sustainable AI assessment	250	20.94	.083	4.37	.210	1.73	4.20	3.53	3.0

Table 2. Convergent and discriminant validity (Fornell-Larcker criterion).

Constructs	AVE	α	1	2	3	4	5	6
Sustainable AI assessment	.502	.778	0.708					
Curriculum viability	.689	.702	0.213	0.830				
Curriculum quality	.602	.822	0.122	.233	0.775			
Curriculum innovation	.647	.712	.321	.102	.292	0.804		
Computer self-efficacy	.500	.734	0.321	.432	.412	-.132	0.707	
Digital literacy	.545	.774	0.211	.132	.102	.132	.432	0.738

Note: The bolded values are discriminant validity values obtained using the Fornell-Larcker criterion. AVE=average variance extracted, α =Cronbach's alpha reliability.

weaknesses. Therefore, it is not advisable that only one fit index be reported. According to Kline (2016), four fit indices such as χ^2 (Chi-Square), RMSEA (Root Mean Square Error of Approximation), "Comparative Fit Index" (CFI), and SRMR can be appropriate to decide whether to accept a CFA model. However, in this study, eight fit indices were reported, which include "Goodness-of-Fit Index" (GFI), "Normed Fit Index" (NFI), "Relative Fit Index" (RFI), "Comparative Fit Index" (CFI), HOELTER's Critical N, "Incremental Fit Index" (IFI), "Root Mean Square Error of Approximation" (RMSEA), and "Tucker-Lewis Index" (TLI). However, the RMSEA is the best measure and is often used as a condition for accepting the model. The results presented in Table 3 and Figure 2 showed that the indices are within the range of values that are used in determining the acceptability of the model and that the models are fit.

Table 3. Goodness-of-fit test of the two CFA models.

S/N	Fit indices	Threshold	CDCSDLs	SADCA
1	χ^2	$p > .05$	.121	.154
2	AGFI	$p \geq .90$	.911	.922
3	NFI	$p \geq .90$	.954	.915
4	CFI	$p \geq .90$	.933	.967
5	GFI	$p \geq .90$	.901	.943
6	TLI	$p \geq .90$	.990	.956
7	IFI	$p \geq .90$	.966	.948
8	RMSEA	$p \geq .08$	.043	.010

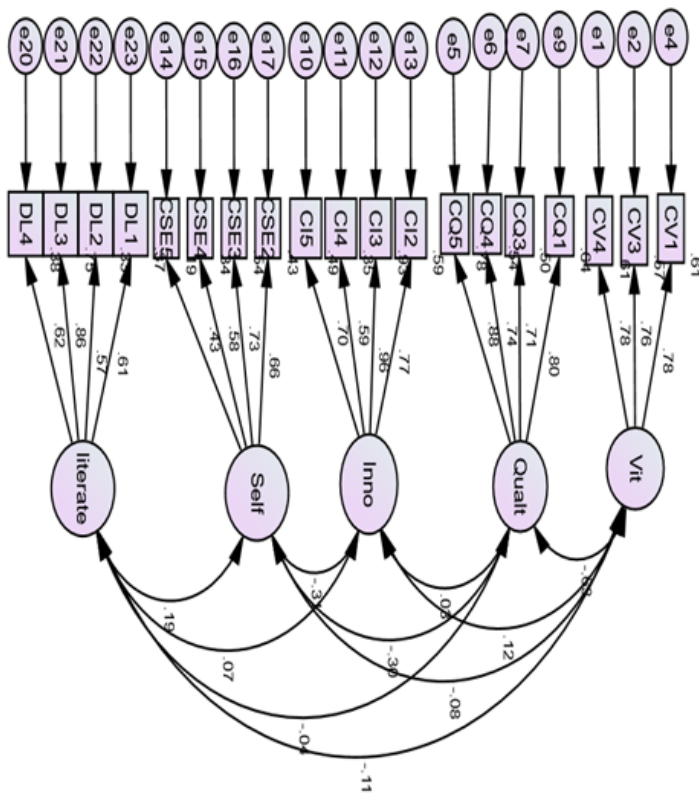


Figure 2. CFA of curriculum viability, quality, innovation, computer self-efficacy, and digital literacy.

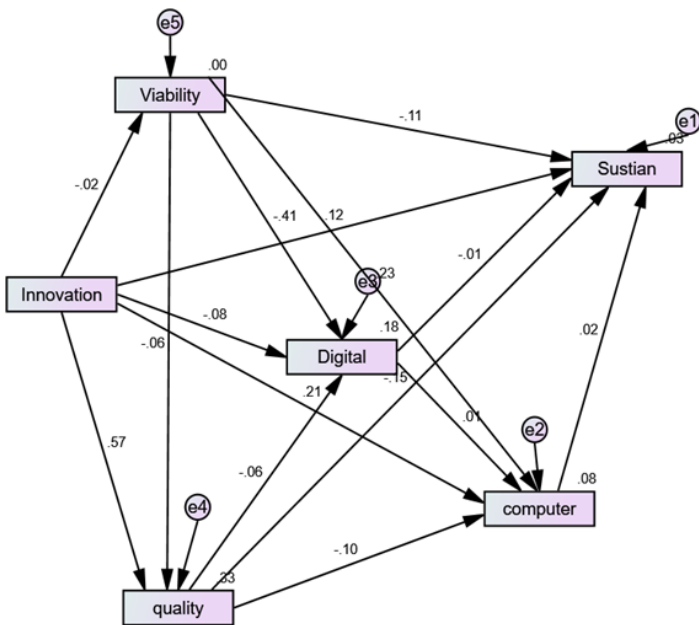


Figure 4. Structural equation of the nexus between the variables.

Hypothesis One states that curriculum innovation does not contribute directly to curriculum viability, curriculum quality, computer self-efficacy, digital literacy, and sustainable AI-driven assessment results. This is presented in Table 4. The results presented in Table 4 and Figure 4 revealed that for INN-> VIA ($\beta = -0.18$, 95% CI [-0.5, -0.1], $t = -0.82$, $p > .05$), for INN-> QUA ($\beta = 0.568$, 95% CI [0.53, 0.60], $t = 37.86$, $p < 0.001$), for INN-> COMP ($\beta = 0.211$, 95% CI [-0.16, 0.25], $t = 10.55$, $p < 0.001$), for INN-> DIGIT ($\beta = -0.18$, 95% CI [-0.11, -0.05], $t = -0.90$, $p > 0.05$) and for INN-> SUSTAIN ($\beta = 3.07$, 95% CI [-0.07, 0.15], $t = 3.07$, $p < 0.001$). This finding

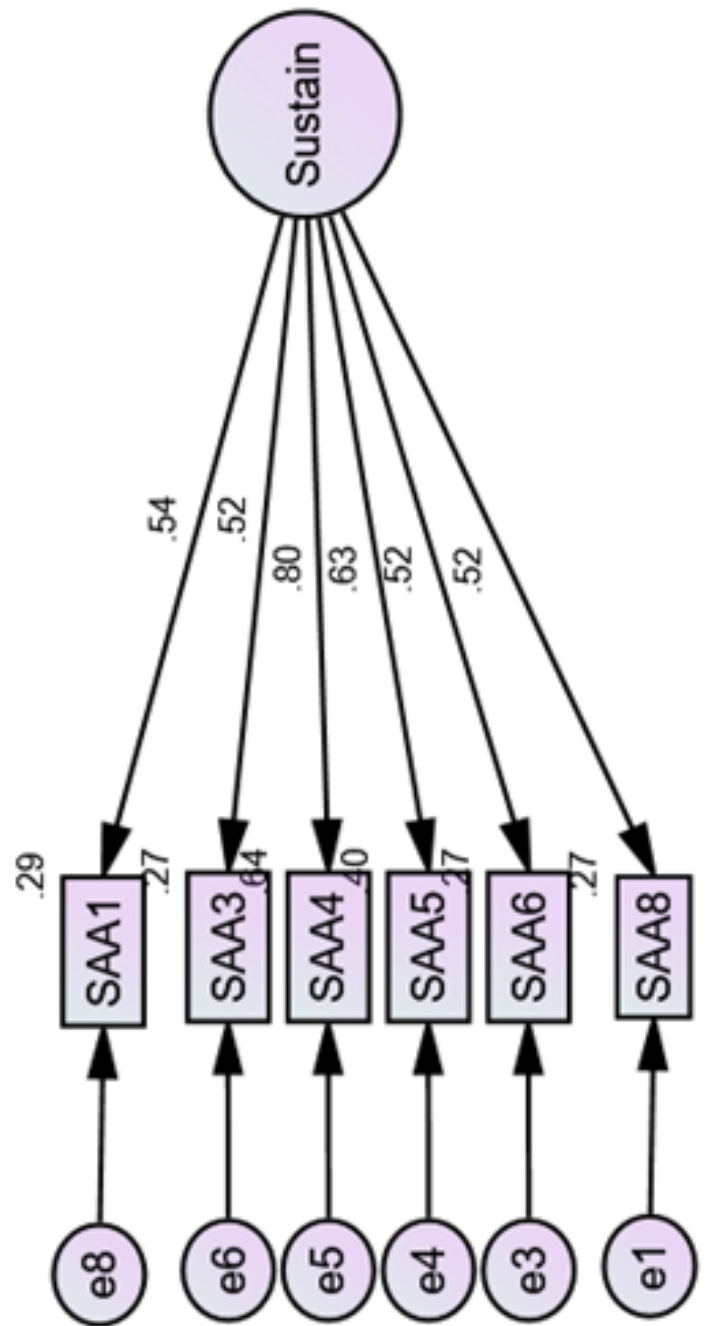


Figure 3. CFA of sustainable AI-driven classroom assessment.

implies that curriculum innovation has a direct effect on curriculum viability, curriculum quality, and sustainable AI-driven assessment. However, the effect was not significant for curriculum innovation and digital literacy.

Hypothesis Two states that curriculum viability does not contribute directly to curriculum quality, digital literacy, computer self-efficacy, and sustainable AI-driven assessment results. This is presented in Table 5. The results presented in Table 5 and Figure 4 revealed that for VIA -> QUA ($\beta = -0.59$, 95% CI [-0.8, -0.3], $t = -4.53$, $p < 0.001$), for VIA -> DIGIT ($\beta = -0.064$, 95% CI [-0.43, -0.06], $t = -4.57$, $p < .001$), for VIA -> COMP ($\beta = 0.235$, 95% CI [0.21, 0.26], $t = 14.68$, $p < 0.001$), and for VIA -> SUSTAIN ($\beta = -0.113$, 95% CI [-0.08, -0.11], $t = -3.77$, $p < 0.001$). This finding implies that curriculum viability has a direct effect on curriculum quality, digital literacy, computer efficacy, and sustainable AI-driven assessment. Thus, the null hypothesis is rejected.

Table 4. Direct effect of curriculum innovation on curriculum viability, curriculum quality, digital literacy, computer self-efficacy and sustainable AI-driven classroom assessment.

Linkages	M	β	95%CI	SD	t-cal	p-val	Remarks
INN-> VIA	-.018	-.018	-.05, .01	.022	-0.82	.342	Not significant
INN-> QUA	.568	.568	.53, .60	.015	37.86	.000	significant
INN-> COMP	.211	.211	-.16, .25	.020	10.55	.000	Significant
INN-> DIGIT	-.018	-.018	.11, .05	.020	-0.90	.000	Significant
INN-> SUSTAIN	.117	.117	.07, .15	.038	3.07	.000	Significant

INN=Curriculum innovation, VIA=Curriculum viability, QUA=Curriculum quality, DIGIT=Digital literacy, COMP=Computer self-efficacy, SUSTAIN=Sustainable AI-driven classroom assessment, M=Mean, SD=Standard deviation, CI=Confidence interval

Table 5. Direct effect of curriculum quality on digital literacy, computer self-efficacy and sustainable AI-driven classroom assessment.

Linkages	M	β	95%CI	SD	t-cal	p-val	Remarks
VIA -> QUA	-.059	-.059	-.08, -.03	.013	-4.53	.000	Significant
VIA -> DIGIT	-.064	-.064	-.43, -.39	.014	-4.57	.000	Significant
VIA -> COMP	.235	.235	.21, .26	.016	14.68	.000	Significant
VIA -> SUSTAIN	-.113	-.113	-.08, -.11	.030	-3.77	.000	Significant

VIA=Curriculum viability, QUA=Curriculum quality, DIGIT=Digital literacy, COMP=Computer self-efficacy, SUSTAIN=Sustainable AI-driven classroom assessment, M=Mean, SD=Standard deviation, CI=Confidence interval

Hypothesis Three states that curriculum quality does not contribute directly to digital literacy, computer self-efficacy, and sustainable AI-driven assessment results, as presented in Table 6. The results presented in Table 6 and Figure 4 revealed that for QUA -> DIGIT ($\beta = -0.064$, 95% CI [-0.09, -0.03], $t = -3.04$, $p < 0.001$), for QUA -> COMP ($\beta = -0.098$, 95% CI [-0.14, -0.06], $t = -4.67$, $p < .001$), and for QUA -> SUSTAIN ($\beta = 0.025$, 95% CI [-0.01, -0.03], $t = 0.62$, $p > .05$). This finding implies that curriculum quality has a direct effect on digital literacy and computer efficacy but is not significant in its relationship with sustainable AI-driven assessment. Thus, the null hypothesis is rejected for curriculum quality on digital literacy and computer efficacy but retained for sustainable AI-driven assessment.

Table 6. Direct effect of curriculum quality on digital literacy, computer self-efficacy and sustainable AI-driven classroom assessment.

Linkages	M	β	95%CI	SD	t-cal	p-val	Remarks
QUA -> DIGIT	-.064	-.064	-.09, -.03	.021	-3.04	.001	significant
QUA -> COMP	-.098	-.098	-.14, -.06	.021	-4.67	.000	Significant
QUA -> SUSTAIN	.025	.025	.01, .03	.040	0.62	.321	Not Significant

QUA=Curriculum quality, DIGIT=Digital literacy, COMP=Computer self-efficacy, SUSTAIN=Sustainable AI-driven classroom assessment, M=Mean, SD=Standard deviation, CI=Confidence interval

Hypothesis Four, which states that computer self-efficacy and digital literacy do not mediate the nexus between curriculum innovation, curriculum quality, and curriculum viability, is presented in Table 7. The result in table 7 revealed that for INN -> VIA->SUSTAIN($\beta = 0.003$, 95% CI [0.00, 0.00], $t = 3.00$, $p < 0.05$), INN -> DIGIT->SUSTAIN($\beta = -0.027$, 95% CI [-0.04, 0.01], $t = 2.45$, $p < 0.05$), for INN -> COMP->SUSTAIN($\beta = -0.055$, 95% CI [-0.08, -0.03], $t = 3.93$, $p < 0.001$). This implies that curriculum viability, digital literacy, and computer self-efficacy significantly mediate the nexus between curriculum innovation and sustainable AI-driven classroom assessment. The result also showed that for VIA -> DIGIT -> SUSTAIN ($\beta = 0.003$, 95% CI [-0.00, 0.01], $t = 3.00$, $p < 0.05$) and for VIA -> COMP -> SUSTAIN ($\beta = 0.000$, 95% CI [-0.01, 0.01], $t = 0.00$, $p > .05$). Thus, only computer self-efficacy mediates the nexus between curriculum quality and sustainable AI-driven classroom assessment, but digital literacy does not. For

QUA->DIGIT->SUSTAIN ($\beta = -0.001$, 95% CI [-0.00, 0.00], $t = -0.01$, $p > .05$) and for QUA->COMP -> SUSTAIN ($\beta = -0.004$, 95% CI [-0.00, 0.00], $t = -1.0$, $p > 0.05$). This implies that digital literacy and computer self-efficacy do not significantly mediate the relationship between curriculum quality and sustainable AI-driven classroom assessment.

Table 7. Indirect effect of digital literacy and computer self-efficacy on the nexus between curriculum variables and sustainable AI-driven classroom assessment.

Linkages	M	β	95%CI	SD	t-cal	p-val	Remarks
INN -> VIA -> SUSTAIN	.003	.003	.00, .00	.001	3.00	.003	Significant
INN -> DIGIT -> SUSTAIN	-.027	-.027	-.04, .01	.011	2.45	.021	Significant
INN -> COMP -> SUSTAIN	-.055	-.055	-.08, -.03	.014	3.93	.000	Significant
VIA -> DIGIT -> SUSTAIN	.003	.003	-.00, .01	.001	3.00	.003	Significant
VIA -> COMP -> SUSTAIN	.000	.000	-.01, .01	.006	0.00	.983	Not significant
QUA -> DIGIT -> SUSTAIN	-.001	-.001	-.00, .00	.000	-0.01	.452	Not significant
QUA -> COMP -> SUSTAIN	-.004	-.004	-.00, .00	.004	-1.00	.381	Not significant

INN=Curriculum innovation, VIA=Curriculum viability, QUA=Curriculum quality, DIGIT=Digital literacy, COMP=Computer self-efficacy, SUSTAIN=Sustainable AI-driven classroom assessment, M=Mean, SD=Standard deviation, CI=Confidence interval

Discussion of findings

The findings that curriculum innovation has a direct effect on curriculum viability and curriculum quality show the important role that innovation plays in educational landscapes. The rationale for this could be that curriculum innovation brings in new ideas and programmes that are adaptable to the needs of earners and the demands of society. Thus, where innovation, such as the use of AI in teaching and learning, is introduced, it ensures relevance and responsiveness to the changes that are occurring in society. The findings align with previous studies by researchers that have emphasized the need for a flexible curriculum that will adapt to new changes and dynamics so as to enhance viability in keeping with contemporary needs and advancements (Khan, 2021). Similarly, curriculum innovation may also impact curriculum quality because quality in the educational system is characterized by relevance and effectiveness. Where innovations that meet the demands of the learner and society, such as artificial intelligence, are integrated into the curriculum, it will enrich the experiences of the learners and promote critical thinking that will foster deeper knowledge of practices that are essential to educational development. This also aligns with the studies of Kopcha et al. (2020), who noted that schools that are innovative in their curriculum practices do not just facilitate improvement in the quality of experiences but also bring about improvement in students' academic achievement.

The findings that curriculum innovation impacts digital literacy and computer self-efficacy directly could also highlight the pivotal role of innovative practices in influencing students' acceptance of technology in learning. This could be a result when curriculum innovations that integrate technology as a vital component of students' learning expose them to experiences with digital tools. This aligns with the social learning theory of Bandura and the National Institute of Mental Health (1986), which posits that individuals' beliefs in their capabilities influence their behaviours and achievements. Thus, curriculum innovation can instil the confidence and capabilities required to handle issues with computers that may be required in all forms of assessment in both teachers and students. The findings concur with those of Martinez-Bravo et al. (2020), who highlight that curriculum innovation in digital literacy could

also arise due to the fact that integrating artificial intelligence with its diverse tools may help in acquiring digital skills required for assessment. This not only enhances students' digital competence but also prepares them for success in an increasingly digital world.

The findings that curriculum innovation has a direct effect on sustainable AI-driven classroom assessment could be a product of the fact that curriculum innovation involves the adoption of new teaching strategies, facilities, and assessment techniques that align with educational objectives and meet the needs of the teacher and students. Thus, when AI-driven tools are incorporated into the curriculum, teachers and students can leverage this to ensure that timely feedback, automated scoring, and assessment planning are carried out that satisfy both the teacher and students. AI-powered assessment systems have the capability to analyse vast amounts of data, identify patterns in student performance, and offer adaptive feedback tailored to individual learning needs. Research by Lunenburg (2011) highlights the potential of AI to enhance assessment practices by promoting fairness, accuracy, and objectivity. Similarly, AI-driven assessment has the intricate capacity to promote equity, mitigate biases, and promote inclusivity. Hong et al. (2012) noted that AI when integrated into the curriculum, could be a driving force to ensure that all forms of practices that promote inequality and insecurity in the data collected are eliminated to ensure the sustainability and efficacy of assessment practices in the classroom.

The findings that curriculum viability has a direct effect on curriculum digital literacy, computer self-efficacy, and sustainable AI-driven classroom assessments underscore the interconnectedness of various digital components that can affect learning. For example, when there is a viable curriculum that is relevant and effective in meeting the needs of the learner and society and has the ability to adapt to changes in the environment, emerging technologies, and evolving learning objectives, it serves as a foundation for delivering high-quality learning and promotes deeper learning experiences. Similarly, curriculum viability directly affects digital literacy because it embraces technological experiences that allow students to develop new skills and techniques that help them access and evaluate digital information effectively. More so, curriculum viability affects computer self-efficacy because the integration of technology practices into the curriculum provides methods and instructional practices that help students develop the beliefs and skills that give them the competence to handle software and hardware matters, which can foster how assessment is planned and executed to align with environmental best practices. The findings align with those of Eastin and LaRose (2000), who noted that exposure to technology-rich learning helps students develop self-efficacy beliefs. Finally, the findings also showed that curriculum viability influences sustainable AI-driven classroom assessment. This is because sustainable AI assessment has the capacity to ensure that assessment maintains fairness, equity, and inclusivity. Research by Jivet et al. (2017) underscores the role of curriculum innovation in facilitating the integration of AI-driven assessment tools into educational settings, ensuring their effectiveness and longevity.

The result of the analysis showed that curriculum viability mediates the nexus of curriculum innovation and sustainable AI-driven classroom assessment. The rationale could be that curriculum viability stimulates viability, adaptability, and functionality that strive to meet the needs of the evolving society and learner. The viability of the curriculum, which could result from the innovative practices that are incorporated into the curriculum, helps ensure an environment conducive to adopting practices that will foster equity, fairness, and inclusivity. This outcome is in line with previous studies that have found that curriculum innovation and viability are essential in ensuring that assessments carried out in the era of AI meet global ethical and environmental standards (Alexander & Flutter, 2009; Haug, 2003). Secondly, computer self-efficacy and digital literacy mediate the nexus between curriculum innovation and sustainable AI-driven assessment. This is because, where the curriculum integrates elements of digital literacy and elements of ICT that will build the self-beliefs of the teacher and students in handling the facilities around them, assessment activities using AI tools will be done to leverage technology for learning and evaluation purposes.

The findings that literacy mediates the link between curriculum viability and sustainable AI-driven classroom assessment suggest that students' proficiency in utilizing digital tools and resources plays a pivotal role in facilitating the integration of innovative assessment practices. However, the lack of mediation by computer self-efficacy indicates that students' confidence in their computer skills may not directly influence the relationship between curriculum viability and sustainable AI-driven assessment. Research by Niederhauser et al. (2018) underscores the significance of digital literacy in preparing students for success in the digital age. Therefore, it is logical to posit that digital literacy acts as a mediator in facilitating the adoption and implementation of sustainable AI-driven assessment practices by enhancing students' capacity to navigate digital learning environments and utilize technological tools effectively. On the other hand, computer self-efficacy does not mediate this nexus. This could be a result of the fact that the skills they possess may not act as a mediator between innovation in curriculum and sustainable AI-driven assessment. The absence of computer self-efficacy could be because there may be other factors that may serve very well in this linkage, like digital literacy, as already discussed (Eastin & LaRose, 2000).

Finally, the outcome of the study revealed that digital literacy and computer self-efficacy are not significant mediators between curriculum quality and sustainable AI-driven classroom assessment. This, according to Chiu and Chai (2020), suggests that while these two mediators are important in the information and communication technology world, they may not be too relevant in facilitating this nexus; rather, other factors may play a more significant role in the relationship between curriculum quality and sustainable AI-driven assessment. One important reason could be that AI tools are so complex that even those with digital skills may not be able to navigate them appropriately. Other factors, such as institutional support, training, and the perceived usefulness of these tools, may influence these linkages. More so, the curriculum quality in intricate dimensions may possess elements that can affect the sustainability of AI

Limitations/suggestions for further studies

The findings, like any other study, have some limitations. First, the study was a cross-sectional study that involved a sample providing information that may be biased. Longitudinal or experimental designs could provide stronger evidence for understanding the dynamics between curriculum quality, digital literacy, computer self-efficacy, and sustainable AI-driven assessment over time. Secondly, the use of these two mediators may not capture other potential mediators that could influence this relationship between curriculum quality and sustainable AI classroom assessment. The quality of the assessment tools may affect the outcome of the study as well. It is expedient that other studies re-establish the quality of this instrument that was developed by the researchers to determine its reliability and validity. The study sample may not be adequate to facilitate the generalization of the findings. A larger sample involving stakeholders could also be used for further studies in the future.

Conclusion/implications

The study's findings revealed that curriculum innovation directly affects curriculum viability, quality, digital literacy, computer self-efficacy, and sustainable AI-driven classroom assessment, while curriculum quality and viability also affect digital literacy, self-efficacy, and sustainable AI-driven classroom assessment. The mediation of digital literacy and computer self-efficacy in the nexus between curriculum innovation and sustainable AI-driven classroom assessment was significant, but these mediators were not significant in the nexus between curriculum quality and sustainable AI-driven classroom assessment. The study underscores the pivotal role of curriculum innovation and viability in shaping innovative assessment methods driven by AI. Thus, when educators and policymakers use AI, they should prioritize developing and implementing high-quality curricula that align with the needs of 21st-century learners and promote the effective use of technology in inclusive education that maintains a high level of equity and fairness. Similarly, while digital literacy and computer efficacy mediate the relationship between curriculum innovation and sustainable AI-driven classroom assessment, integrating AI into the curriculum requires that teachers and students be trained in ICT skills that will help them evaluate the quality of digital information they are exposed to. The curriculum that is developed in school should ensure that assessments that are practiced with AI mitigate all forms of bias, inequality, and data insecurity.

Data availability statement

This will be made available on reasonable request.

Acknowledgement

The researchers wish to thank the team of validators that were used for this study, especially Prof Isaac Ubi, who painstakingly looked at the pages and items of the instrument. The respondents who provided consent for this study are also appreciated for the time to be involved in this study. The research assistants that stood as contact points to the respondents are also thanked for their active role in the study.

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