KNUST
Kwame Nkrumah University
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E–LRP
Issue 1
Voume 1, 2026

E-Learning RESEARCH *and* PRACTICE

Expanding access to research and practice on using electronic learning technologies,

ISSN 3134-5425
9 773134 542005

E-Learning RESEARCH *and* PRACTICE

Published in 2026 by the
KNUST E-Learning Centre
Box: PMG, KNUST
E-Learning Centre Directorate,
CCB Auditorium

ISSN 3134-5417 (Paperback)
3134-5425 (Online)

Production Editor
Francis Kofi Nimo Nunoo (PhD)
Department of Publishing
KNUST

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Global Perspectives on Artificial Intelligence in Mathematics Education: A Systematic Review and Its Implications for Students' Learning Outcomes

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Article History
Received 24 October 2025
Accepted 23 January 2026

ABSTRACT

This systematic review examined the integration of artificial intelligence (AI) in mathematics education, focusing on four key dimensions: (1) the types of AI applications and computational techniques employed, (2) their impact on students' learning outcomes, (3) the distribution of research designs, and (4) geographical trends in existing studies. Thirty-one peer-reviewed articles published between 2015 and 2025 were analysed. The findings revealed that intelligent tutoring systems, adaptive algorithms, and generative AI tools are the most frequently utilised applications. Across contexts, AI interventions were associated with measurable improvements in mathematics achievement, motivation, and conceptual understanding. Methodologically, quasi-experimental and experimental designs predominated with 10 (32%) and 4 (12%) studies, respectively, reflecting a strong orientation toward quantitative, intervention-based inquiry. Geographically, research was concentrated in the United States and China, with growing representation from Europe, the Asia-Pacific region, and the Global South. Overall, the review highlights AI's pedagogical potential in mathematics education while stressing the need for more context-based, longitudinal, and mixed-methods research to capture its evolving classroom impact.

Keywords: Artificial intelligence, Mathematics education, Students' achievement, Adaptive learning tools, AI tools

INTRODUCTION

Mathematics is a foundational subject that develops problem-solving, logical reasoning, and analytical thinking skills (Geiger *et al.*, 2023; Khusna *et al.*, 2024). These cognitive skills are applicable in everyday life and across a broad spectrum of professions. Learning mathematics enhances critical thinking, enabling students to make informed, methodical decisions. As a fundamental discipline in science, technology, the arts, engineering, and economics, a strong understanding of mathematical concepts is necessary for reading and interpreting data, recognising patterns, and engaging in abstract thinking (Mangarin and Caballes, 2024).

Despite its importance, mathematics remains challenging for many students for various reasons. Key among these reasons is the use of traditional teaching approaches that emphasise memorisation and repetitive practice over conceptual understanding (Hussein and Csíkos, 2023). Topics such as algebraic manipulations, calculus, geometric proofs, and mathematics word problems often require multi-step reasoning and a sense of non-intuitive principles.

Overreliance on rote memorisation can lead to disconnection from the subject, thereby reducing student motivation and engagement. Furthermore, many students fail to recognise the relevance of mathematics in real-life contexts, further diminishing their interest and willingness to persist in learning the subject (Kaya and Keşan, 2023). Several other challenges that hinder effective mathematics learning include conceptual misunderstandings and cognitive barriers, anxiety, ineffective pedagogical methods, and socio-cultural challenges (Mangarin and Caballes, 2024). The primary challenge most students face in learning mathematics is their inability to grasp basic concepts (Waswa and Al-kassab, 2023). This causes them to rely on rote learning, which limits their ability to apply mathematical concepts in unfamiliar situations (Hussein and Csíkos, 2023). Kaya and Keşan (2023) emphasised that this results in students' inability to apply mathematical concepts in real-life situations. Furthermore, cognitive challenges, such as lower working memory skills, compound these issues, making it difficult for students to visualise and understand abstract mathematical concepts.

Additionally, mathematics anxiety negatively affects students' focus and problem-solving abilities, often stemming from early adverse experiences and external pressures, such as performance expectations and peer comparisons (Mangarin and Caballes, 2024; Waswa and Al-kassab, 2023). Moreover, ineffective teaching methods, particularly traditional lecture-based approaches, fail to foster critical thinking and engagement, while inadequate teacher preparation further impedes learning outcomes (Hissan and Ntow, 2021). Studies have shown that socio-cultural and resource-based challenges also contribute to disparities in mathematics education, with students from low-income backgrounds experiencing limited access to quality instruction and essential learning materials (Brand *et al.*, 2006). Given these persistent challenges in mathematics education, there is a growing need for innovative solutions that enhance conceptual understanding, alleviate anxiety, and improve instructional effectiveness, as traditional teaching methods have often fallen short in encouraging a deep understanding of mathematics.

In response, artificial intelligence (AI) technologies have emerged as powerful tools that can transform mathematics education in various ways. These tools have gained significant popularity and are attracting considerable attention, with several studies on the use of AI in mathematics teaching and learning underway. Luckin *et al.* (2016) and Opesemowo (2024) revealed that AI technologies transform mathematics teaching by offering personalised instruction and adaptive feedback. Unlike traditional methods, AI systems analyse students' performance and tailor lessons to their needs, fostering a more profound understanding beyond rote memorisation (Hu, 2024; Saira *et al.*, 2021). One of the primary advantages of AI in mathematics education is its ability to provide real-time adaptive feedback. Luckin *et al.* (2016) opine that Intelligent Tutoring Systems (ITS) assess students' problem-solving strategies and offer immediate guidance. This feedback enables students to correct misconceptions early, thereby improving their comprehension of mathematical concepts. Again, AI-powered virtual tutors, which can simulate human-like interactions and provide step-by-step solutions, have been found to enhance accessibility to quality education, particularly for under-resourced students and those with disabilities (Cardona *et al.*, 2023).

Psychologically, AI tools have been found to help reduce mathematics anxiety by providing supportive, gamified learning environments that make mathematics more enjoyable for students who struggle with traditional methods (Li *et al.*, 2024; Wulan *et al.*, 2024). Moreover, AI-powered assessment tools offer continuous evaluation without reinforcing

negative attitudes. Zawacki-Richter and Jung (2023) assert that AI tools support teachers by automating routine tasks, such as grading, enabling more personalised instruction, while AI analytics help identify at-risk students for timely interventions (Chassignol *et al.*, 2018). Despite its potential, AI implementation in mathematics education faces challenges such as data privacy, ethics, and digital divide issues (Ng *et al.*, 2025; Nsoh *et al.*, 2023). As AI evolves, its role in enhancing mathematics education will expand, offering solutions to educational challenges. While existing systematic reviews have broadly examined AI in education, they lack domain-specific insights. For instance, Gligorea *et al.* (2023) analysed AI's role in instructional methods through robotics and adaptive learning platforms. Bond *et al.* (2024), Fadlelmula and Qadhi (2024), and Zawacki-Richter *et al.* (2019) also focused on AI in education at various levels. Given the unique traits of mathematics learning and AI's potential, this study systematically synthesises evidence on AI tools in mathematics education, focusing on student learning outcomes.

In the context of this review, student learning outcomes are understood to include indicators of cognitive, affective, and behavioural changes the learner exhibits after using AI tools in the mathematics classroom. The studies reviewed in this paper mostly defined learning outcomes using achievement test scores, problem-solving performance, motivation and engagement, and variables related to mathematics anxiety. Interpreting the results through this view of learning outcomes makes it possible to understand how AI tools influence students' performance and experiences when they interact with AI tools in the mathematics classroom.

The review will address the following key research questions:

1. What types of artificial intelligence applications and related computational techniques have been employed to support the teaching and learning of mathematics?
2. What evidence exists regarding the impact of AI-driven or AI-supported approaches on students' mathematical learning outcomes and achievement?
3. How is research on AI in mathematics education distributed across different research designs and methodological approaches?
4. How is the use of AI in mathematics education distributed across different countries and educational contexts?

METHOD

This study followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to answer the research questions. PRISMA provides a standardised framework for conducting systematic reviews, encompassing literature searches, screening, data extraction, analysis, and reporting (Page *et al.*, 2021).

Search Strategy

The search for relevant literature was conducted in the following databases: Google Scholar, ScienceDirect, Scopus, ERIC, and ProQuest. The search string was created using Boolean operators and structured as follows: ("artificial intelligence") AND ("mathematics education") AND ("learning outcome").

Selection criteria

The study included articles that focused on the integration of AI tools and their impact on student performance. Only peer-reviewed articles written in English and published between January 2015 and January 2025 were included. Conference proceedings, theses, technical papers, reports, and other grey literature were excluded from the review.

These criteria were designed to ensure that the selected papers were relevant to the research questions and maintained a certain level of excellence, uniformity, and rigor. By incorporating studies on AI applications in mathematics education, this review sought to thoroughly examine the prevailing trends and potential influence of AI in the field. The emphasis on peer-reviewed journal publications ensured the credibility and accessibility of information. This method aligns with the viewpoints of Hwang *et al.* (2021) and Tang *et al.* (2023), who recommend that systematic reviews aimed at high-quality articles are more likely to reveal significant trends in the literature. Conference papers and non-empirical studies were excluded because of their insufficiently robust research design and limited reproducibility (Booth *et al.*, 2016). Furthermore, this approach aligns with systematic review standards that prioritise rigorously validated sources to strengthen the reliability of results (Page *et al.*, 2021). By setting these specific standards, this study endeavoured to uphold a clear and balanced approach to the literature analysis of AI in mathematics education literature.

The initial search of the selected databases and other sources yielded 374 screened records. After removing 12 records (7 duplicates and 5 irrelevant), 362 records remained for analysis. These records were screened based on their titles and abstracts, resulting in the exclusion of 308 studies that did not meet the predefined inclusion criteria. The full texts of 54 articles were assessed for their eligibility. Of these, 23 of the studies were excluded from the analyses. Ultimately, 31 studies met the inclusion criteria and were included in the final synthesis of this review. Two reviewers independently reviewed the articles. Disagreement about some aspects of the articles, especially the study design, where some were not explicitly stated, was resolved by consensus. The study selection process is visually summarised in the flow diagram (see Figure I), which provides a transparent overview of the inclusion and exclusion criteria used.

Table I: Inclusion criteria for selecting studies on AI integration in mathematics education

Criterion	Inclusion factor
Period	2015 to 2025
Language	English
Focus of the paper	AI in mathematics education
Paper type	Empirical study

Source: Authors

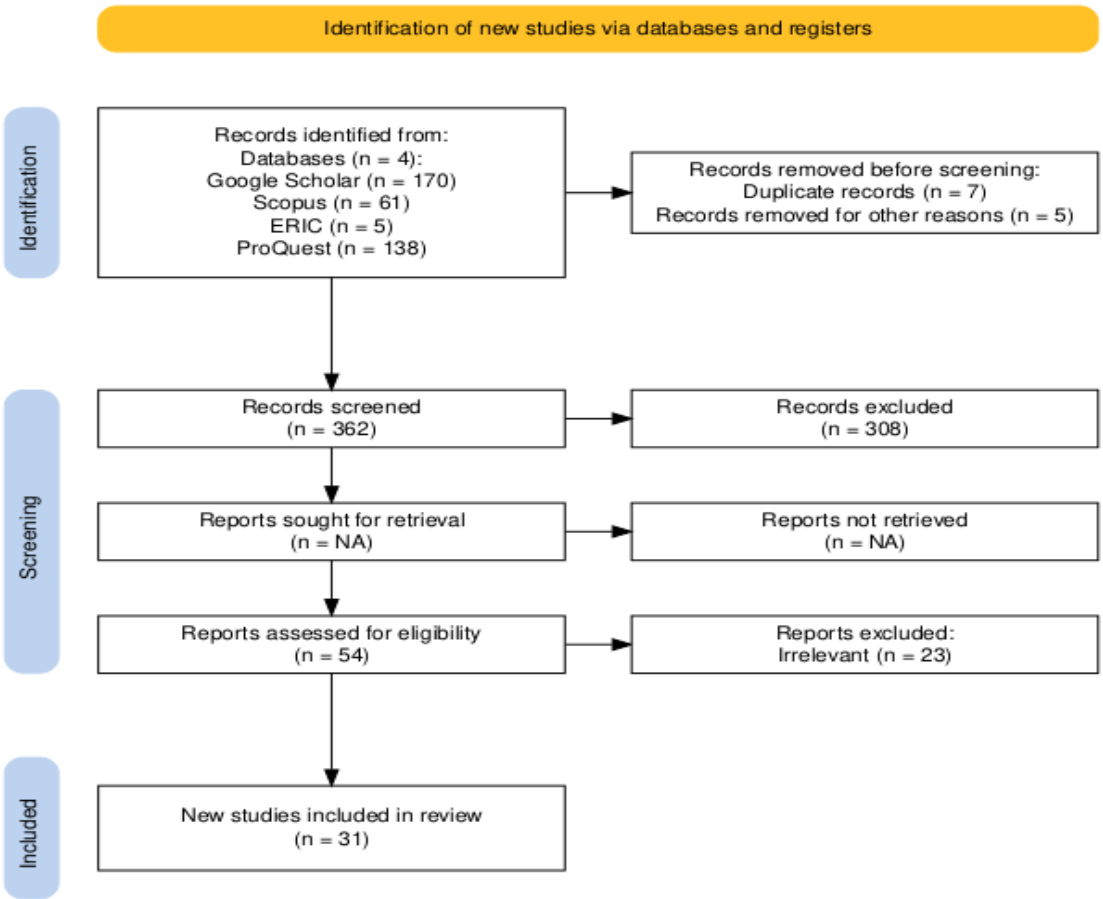

Figure I: *Flow chart of the selection process*

RESULTS

This section presents the findings from a systematic review of 31 articles that examined how AI tools have been employed in mathematics teaching and their impact on students' learning outcomes. Both narrative and thematic synthesis were used in presenting the findings of this review. The themes were organized around the research questions. For each question, the result is summarized using text and then supported by descriptive tables.

Question 1: Artificial intelligence applications and related computational techniques

Table II: *Studies and their AI tools used*

S/N	Author(s)/ year	AI Application/Technique
1	Cai *et al.* (2021)	MathBot
2	Jones *et al.* (2023)	Virtual reality
3	Khazanchi *et al.* (2025)	Edmentum Exact Path
4	Mills (2021)	ALEKS
5	Nehring *et al.* (2023)	ALEKS
6	Ryan *et al.* (2025)	ALEKS

S/N	Author(s)/ year	AI Application/Technique
7	Lopez-Caudana *et al.* (2020)	Educational robotics platform
8	Bernhardt-Walther and McKeown (2023)	ALEKS
9	Shi and Rao (2022)	Backpropagation Neural Network (BPNN)
10	Tan (2022)	Particle Swarm Optimization (PSO)
11	Wang *et al.* (2022)	Squirrel AI Learning
12	Zhang (2023)	AI-based learning model
13	Inoferio *et al.* (2024)	AI-assisted learning models
14	Alvarez (2024)	MathGPT and Flexi 2.0
15	Chen *et al.* (2023)	Gamified educational robot
16	Wardat *et al.* (2023)	ChatGPT
17	Elsayed (2023)	ChatGPT, Metaverse
18	Qawaqneh *et al.* (2023)	Virtual lab
19	Moral-Sánchez *et al.* (2023)	SnatchBot
20	Romero *et al.* (2023)	Immersive Virtual Reality
21	Sáez-López *et al.* (2019)	mBot
22	Ferro *et al.* (2021)	Gea2
23	Azevedo *et al.* (2024)	MathE platform
24	Xhako *et al.* (2025)	Python-based AI modules
25	Annuš & Kmeť (2024)	Learn With M.E
26	Torres-Peña *et al.* (2024)	ChatGPT, MathGPT, Gemini, Wolfram Alpha
27	Deo *et al.* (2020)	A custom-built artificial intelligence model
28	Getenet (2024)	ChatGPT
29	Moreno-Esteva *et al.* (2018)	Machine-learning techniques
30	Nindiasari *et al.* (2024)	Augmented Reality (AR)
31	Henkel *et al.* (2024)	Rori

Source: Authors

The review showed that artificial intelligence has been widely applied in mathematics education using various tools and techniques. A significant number of studies used intelligent tutoring systems such as MathBot, ALEKS, Edmentum Exact Path, and Squirrel AI to provide adaptive feedback and personalised learning instructions (Cai *et al.*, 2021; Khazanchi *et al.*, 2025; Mills, 2021; Nehring *et al.*, 2023; S. Wang *et al.*, 2023). Other studies explored Virtual and Augmented Reality platforms to support visualisation and spatial reasoning (Annuš and Kmeť, 2024; Jones *et al.*, 2023; Nindiasari *et al.*, 2024). Machine learning and neural network techniques, such as Backpropagation Neural Network and Particle Swarm Optimisation, were used to develop adaptive learning algorithms to optimise the instruction processes (Shi and Rao, 2022; Tan, 2022; Zhang, 2024). Additionally, educational robots (Chen *et al.*, 2023;

Lopez-Caudana *et al.*, 2020) and Generative AI chatbots, including *Rori*, ChatGPT, MathGPT, *Flexi 2.0,* and Gemini, have been incorporated to improve problem-solving and independent learning (Alvarez, 2024; Henkel *et al.*, 2024; Torres-Peña *et al.*, 2024; Wardat *et al.*, 2023).

This indicates a clear trend towards personalisation, automation, and a shift from conventional instruction to more effective, data-driven teaching. Moreover, the review showed that Adaptive Learning Systems and chatbots/virtual assistants are the most frequently studied AI tools, indicating their broad applicability in mathematics education. Machine Learning models are emerging, with high potential for forecasting student performance. Meanwhile, Generative AI tutors continue to gain popularity, but still need improvements to detect procedural errors. The review identified a diverse range of AI tools supporting math education. While traditional Adaptive Learning systems remain dominant, there is growing interest in robotics, machine learning models, and generative AI, each offering unique advantages and challenges.

Question 2: Impact of AI-driven or AI-supported approaches on students' mathematical learning outcomes and achievement

Table III: *Studies and their key findings*

Author	Title	Findings
Cai *et al.* (2021)	Bandit algorithms to personalise educational chatbots	The chatbot was as effective as traditional tutorials and reduced participant dropout rates.
Jones *et al.* (2023)	Design of virtual reality modules for multivariable calculus and an examination of student noticing within them	Animations improved students' understanding of multivariable calculus concepts, whereas narration had a limited impact.
Khazanchi *et al.* (2025)	The Effect of AI-Based Systems on Mathematics Achievement in Rural Context: A Quantitative Study	The system improved 8th-grade rural students' math achievement but did not affect cognitive engagement; teacher-led instruction had higher affective engagement.
Mills (2021)	ALEKS constructs as predictors of high school mathematics achievement for struggling students	Engagement time and the ratio of topics mastered to topics practised significantly predicted final course grades in algebra; retention was the only significant predictor of PSAT Math scores.
Nehring *et al.* (2023)	Assessing the effectiveness of an artificial intelligence tutoring system for improving college-level mathematics preparedness in high school students	High school students' completion of the ALEKS PPL modules was positively correlated with their scores on a college-level mathematics placement exam; the tutoring system effectively supported improved preparedness for college mathematics.

Author	Title	Findings
Ryan *et al.* (2025)	Understanding the Effects of a Math Placement Exam on Calculus 1 Enrollment and Engineering Persistence	The placement exam cutoff of 80% is appropriate; scoring above the cutoff strongly predicts enrollment in Calculus 1, and taking a remedial Pre-Calculus course is associated with a significant decline in probability of enrolling in Calculus 1, though not with lower grades once enrolled.
Lopez-Caudana *et al.* (2020)	Using Robotics to Enhance Active Learning in Mathematics: A Multi-Scenario Study	Robotics-enhanced lessons significantly improved student attention and motivation; effectiveness depended on educational level, student motivation, and teacher training.
Bernhardt-Walther and McKeown (2023)	The Impact of ALEKS on Student Learning in First-Year University Mathematics for Economics	Higher performance on ALEKS assessments correlated with better performance in the calculus component; over 85% of students reported an increased likelihood to remain in a math-based program; female and ESL students were more likely to report increased confidence and intent to stay in a math-based program.
Shi and Rao (2022)	Construction of STEAM Graded Teaching System Using Backpropagation Neural Network Model under Ability Orientation	The STEAM graded teaching system achieved significantly higher student answer accuracy than traditional methods, and the BPNN model's evaluation error was below 1%, indicating high reliability in evaluating teaching effectiveness.
Tan (2022)	Information Analysis of Advanced Mathematics Education-Adaptive Algorithm Based on Big Data	The AI system improved the organisation and management of advanced mathematics teaching resources, enhancing teaching efficiency.
Wang *et al.* (2022)	When adaptive learning is effective learning: comparison of an adaptive learning system to teacher-led instruction	Students using the AI system made greater mathematics gains than those in large–group or small–group teacher–led instruction.
Zhang (2023)	An Innovative Model of Higher Mathematics Curriculum Education Incorporating Artificial Intelligence Technology	Students in the experimental group achieved higher post-test scores (mean = 75.631) than those in the control group (mean = 66.314), with a difference of 9.317 that was statistically significant ($p < 0.05$), indicating that the AI-supported teaching mode improved learning performance.

Author	Title	Findings
Inoferio *et al.* (2024)	Coping with math anxiety and lack of confidence through AI-assisted Learning	The AI-assisted models helped students cope with math anxiety and lack of confidence by offering personalised guidance, fostering independence, and enhancing motivation for self-guided learning.
Alvarez (2024)	Evaluating the Impact of AI–Powered Tutors MathGPT And Flexi 2.0 In Enhancing Calculus Learning	Both AI tools improved calculus learning outcomes, but Flexi 2.0 produced a greater improvement (8.40 points) compared to MathGPT (5.70 points) between pre-test and post-test
Chen *et al.* (2023)	Gamified Educational Robots Lead An Increase In Motivation And Creativity In STEM Education	Use of the gamified robots significantly increased students' learning motivation (attention, relevance, self-confidence, satisfaction) and enhanced creativity compared to conventional instruction.
Wardat *et al.* (2023)	ChatGPT: A revolutionary tool for teaching and learning mathematics	ChatGPT is recognised for improving students' access to mathematics knowledge and support; however, it lacks deep geometric reasoning, cannot reliably correct misconceptions, and its effectiveness depends on instructions, input complexity and context
Elsayed (2023)	Applications of Artificial Intelligence and Their Relationship to Spatial Thinking and Academic Emotions Towards Mathematics: Perspectives from Educational Supervisors	Educational supervisors perceive a strong positive relationship between the use of AI applications and students' spatial thinking skills (Rank = 5) and a significant positive relationship between AI applications and students' academic emotions towards mathematics (Rank = 4)
Qawaqneh *et al.* (2023)	The Impact of Artificial Intelligence-Based Virtual Laboratories on Developing Students' Motivation Towards Learning Mathematics	Students in the AI-based VLabs group showed significantly higher motivation toward learning mathematics than both the 3D-based VLabs group and the traditional teaching group.
Moral-Sánchez *et al.* (2023)	Analysis of artificial intelligence chatbots and satisfaction for learning in mathematics education	Students reported high satisfaction with their self-created chatbots (average satisfaction > 4/5), found the tool easy to use and integrate, improved their digital competence, and believed the experience could be transferred to other subjects.

Author	Title	Findings
Romero *et al.* (2023)	Optimizing the surface of orthohedra with virtual reality in primary school	Students aged 11-12 successfully tackled the challenge of optimising the surface area of given-volume orthohedra using IVR; the study highlights both the benefits (improved engagement, spatial reasoning) and drawbacks (technical and classroom implementation issues) of using immersive VR in a primary-school geometry context.
Sáez-López *et al.* (2019)	The effect of programming on primary school students' mathematical and scientific understanding: educational use of mBot	Students who used mBot and visual programming showed statistically significant improvements in understanding mathematical and scientific concepts, as well as computational thinking elements such as motion, sequences, and conditionals.
Ferro *et al.* (2021)	*Gea2*: A Serious Game for Technology-Enhanced Learning in STEM	Students reported that the game was enjoyable and more engaging than traditional lessons. However, the measurable learning gains were modest (~13.9% average growth), and the tool did not clearly outperform traditional instructional methods across all categories.
Azevedo *et al.* (2024)	Dataset of mathematics learning and assessment of higher education students using the MathE platform	The dataset includes 9,546 answers to 833 questions from 372 students in eight countries. It enables analysis of student learning patterns, assessment of platform efficacy, and supports research into active learning tools in higher-education mathematics.
Xhako *et al.* (2025)	Integrating AI applications into university STEM study programs using Python	Although 92% of faculty agreed AI is essential for STEM education, only 40% felt prepared to teach AI and 30% reported adequate resources; only 40% of analysed STEM curricula included dedicated AI coursework.
Annuš & Kmeť (2024)	Learn with M.E.—Let Us Boost Personalized Learning in K-12 Math Education!	Use of the software significantly improved students' mathematics performance compared to traditional instruction; students and teachers rated it positively for its usability, motivation, and support for differentiated learning.

Author	Title	Findings
Torres-Peña *et al.* (2024)	Updating Calculus Teaching with AI: A Classroom Experience	Students improved their accuracy in derivative calculations and developed clearer conceptual understanding of average vs instantaneous rates of change; AI tools increased engagement and motivation but had limitations in detecting procedural errors.
Deo *et al.* (2020)	Modern Artificial Intelligence Model Development for Undergraduate Student Performance Prediction: An Investigation on Engineering Mathematics Courses	The model achieved strong predictive accuracy ($R^2 \sim 0.81$) in forecasting student final grades in engineering mathematics; key predictors included earlier course grades, attendance, and demographic features, suggesting institutions can leverage such AI models to identify at-risk students and tailor interventions.
Getenet (2024)	Pre-service teachers and ChatGPT in multistrategy problem-solving: Implications for mathematics teaching in primary schools	Pre-service teachers used a variety of problem-solving strategies and mostly achieved correct solutions; ChatGPT employed similar strategies but generated mostly incorrect solutions, indicating limitations when applied in a primary-school mathematics context.
Moreno-Esteva *et al.* (2018)	Application of mathematical and machine learning techniques to analyse eye-tracking data enabling better understanding of children's visual-cognitive behaviours	Children who answered correctly exhibited more focused, logical visual-scan patterns (fewer dwell areas and a sequence of critical zones) than those who answered incorrectly, highlighting links between visual cognition and graph comprehension performance.
Nindiasari *et al.* (2024)	The use of augmented reality to improve students' geometry concept problem-solving skills through the STEAM approach	The ARM media was rated "very good" by media and education experts, was practical for teachers, elicited excellent student responses, and improved students' geometry problem-solving ability to a moderate level.
Henkel *et al.* (2024)	Effective and Scalable Math Support: Experimental Evidence on the Impact of an AI-Math Tutor in Ghana	Students using Rori had significantly higher maths growth scores (effect size ≈ 0.36, $p < 0.001$) than the control group; the tool is low-cost, mobile-friendly, and scalable in low-resource settings.

Source: Authors

The review found that AI tools consistently improve students' learning outcomes, engagement, and motivation. However, the degree of improvement varies depending on the tool and its implementation. Intelligent tutoring systems such as ALEKS, Edmentum Exact Path, MathBot, and Squirrel AI Learning were the most frequently examined. These tools demonstrated

notable improvements in students' mathematics achievement and readiness, with positive correlations between engagement with these systems and final course grades (Cai *et al.*, 2021; Khazanchi *et al.*, 2025; Mills, 2021; Nehring *et al.*, 2023; S. Wang *et al.*, 2023). Furthermore, Studies on Immersive and Interactive technologies, including virtual and augmented reality and gamified robotics, showed notable gains in motivation, spatial reasoning and conceptual understanding (Chen *et al.*, 2023; Jones *et al.*, 2023; Lopez-Caudana *et al.*, 2020; Nindiasari *et al.*, 2024). Evidence from the generative AI tools suggests that they enhance accessibility and engagement. However, they struggle with procedural accuracy and deep reasoning (Alvarez, 2024; Getenet, 2024; Wardat *et al.*, 2023). Furthermore, machine learning and predictive models (e.g., Deo *et al.*, 2020; Shi and Rao, 2022; X. Zhang, 2024) enabled precise performance predictions and helpful adaptive feedback.

Together, these studies confirm that AI can greatly enhance mathematical learning, particularly when paired with solid pedagogy and teacher guidance.

Question 3: Study designs employed in AI in mathematics education studies.

Table IV: *Distribution of Study Designs*

S/N	Design	Frequency	Cumulative freq.
1	Multi scenario	1	1
2	Quasi experimental	10	11
3	Correlational	2	13
4	Experimental	4	18
5	Developmental	3	21
6	Exploratory	1	22
7	Case study	2	24
8	Descriptive	2	26
9	Design based	2	28
10	Convergent parallel	1	29
11	Comparative	1	30
12	Observational	1	31

Source: Authors

This current review shows a methodologically diverse landscape in research on AI in mathematics education. This suggests that scholars use a wide range of designs to capture AI's multifaceted influence on teaching and learning. Quasi-experimental designs dominated the field, appearing in 10 of 31 studies (Bernhardt-Walther and McKeown, 2023; Cai *et al.*, 2021; Chen *et al.*, 2023; Ferro *et al.*, 2021; Jones *et al.*, 2023; Khazanchi *et al.*, 2025; Nehring *et al.*, 2023; Qawaqneh *et al.*, 2023; O. Ryan *et al.*, 2025; Sáez-López *et al.*, 2019). These designs often include pre- and post-tests with control groups to evaluate the effect of AI-based interventions on student achievement and motivation. This common approach reflects researchers' focus on establishing causal relationships while considering the practical limitations of educational

environments. Four studies (Alvarez, 2024; Annuš and Kmeť, 2024; Henkel *et al.*, 2024; S. Wang *et al.*, 2023) employed an experimental design, while three studies (Deo *et al.*, 2020; Tan, 2022; X. Zhang, 2024) used developmental study designs. This highlights the field's focus on testing and developing innovative AI tools and learning systems. Meanwhile, two studies (Elsayed, 2023; Mills, 2021) employed a Correlational design, while comparative (Getenet, 2024) and observational (Moreno-Esteva *et al.*, 2018) designs were used once each. These were used to analyse relationships among variables such as engagement, learning behaviours, and performance outcomes. Less common but valuable methods include case studies (Torres-Peña *et al.*, 2024; Wardat *et al.*, 2023), design-based research (Nindiasari *et al.*, 2024; Romero *et al.*, 2023), and exploratory studies (Inoferio *et al.*, 2024), providing detailed qualitative insights into user experiences and implementation contexts. Overall, the distribution of methods indicates that AI in mathematics education research remains primarily quantitative and intervention-based. Nonetheless, recent developments point towards greater methodological diversity, aiming to encompass both learning results and experiential aspects.

Question four: Countries of publication on AI in mathematics education

Table V: *Countries and contexts of publication*

Country (Geographical context)	Frequency
United States of America	6
Mexico	1
Canada	1
China	4
Philippines	2
Taiwan	1
United Arab Emirates	1
Saudi Arabia	1
Jordan	1
Spain	3
Italy	1
Portugal	1
Albania	1
Slovakia	1
Colombia	1
Australia	3
Indonesia	1
Ghana	1

Source: Authors

The distribution of research on AI in mathematics education shows substantial geographical diversity, with studies spanning multiple continents and educational contexts.

The United States leads with six studies (Cai *et al.*, 2021; Jones *et al.*, 2023; Khazanchi *et al.*, 2025; Mills, 2021; Nehring *et al.*, 2023; Ryan *et al.*, 2025), reflecting its longstanding

investment in adaptive learning technologies, intelligent tutoring systems, and instructional design. China, closely followed by four studies (Shi and Rao, 2022; Tan, 2022; Wang *et al.*, 2023; Zhang, 2024), many of which focused on algorithm development and model-based approaches such as neural networks and optimisation algorithms.

European nations, notably Spain (Moral-Sánchez *et al.*, 2023; Romero *et al.*, 2023; Sáez-López *et al.*, 2019), Italy (Ferro *et al.*, 2021), Portugal (Azevedo *et al.*, 2024), Slovakia (Annuš and Kmeť, 2024), and Albania (Xhako *et al.*, 2025), have produced a growing body of work emphasising virtual reality, chatbots, and personalised learning environments. These contributions often explore AI's integration into mathematics curricula from a pedagogical and cognitive perspective.

In the Asia-Pacific region, research from the Philippines (Alvarez, 2024; Inoferio *et al.*, 2024), the United Arab Emirates (Wardat *et al.*, 2023), Indonesia (Nindiasari *et al.*, 2024), Taiwan (Chen *et al.*, 2023), and Saudi Arabia (Elsayed, 2023) highlights AI's emerging role in enhancing motivation, spatial reasoning, and engagement, often within higher education contexts.

Studies from Australia (Deo *et al.*, 2020; Getenet, 2024; Moreno-Esteva *et al.*, 2018), Mexico (Lopez-Caudana *et al.*, 2020), Ghana (Henkel *et al.*, 2024), Canada (Bernhardt-Walther and McKeown, 2023), and Colombia (Torres-Peña *et al.*, 2024) extend the geographical scope and provide evidence of AI's potential across diverse educational systems, including resource-constrained settings.

Overall, the findings show that while AI in mathematics education is a global research concern, the United States and East Asia remain the most active contributors, with recent growth in representation from developing and Global South regions such as Ghana and the Philippines.

CRITICAL APPRAISAL OF REVIEWED STUDIES

Inasmuch as most of the reviewed studies reported positive learning improvements, it is worth noting that the strength of these outcomes varies considerably across studies. Most studies used relatively small sample sizes, limiting the generalizability of their findings. In addition, many of the studies that implemented interventions did so for a short period. This short intervention period tends to undermine the claim of sustained learning benefits. Moreover, a few (approx. 3%) of the studies reported effect size. This makes it difficult to compare the magnitude of learning across the studies. Another key observation made during the review was the seemingly over-reliance on quasi-experimental designs, without transparent reporting of selection bias and of how uncontrolled classroom variations affected the outcomes of the various studies. Lastly, we observed publication bias, with most studies reporting no effect or an adverse effect of AI on learning outcomes. This scenario tends to give the impression that AI tools are highly effective, which may not be the case.

DISCUSSION

This systematic review analysed recent research on artificial intelligence (AI) in mathematics education, synthesising evidence across four main aspects: the types of AI tools and computational methods used, their effects on students' learning outcomes, the research methodologies applied, and the geographic distribution of the studies. Where the opinions

espoused in this section extend beyond the reviewed articles, they are explicitly informed by the broader literature on the application of AI in education.

AI Tools and Computational Techniques

Regarding the types of AI tools used, the findings identified five main categories: Intelligent Tutoring Systems (ITS), AI-based predictive models, educational robots, generative AI tutors, and AI-driven gamified applications. ITS such as ALEKS, MathBot, and Edmentum Exact Path were the most widely adopted, offering adaptive feedback, personalised instruction, and measurable gains in students' conceptual understanding. Likewise, educational robots like mBot encouraged active engagement and problem-solving through experiential learning. Recent advancements in generative AI (e.g., ChatGPT, MathGPT) show potential for supporting personalised learning. This observation is consistent with that of Yilmaz and Yilmaz (2023), who found that students who used ChatGPT in a programming course showed significantly higher computational thinking skills, programming self-efficacy, and motivation for the lesson than those in the control group, and Ezeoguine and Eteng-Uket (2024), who observed that AI tools significantly influenced students' engagement, with a marked difference in engagement levels between students who were and were not influenced by AI tools.

Research Design and Methodological Trends

Most studies used quasi-experimental and experimental designs, emphasising a quantitative focus on learning outcomes. The prevalence of quasi-experimental studies is understandable, given the challenges in achieving complete experimental control in the real world (Giannakos, 2022). Although these methods are effective for measuring performance, they often overlook behavioural and contextual factors that affect AI adoption (Savela, 2018). Fewer qualitative and mixed-method studies yielded deeper insights into teachers' and students' experiences, underscoring the need for methodological diversity in future research.

Geographical Patterns

Geographically, research was heavily concentrated in the United States and China, with growing contributions from Europe, Asia-Pacific, and emerging interest from the Global South. This may be attributed to the sustained investment in educational technology over the years. More recently, both the USA and China have passed legislation allowing full implementation of AI in the classroom (Pessarlay, 2025). This gives credence to the evidence demonstrated in the studies reviewed, as these countries' top research on the use of AI in mathematics teaching and learning**.** However, African contexts, despite their increasing engagement with digital learning, remain underrepresented. This underrepresentation may result from how these AI tools are developed to favour developed countries with sophisticated infrastructure, possibly neglecting issues of equity, infrastructure inadequacies, and pedagogical differences in the Global South. This imbalance highlights global disparities in technological access and research funding, emphasising the need for more inclusive inquiry that reflects diverse educational realities.

Effect of AI Tools on Learning Outcomes

Regarding students' learning outcomes, AI-supported instruction consistently resulted in improved mathematical achievement, motivation, and problem-solving skills. These benefits mainly result from AI's ability for adaptive feedback, personalised learning, and immediate feedback. However, several studies warn that observed improvements may partly result

from novelty effects (Rodrigues *et al.*, 2022) or increased teacher facilitation during AI interventions. Hence, sustainable implementation requires pedagogical alignment, teacher professional development, and careful evaluation of the cognitive validity of AI tools.

Overall, the review indicates that AI is evolving from a simple technological tool to a cognitive-enhancing companion in mathematics education. Its success relies on careful integration into teaching methods, ensuring equitable access, and conducting thorough, context-aware research that includes both learning results and human experiences.

LIMITATIONS

The limitations of the current review include the exclusion of non-English studies, a focus on recent publications (2015–2025), and a relatively small number of studies. These factors may limit the generalizability of our findings to other populations and settings. Future systematic reviews should expand their scope to include a broader range of sources and methods.

CONCLUSION

This systematic review aimed to investigate how AI tools are being employed in mathematics education, focusing on identifying primary AI tools, research design trends, geographic distribution, and key findings. The review revealed that Intelligent Tutoring Systems (ITS) and Educational Robots are the most effective AI tools for promoting improved mathematical outcomes. Most studies utilised quasi-experimental designs and predominantly originated from high-income countries, highlighting the disparity in research representation.

The findings consistently indicate that AI technology enhances students' academic performance, motivation, and engagement. Nevertheless, concerns regarding students' overreliance on AI systems and limited faculty preparedness emphasise the need for the critical integration of these technologies into educational practices. Educational stakeholders should prioritise the adoption of AI tools, ethical considerations, faculty training, and efforts to bridge the digital divide.

Overall, AI technologies hold significant promise for transforming mathematics education. Realising this potential requires thoughtful, inclusive, and evidence-based implementation strategies that ensure equitable and effective learning opportunities for all students.

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Integrating AI in Mathematics Education while Preserving the Human Element: The Ghanaian Perspective

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Article History
Received: 04 Nov. 2025
Accepted: 23 January 2026

ABSTRACT

The rapid use of Artificial Intelligence (AI) in academic activities offers increased efficiency. It presents clear concerns on human judgment, creativity, and ethical responsible use. The purpose of this study is to examine how mathematics educators in Ghana use AI tools and how they perceive AI's influence on critical thinking, ethics, and creativity. Grounded on Socio-Technical Systems (STS) Theory, the report utilized a convergent mixed-methods design within a pragmatist paradigm. Data was obtained from 47 mathematics educators through closed-ended questions for quantitative and open-ended questions for qualitative. The data were analysed using descriptive statistics and thematic analysis. Findings revealed that participants frequently use AI in conducting literature review, academic writing, clarifying mathematical concepts, and assisting in data analysis. The participants expressed concerns about mathematics educators' over-reliance on AI, reduced critical engagement, copy and paste risks, limited AI literacy, and the absence of clear institutional ethical guidelines. The results highlighted that responsible AI integration requires both technological tools and social elements, which include human skills, ethics, and institutional policies. The study provides empirical evidence from a developing-country context and underscores the need for AI literacy training and ethical frameworks to preserve the human element in mathematics education and research.

Keywords: Artificial Intelligence, Mathematics Education, Socio-Technical Systems Theory, Ethics, Human Judgment

INTRODUCTION

Mathematics education is central to daily life activities, be it decision-making or progress. Mathematics is more than a school subject in Ghana; it is widely believed to be an entrance to critical thinking, problem-solving skills, logical reasoning, and technological competence (Abakah 2024). Mathematical understanding helps shape the capacity of individuals across all fields, be it in engineering, finance, or health sciences. Also, beyond its economic utility, mathematics education appears to play a subtler role in cultivating habits of mind such as logical discipline, persistence, creativity, and reflective judgment (Ayebo *et al.*, 2022; Nyala, 2021). These human capacities, though often taken for granted, remain essential for meaningful

learning and informed citizenship, mostly in a world that requires speed and automation over depth of understanding.

Despite the importance of mathematics, it remains a significant challenge for many students in Ghana. A primary reason is the persistent use of teacher-centered, rote-learning methods, which emphasize memorization of formulas and procedures over conceptual understanding (Agyei & Voogt, 2016; Asante & Mereku, 2020). Since topics like algebra, calculus, and problem-solving require logical reasoning, this instructional approach often leads to student disengagement and anxiety. Many learners also struggle to connect classroom mathematics to their daily lives and future aspirations, which weakens their motivation and perceived relevance of the subject (Boakye & Ampiah, 2019). Other critical barriers documented in the Ghanaian context include widespread misconceptions of fundamental concepts, high levels of mathematics anxiety among both students and teachers, and socio-cultural beliefs that label the subject as inherently difficult (Ayebo *et al.*, 2022; Nyala, 2021). The core issue is that without a solid grasp of foundational principles, students resort to memorization, which prevents them from applying knowledge to unfamiliar or practical situations (Agyei & Voogt, 2016). This deficit limits their capacity to use mathematics effectively beyond school (Boakye & Ampiah, 2019). Furthermore, the language of instruction, particularly in early grades where English proficiency is low, creates an additional cognitive hurdle for understanding abstract mathematical ideas (Adzahlie-Mensah & Dunne, 2021).

However, these challenges have prompted continued calls for more innovative pedagogies and tools that can support problem-solving and creativity in mathematics classrooms (Takahashi, 2021). In this context, Artificial Intelligence (AI) tools are increasingly being explored as potential mechanisms for transforming how mathematics is taught, learned, and researched (Egara & Mosimege, 2024). The extensive use of AI tools raises important questions about how to safeguard the human elements at the heart of mathematical thinking (Holmes *et al.*, 2022).

The way society interacts with technology has changed due to the rise in AI tools (Sheikh 2020). In the interaction between humans and Artificial Intelligence (AI) tools, there are issues regarding ethics, responsibility, and accountability. There remains a high argument on ‘who or what’ can be held responsible for the outcome of such interaction (Verdicchio & Perin, 2022). Hence, responsible AI use is not just deploying technological tools, but it involves applying principles that align technological progress with social, cultural, and educational realities (Ifenthaler & Schumacher, 2023). It is revealed in literature that AI platforms such as ChatGPT, Scopus AI, MathGPT, Wolfram Alpha, Microsoft Math Solver, and other mathematics-focused tools have gained influence in mathematics education research. These AI platforms are used for tasks such as generating ideas, rephrasing explanations, clarifying difficult concepts, and supporting data interpretation and analysis (Bianchini *et al.*, 2022; Borger *et al.*, 2023; Verma *et al.*, 2025). What makes these tools attractive for users is their user-friendly interfaces, speed, and adaptability make them attractive for creating step-by-step worked examples and producing large banks of practice questions and solutions. Despite their obvious advantages, these AI tools present significant challenges (Sarpong *et al.*, 2021), which include the risk that users may copy solutions without engaging in genuine human mathematical reasoning (Kozyreva, 2020) and that educators may rely on AI outputs without critically verifying their correctness (Zhai *et al.*, 2024) or pedagogical appropriateness. In the Ghanaian context, these concerns are already visible in practice.

The lens for understanding the development of how AI tools are integrated into mathematics education is Socio-Technical Systems Theory (STS) (Zhang & Dong, 2024). It reshapes how educators and learners engage with mathematical problems, as well as how ethical and cognitive issues arise in AI-supported learning. Trist and Bamforth (1951) are the pioneers of STS theory. The theory emphasizes the joint optimization of social and technical subsystems as stated by Ouyang and Jiao (2021). Trist and Bamforth argue that the success of any system depends on how well human elements (relationships, roles, values, ethics, and institutional context) are aligned with technological elements such as tools, processes, and methods (Brown & Harvey, 2006; Sony & Naik, 2020). Overuse of technology can lead to a loss of human touch, whereas only human focus or social factors can hinder efficiency and innovation (George, 2024). Therefore, effective systems require a careful balance between technology and human interactions (Chaturvedi, 2025). In the context of AI integration in mathematics education and research, this balance means ensuring that AI tools support rather than replace critical thinking, ethical judgment, and human touch.

From a socio-technical point of view, responsible AI in education should not only be technically efficient but also attentive to ethical, cultural, and human-centered considerations (Münch *et al.*, 2024). In Ghana and other African settings, this involves creating AI practices that resonate with local values, community decision-making, and respect for human dignity (Gwagwa *et al.*, 2022), while acknowledging infrastructural challenges such as digital inequality and uneven access to AI premium platforms. The STS theory, therefore, aligns closely with this study's main theme of blending intelligence. conceptualizing AI as part of a developing socio-technical ecosystem in which human creativity, ethical responsibility, and cultural significance coexist with technological advancements.

Some studies documented that the use of AI tools increases in mathematics education and research (Meylani, 2024; Wardat *et al.*, 2023; Yildiz & Korpeoglu, 2025). AI tools such as ChatGPT, SciSpace, MathGPT, and Wolfram Alpha enhance learning productivity by supporting solving abstract concepts, literature reviews, data interpretation, and writing (Imran & Almusharraf, 2023; Borger *et al.*, 2023), while dynamic and intelligent systems in education offer personalised learning opportunities in mathematics (Hwang *et al.*, 2020). At the same time, scholars warn that over-reliance on AI may diminish critical thinking and analytical skills, encourage superficial engagement with tasks, and create risks related to data privacy, bias, authorship, and academic integrity (Gerlich, 2025; Rusandi *et al.*, 2023; Kasneci *et al.*, 2023; Schicktanz, 2023). Researchers have also highlighted the importance of AI literacy and training so that educators understand AI's capabilities and limitations, and can use these tools critically and ethically (Pedro *et al.*, 2019; Popenici & Kerr, 2017; Pushparani & Sanjana, 2025).

However, much of this evidence comes from developedcountry contexts and treats "academic research" or "higher education" in general terms (Adjei & Agyeman 2024), with relatively limited focus on mathematics education and very little empirical work in Ghana. There remains a notable gap in understanding how mathematics educators and mathematics education researchers in developingcountry settings actually use AI tools, how they perceive AI's influence on mathematical reasoning, creativity, and ethical behaviour, and how institutional and cultural conditions shape responsible AI integration. Addressing this gap is essential for designing policies, professional development, and classroom practices that

ensure AI strengthens rather than undermines the human element in mathematics teaching and learning.

This study, therefore, examines how mathematics education researchers in Ghana use AI tools across different stages of the research process and explores their perceptions of AI's influence on human-centred aspects of research in Ghana. The evidence from the study is intended to inform institutional policies, AI literacy initiatives, and teachereducation programmes, so that technological advancements in AI support rather than erode the critical and creative human faculties that underpin meaningful mathematical understanding. To achieve this aim, this study seeks to answer two research questions: 1. To what extent do academic researchers in Ghana use AI tools at different stages of the research process? 2. How do academic researchers in Ghana perceive the influence of AI on human-centred aspects of the research process?

METHODOLOGY

This study adopted a mixed methods approach. The choice of mixed methods aligns with the pragmatics paradigm, which emphasizes the use of multiple approaches to derive actionable knowledge (Creswell & Clark, 2017). The pragmatic stance was appropriate because the study aimed to investigate the extent to which Artificial Intelligence (AI) tools are used by Ghanaian academics in the academic research process and to further examine their views on the associated concerns regarding AI's influence on human judgment, ethical reasoning, and creativity.

A convergent parallel design was employed. In this design, quantitative and qualitative data were collected during the same phase of the study and analyzed separately before being integrated (Creswell & Clark, 2017). This allowed the quantitative strand to provide an overview of patterns of AI use, while the qualitative strand offered deeper insight into how academics interpret the ethical and human-centred implications of AI.

The study population consisted of mathematics educators in the selected institutions selected institutions in Ghana who had experience using AI tools in academic settings. A purposive sampling technique was used to select 10 educators for the qualitative data. Purposive sampling was appropriate because the study required participants with substantial and recent experience in using both traditional and AI tools in mathematics education. For the quantitative data, 37 additional mathematics educators who met the same inclusion criteria (teaching or researching mathematics and having used AI tools in their work) were recruited using a non-probability sampling through Institutional WhatsApp platforms. This broader group provided a wider range of perspectives on how AI is integrated into day-to-day mathematics education practice, but the recruitment process did not involve a complete sampling frame or random selection. The qualitative sample was purposively selected, while the quantitative sample was selected through convenience sampling. As a result, the findings should be interpreted with consideration for this non-random sampling.

The data was collected using closed-ended questions for quantitative and open-ended questions for qualitative. The closed-ended items enabled the collection of quantifiable data on the frequency, perceived usefulness, and patterns of AI tool usage. Open-ended items invited participants to elaborate on their experiences and perspectives, allowing deeper qualitative insights (Bazen *et al.*, 202). It further helped to explore the issues of human judgment, ethical implications, and reliance on AI. The researchers sought informed consent from all

respondents. The questionnaire was distributed digitally via Google Forms to accommodate the participants' varied schedules and locations. The quantitative data, and thus responses from closed-ended questionnaire items, were analyzed using descriptive statistics (means and deviation) via SPSS. The qualitative data, and thus open-ended responses, were analyzed using thematic analysis following Braun and Clarke's (2006) six-phase process: familiarization with data, coding, theme development, theme review, definition/naming of themes, and report writing. Thematic analysis is well-suited for identifying patterns in subjective experiences and attitudes, especially concerning nuanced topics such as ethics and human judgment.

RESULTS

Respondents were asked to indicate the extent to which they used AI tools at different stages of their research, as well as their perception of AI tools in the research process. The results are shown in Figures I and II, and Table I.

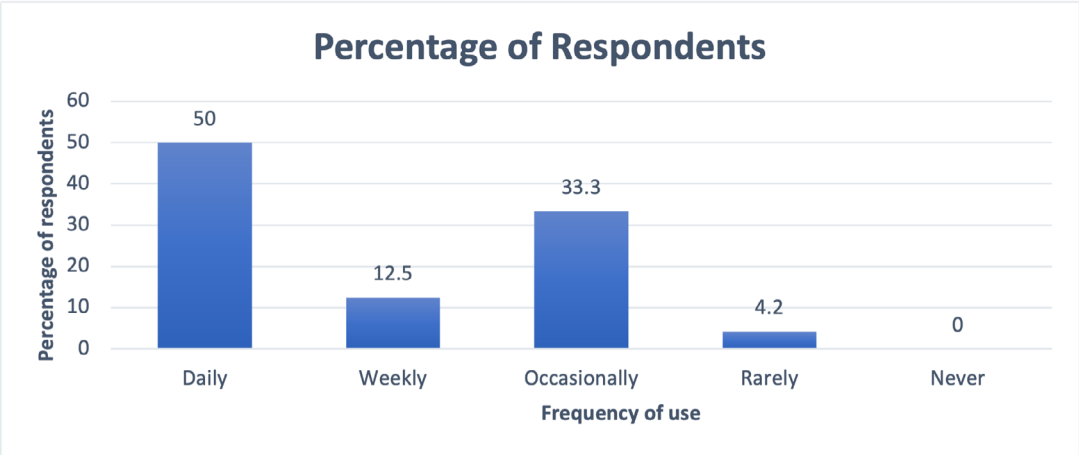

Figure I: *Frequent use of AI tools by Researchers*

Source: Field Data (2025)

Figure I revealed that Mathematics educators reported frequent use of AI tools in their professional work. Fifty percent (50%) of academic researchers in Ghana reported using AI tools daily, 12.5% them weekly, and 33.3% of respondents used AI tools occasionally. Only 4.2% reported using AI rarely, and none indicated that they never used AI tools. These findings suggest that AI has become a routine component of academic activities among the participants.

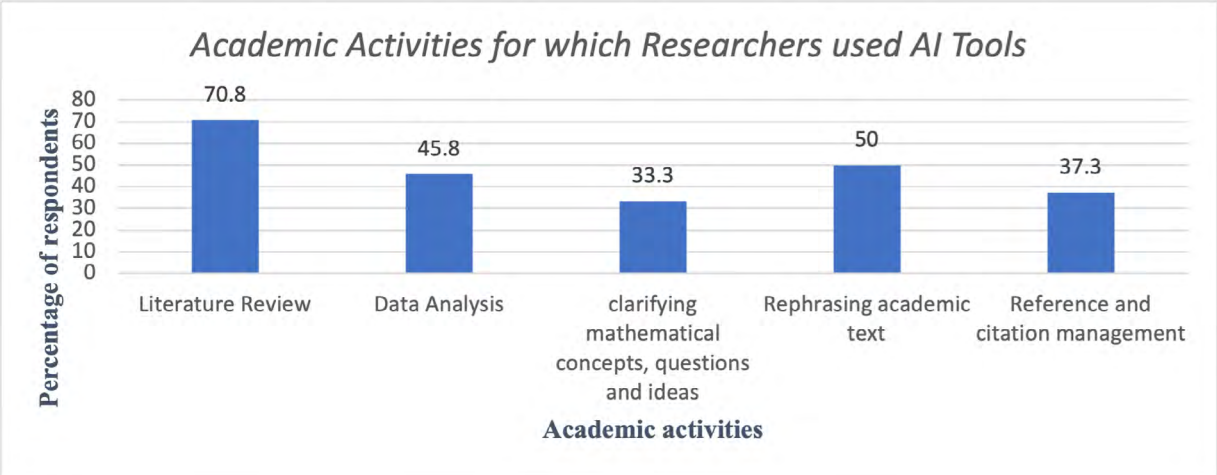

Figure II: *Academic Activities for which Researchers used AI Tools*

Source: Field Data (2025)

From Figure II, respondents revealed that AI tools were used across a range of academic activities. The most common application was in conducting literature reviews, reported by 70.8% of respondents. Rephrasing academic text was the second most common use, reported by 50% of respondents, followed by data analysis (45.8%). Participants also used AI to manage references and citations (37.5%), clarifying mathematical concepts, questions, and ideas (33.3%). These results indicate that AI tools support multiple stages of the mathematics education activities.

Table I. *Researchers' Perceptions of AI Tools*

Statement	Mean	Standard Deviation	Rank
AI tools help me save time in research	3.29	0.98	2nd
I trust the output generated by AI tools	3.21	0.87	3rd
I often cross-check AI outputs with traditional sources	3.04	0.98	4th
AI tools are useful for concept analysis and literature reviews	3.46	0.82	1st
I feel confident using AI tools independently	2.92	1.00	5th

Note. Table I presents the perceptions of the academic researchers in Ghana.

Source: Field Data (2025)

Descriptive statistics for educators' perception of AI tools are presented in Table I. The statement "AI tools are useful for data analysis and literature reviews (ranked 1st). indicating a strong consensus on the practical utility of AI in these core research tasks. They also agreed that 'AI tools help me save time in research.' (ranked 2nd), indicating strong agreement among respondents, even though there was some variability. Similarly, the statement "I trust the output generated by AI tools (ranked 3rd) reflecting a generally positive and consistent level of trust. At the same time, respondents reported that they "often cross-check AI outputs with traditional sources' (ranked 4th), suggesting a cautious approach in which mathematics

educators value AI but still rely on traditional verification methods. The lowest mean score was the statement "I feel confident using AI tools independently" (ranked 5th), suggesting ongoing needs for training and support in AI use.

The qualitative data from the open-ended questionnaire responses were analyzed using thematic analysis. Three major themes emerged concerning perceptions of AI in mathematics education (see Figure III).

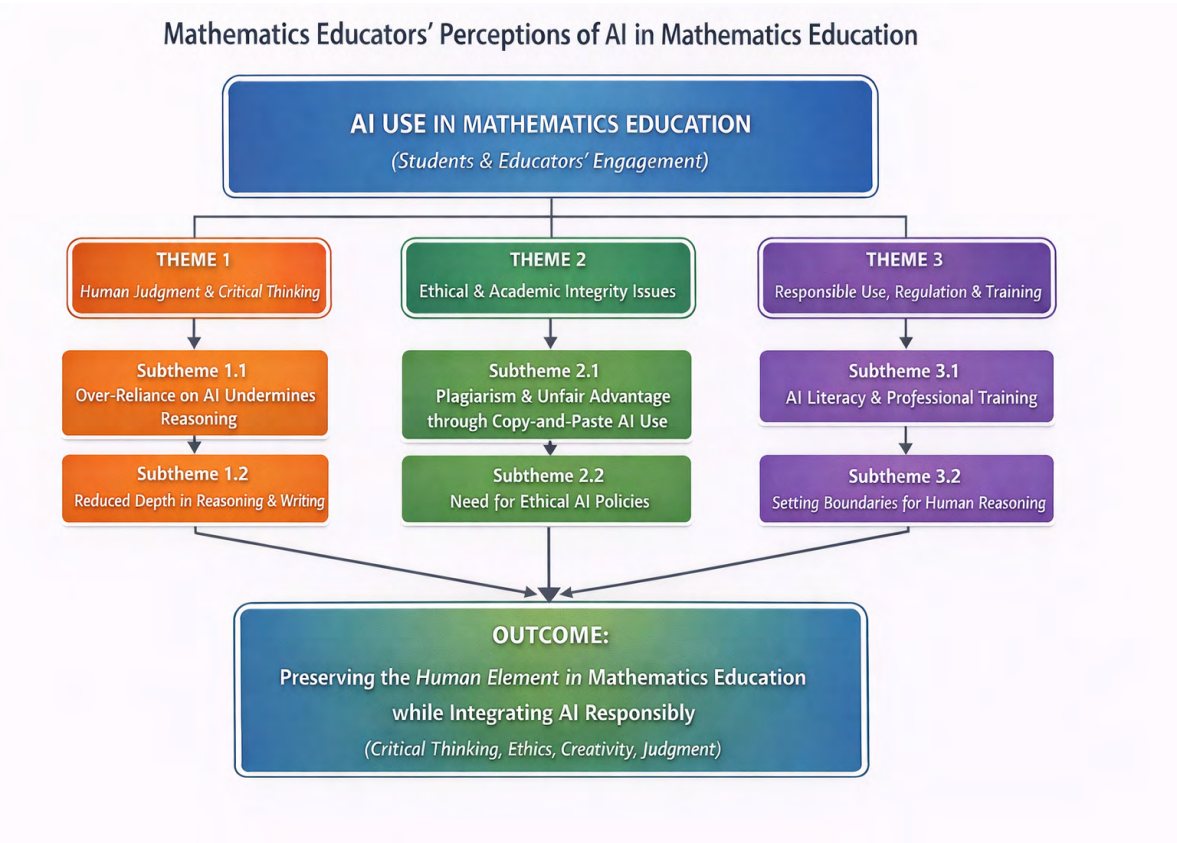

Figure III: Results from Thematic Analysis

The first theme: Human Judgment and Critical Thinking, educators expressed concern that excessive reliance on AI weakens students' independent mathematical reasoning. Participants noted that students often accept AI-generated solutions without engaging in the underlying reasoning processes. As one educator remarked, *AI kills creativity and critical thinking*, while another observed that *AI makes both students and educators lazy to think these days*. Additionally, educators reported that heavy AI use reduces the depth of reasoning and written explanations, with one participant stating that *AI may reduce the depth of academic reasoning*.

The second theme: Ethical and Academic Integrity Issues highlights concern about fairness and honesty in mathematics learning. Educators reported instances where students submit AI-generated work without understanding the concepts involved. One participant explained that *"students copy and paste what they don't understand,"* which was perceived as undermining valid assessment practices. Participants further emphasised the need for institutional guidance, noting that *"there should be clear policy guidelines on the ethical use of AI."*

The third theme, Responsible Use, Regulation, and Training, reflects educators' emphasis on capacity building and regulation. Participants stressed the importance of training students and educators to use AI critically, with one stating that *"there should be training on the proper and efficient use of AI tools."* Others advocated for explicit limits on AI use to preserve human reasoning, suggesting that *"the use of AI should be limited to 20%."*

The themes converge on the need to integrate AI in ways that support, rather than replace, human judgment, creativity, and critical thinking in mathematics education.

DISCUSSION

The results of this study demonstrated that artificial intelligence (AI) tools are becoming indispensable for academic efficiency and productivity in Ghana. However, the findings also reveal critical gaps in ethical awareness, critical thinking, and institutional preparedness for responsible AI use. Most Ghanaian mathematics educators reported using AI tools daily or weekly, confirming the global trend of increasing AI integration in academic work (Egara & Mosimege, 2024). This pattern reflects the joint optimization principle of Socio-Technical Systems (STS) theory, which emphasizes that effective performance emerges from the interaction between technical systems and social systems rather than from either subsystem alone (Trist & Bamforth, 1951). While similar trends have been widely documented in technologically advanced contexts, this study extends existing literature by providing empirical evidence from a developing country setting. Although the findings demonstrate widespread AI adoption, this study does not examine how infrastructural inequalities across institutions may shape differential access and depth of AI use among Ghanaian researchers. The results indicate that AI usage among Ghanaian academics reflects a global academic transformation rather than a phenomenon restricted to high-income or technologically advanced environments.

The study further revealed that AI tools are primarily used for literature review, academic writing, and clarification of mathematical concepts and idea generation. This aligns with previous studies (Borger *et al.*, 2023; Liu-Schuppener, 2023), which report that AI platforms are increasingly adopted to enhance research efficiency. From an STS perspective, this finding illustrates the interaction between social and technical subsystems, where technology supports but does not replace human intellectual labour (Brown & Harvey, 2006). The Ghanaian context adds nuance to this understanding, as AI is often used to manage information overload and to support academic writing in multilingual environments where English may not be the first language. Thus, AI serves as a cognitive support tool that complements researchers' intellectual efforts rather than functioning as an autonomous knowledge producer.

The findings indicate that while respondents generally trust AI outputs, they continue to cross-check results using traditional academic sources. This cautious optimism mirrors findings by Ouyang and Jiao (2021), who observed that users tend to calibrate trust based on AI system reliability. This behaviour exemplifies STS's joint optimization principle, reinforcing that effective system performance depends on balanced human oversight and technological assistance (Pasmore *et al.*, 2019). However, the study does not quantitatively assess the depth or consistency of this verification process across different academic disciplines. The results reveal a distinct "confidence gap" among Ghanaian researchers, rooted not in distrust of AI, but in limited formal AI training and the absence of clear institutional guidelines.

Qualitative findings reveal deep concern that AI use may undermine creativity, originality, and critical engagement in academic work. These concerns echo warnings by Federspiel *et al.* (2023) and Gerich (2025) that excessive AI reliance risks eroding "genuine humanity" in scholarly practice. This study contributes a uniquely African perspective by situating these concerns within Ghana's academic culture, where reflective reasoning, originality, and communal knowledge construction are highly valued. As STS theory suggests, over-emphasizing technological efficiency without preserving human meaning and autonomy threatens long-term system sustainability (Gwagwa *et al.*, 2022). The findings highlight that creativity in academia is not merely cognitive, but also cultural and ethical, requiring deliberate protection alongside technological innovation.

Strong calls emerged for institutional ethical guidelines to regulate AI use in academic research. This aligns with global concerns about AI governance (Munch *et al.*, 2024), yet this study uniquely documents an ethical vacuum within Ghanaian education, where AI adoption is advancing faster than regulatory frameworks. From an STS standpoint, this reflects the need for system redesign, where social norms, policies, and institutional responsibilities evolve alongside technological systems. The absence of clear ethical policies risks misalignment between human values and technological practices within academic institutions.

Finally, respondents emphasized the urgent need for AI literacy training and responsible AI use. This resonates with global calls for AI literacy in higher education (Popenici & Kerr, 2017; Pushparani & Sanjana, 2025). However, this study extends theory by showing that in low-resource contexts, sustainable AI integration depends more on human capacity building than on advanced technological infrastructure. This reinforces STS's central principle that social and technical systems must be developed together to achieve ethical stability and adaptability (Trist & Bamforth, 1951).

CONCLUSION

This study reveals that AI tools are increasingly integrated into academic research practices among Ghanaian scholars, enhancing efficiency and productivity. However, the findings also highlight persistent concerns related to ethical awareness, critical thinking, and institutional readiness for responsible AI use. While researchers demonstrate cautious trust in AI outputs through verification practices, gaps in formal AI training and clear policy guidance remain evident. The study underscores the importance of balancing technological innovation with human judgment, creativity, and ethical responsibility. Overall, sustainable AI integration in Ghanaian higher education depends on coordinated efforts in policy development, capacity building, and ethical regulation.

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PILOTING AN ASYNCHRONOUS HANDS-ON STEM TEACHER TRAINING IN GHANA

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Article History
Received 04 October 2025
Accepted 23 January 2026

ABSTRACT

Piloting a fully asynchronous training model in a low-resource African setting presents both unique challenges and critical insights for digital education stakeholders. Guided by the Community of Inquiry (CoI) framework and the Technology Acceptance Model (TAM), this study examines teacher persistence within asynchronous online learning environments. Together, these frameworks inform an initial inquiry into how teachers in African settings can navigate self-paced digital training. The study gathered insights from Practical Education Network's (PEN) asynchronous online training organized in October 2024 for Ghanaian basic school teachers who handle Mathematics and Science. A mixed-methods approach was used to uncover the impact of the training, leveraging pre-post surveys and reflections from both the trainer and participants. Although many teachers appreciated the flexibility of asynchronous learning, only 21% of those who attended the onboarding session completed the full training. This low persistence appeared to be linked to difficulty in navigating the Learning Management System (LMS), inadequate orientation, and insufficient ongoing support during the training. The findings suggest the centrality of onboarding sessions and stakeholder reinforcement in sustaining engagement. Future iterations should pursue approaches that balance personalised support with scalability. These insights can be used to inform future online approaches for teacher professional development in the African context.

Keywords: Asynchronous Training, STEM Education, Hands-on Learning, Teacher Persistence, Professional Development, Digital Literacy.

INTRODUCTION

Digital teacher training has emerged as a promising approach for expanding access to professional development at scale, particularly through asynchronous and self-paced models. Technology-mediated training allows ministries of education and non-governmental organizations to reach large numbers of teachers more efficiently, and an increasing number of initiatives across Africa now integrate digital platforms into teacher education programs (Oubibi *et al.*, 2024). Evidence, which has largely been drawn from Western contexts, suggests that asynchronous learning can support flexibility, autonomy, and learning gains when well-designed. However, the effectiveness of these models ultimately depends on teachers' ability to persist in self-directed, unsupervised learning environments. While access can be facilitated by technology, sustained participation is necessary for meaningful learning to occur, and

there remains limited empirical evidence on what supports teacher persistence once direct facilitation diminishes.

In African contexts, a range of structural and contextual challenges complicate the implementation of digital teacher training, which may limit the direct transferability of existing research findings. Teacher education systems face constraints related to infrastructure, digital literacy, training quality, and the need for pedagogical adaptation (Theodorio *et al.*, 2024; Amemasor *et al.*, 2025; Li, 2024). These challenges are often intensified in rural settings, where connectivity, power supply, and device access remain unreliable (Mukuni, 2019; Sepadi *et al.*, 2025; UNICEF, 2023; Culduz, 2024). Gendered social and economic barriers further shape participation for many women teachers (UNICEF, 2023). Within this landscape, asynchronous learning presents both opportunity and risk. While its flexibility can support equitable access, studies of MOOCs and similar models show low persistence rates when interaction and guidance are limited (Jordan, 2015; Billsberry & Alony, 2024). African-based studies suggest that persistence improves when courses provide early support, regular facilitator contact, and social learning structures, including the use of familiar communication tools such as WhatsApp or short live sessions (Hanson & Beem, 2022; Moorhouse & Wong, 2022).

Identifying contextually-appropriate approaches to asynchronous teacher training in Africa, and understanding the factors that influence persistence, is therefore critical. Practical Education Network (PEN), a Ghana-based STEM teacher training nonprofit, has worked since 2020 to adapt hands-on professional development models using locally-available materials to blended and online formats. While PEN has observed comparable learning outcomes across delivery modalities, persistence has varied significantly (Hanson & Beem, 2024). In October 2024, PEN implemented its first fully asynchronous online training for Mathematics and Science teachers as a pilot to explore the feasibility of that modality. This study draws on that pilot to examine how teachers experienced asynchronous training and what supported or discouraged sustained participation. Specifically, it addresses two research questions: (1) To what extent do Ghanaian basic school teachers persist through asynchronous hands-on training? and (2) What factors support or discourage persistence?

1.1 Theoretical Framework

Two frameworks are used to guide this study's exploration, based on the recognition that teacher engagement in asynchronous professional development may depend on both instructional design and technology adoption. The Community of Inquiry (CoI) framework emphasizes the interaction of teaching presence, social presence, and cognitive presence as critical for meaningful online learning (Garrison, Anderson, & Archer, 2000). Teaching presence involves instructional design and facilitation, social presence captures connection and interaction, and cognitive presence reflects the construction of understanding through reflection and discourse (Garrison, Cleveland-Innes, & Fung, 2010). Weak facilitation and limited interaction can increase isolation and dropout in asynchronous contexts (Arbaugh *et al.*, 2008; Kozan & Caskurlu, 2018; Bhatty, 2020; Vonderwell & Turner, 2005). Evidence shows that teacher persistence improves when learning tasks align with classroom practice and when peer or facilitator engagement supports learners (Bhatty, 2020; Vonderwell & Turner, 2005). The Technology Acceptance Model (TAM) complements CoI by explaining how perceived ease of use and perceived usefulness shape engagement with technology (Davis, 1989). In African settings, these perceptions may be affected by constraints in infrastructure, digital literacy,

platform familiarity, and reliability (Abdullahi, 2021; Aidoo & Chebure, 2024; Hennessy *et al.*, 2022; Liaw, 2008; Muyambi & Ramorola, 2025). Together, CoI and TAM offer a framework for understanding teacher persistence in asynchronous learning: instructional and social support promote engagement, while usability and relevance of the technology shape sustained participation

METHODOLOGY

RESEARCH DESIGN

This mixed-methods study used both quantitative and qualitative data to capture statistics as well as the experiences and opinions (Creswell & Plano Clark, 2018) of teachers who took part in the asynchronous training. The approach followed an explanatory sequential design, where the quantitative data were collected and analysed first, and the findings guided the collection of qualitative data (Tashakkori & Teddlie, 2010). This made it possible to compare persistence with personal stories and feedback to understand why teachers either persisted or dropped out.

Participants and Sampling

The study involved the in-service Mathematics and Science teachers who participated in Practical Education Network (PEN)'s online training. Participants were invited through an open call, which was published on the PEN website and shared on WhatsApp and other social media platforms. Teachers self-selected to join the training, meaning they opted-in to participate without any external requests from other stakeholders. Participation was free and open to all interested teachers, which reflects the inclusive goal of the program.

Training Deployment

PEN's hands-on teacher training equips teachers with hands-on pedagogies on using locally available materials to teach Science, Technology, Engineering, and Mathematics (STEM) using inquiry-based and project-based methodologies. The objective of Stage One of PEN's hands-on training is to expose teachers to the use of locally available materials to carry out science practicals. This training, which had been offered both in-person and online (synchronous) previously, was set up on Google Classroom for use in an asynchronous mode. Google Forms were used to collect pre-training and post-training survey data, user experience data, and feedback data. Participants used Google Classroom to read instructional material and watch instructional videos at their own pace. As they finished each module, they submitted an assignment. These assignments were pictures and videos of hands-on activities that the teachers tried with their learners in their schools. Those who had difficulty using the LMS were directed to use WhatsApp in submitting their assignments to the facilitators. The facilitators reviewed these assignments, provided feedback to the teachers, and where the teachers had challenges, they were assisted to resolve them before the next task. Completion of the training required teachers to go through this process five times, ultimately conducting five hands-on lessons with their learners which they took pictures and/or videos of and submitted.

Data Collection Tools

This study used a qualitative-dominant mixed-methods approach, combining platform analytics, facilitator observation notes, and participant feedback to examine teacher persistence in an asynchronous online training. Each data source captured a distinct aspect

of engagement, focusing on persistence rather than completion alone. Platform analytics provided objective measures of participation, including logins, assignment submissions, and course completion. These data allowed identification of dropout points without relying on self-reports, which can be affected by recall bias (Varkey *et al.*, 2023; Jordan, 2015).

Facilitator observation notes and communication logs documented onboarding interactions, follow-up messages, learner questions, and informal support provided via WhatsApp. Such qualitative insights supported understanding how teaching presence and social presence were enacted in a low-facilitation, asynchronous setting, aligning with the Community of Inquiry framework (Garrison *et al.*, 2000; Bhatty, 2020).

Participant feedback, collected through reflections and follow-up responses, captured teachers' perceptions of usability, motivation, and perceived relevance of the training. These perceptions are crucial for interpreting engagement through the Technology Acceptance Model, which emphasizes perceived usefulness and perceived ease of use as determinants of continued participation (Davis, 1989; Venkatesh & Davis, 2000).

Triangulating these data sources strengthened the credibility and trustworthiness of the findings by allowing convergence across behavioural, observational, and perceptual evidence. Patterns observed in platform analytics were cross-checked against facilitator records and teacher feedback to confirm consistency and identify discrepancies. This approach reduced reliance on a single data source and enhanced interpretive validity, particularly in contexts with variable digital literacy and infrastructure (Creswell & Plano Clark, 2018).

Data were collected using several tools:

- Registration records to track enrolment and completion.
- Pre-training and post-training surveys that gathered information on participants' confidence to use online learning platforms, level of access to technology, and reflections on the training experience.
- Feedback forms and WhatsApp group messages, which allowed for open-ended responses and discussions on teachers' experiences and challenges.
- Trainer reflections, recorded during and after the training, were also used to understand the challenges observed in implementing the training.

The survey instruments included both closed-ended and open-ended questions. They are included in the Appendix.

Data Analysis

Quantitative and qualitative data were analysed in complementary ways to understand participation and persistence during the training.

Quantitative Analysis

Descriptive statistics such as frequencies and percentages were used to measure participation, completion, and persistence rates. Persistence was calculated as the percentage of teachers who completed all four stages: 1) Recruitment, which required meeting PEN's selection criteria, 2) Enrolment, which required the participant to sign on and complete the pre-survey form, 3) Onboarding, which required the participant to join the first session which provided onboarding and orientation, and 4) Completion, which required the participant to complete

100% of assignments. Attendance records, onboarding participation, and assignment submissions were also compared to identify trends in persistence.

Additional quantitative data from the pre- and post-training surveys were analysed to measure changes in teachers' confidence in using online learning platforms and their level of access to technology. Confidence levels were based on self-ratings from 1 (least confident) to 5 (most confident), while access was assessed through survey items on internet availability, device ownership, and platform use.

Qualitative Analysis

Open-ended responses from surveys, interviews, and feedback forms were examined to understand teachers' experiences during the training. The first author read through the data several times to identify patterns, categorize responses, and assign descriptive codes. These codes were then organized into sub-themes, which informed the development of main themes.

Initial trends such as "digital difficulty," "onboarding experience," "lack of support," and "content relevance" were identified and later grouped into broader categories, including system usability, social connection, and curriculum alignment.

Results from both the quantitative and qualitative analyses were compared to explore how persistence, confidence, and support influenced teachers' engagement in the training. Detailed findings from the thematic coding process are provided in the Appendix.

Ethical Considerations

Participation was voluntary, and all teachers provided their consent before joining the study. Teachers were informed that their responses would be used only for research and to improve future training design. Personal data such as phone numbers and emails were not shared outside of the organization - they were used solely for the purpose of follow-up in the course of the training program. The study respected participants' right to withdraw at any stage.

RESULTS

Participant Overview

A total of 162 teachers took part in the training. Participants were Mathematics and Science teachers working in basic and secondary schools. About 36% were women, and 64% were men. The majority came from Ghana, while a few joined from Liberia, Nigeria, and one from Belize. This shows that online platforms offer the potential to reach teachers across a wide set of countries.

Table I. Participant Demographics

Attribute	Category	Frequency	Total
Gender	Female	59	162
	Male	103	

Attribute	Category	Frequency	Total
Location	Ghana	153	162
	Other African Countries	8	
	Belize	1	
Teaching Level	Basic (Primary/JHS)	139	162
	SHS	23	

Although participation was not determined through random sampling, the participants represented teachers from both basic and secondary schools, giving a broad view of experiences across grade levels.

Persistence

Persistence results are shown in Figure I, with equivalent results from PEN's 2021 offering of this training in a synchronous online model included for comparison.

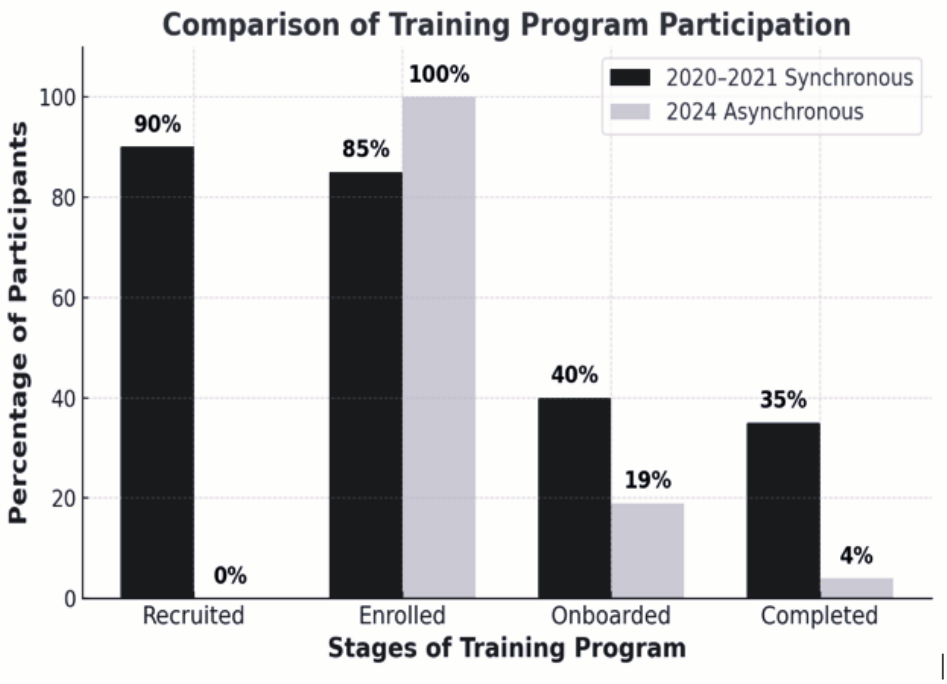

Figure I. *Comparison of persistence rates between PEN's 2020/21 blended and 2024 asynchronous training programs. Earlier dataset drawn from Hanson & Beem (2022).*

Out of the 162 teachers who enrolled (100%), 31 attended the onboarding session (19%), and 7 completed the full course (4%). This means that 21% of those who joined the onboarding session completed the training in full. These figures are generally lower than those measured in PEN's earlier online synchronous model (Hanson and Beem, 2022), in which 90% of the people listed to partake in the training were recruited based on the selection criteria. 85% enrolled in that training. 40% were onboarded and 35% completed that training. Note that the 0% recorded in the first stage of the asynchronous model for 2024 is because there was no recruitment stage - participants enrolled themselves directly for the training.

Factors influencing teacher persistence

Using a combination of survey responses, interview data, and observation records taken by the facilitator, three factors were identified as influencing teacher persistence in this training: effective onboarding, system usability, and social interaction.

Factor 1: Effective onboarding

The initial onboarding emerged as a key factor influencing teachers' persistence in the asynchronous training. Teachers who participated in live or guided orientation were more confident about the training and what they stood to gain from it. Some teachers noted that early guidance on logging in and submitting assignments helped them remain active, while those who missed the session felt confused about what to do next. Even some participants who did join the onboarding still felt uncertain about how to proceed. The following quotes shed light on these sentiments:

"When I joined the onboarding, it became clear what I was supposed to do. Before that, I thought it was like other online trainings where you just watch videos." -

Ghanaian Science teacher (WhatsApp message from participant, November 2024)

"I was excited to try something new. But after onboarding, I didn't know how to continue… I needed someone to guide me." – Ghanaian Math teacher (Feedback Form, December, 2024)

Factor 2: System usability

Teachers cited several practical challenges in carrying out the training. Many participants found it difficult to use the Learning Management System (LMS) and were unsure if their assignments had been received. Some also said that parts of the training did not match the subjects or grade levels they teach. Facilitator observations confirmed these issues and added that unstable internet connections and limited access to devices made participation harder. Some teachers needed direct guidance to navigate the online platform. When they were unable to navigate the LMS, some reverted to using WhatsApp to submit assignments or ask questions. Overall, of the 33 teachers (20% of participants) from whom qualitative data was collected), 73 percent of teachers reported challenges using the LMS, 58 percent were unsure about assignment submissions, and 22 percent said some activities did not align with their teaching levels.

"I didn't even know if my assignment had been received. There was no confirmation or feedback." – Liberian Science teacher (Open ended comment from feedback survey December, 2024)

"I could not upload the file on Google Classroom, but I sent it on WhatsApp, and that saved me." – Ghanaian Science teacher (Open ended comment from Post Survey Form; December 2024)

"The activity with chemical reactions was interesting, but I teach grade 4. I wasn't sure how to connect it." – Ghanaian Science teacher (Open ended comment from Feedback Form; December 2024)

Factor 3: Social interaction

The third factor, social interaction, played a vital role in sustaining motivation and course completion. Teachers who interacted with peers or facilitators through the WhatsApp group created for communication and short follow-up calls showed higher levels of engagement. Comments from participants emphasized that communication and feedback helped them "stay connected," "learn from each other," and "avoid dropping out." Because they were in the same WhatsApp group, there appeared to be some level of peer influence when they saw their friends submitting their assignments. In the interviews, participants described challenges related to platform navigation, assignment submission, and the need for continuous guidance during the course. Others referred to differences between earlier blended training experiences and the recent asynchronous model, as well as the use of alternative communication platforms to manage technical limitations.

One Ghanaian Math teacher who had participated in an earlier PEN training, which had been offered in a synchronous format, said, *"In 2021, my director encouraged us. This time, I felt alone."* It is worth noting that in the earlier iteration, teachers were Recruited (the first stage shown in Figure I), which meant that their District Education Officials were engaged in the process. When those stakeholders played that role effectively, they encouraged and followed-up on the teachers' progress through the training. With that stage having been skipped in this version of the offering, the teacher signed him/herself up directly for the training, therefore not having that extra stakeholder present.

Improvement in Teacher Confidence After Training

Overall, teachers' confidence in teaching science improved after the training. In five areas, teaching hands-on activities, explaining science ideas, addressing student concerns, increasing engagement, and teaching in an interesting way, on a scale of 1 to 5, the average confidence score rose from 4.2 before training to 4.7 after, showing about a 12 percent increase. The biggest improvements were in explaining science ideas and responding to students' questions, which both increased by about 15 percent. These results indicate that the training helped teachers become more confident and better prepared to use practical, hands-on methods in their classrooms.

DISCUSSION

Learning gains are notable but persistence should be improved

The findings show that asynchronous teacher training can lead to meaningful learning, but only when teachers are able to stay engaged. Although only a small number of teachers completed the full training, those who did reported clear gains in confidence and teaching skills. This suggests that the training content itself was useful, but the programme design did not sufficiently support teachers to persist. As seen in PEN's earlier synchronous trainings, the largest drop-off happened at the onboarding stage. This indicates that persistence problems begin early and are linked more to how programmes are structured and supported than to teachers' motivation. This aligns with research showing that communication, facilitation, and

perceived relevance matter more for persistence than access to content alone (Hennessy *et al.*, 2022; Varkey *et al.*, 2023; Dzidzornu & Xu, 2025).

From the Community of Inquiry perspective, early drop-out can be explained by a loss of teaching and social presence once active facilitation reduces. Persistence in this context is not only an individual choice but a social process shaped by programme design. Low completion rates are common in asynchronous courses such as MOOCs (Jordan, 2015), but research suggests that dropout often reflects weak social and organisational support rather than lack of interest (Billsberry & Alony, 2024, Mehta & Aguilera, 2020). In this study, even small amounts of human contact, such as WhatsApp messages or short phone calls, helped teachers remain engaged. This suggests that asynchronous training in low-resource settings may need regular points of interaction or new ways to provide timely feedback.

System usability also played a major role in teachers' ability to persist. Although Google Classroom was used to organise content, many teachers found it difficult to navigate and submit assignments. As a result, they often turned to WhatsApp for help and clarification. This supports the Technology Acceptance Model, which shows that people are more likely to use systems they find easy and useful (Davis, 1989). In African contexts, research shows that familiar and reliable tools are often more effective than complex platforms (Aidoo & Chebure, 2024; Hennessy *et al.*, 2022). In Ghana, differences in digital skills and confidence further highlight the need for clear guidance and support when introducing new technologies (UNESCO ICT-CFT, 2025; Gaible & Burns, 2005; Hennessy *et al.*, 2015).

Content relevance was another important factor affecting persistence. Some teachers became less engaged when activities did not clearly match their grade levels or subject areas. This shows that training content must align closely with teachers' real classroom needs (Ngema & Ajani, 2024; Oubibi *et al.*, 2024). At the same time, several teachers adapted the activities to fit their own contexts, showing strong teacher agency. These adaptations reflect teachers' ability to shape learning to suit their environments and constraints (Ahiaku *et al.*, 2025; Jita & Dhliwayo, 2024). Highlighting such adaptations may encourage other teachers to engage more actively rather than disengage.

Teachers who completed the training consistently received ongoing support from PEN. Interaction through WhatsApp groups and regular follow-ups helped reduce isolation and maintain motivation. This supports earlier findings that emotional and instructional support are important for success in online learning (Gutiérrez Chara *et al.*, 2023), especially in contexts where teachers face digital challenges and heavy workloads (Ahiaku *et al.*, 2025; Okunlola, 2024). Persistence was strongest among Mathematics and Science teachers who saw a clear connection between the training and their classroom practice. In contrast, teachers were more likely to disengage when they faced technical difficulties, limited feedback, or competing work demands.

Overall, the findings suggest that both the Community of Inquiry framework and the Technology Acceptance Model help explain persistence in asynchronous teacher training in Africa (King & He, 2006). Reduced teaching and social presence weakened engagement, while difficulties using the learning platform lowered teachers' willingness to continue. These results show that self-paced learning still requires structure, guidance, and human connection.

Effective asynchronous training must balance independence with support, relevance, and regular interaction.

Potential gaps in the theoretical framework

Social interaction emerged as a thematic area describing what would have encouraged higher persistence. While the Community of Inquiry Model captures this to a large extent, particularly through the dimensions of Social Presence and Teaching Presence, it may also be lacking an aspect that emerged from the results here. The sentiment expressed by the participant who compared their experience this time with the previous iteration of the training (when their local education office was involved) that they felt "alone" opens a window onto a potentially common conception amongst the population. In the earlier iteration, participants were recruited through their local education office, which the training provider had engaged as the first point of call. In the recent iteration, participants signed up for the training directly with the training provider, meaning that the local education office had no oversight over their engagement in this training. Hence, in addition to the sense of community amongst peers that the COI model highlights as a key element, it is possible that in this context, teachers expect a level of involvement from their authority figures- an Oversight Presence. Where in other contexts this may be seen as counter-productive to cultivating a learning community, it may be key here, according to Sharma & Hannafin (2007). Rather than feeling forced to do something by their higher-ups, it may serve as a positive reinforcement, knowing that what they are learning is indeed what is being prioritized in the structure in which they operate.

LIMITATIONS AND DIRECTIONS FOR FUTURE WORK

This study was exploratory and based on a small, self-selected sample, and the findings should therefore be interpreted cautiously. Future studies could examine persistence across larger cohorts, or they could compare rural and urban contexts where infrastructure and access differ significantly (Ahiaku *et al*., 2025; Muyambi & Ramorola, 2025). Longitudinal designs would also help clarify how sustained facilitation and system design influence persistence and classroom application over time.

Further research should explore how low-cost, context-aware digital systems can support continuous teacher professional development without assuming ideal technological conditions. Such work would contribute to ongoing debates on scalability, sustainability, and inclusion in African digital education reforms (UNICEF, 2023).

RECOMMENDATIONS FOR PRACTICE

Based on the findings, several actions can strengthen teacher participation in asynchronous training. Live onboarding sessions are valuable, and a challenge lies in ensuring that teachers actually attend them. Training organizations could experiment with creative strategies to improve attendance, such as flexible scheduling, short preview videos, or small recognition incentives for those who complete onboarding. Partnering with school heads to make onboarding attendance a formal expectation may also help.

The learning management system should be highly easy to navigate, with clear steps and confirmation messages when teachers submit their work. This will help increase teacher confidence in using the platform.

Given that social interaction is desired, various methods for achieving that should be tested. For example, regular feedback and recognition in the form of simple messages of appreciation, certificates, or short notes of encouragement could help them stay committed. Engaging teachers through local leaders such as headteachers and district officers, instead of encouraging direct sign-ups, could enable an extra layer of encouragement, follow-ups, and a sense of rigor. Although the scope of work here was to pursue an asynchronous model, given the desire for social interaction, a more structured approach may still be helpful. Designing in occasional live sessions would strengthen the connection among participants. Short check-ins or group discussions may help participants more strongly feel part of a learning community.

CONCLUSION

This study examined the experiences of Mathematics and Science teachers who participated in a fully asynchronous online training organised by the Practical Education Network (PEN) in October 2024, with the aim of identifying factors that supported or discouraged persistence. The findings show that while asynchronous training can reach teachers across multiple countries, successful completion depends on more than access to content. Only 4% of participants completed the full training. While this persistence rate is similar to global trends for MOOCs, it is less than that which was measured in the same training when it was offered in a synchronous manner (35%). Hence, it is worth pursuing approaches that can increase persistence while maintaining a level of asynchronicity.

Interpreted through the Community of Inquiry framework (Garrison, Anderson, & Archer, 2000), limited teaching and social presence after onboarding weakened persistence. Teachers who participated in onboarding and actively sought support were more likely to complete the programme. Those who didn't tended to feel they were going through the training alone and were more likely to drop off. AI tools can be explored to enable live feedback while maintaining a personal feel. Recruiting participants through the local education officials adds a level of bureaucracy but may also provide a sense of community for teachers in a way that the COI model has not fully captured. The Technology Acceptance Model (Davis, 1989) can also be used to interpret these results, as usability challenges with the technology reduced perceived ease and usefulness. Leveraging technology that is already familiar to the users will likely increase persistence as well.

For teacher development in Africa, structured onboarding, simple and reliable platforms, and ongoing communication are key. Program design should reflect local realities, including internet instability and reliance on familiar tools like WhatsApp, to sustain engagement. Future research could examine larger, more diverse samples, compare rural and urban contexts, and investigate low-cost digital supports such as AI coaching, automated chat, or peer mentoring to strengthen teaching and social presence over time.

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APPENDICES

Appendix I: Thematic Analysis of Participant Follow-up Calls

To understand low course completion during PEN's asynchronous teacher training, a Google form was shared with participants to complete. Responses were analysed thematically to identify common challenges and motivations influencing teacher persistence.

Summary of Common Themes

Theme	Description	Illustrative Quote
Over-commitment	Many teachers registered for several online courses simultaneously, making it difficult to keep up. Some forgot about their PEN training after subscribing.	"I subscribed to several training programmes… mostly I forget that I have subscribed."
Forgetfulness and Lack of Reminders	Participants often forgot about the training, especially without reminders or follow-up messages.	"I didn't get any reminder, and I forgot about the training."
Poor Network Access	Teachers in rural or remote areas experienced serious internet connectivity problems.	"My station is in a remote area… I have serious challenges with the network."
Device and Technical Constraints	Some teachers had broken or outdated phones or struggled to use the online platform.	"I had challenges with my phone and I am no longer using a smartphone."
Personal Emergencies	Life events such as bereavement, family responsibilities, and busy school schedules prevented consistent participation.	"I have been bereaved and need some time before I can return to the training."
Platform Navigation Confusion	Several participants found it difficult to navigate Google Classroom or access materials.	"I had challenges navigating Google Classroom. I got lost often."
Recognition as Motivation	NTC accreditation motivated participants to plan future completion.	"I will go back and complete it since it is NTC-accredited."

Appendix II Thematic Coding Framework

Research Question	Initial Codes	Sub-Themes / Categories	Main Themes	Interpretation
RQ1: Extent of persistence	Completion vs dropout, onboarding, login frequency, consistency of submissions, platform interaction, confidence/ motivation	Engagement frequency, completion behavior, self-directed participation	Extent and Patterns of Persistence	Persistence was generally low. Teachers who attended onboarding and engaged via WhatsApp were more likely to complete.

Research Question	Initial Codes	Sub-Themes / Categories	Main Themes	Interpretation
RQ2: Factors supporting or discouraging persistence	Digital difficulty, lack of support, onboarding, workload, relevance, internet access, peer encouragement, feedback delay, LMS familiarity, social interaction	System usability, curriculum alignment, social connection, contextual/ technical barriers	Enablers and Barriers to Engagement	Persistence depended on onboarding, relevant content, feedback, platform function, and connectivity. WhatsApp helped teachers adapt when LMS access was difficult.

Appendix III: Summary of Theme Relationships

Main Theme	Linked Sub-Themes	Represents	Connection to Data Patterns
Extent and Patterns of Persistence	Onboarding, consistent participation, practical relevance	Quantitative & qualitative indicators	Teachers attending onboarding and using WhatsApp were more likely to complete the course.
Enablers and Barriers to Engagement	System usability, curriculum relevance, feedback quality, workload, connectivity	Factors influencing persistence	Persistence depended on platform function, content relevance, and timely support/feedback.

Appendix IV: Comparison of Teachers' Confidence Levels Before and After Training

Confidence Indicator	Pre-Training Mean	Post-Training Mean	Change (%)	Interpretation
Teaching a hands-on activity	4.4	4.8	+9%	Strong improvement in practical teaching confidence
Explaining science phenomena practically	4.1	4.7	+15%	Greater ability to connect concepts with real-world examples
Addressing students' concerns	4.0	4.6	+15%	Improved responsiveness during practical sessions
Increasing student engagement	4.2	4.7	+12%	Better classroom participation and motivation
Teaching science in an engaging way	4.3	4.8	+12%	Enhanced overall instructional confidence
Overall Average	4.2	4.7	+12%	Higher self-efficacy and readiness to apply hands-on methods

Here, There, and Everywhere: Generative AI Literacy as a Predictor of Academic Performance among Ghanaian University Students

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Article History
Received 24 Nov. 2025
Accepted 23 January 2026

ABSTRACT

The recent adoption of Generative Artificial Intelligence (GenAI) in universities is associated with the emergence of new learning affordances, but the concern about student preparedness in under-resourced environments. This paper is built on the foundation of the connectivism, exploring whether perceived GenAI literacy is an indicator of academic performance among Ghanaian university learners, a relationship which has not been explored in resource-constrained contexts. In July 2024, a cross-sectional survey was conducted, which gathered information about 193 students with varying disciplines. Testing of the validated GenAI literacy and academic performance was done through Partial Least Squares Structural Equation Modelling (PLS-SEM) in SmartPLS 4. Students reported moderate GenAI literacy (M = 59.10, SD = 8.72) and academic performance (M = 16.33, SD = 2.84). GenAI literacy significantly predicted academic performance ($\beta = 0.478$, $p < 0.001$), explaining 21.3% of the variance ($R^2 = 0.214$) with a medium-to-high effect size ($f^2 = 0.269$). There were no significant differences in age and gender. GenAI literacy is an academic facilitator that cuts across demographics. It is thus necessary to integrate AI skills into curricula in a bid to be fairly and successfully involved in AI-mediated higher education systems in Africa

Keywords: Generative AI literacy, Academic achievement, Higher education, Connectivism, PLS-SEM

INTRODUCTION

The rapid advancement of artificial intelligence technologies is transforming various sectors of national development, and education is no exception. Among these cutting-edge technologies, the Generative Artificial Intelligence (GenAI) tool has emerged at the forefront of educational technology discussions. GenAI refers to a class of technology that is capable of producing content and imitating human-like intelligence (Belkina *et al.*, 2025; Bozkurt, 2024; Essel, Vlachopoulos, Tachie-Menson, *et al.*, 2025; Kalota, 2024; O'Dea *et al.*, 2024). These technologies offer new tools that can enhance teaching and learning, academic achievement, and learners' ability to critically engage with and ethically utilise GenAI, referred to as GenAI literacy, which has emerged as a critical component of digital competence (Essel, Vlachopoulos, Tachie-Menson, *et al.*, 2025; Fitriana, 2025; Ng *et al.*, 2021b)

Due to the user-friendly interface and the fact that users are not required to possess specialised AI knowledge and coding skills, GenAI tools quickly gain traction among university students

globally (Bender, 2024; Dwivedi *et al.*, 2021; O'Dea *et al.*, 2024). The wide usage by students highlighted ethical issues eroding critical engagement and over-dependence on GenAI-generated outputs (O'Dea, 2024; Tlili *et al.*, 2025). It is therefore essential for universities to promote transparency in the AI process and to foster GenAI literacy among students to enable informed and ethical use (O'Dea *et al.*, 2024; Polat, 2025; Wang *et al.*, 2023; Yurt, 2025).

While earlier studies in the pre-GenAI era concentrated on AI literacy (Long & Magerko, 2020; Ng *et al.*, 2021a, 2021b; Park, 2025) varying definitions have emerged. For instance, Kandlhofer *et al.* (2016) describes AI literacy as technological knowledge underpinning AI systems, while Long and Magerko (2020) emphasise user competencies to understand, apply and evaluate AI in both professional and daily contexts. Ng *et al.* (2021b) further outline four competencies: understanding, application, evaluation/creation and ethical awareness. According to Wang *et al.* (2023) AI literacy research serves three main purposes: to understand human-AI interaction, assess user competencies, and guide curriculum development.

AI literacy has been broadly acknowledged as essential for all users, beyond just the technical experts (Asghar *et al.*, 2025; Černý, 2024; Laupichler *et al.*, 2022; Obenza *et al.*, 2024). Nonetheless, a conceptual distinction between AI and GenAI literacy must be made. Traditional AI literacy is rooted in technical competencies – typically associated with STEM fields, such as machine learning and data science. In contrast, GenAI literacy places greater emphasis on ethical, social and responsible usage of (say ChatGPT, DALL-E, Midjourney) tailored for non-STEM users. GenAI tools, designed to be accessible and intuitive, allow users to generate multimodal content with minimal technical knowledge. Despite the growing ubiquity of GenAI, research on GenAI literacy remains underexplored globally compared to the broader AI literacy discussion.

In addition, the introduction of GenAI tools into the educational context has reshaped how learners access information, generate content, and complete academic tasks. The actual integration of AI in university lecture halls has been left primarily to the discretion of the faculty(Abreh *et al.*, 2025; Adarkwah, 2024; Essel *et al.*, 2024). Recent studies highlighted that Ghanaian higher education students are familiar with ChatGPT as a learning tool, indicating a growing awareness and adoption of GenAI applications in academic settings (Baidoo-Anu *et al.*, 2024; Baidoo-Anu & Owusu Ansah, 2023; Bonsu & Baffour-Koduah, 2023; Salifu *et al.*, 2024). However, GenAI literacy encompasses more than tool usage; it includes knowledge of GenAI capabilities and limitations, prompt engineering, ethical and responsible use, critical evaluation of AI outputs and integration into academic tasks. Without this understanding, educational institutions may face challenges aligning curricula to the demands of an AI-enhanced learning environment.

Although research on the adoption and impacts of particular generative AI tools in tertiary education has expanded, there is still limited empirical research on how GenAI literacy as a holistic competence is also connected to academic success among students, especially in resource-limited settings. Existing literatures investigate the usage of GenAI tools, their perception, or their short-term learning effects (Baidoo-Anu, 2024; Bonsu & Baffour-Koduah; Essel *et al.*, 2024; Salifu *et al.*, 2024), which leaves the research gaps concerning the ability of students to utilise GenAI critically, ethically, and strategically in a meaningful way, which leads to better academic results. This gap is important because it becomes necessary to address to inform the implementation of curriculum design and policy, as well as the responsible

involvement of AI in higher education. This research, therefore, aims to address this gap by comparing in the empirical research the predictive nature of the relationship between GenAI literacy and academic performance in Ghanaian students in universities.

THEORETICAL FRAMEWORK AND HYPOTHESIS FORMULATION

This study is underpinned by Connectivism learning theory (Downes, 2022; Siemens, 2018). This theory posits that leaning in the digital age occurs across distributed networks, thus, both human and non-human. Knowledge is no longer limited to individual cognition of formal instructions (Corbett & Spinello, 2020; Carto *et al.*, 2022; Liu & Li, 2022). Students acquire knowledge, create, and apply it, including knowledge of AI systems (Al-Hail *et al.*, 2024). In the context of this study, GenAI literacy reflects a student's ability to effectively navigate and utilise GenAI tools (say ChatGPT, DALL-E, Bard) to access, evaluate and synthesize information across digital platforms. This aligns with Siemens' assertion that the "capacity to know is more critical than what is currently known" (Siemens, 2005, p. 5). Connectivism theory emphasises that knowledge is composed of a set of connections between entities (i.e humans and non-humans) in such a way that a change in one entity may result in a change in the other entity, and as a result, learning is regarded as growth, development and strengthening of the connections between nodes in the network (Corbett & Spinello, 2020; Dziubaniuk *et al.*, 2023; Mukhlis *et al.*, 2024; Omodan, 2022).

AI and GenAI literacy

The rapid emergence of generative AI has transformed the landscape of teaching and learning. Both educators and learners alike must develop a deep, critical know-how of these disruptive technologies (Bozkurt, 2024; Chen *et al.*, 2024). Generative AI technologies have gained more popularity with the release of ChatGPT by OpenAI in November 2022 and have since formed a part of daily lives (Blancia *et al.*, 2024; Wiredu, 2023). GenAI literacy emerges as a subset of AI literacy with a prime focus on how learners use and evaluate GenAI outputs ethically (Annapureddy *et al.*, 2025; Bozkurt, 2024; O'Dea *et al.*, 2024). GenAI literacy involves basic skills in prompt creation, results evaluation and understanding ethical implications (Bozkurt, 2024; Jin *et al.*, 2024; Zhao *et al.*, 2022).

Generative AI like ChatGPT is being widely used in education. Božić & Poola (2023) showed that ChatGPT helps students improve language acquisition through chatbots and online tutors. At Harvard, Hirabayashi *et al.* (2024) found that about 90% of students use GenAI, which is changing how they study, choose courses, and think about future jobs. However, many students are also worried that AI could reduce job opportunities and increase inequality. Deschenes & McMahon (2024) found that 65% of Harvard students use or plan to use GenAI for tasks like summarising and proofreading. Still, 80% are concerned about how trustworthy and ethical these tools are. Sharples (2023) suggested that GenAI could support teamwork in schools and act as a team partner. Ng *et al.* (2024) also found that a GenAI chatbot called SRLbot helps secondary school students learn science better than the older AI system by boosting their motivation and interest.

With AI not just a frontier technology, studies have investigated the proficiency levels of university students, prospective teachers, and nurses. This is in line with one of the basic tenets of studying AI literacy (Wang et al., 2023). Bozkurt (2024) opines that different users of GenAI would have varying proficiency levels from basic to advanced, which will be sufficient in all cases. In a study by Özden et al. (2025), pre-service teachers were reported to have demonstrated high AI literacy. Obenza et al. (2024), Shen and Cui, (2024) and Wang et al. (2023) reported above-average perceived proficiency levels of GenAI technologies. This finding suggests that students have a good, comprehensive understanding and practical use of AI tools. In contrast, Chenqi et al. (2023) and Sari et al. (2025) reported a low GenAI literacy competency level of prospective teachers in China and undergraduate students in Indonesia, respectively.

Several studies in Ghana have explored the educational use and impact of generative AI tools like ChatGPT and virtual assistants. (Essel et al., 2022;2025) develops and tests AI-powered teaching assistants – KNUSTbot and KNUST-Vbot, operationalised with zero coding on WhatsApp and Voicebots, respectively, showing improved academic performance among students. A study by Essel et al. (2024) further revealed that students who used ChatGPT for class assignments significantly enhanced their critical, creative, and reflective thinking skills compared to using traditional methods. Bonsu and Baffour-Koduah (2023) reported positive students' attitudes and strong intention to integrate ChatGPT into learning, while Baidoo-Anu and Owusu Ansah (2023) highlighted ChatGPT's benefits, such as automated tutoring and grading, but they also raised concerns about privacy and lack of interpersonal interactions. Salifu et al. (2024) using the UTAUT2 model found that factors like trust, social influence, and especially hedonic motivation significantly shaped students' behaviour intention and actual use of Chat GPT in higher education.

Academic Performance

The main focus of any educational innovation is to improve the performance of students in academic and non-academic tasks. In general, the Academic performance of the learner is reflected by assessing the results achieved by the learner in various subjects. Students' academic performance may likely determine their future goals and objectives (Commey-Mintah et al., 2023; Tetteh & Agyei, 2022). The degree of students' academic performance is measured based on the laid down benchmark of the school, but it is mostly measured using students' Grade Point Average (GPA) (Mehrvarz et al., 2021; Singh et al., 2024) In this study, a self-reporting scale will be used to measure the academic performance of the university students.

GenAI Literacy and Academic Performance

The academic performance of students can be improved through the integration of digital media with learning. With higher educational institutions integrating GenAI technologies into their curriculum, GenAI literacy has become a pervasive skill to make this transformation possible (Kamau, 2025; Ng *et al.*, 2023). Liang *et al.* (2023) opine that GenAI literacy is an essential driver in global education. It is identified as a potential predictor of academic performance in an AI-mediated learning environment (Chiu *et al.*, 2024; Mwilongo & Mwita, 2025). Several studies have looked at the relationship between AI literacy and academic performance. Singh *et al.* (2024) report that AI literacy significantly impacts the academic performance of Gen Z students in India. Thus, AI literacy is essential in improving their

learning experiences and fosters critical and innovative thinking among Gen Z students. Xiao *et al.* (2024) undertook a study to understand the role of AI literacy in enhancing student achievement in online learning environments. Their analysis shows that AI literacy is not only a direct determinant of academic well-being and educational success but also mediates the effect of academic well-being on educational success. According to Youssef *et al.* (2024), using ChatGPT positively and statistically contributes to Emirati students' academic achievements. Al-Mamary *et al.* (2024) and Elbaz *et al.* (2024) discovered that implementing ChatGPT in e-learning positively influences the academic performance of university students. Kamau (2025) reported a significant positive relationship between generative artificial intelligence and learning outcomes among undergraduate students in Kenya ($\beta = 0.387$, $t = 7.353$, $p < 0.000$).

While some studies indicated a significant correlation between academic performance and AI literacy, others reported contrasting findings. Asio (2024) identified a weak positive correlation between academic performance and AI literacy. Bancoro (2024) reported no significant relationship between the use of AI and academic performance. Furthermore, the research conducted by Mansoor *et al.* (2024) indicates a negative correlation between academic performance and AI literacy. Students who demonstrate inferior academic performance may be inclined to depend more heavily on AI tools to accomplish their academic assignments. Based on the above findings, the researcher posits;

H_1: GenAI literacy positively and significantly impacts the academic performance of university students

RESEARCH METHODOLOGY

Research Model

This study aimed to explore the relationship between GenAI literacy and Academic performance among university students, as given in the model explaining the hypothesised connections among the research constructs (Figure I)

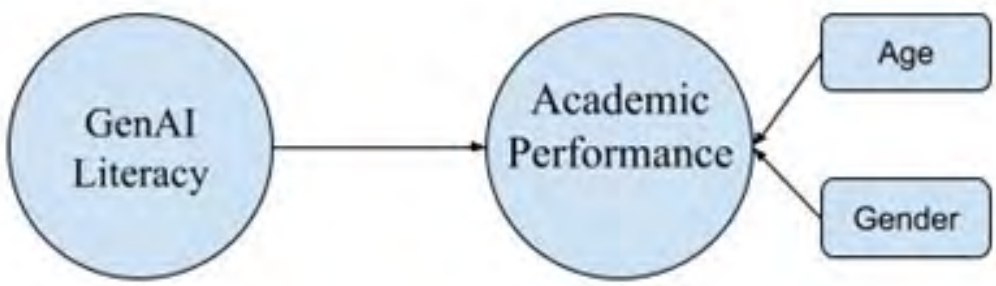

Figure I. Research Model

(Source: The Authors)

Research Design and Method

This research utilised a quantitative research design with a survey method to conduct the investigation. Data were collected from undergraduate students of Kwame Nkrumah University

of Science and Technology, Kumasi, using a structured questionnaire. The structured questionnaire is made up of 16 statements associated with GenAI literacy (12 items) and academic performance (4 items). All the statements were measured on a 7-point Likert-type scale ranging from strongly disagree to strongly agree. Demographic data like age, gender, and GenAI tools usage were also collected. This study adhered to the Helsinki Declaration and received approval from the ethics committee of the Department of Educational Innovation in Science and Technology, KNUST (EIST-EC-0107-2024s, approved July 1, 2024). Data collection began after the approval. Participant first read a research preamble and provided informed consent; survey submission indicated voluntary participation.

Measurement instrument

GenAI Literacy Scale

The GenAI literacy proficiency of the university students was assessed using the 12 items AILS developed by Wang *et al.* (2023). The 7-point Likert-type scale has four sub-dimensions: Awareness, usage, evaluation, and ethics. The scale items are carefully designed to measure participants' levels of GenAI literacy, giving rise to a comprehensive understanding of students' GenAI literacy. A maximum score of 84 and a minimum score of 12 can be obtained. The higher the score, the higher the perceived GenAI literacy and vice versa. The internal consistency of the overall scale is 0.85. In the context of this study, the internal consistency was 0.853.

Academic Performance Scale

Scholarly studies measure academic performance using various methods, including self-reported GPA or CWA (Essel *et al.*, 2021; Katalbas *et al.*, 2023), and students' perceived ability to complete an academic task (Han & Yi, 2019; Mehrvarz *et al.*, 2021). This study adopted a four-item academic performance scale from Merhvaz *et al.* (2021), who had a reported reliability of 0.86. The student rated each item on a 7-point Likert scale. The internal consistency of the scale in this study was 0.824.

Population and Sampling

The study population consisted of undergraduate students drawn from Kwame Nkrumah University of Science and Technology (KNUST), a public university in Ghana offering a diverse range of academic programmes. The participants were selected through a convenience sampling method. This approach was selected due to practical considerations in reaching the students. G*Power, a priori statistical tool, suggests that a minimum of 89 valid responses is necessary to achieve 95% statistical power for conducting a Partial Least Squares- Structural Equation Modelling (PLS-SEM) analysis (Faul *et al.*, 2007, 2009). 193 valid responses were used for the analysis in this study, which is above the minimum sample size. Students were included in the study based on: being a KNUST student, ability to read and understand English, having access to the internet, and volunteering for the study. The exclusion criteria are that the participant can leave the study at any time or by not consenting to partake in the study. Data was collected between 1st July and 31st July, 2024. Age and gender were included in the model as control variables to account for potential demographic influence on Academic performance. Both were modelled as single-item constructs with direct paths to the outcome variable.

Data Collection and Analysis

The scales were created in a survey format using Google Forms. The survey link was sent to teaching assistants to be put on students' WhatsApp groups, and QR codes were printed and posted at vantage points on campus. The participant was directed to the Google Forms survey by clicking on the link. Participants who consented to the survey were directed to the main survey, while the survey was terminated for those who did not consent. The researchers received a total of 262 survey responses from the students. The responses were carefully screened for data accuracy before data analysis.

This study employed the PLS-SEM to analyse the relationship between GenAI literacy and Academic performance. Since PLS-SEM is a non-parametric technique, it doesn't require the assumption of multivariate normality to be met. The dataset was examined for multivariate normality through the WebPower analysis tool (Cain *et al.*, 2017; Zhang & Yuan, 2018). Mardia's multivariate skewness and Kurtosis measures were found to be significant, indicating non-normality, and therefore, Covariance-based SEM (CB-SEM) would not be appropriate for the analysis. The reliability and validity of the measures were analysed through measurement modelling, and the SEM was performed to measure the relationship between the variables.

FINDINGS AND DISCUSSION

Demographic Characteristics

The study involved 193 participants with a mean age of 22.07 years (SD = 2.87). Of these, 117 identified as male and 76 as female. When asked about their use of generative AI tools for generating ideas in assignments or projects, the top three tools reported were ChatGPT (169 users, 87.6 %), Grammarly AI (74 users, 38.8%), and Microsoft Copilot (50 users, 25.9 %). The result indicated that ChatGPT is the dominant tool among students, with many also leveraging additional tools to support their academic pursuits (see Table I).

Table I: *Sample Demographics*

Variables		N	Mean	SD	%
Age		193	22.10	2.87	
Gender	Male	117			60..6
	Female	76			39.4
GenAI used	ChatGPT	169			87.6
	Grammarly AI	74			38.8
	Microsoft Copilot	50			25.9

(Source: The Authors)

Descriptive Analysis

The level of GenAI literacy and academic performance was assessed by performing descriptive analysis on the surveyed sample (Table II). All constructs were measured on a 7-point Likert-type scale. The total mean scores are AIL (M= 59.098, SD=6.718) and AP (M=16.326, SD=2.836), respectively. The average GenAI literacy score of 59.098 reflects a

good understanding and practical use of GenAI tools among the university students. There is a positive moderate correlation between AIL and AP (r =.382, p <.001)

Table II: *Descriptive Statistics*

Variables	N	Minimum	Maximum	Mean	SD
AIL	193	1	7	59.098	8.718
AP	193	1	7	16.326	2.836
Correlation among variables					
AIL and AP	0.382***				

***p<0.001

(Source: The Authors)

Common Method Bias

Before estimating the model, the dataset was checked for common method bias (CMB). CMB may exist in research where variables are latent and measured through instruments on a similar type of scale. This type of bias can occur because of various reasons, such as the effect of general instruction at the beginning of the instrument in influencing different people to give responses in a similar direction, reflecting social desirability, which leads to shared common variance among the various items (Kock, 2015a; Memon et al., 2023). This study employed a 7-point Likert scale to measure the variables, full collinearity assessment was conducted to rule out the presence of CMB in the data. Using the full approach, inner VIF values of the constructs are tested against a random endogenous variable, and any value coming above 3.3 indicates a problem of CMB (Kock & Lynn, 2012). In this study, none of the inner VIFs for the variables exceeded 3.3. This implies that the problem of CMB does not exist (Kock, 2015)

The Measurement Model Assessment

The measurement model assessment entails the examination of the indicator reliability, the internal consistency reliability, convergent validity and the discriminant validity of the construct. Validity refers to how the scale measures the intended construct accurately (Hair et al., 2019). Construct validity comprises both convergent and discriminant validity, which are evaluated through established benchmark values (Sarstedt et al., 2021). Convergent validity, which is a key component of construct validity, assesses the degree to which several items of the same construct are in harmony (Henseler et al., 2015). Convergent validity in PLS-SEM is mostly evaluated using two major criteria: factor loading and the average variance extracted (AVE). The acceptable benchmark in current literature for these criteria is factor loading ☐ 0.70 and AVE ☐ 0.50 (Henseler et al., 2015). Multiple iterations of the PLS-SEM were run to achieve satisfactory factor loadings. This led to the removal of several items due to factor loadings below the 0.707 threshold if they do not affect the construct validity (i.e., CR and AVE). We eliminated six items (AIL 11, AIL 5, AIL 2, AIL 12, AIL 10, AIL 1) from the construct measuring GenAI literacy. Despite being below the threshold, we retained item AIL 3 because the CR is greater than 0.70 and the AVE is greater than 0.50 (Hair et al., 2019)

We expect the internal consistency reliability to account for approximately 70% of the construct, and we should also take a composite reliability of more than 0.70 into consideration (Ringle et al., 2020; Taber, 2018). The Table xx demonstrates that the composite reliabilities for the GenAI literacy factor (0.853) and Academic Performance (0.824) are all higher than the benchmark value of 0.70. Convergent validity checks how all the items add up and explains about half of the construct. This was measured through the average variance extracted (AVE); the acceptable value must be more than 0.50 (Hair et al., 2019). Table III shows that all AVE for the respective constructs are well above 0.50.

Table III: *Reliability and Validity*

Construct	Factor loadings	Cronbach Alpha	rho_A	rho_C	AVE
AIL		0.853	0.871	0.891	0.578
AIL3	0.619				
AIL4	0.790				
AIL6	0.755				
AIL7	0.798				
AIL8	0.761				
AIL9	0.823				
AP		0.824	0.828	0.883	0.654
AP1	0.809				
AP2	0.781				
AP3	0.829				
AP4	0.815				

(Source: The Authors)

Discriminant validity

The discriminant validity of a construct in the structural model refers to how distinct it is from other constructs (Hair *et al.*, 2018; Lim, 2024). Consequently, there should be no overlap of questions among constructs. We use the HTMT to measure the discriminant validity, with a benchmark requiring the HTMT to not exceed 0.90 (Henseler *et al.*, 2015; Kline, 2023). Table IV demonstrates that each construct has an HTMT of less than 0.90, thereby satisfying the criterion for confirming the model's discriminant validity.

Table IV: *HTMT Criterion for Discriminant Validity*

	AIL	AP
AIL		
AP	0.526	

(Source: The Authors)

The structural model Assessment

As the initial step in structural model analysis, the inner VIF values were examined to rule out the tendency of multicollinearity, and all inner VIF values were found to be below 5, thus ruling out the presence of any serious multicollinearity issues among the variables of the model (Hair et al., 2019). The model was then assessed for explanatory power through the coefficient of determination (R2) using the bootstrapping procedure for the assessment of the structural relationships. The effect size of the predictor variable was also calculated. The model fit assessment in PLS-SEM was done through the recommended Standardised Root Mean Square Residual (SRMR) value (Hair et al., 2022; Henseler et al., 2015). The SRMR value below 0.08 indicates a satisfactory model fit (Hu & Bentler, 1999; Kock, 2015b). To ensure the robustness of our model, potential nonlinearities and endogeneity were assessed. We assessed the quadratic effect (Becker et al., 2022; Liengaard et al., 2024). The results of the 10000 samples indicate that the quadratic effect is insignificant. The Gaussian Copula test (Hult et al., 2018; Sarstedt et al., 2020) was also performed. As shown in Table VI, the Gaussian Copula test shows there was no problem of endogeneity.

Explanatory Power (R^2)

The R^2, called the in-sample predictive power, measures the model's explanatory power. For each path between constructs, the ideal R^2 value should be at least 0.1 or higher (Falk & Miller, 1992). Understanding R^2 values within the study context is crucial. Values of 0.75, 0.50, and 0.25 are considered substantial, moderate, and weak, respectively (Hair et al., 2011; Hair et al., 2018; Lim, 2024). Table V. above demonstrates that the R^2 for academic performance is 0.213, signifying that Gen AI competency accounts for 21.3 % of the variation in academic performance.

Effect size (f^2)

The effect size (f^2) checks how important each independent variable is in explaining the dependent variable. It is classified as large, medium, or small when it exceeds or equals 0.35, 0.15, and 0.02, respectively (Cohen, 1992). Gen AI literacy ($f^2 = 0.268$) has medium to strong effects in explaining academic performance (Table V)

Table V: *Explanatory Power & Model Fit*

Explanatory Power: R^2			
	R^2	**R^2 Adjusted**	**SRMR**
AP	0.214	0.201	
Effect size: f^2			
	AIL	AP	
AIL		0.269	
Model fit			
SRMR			0.068

(Source: The Authors)

Table VI: *Quadratic effect and Gaussian Copula Test results*

Effect	**Path coefficient**	**T-values**	**p-values**
QE (AILS) -> AP	0.025	0.386	0.699
GC (AILS -> AP) -> AP	0.136	0.448	0.654

(Source: The Authors)

The inner model presents the hypothesised model paths within the research framework for empirical testing. The Hypothesis was tested by running the consistent PLS algorithm in SmartPLS 4 software. Bootstrapping was run using 10,00 subsamples to test the significance of the coefficients. The structural model for the result is presented in Table VII, and Figure II shows the model estimation results. The relationship between AIL and AP is significant except for the path coefficients of the control variables.

Table VII: *Structural model Results*

			BCCI			
Path	**Path Coefficient**	**T-statistic**	**Lower**	**Upper**	**p-value**	**Decision**
AIL⟶AP	0.478	5.984	0.239	0.617	0.000	Supported
Control variables						
Age ⟶AP	-0.085	1.043	-0.239	0/079	0.297	Unsupported
Gender⟶ AP	0.020	0.130	-0.228	0.280	0.876	Unsupported

Note: BCCI = Bias-corrected confidence intervals

(Source: The Authors)

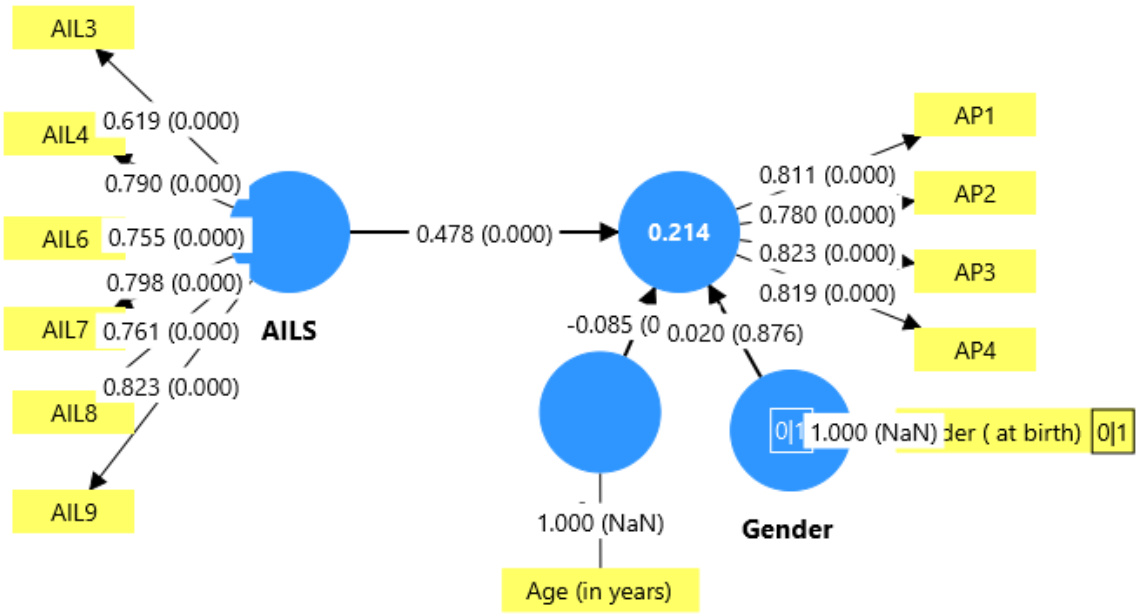

Figure II: *Model Estimation Results*

(Source: The Authors)

Predictive model assessment

The structural model's out-of-sample predictive ability was evaluated using PLSpredict, employing 10-fold cross-validation and 10 replications (Hair et al., 2019; Manley et al., 2021; Sarstedt et al., 2020; Shmueli et al., 2019). This assessment determines the model's capacity to forecast new or future observations (Hair et al., 2022; Sarstedt et al., 2023). The results indicated that the model possesses predictive relevance, as Q2 predicted values exceeded 0.0 (ranging from 0.101 to 0.138) (Hair et al., 2020). All dependent construct indicators exhibited lower errors as compared to the naïve LM benchmark, indicating that the model has high predictive power (Hair et al., 2022; Shmueli et al., 2019). To further complement this evaluation, the cross-validated predictive ability test (CVPAT) was conducted to statistically compare the prediction errors between the PLS-SEM and LM benchmarks (Liengaard et al., 2021; Richter & Tudoran, 2024; Sharma et al., 2023). The findings suggest that our proposed model demonstrates a significantly reduced average loss compared to the baseline model (PLS-IA = -0.091, $p < 0.042$), thereby indicating meaningful predictive validity (see Table VIII).

Table VIII: *Predictive model assessment for Academic performance.*

PLSpredict					
		Prediction Error Comparison			
Indicators	**Q^2predict**	**PLS-SEM_ RMSE**		**LM_RMSE**	
AP1	0.101	0.813		0.823	
AP2	0.093	0.819		0.843	
AP3	0.132	0.830		0.837	
AP4	0.138	0.854		0.859	
Latent variable			Q^2		
AP			0.181		
CVPAT-PLS-SEM vs Indicator average (IA)					
Construct	PLS loss	IA loss	Average loss difference	t-value	p-value
AP	0.687	0.779	-0.091	2.045	0.042

(Source: The Authors)

DISCUSSION

This study, grounded in Connectivism learning theory, employs structural equation modelling to investigate the relationship between perceived GenAI literacy and academic performance of university students, specifically in the context of a resource-constrained GenAI-mediated learning environment in Ghana.

The students rated their perceived GenAI literacy levels as moderate because their proficiency in using the GenAI tool for academic tasks in its an elementary stage, and they will need more training to have a more comprehensive knowledge of its application and usefulness. Considering the pace with which GenAI technologies are supercharging all aspects of life, it is therefore desirable that the perceived levels of university students are not low. This finding is in line with a similar study by Cegiz and Peker (2025), Kahraman et al. (2025), Cayak (2024), who reported a moderate proficiency level of AI literacy in their studies. This moderate perceived proficiency levels of the university students differ from Ozden et al. (2025) and Obenza (2024) high AI literacy level of AI literacy and Chenqi et al. (2023) and Sari et al. (2025 who reported a low AI literacy level in their study.

This study highlights a significant positive relationship between GenAI literacy and the academic performance of university students. GenAI literacy accounts for 21.4 % of variance in student academic performance, with a medium to high effect size ($f^2 = 0.268$). Although modest, this level of explanatory power is considerably acceptable within social and educational research, where numerous factors affect learning outcomes. This underscores the importance of GenAI literacy in fostering meaningful learning experiences. Thus, students with high AI

literacy are able to leverage GenAI tools in streamlining their academic tasks. These findings resonate with prior studies (Singh *et al.*, 2024; Kamau, 2025; Xiao *et al.*, 2024), highlighting the positive and significant relationship between GenAI literacy and academic performance. University students are highly receptive to technological tools in improving their learning outcomes and a broader education experience due to the digitalisation drive and technology-mediated learning environment. In addition, the proficiency of students in GenAI literacy empowers the students with the requisite skills to explore the AI-driven ecosystem seamlessly (Essel et al. 2024; Baidoo-Anu and Owusu Ansah, 2023). This consequently influences the students' academic achievement and enhances their self-efficacy in executing academic tasks (Setsoafia et al., 2025). This finding is, however, contrary to those of Abbas et al. (2019), Asio and Gadia (2024), reporting a weak but positive relationship between AIL and academic performance. Moreso with Mansoor et al. (2024) reporting a negative correlation between AIL and academic performance. Contrary to the findings of this study, Bancoro (2024) reported no significant relationship between AI literacy and academic performance. This highlights the existence of several dynamics that might influence academic achievement other than AI literacy.

The non-significant effect of age and gender is consistent with studies suggesting that demographic variables may play a limited role in predicting proximal cognitive factors like GenAI literacy (Sari et al.,2025; Mansoor et al,.2024; Ozden et al., 2025; Shen & Cui,2025). This reinforces the central role of GenAI literacy as a key predictor of academic performance.

The research contributes to the GenAI literature by defining GenAI literacy as a measurable and specific cognitive enabler in the context of AI-mediated learning and empirically supports the argument of connectivists that the digital age competence of learning is the ability to operate within a network of humans and machines, rather than the acquisition of knowledge. The findings add theoretical insights to the existing theoretical knowledge on networked learning by showing a significant predictive value of GenAI literacy on academic performance and differentiating between GenAI literacy and traditional AI literacy by clarifying the importance of ethical judgment, critical appraisal, and strategic content generation. In effect, the findings propose GenAI literacy to be integrated as a fundamental institutional priority in higher education by integrating it into the curriculum, restructuring process, training faculty members, and establishing dynamic and organized student skill acquisition frameworks. On the policy front, the paper explains the pressing need to put in place an institutional and national GenAI literacy framework and competency standards, and ethical governance systems in place to enable equitable, responsible and academically significant application of GenAI in resource-constrained higher education systems.

CONCLUSION, LIMITATIONS, AND RECOMMENDATIONS FOR FURTHER RESEARCH

This study examined the predictive role of perceived Generative Artificial Intelligence (GenAI) literacy on the academic performance of university students, grounded in the theoretical lens of Connectivism. The findings demonstrate that GenAI literacy explains a meaningful proportion of variance in academic performance ($R^2=0.214$), thereby confirming its status as an emerging cognitive competency essential for navigating an AI-mediated learning environment. The results extend connectivists' thought by empirically validating the function of GenAI literacy as a learning enabler within human-machine knowledge networks, where the

capacity to access, interpret, and refine AI-generated knowledge becomes central to academic success.

In doing so, this study advances existing scholarship by conceptualising GenAI literacy not merely as a technical skillset, but as an evaluative, ethical and constructivist capability that enhances students' engagement with digital cognitive agents.

Beyond its theoretical contribution, the study underscores the practical significance of GenAI literacy in higher education systems, particularly in resource-limited contexts where structured AI integration policies are still nascent. The demonstrated influence of GenAI literacy on academic performance suggests that higher education institutions should prioritise the systematic development of AI-oriented competencies within curricula, faculty training programs and students' support services. The finding also resonated with the broader educational transformation agendas with broader educational transformation agendas that emphasise digital readiness, critical engagement with intelligent systems, and the cultivation of adaptable learners equipped for AI-driven knowledge economies.

Consequently, this study provides an empirical foundation for fostering equitable, responsible and performance-oriented GenAI adoption within digital ecosystems.

This study relied on self-reported data and a cross-sectional design, which may affect the accuracy and causality of the findings. Additionally, the focus on a single university in Ghana limits the generalisability of the results.

Future research should explore how structured GenAI training imparts learning outcomes over time using a longitudinal or experimental design. Expanding to diverse disciplines, academic levels, and contexts would ensure generalisability, while attention to instructional and policy-level readiness could inform more equitable and effective integration of GenAI in the higher education system.

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TOWARD AN AI-DRIVEN VIRTUAL LABORATORY FRAMEWORK (AI-VLAB): ENHANCING SCIENTIFIC INQUIRY AND DISCOVERY IN TEACHER EDUCATION

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Article History
Received 06 Nov. 2025
Accepted 23 January 2026

ABSTRACT

Virtual laboratories (VLabs) are revolutionizing science education by offering interactive and scalable platforms, especially in settings with limited access to physical laboratory infrastructure. However, their full pedagogical potential remains underutilized without the intentional integration of Artificial Intelligence (AI). This conceptual paper introduces the AI-VLab Framework, a model designed to incorporate AI into virtual laboratory environments to enhance scientific inquiry, adaptive learning, and teacher effectiveness within Colleges of Education in Ghana. Employing a design-based research methodology, this study integrates existing frameworks of AI in education with previous research in both virtual and practical science education. The framework underwent refinement through expert consultation, simulation analyses, and the evaluation of AI-supported virtual lab prototypes, with a focus on adaptive feedback, ethical application, accessibility, curriculum alignment, and teacher empowerment. The AI-VLab Framework presents a context-sensitive model that integrates elements of Technological Pedagogical Content Knowledge (TPACK) and Unified Theory of Acceptance and Use of Technology (UTAUT) with AI functionalities to enhance student engagement, equitable access, and deeper understanding of scientific concepts. It provides a scalable approach for incorporating AI into educational settings with limited resources. In practical terms, the framework facilitates the empowerment of pre-service teachers through targeted professional development focused on artificial intelligence. It also broadens opportunities for virtual experimentation and advocates for the institutionalization of ethical and inclusive AI practices within science education.

Keywords: Artificial Intelligence, Virtual Laboratories, Adaptive Learning, Digital Transformation, Framework

INTRODUCTION

The rapid evolution of educational technologies has catalysed a transformation in science education, particularly in how laboratory experiences are delivered. Traditional physical laboratories, while effective, are often constrained by limited infrastructure, cost, and accessibility challenges that are particularly pronounced in Colleges of Education across

developing regions. As a response to these limitations, Virtual Laboratories (VLab) have gained prominence as scalable and flexible platforms for facilitating scientific experimentation and inquiry (Zhang *et al.*, 2024; Sellberg *et al.*, 2024). VLabs are computer-based platforms that simulate real laboratory environments, enabling learners to conduct experiments and engage with scientific processes in a safe and interactive manner (Raman *et al.,* 2022). However, many existing VLab platforms remain static and lack the capacity to provide real-time feedback (Kumar *et al.*, 2021; Kok *et al.*, 2021), adapt to learners' needs, or simulate authentic scientific reasoning thus limiting their pedagogical potential. Artificial Intelligence (AI) offers an opportunity in education to close this gap by enhancing interactivity, personalization, and data-driven assessment (Samala *et al.*, 2025). Despite this potential, there remains a significant lack of conceptual models or frameworks guiding the meaningful integration of AI into VLab environments, especially within the teacher preparation landscape in science education (Aiyedun, 2024). In Ghana, there exist "ICT in Education Policy," embedded within the Education Strategic Plan and Sustainable Development Goals (2018–2030), that aims to align the educational system with evolving national priorities and technological advancements. However, its practical application in science education and teacher preparation remains limited (Agyemang *et al.*, 2025), in terms of leveraging AI for laboratory-based science instruction. This policy-practice disconnect, highlights an urgent need for innovative frameworks that translate national aspirations into classroom-level transformation. In Ghana, Colleges of Education (COE) serve as the primary institutions for training pre-service teachers, playing a pivotal role in shaping the quality of basic education through structured professional and pedagogical preparation (Tetteh & Agyei, 2022)

In response, this article proposes an AI-VLab Framework, a conceptual model for integrating AI technologies into VLab to enhance scientific discovery and inquiry-based learning in Ghana's COE. The framework seeks to foster personalized learning pathways, simulate complex scientific phenomena, and support the development of metacognitive and inquiry skills among pre-service teachers. The overarching aim is to design a context-relevant, inclusive, and accessible framework that aligns with the goals of 21st-century science education incorporated in the 4-year B.Ed. curriculum.

The specific objectives of the study are to:

1. To identify key pedagogical and technological principles that inform AI integration in VLab environments.
2. To develop a conceptual framework for effective and inclusive AI integration in science VLab; and
3. To recommend scalable policy and instructional strategies for implementation across diverse educational contexts.

Despite the increasing incorporation of artificial intelligence and virtual laboratory technologies in science education, there remains an absence of coherent, context-sensitive frameworks to guide their pedagogically meaningful integration within teacher education. Existing research frequently concentrates on isolated tools or short-term interventions, offering limited guidance for curriculum design, teacher preparation, and policy alignment, particularly in resource-constrained contexts. This study addresses this gap by proposing an AI-integrated Virtual Laboratory (AI-VLab) Framework that aligns artificial intelligence capabilities with science pedagogy to support effective teaching and learning in colleges of education. The paper is structured as follows: initially, it synthesizes existing literature on

artificial intelligence in science education, virtual laboratories, and pedagogical integration frameworks; subsequently, it outlines the methodological approach underpinning the framework's development; it then presents and critically examines the proposed framework, highlighting its theoretical foundations and practical significance; and finally, it concludes by discussing implications for teacher education, educational policy, and future research.

CONCEPTUAL FOUNDATIONS FOR AI INTEGRATION IN VLAB

Growing interest in AI integration within education has led to a number of frameworks proposing diverse approaches to curriculum transformation, digital tool adoption, and virtual experimentation. These conceptual models offer valuable insights for designing AI integrated VLab, especially in contexts with evolving pedagogical and technological needs. AI integration in education has catalysed efforts to reform curriculum, pedagogy, and learning environments. Zhou and Schofield (2024) propose a flexible framework to enhance AI literacy in higher education by integrating generative AI (GenAI) tools across disciplines. Grounded in Bloom's taxonomy, this model scaffolds student learning through understanding, application, creation, and ethical evaluation of AI. It includes a pedagogical toolkit that maps GenAI tools to strategies like brainstorming, critical evaluation, and ethical reflection (Laupichler *et al.*, 2022; Ng *et al.*, 2023). While it offers strong alignment between pedagogy and technology, the framework is limited by its conceptual nature, lack of empirical validation, and underdeveloped considerations of institutional readiness and lifelong learning.

Also, Ajayi (2023) advances a model for AI-driven curriculum adaptation in STEM education, emphasizing responsiveness to evolving industry needs. The framework integrates AI technologies including machine learning and natural language processing to support dynamic curriculum updates, skill-gap analysis, and personalized learning. Drawing on theories such as constructivism and experiential learning, it features tools like intelligent tutoring systems. Notable strengths include responsiveness and collaboration. However, challenges such as faculty resistance, infrastructure gaps, and algorithmic bias persist. The author calls for studies to evaluate outcomes, safeguards, and inclusive implementation.

Additionally, recent advancements in VLab design have produced other conceptual frameworks aimed at integrating AI and digital technologies into science education. Klami *et al.* (2024) offer a cross-disciplinary framework that merges AI techniques such as Bayesian optimization and reinforcement learning with modular software and digital twins to simulate scientific inquiry. While their emphasis on FAIR data and user personalization is commendable, the framework may lack empirical grounding and overlooks ethical and contextual challenges in low-resource settings. Birkeland (2022) introduces a model driven by learning analytics aimed at enhancing collaboration within bioscience virtual laboratories (VLs). This model, grounded in the Learning Analytics Life Cycle, employs dashboards and monitors interactions; however, it is not integrated with mainstream educational platforms and lacks automation and scalability. Siddique *et al.* (2024) highlight the importance of accessibility and curriculum alignment through a lightweight, web-based simulation system that prioritizes interactivity and independence. Nonetheless, this framework is constrained by inadequate analytics, weak pedagogical integration, and a lack of evidence-based validation. Collectively, these frameworks provide diverse perspectives on the integration of AI with virtual labs, yet they share common deficiencies in empirical testing, theoretical robustness, and inclusivity. This underscores the necessity for a comprehensive, adaptable model that is grounded in both pedagogical theory and technological feasibility.

Recent frameworks for AI-integrated virtual laboratories have yielded valuable insights into the design and implementation of digital learning environments within science education. Nevertheless, several studies suggest that many of these models are insufficiently grounded in established theories of technology integration and adoption, such as the Unified Theory of Acceptance and Use of Technology (UTAUT), the Technology Acceptance Model (TAM), and the Technological Pedagogical Content Knowledge (TPACK) framework (Xue & Rashid, 2024; Shambare & Jita, 2024). Consequently, their explanatory power and applicability across diverse educational contexts remain constrained. Furthermore, the literature indicates that relatively few AI-VLab frameworks explicitly consider contextual factors in the development of education systems, including infrastructural limitations, variations in digital literacy, and the necessity for culturally responsive pedagogy. These omissions have been identified as potential impediments to the pedagogical relevance, equity, and scalability of AI-supported virtual laboratory implementations.

RESEARCH METHODOLOGY

This study employed a Design-Based Research (DBR) methodology to facilitate the conceptualization and iterative refinement of the AI-VLab Framework. DBR integrates theory-driven inquiry with practical innovation, allowing for the systematic design, testing, and refinement of educational interventions within authentic learning environments (Reeves, 2006; Bowler & Large, 2008; Armstrong *et al.*, 2020). This approach was deemed suitable as the study aimed not only to describe a phenomenon but also to develop and validate a framework that effectively bridges theory and practice in technology-enhanced science education. Although DBR provides a flexible and context-responsive pathway for developing educational innovations, it is not without its limitations. Potential researchers influence on participant input and the uncertainty in determining the conclusion of iterative cycles are recognized challenges (Vaezi *et al.*, 2019). To address these concerns, the study incorporated expert consultation and peer validation at each stage of framework refinement.

The study was guided by Reeves' (2006) four-phase DBR model, adapted to the context of pre-service science teacher education in Ghanaian Colleges of Education:

i. *Problem and Context Analysis:* Analysis of B.Ed. science curricula, encompassing the National Teacher Education Curriculum Framework, National Teacher Standards, institutional objectives and scholarly literature on virtual and AI-enhanced learning environments revealed essential requirements, including adaptive experimentation, feedback mechanisms, and equitable access to laboratory experiences.
ii. *Design and Development***:** Informed by the findings from the analysis phase, four interrelated components were conceptualized: Pedagogical Intent, AI Functional Capabilities, VLab Affordances, and Learner Engagement Pathways. These components were aligned with the principles of inquiry-based learning, ethical AI use, and digital pedagogy. The design process also integrated constructs from the TPACK and UTAUT models to ensure both technological and pedagogical coherence.
iii. *Implementation and Iteration*: Prototype iterations of the AI-VLab framework underwent evaluation by experts in the fields of science education, instructional technology, and artificial intelligence systems. The qualitative feedback obtained from these experts, along with insights derived from virtual laboratory simulations and secondary data from existing AI-supported platforms, contributed to the iterative refinement of the framework.

iv. *Evaluation and Refinement*: The final framework was evaluated on the basis of its coherence, usability, adaptability, and adherence to ethical standards. The evaluation criteria included the degree of alignment with curriculum objectives, the facilitation of adaptive learning pathways, and the potential to enhance scientific inquiry and teacher competence in resource-constrained environments.

The target group informing the contextual design consisted of pre-service teachers enrolled in science-related courses at Colleges of Education, with a particular focus on those specializing in elective science and primary education. Although direct empirical data collection was limited, the framework's design was informed by simulated classroom scenarios and expert feedback to ensure its applicability in authentic teacher education settings. This DBR process resulted in a context-sensitive conceptual model that not only addresses identified gaps in virtual laboratory integration but also offers a scalable blueprint for AI-enhanced teaching and learning in resource-constrained contexts.

DESIGN AND IMPLEMENTATION OF PROPOSED FRAMEWORK

This section presents the design rationale of the AI-VLab Framework, a model integrating Artificial Intelligence (AI) into virtual laboratories to enhance scientific inquiry within Colleges of Education (COEs). As prospective science educators must develop inquiry-based learning competencies, intelligent laboratory environments have become essential for promoting engagement, experimentation, and reflection. The framework aligns AI capabilities with pedagogical principles in teacher education and follows the Design-Based Research (DBR) approach, using iterative cycles that bridge theory and practice (Armstrong *et al.*, 2020). The design incorporates established models like TPACK, SAMR, and UTAUT, along with research on AI-enhanced learning environments (Zawacki-Richter *et al.*, 2019; Miao & Holmes, 2021). Through this synthesis, five key design domains emerged. These were content delivery, adaptive experimentation, real-time feedback, learner support, and ethical practice thus reflecting discourses that emphasize personalization, data-driven decision-making, and equity in digital learning (Chan, 2023; Kayal, 2024). The framework comprises four interacting components: Pedagogical Intent, AI Functional Capabilities, VLab Affordances, and Learner Engagement Pathways, connected through feedback loops that enhance adaptation and assessment. These elements form a blueprint for designing interactive, ethical science learning experiences that prepare pre-service teachers for AI-driven educational environments.

Framework conception stage

This phase marks the foundation in developing an AI-integrated VLab (AI-VLab) framework for teaching scientific concepts in theory and practice. A collaborative effort among stakeholders including educators and researchers helps define objectives, scope, and theoretical underpinnings that guide implementation. It involves reviewing existing pedagogical models, AI capabilities, and technological infrastructure to ensure the framework is innovative and practical. Considerations of learner engagement, accessibility, and adaptability are integrated to create a responsive virtual learning environment. This stage sets the groundwork for further refinement and application.

Conceptualisation of key concepts for the framework

This AI-VLab framework is categorized into build levels. In defining key concepts, AI's roles in VLab were identified, including adaptive learning to personalize experiences, intelligent assistants for feedback, and enhanced simulations for complex experiments. These aligned with accessibility, usability, scalability, and cost-effectiveness to ensure practical design. Key elements included: Educational goals, learning outcomes and discovery, AI functions in VLab, User interaction and competences, pedagogical alignment, Infrastructural support, Ethical consideration and assessment.

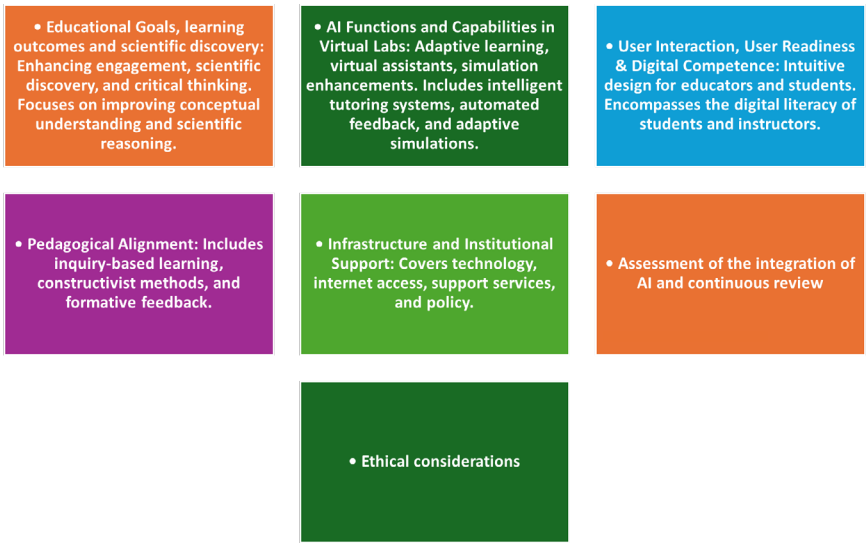

Figure 1: *Key areas for consideration in the proposed framework*

(Source: From authors own creation)

DISCUSSION AND IMPLICATIONS

This section discusses theoretical, pedagogical and technological implications of the AI-VLab Framework within teacher education and e-learning transformation. It critically interprets the framework's components within global discourses on artificial intelligence in education, digital pedagogy, and equitable technology integration. The discussion connects the framework's design to emerging research on AI-enabled personalization, adaptive learning, and virtual experimentation, while reflecting on its relevance for pre-service teacher development in low-resource contexts. It explores how the AI-VLab Framework addresses gaps in virtual lab implementation, aligns with contemporary models of technology adoption, and offers pathways for policy, pedagogy, and institutional innovation in intelligent learning ecosystems.

Structure of the Framework

The AI-VLab framework is structured to address multiple dimensions of educational design and implementation. It emphasises enhancing user readiness, aligning with vigorous pedagogical practices, and incorporating advanced AI capabilities like adaptive learning and simulation tools. Designed with scalability, accessibility, and ethical considerations in mind, the framework spans six levels, covering essential aspects like curriculum integration, theoretical underpinnings, and continuous assessment. This approach ensures an inclusive

practical design to foster scientific discovery, critical thinking, and meaningful educational outcomes. The framework was "built" on six (6) defined levels that included

- Level 1: Users and Competence
- Level 2: Curriculum and Pedagogical alignment
- Level 3: Theoretical foundations
- Level 4: AI integrated VLab (AI-VLab)
- Level 5: Ethical and Inclusive Design
- Level 6: Assessment and Continuous Improvement

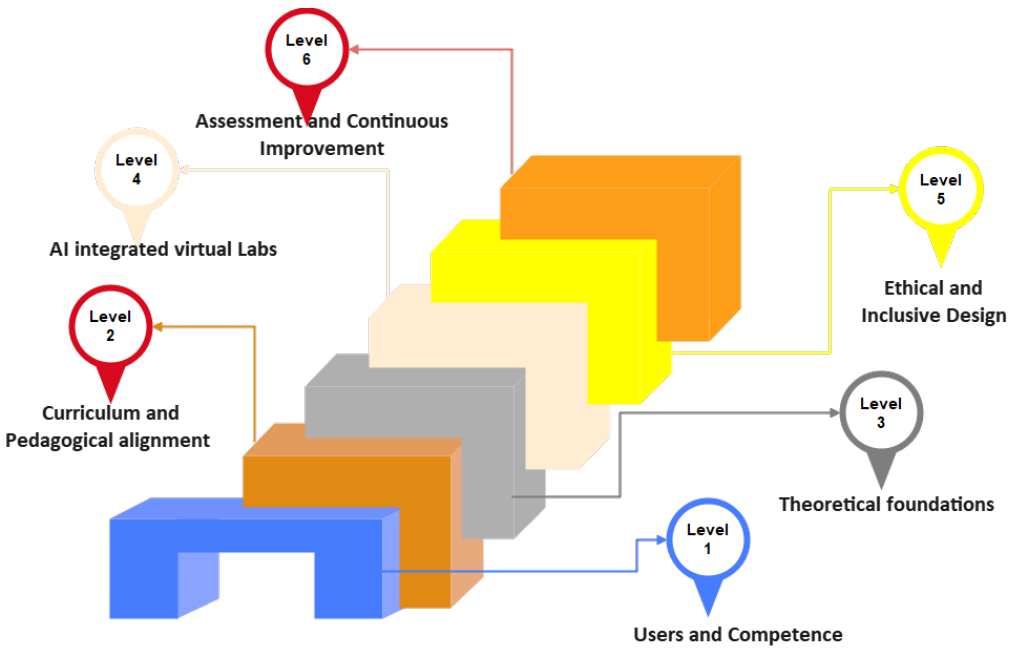

Figure 2: *Skeletal structure of the framework based on the levels*

(Source: From authors' own creation)

The proposed AI-VLab framework interconnects levels addressing critical aspects of its implementation. These levels guide the systematic development of AI-driven VLab to enhance scientific discovery in COE. The framework captures the relationship between technology, pedagogy, institutional capacity, and user competence, ensuring a holistic approach that meets science education needs in Ghana's teacher training institutions.

Users and Competence (Level 1)

User competence constitutes the cornerstone of the AI-VLab Framework, highlighting the preparedness of educators and pre-service teachers to integrate AI-driven virtual laboratories. This framework emphasizes the evaluation of digital literacy, pedagogical content knowledge, and overall competence in the application of AI within science instruction. Drawing upon established models such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), this level emphasizes key factors influencing technology adoption such as perceived usefulness, ease of use, performance expectancy, and effort expectancy (Xue & Rashid, 2024). These constructs facilitate the identification of

attitudinal, motivational, and contextual barriers to AI adoption within Colleges of Education (COEs). Concurrently, the integration of Pedagogical Content Knowledge (PCK) ensures that the use of technology remains pedagogically purposeful, aligning AI tools with instructional objectives and the delivery of science content (Shambare & Jita, 2024). In low-resource educational contexts such as Ghana, where disparities in digital access and technological competence persist, this level underscores the necessity for capacity development and user-centred design. Consequently, user competence is not merely a prerequisite for AI integration but a transformative enabler for effective curriculum delivery, innovation, and inclusivity in science education.

Curriculum and Pedagogical alignment (Level 2)

The second level emphasizes the importance of aligning AI integration within virtual laboratories with the 4-Year Bachelor of Education (B.Ed.) curriculum and broader teacher education objectives. This alignment ensures that AI-supported virtual laboratories enhance learning outcomes rather than function as isolated technologies. The Technological Pedagogical Content Knowledge (TPACK) framework offers a conceptual foundation for this integration, fostering a balanced relationship between technology, pedagogy, and content (Latip *et al.,* 2023). Through the TPACK lens, the AI-VLab Framework incorporates intelligent tutoring systems, adaptive simulations, and learning analytics to facilitate inquiry-based and experiential learning (Shambare & Jita, 2024). These AI-enabled environments assist pre-service teachers in connecting theoretical knowledge to practice by enabling experimentation in safe, virtual spaces. Furthermore, emerging research on AI-driven curriculum adaptation illustrates how artificial intelligence can dynamically align instructional content with evolving STEM industry demands (Abisoye, 2023), while other studies underscore the importance of integrating AI principles at the curriculum design stage to ensure coherence between pedagogical intent and technological capacity (Long *et al*., 2025). Such perspectives reinforce the argument that curriculum design should not merely incorporate AI tools but reimagine pedagogy and content structure to reflect 21st-century digital competencies. Additionally, aligning the AI-VLab Framework with national teacher education policy documents such as the National Teacher Education Curriculum Framework (NTCEF) and the National Teachers' Standards (NTS) ensures coherence between AI-VLab activities and national competency expectations for teacher preparation. This integration also supports formative assessment, reflective practice, and critical thinking through AI-driven feedback systems. By promoting pedagogically informed and context-responsive AI adoption, the framework addresses both curriculum quality and technological equity in Ghanaian COEs.

Theoretical foundations (Level 3)

A comprehensive AI-VLab framework must be founded on robust educational theories that inform the integration of technology in enhancing learning and teaching processes. This framework is anchored in Constructivist Learning Theory and the Technological Pedagogical Content Knowledge (TPACK) framework, while also incorporating emerging theoretical perspectives on the integration of AI in curriculum and pedagogy (Tong, 2024; Kayal, 2024; Long *et al*., 2025). Collectively, these perspectives ensure that the design of AI-driven virtual laboratories (AI-VLabs) is aligned with learner-centred, inquiry-based, and technologically adaptive educational practices. Constructivism asserts that learners actively construct knowledge through engagement, exploration, and reflection, rather than through passive reception (Behnagh & Yasrebi, 2020). AI-powered virtual laboratories embody these

principles by enabling pre-service teachers to interact with dynamic simulations, manipulate variables, test hypotheses, and receive real-time feedback. Such environments promote deeper conceptual understanding, scientific inquiry, and critical thinking, which are fundamental to teacher preparation in science education. Recent studies have highlighted that AI can operationalize constructivist principles by creating adaptive, data-driven, and personalized learning pathways that foster autonomy and reflection (Tong, 2024; Kayal, 2024).

Complementing constructivism, the TPACK framework (Technological Pedagogical Content Knowledge) offers guidance on how pre-service teachers can effectively integrate AI into instructional practices. Technological Knowledge (TK) involves the utilization of intelligent tutoring systems, simulation platforms, and AI analytics to monitor learning and optimize experimentation (Latip *et al.*, 2023). Pedagogical Knowledge (PK) focuses on designing inquiry-based, collaborative, and adaptive tasks that employ AI scaffolding to facilitate problem-solving. Content Knowledge (CK) is enhanced through AI-powered visualizations and simulations, which render complex scientific concepts more accessible and contextually relevant (Shambare & Jita, 2024). These theoretical intersections align with Long *et al.*'s (2025) advocacy for curriculum design frameworks that integrate AI capabilities with sound pedagogical principles to enhance relevance and learner engagement. By integrating these perspectives, the AI-VLab framework emerges as a transformative pedagogical tool that bridges theory and practice. It advances teacher education models that are reflective, adaptive, and evidence-based, enabling pre-service teachers to develop digital fluency alongside scientific literacy. In resource-constrained contexts, such as Ghanaian Colleges of Education, this theoretical foundation provides a roadmap for scaling AI integration ethically and sustainably, supporting the transition from traditional content delivery to active knowledge construction, experimentation, and inquiry-driven discovery in science education.

AI integrated virtual Labs (Level 4)

Prior to the integration of AI-driven components into virtual laboratories (VLab), it is imperative to identify the type of VLab environment that most effectively meets the requirements of student teachers within the College of Education (CoE) context. The choice of VLab, be it 3D immersive simulations, 2D interactive models, online-based labs, or systems with real-time feedback establishes the technological framework necessary for AI integration (Klami *et al.*, 2024). Ensuring that the selected VLab type aligns with contextual factors such as internet connectivity, device availability, and user competence is crucial for maintaining the effectiveness and contextual relevance of AI applications (Aiyedun, 2024). Once the lab format is determined, AI-enabled components, including intelligent experimentation engines, adaptive feedback modules, and performance analytics, can be incorporated to enhance learning engagement and experimentation (Samala *et al.*, 2025; Murali *et al.*, 2024). This sequence of selecting the lab type before AI integration, facilitates coherence between technological design and pedagogical objectives. It also ensures that AI functionalities operate effectively within the virtual environment and complement inquiry-based science instruction. This alignment is supported by the Unified Theory of Acceptance and Use of Technology (UTAUT), which emphasizes that factors such as performance expectancy, effort expectancy, social influence, and facilitating conditions influence users' adoption of new technologies. Consequently, understanding users' readiness and expectations is critical for successful implementation. When educators and pre-service teachers perceive AI-VLab as both useful and manageable, they are more likely to integrate it meaningfully into teaching and learning (Agyemang *et al.*, 2025).

Selection of VLab Types

The effectiveness of AI-VLab implementation is strongly influenced by the type of lab environment selected, which must align not only with infrastructural conditions and pedagogical goals but also with users' technological competence and readiness as assessed in Level 1. According to the UTAUT framework, factors such as performance expectancy, effort expectancy, social influence, and facilitating conditions shape users' acceptance and use of technology. Therefore, the choice between 3D immersive simulations, 2D interactive environments, online-based labs, or real-time feedback systems should consider how these formats meet the perceived usefulness and ease of use for educators and pre-service teachers. When users believe that a particular VLab format will enhance teaching effectiveness with manageable effort, they are more likely to adopt it (Agyemang *et al.*, 2025). Thus, selecting an appropriate VLab environment that matches users' competencies and expectations ensures that AI functionalities are integrated in a way that promotes engagement, usability, and pedagogical effectiveness. Below are some suggestions that may determine selection of the type of VLab.

- 3D VLab: This platform offers immersive simulated experiments, enabling student teachers to engage with digital laboratory equipment and conduct investigations within realistic environments. These settings are particularly conducive to the development of inquiry skills and the conceptual understanding of complex phenomena.
- 2D VLab: This platform provides simpler interactive models that facilitate essential concept visualization and basic experimentation, while requiring minimal computing resources. Consequently, they are well-suited for resource-limited Centers of Excellence (CoEs).
- Online-Based/Real-Time Feedback Systems: These systems facilitate remote experimentation, supported by AI algorithms that deliver real-time feedback, performance tracking, and personalized suggestions. Such systems enhance flexibility, inclusivity, and continuous learning through adaptive feedback mechanisms (Siddique *et al.*, 2024).

By judiciously selecting the appropriate type of VLab, CoEs can ensure that AI integration is both pedagogically meaningful and technologically viable. This strategy guarantees that AI-driven scientific discovery aligns with curriculum expectations, supports diverse learning outcomes, and elevates the overall quality of science education. The resultant AI-VLab model fosters adaptive, interactive, and data-driven learning, advancing inquiry-based pedagogy and preparing teachers for future classrooms (Klami *et al.*, 2024; Murali *et al.*, 2024; Siddique *et al.*, 2024).

VLab Components

The AI-enabled components are crucial, in that. It operationalizes the VLab environment, transforming it into a dynamic, intelligent learning space. These components function as the main technological pillars that enable science teaching and learning to be more interactive, personalized, and data-informed in Colleges of Education (Naah *et al.*, 2021; Bonney *et al.*, 2022). Each component plays a distinct role in transforming traditional lab activities into dynamic, adaptive, and data-driven processes. The components of a VLab such as AI feedback tools, simulation engines, or learning dashboards must be technically and pedagogically compatible with the type of VLab environment chosen. The VLab type sets the foundation for what is possible, while the components operationalize its educational value. Some of these can be listed as:

a. Intelligent Experimentation Engine: This AI-powered module guides scientific inquiry by assisting students in formulating hypotheses, designing experiments, and analysing results. It employs simulation-based modelling and predictive analytics to help students explore complex scientific phenomena, providing interactive and exploratory learning opportunities.
b. Adaptive Feedback Module: AI ensures real-time corrections and personalized suggestions during experimentation. This component monitors student responses, offering instant guidance to refine their approach, correct misconceptions, and deepen understanding. Through adaptive learning, students receive tailored feedback based on their individual learning styles and pace.
c. Conceptual Understanding Tracker: Using Natural Language Processing (NLP), this tool analyses student reflections and responses to assess their depth of comprehension. By tracking learning patterns, it helps educators determine whether students grasp fundamental concepts or require additional instructional support. This AI-driven insight enhances student engagement with scientific content.
d. Pedagogical Analytics Dashboard: This component visualizes student progress through data-driven insights, assisting educators in identifying strengths, weaknesses, and learning trends. AI aggregates performance metrics, allowing instructors to refine teaching strategies, adjust instructional methods, and ensure students meet key learning objectives.
e. Collaboration and Reflection Support: AI enhances peer interaction and metacognition by facilitating collaborative learning experiences. It supports virtual group discussions, shared experiment analysis, and interactive study sessions where students collectively reflect on their findings. AI-powered reflection tools guide students in articulating their thought processes, fostering critical thinking and knowledge-building.

(Kumar *et al.*, 2021 ; Birkeland, 2022 ; Klami *et al.*, 2024 ; Samala *et al.*, 2025)

These modules when put into practice can create a robust AI -VLab that boosts experimentation, customization, evaluation, and teamwork, all of which are vital for successful science education in teacher training colleges.

Ethical and Inclusive Design: Contextual Layer (Level 5)

For the integration of AI-VLab to be both meaningful and sustainable, it is imperative to establish certain enabling conditions that ensure accessibility, ethical deployment, and effective faculty adoption. This focus is on the infrastructural, ethical, and professional foundations necessary to sustain AI-enhanced scientific discovery within Colleges of Education (CoEs). These enabling conditions dictate the extent to which student teachers can effectively engage with AI-driven simulations, conduct virtual experiments, and receive adaptive feedback that enhances their professional preparation (Skulmowski, 2023; Eden *et al.*, 2024). Access to reliable technological infrastructure and trained faculty not only facilitates experimentation and inquiry but also empowers student teachers to design lessons utilizing AI tools, interpret data through pedagogical dashboards, and apply AI-supported experimentation in authentic teaching contexts. These competencies are crucial for 21st-century inquiry-based science instruction and for cultivating reflective, technologically fluent educators (Long *et al.*, 2025; Tong, 2024). Some of these considerations are:

i. Infrastructure and Accessibility: A robust technological infrastructure is imperative for implementing AI-VLab. Essential components include reliable internet connectivity,

computing devices, and compatible software platforms for AI-enhanced simulations. Addressing infrastructural disparities among Centers of Excellence (CoEs) in underserved regions is vital for bridging the digital divide and promoting equitable participation in scientific education (Eden *et al.*, 2024). Ensuring AI-VLabs are accessible across diverse institutional contexts fosters inclusivity and supports national efforts toward digital transformation in education (Tong, 2024).

ii. Ethical AI and Data Privacy: The responsible integration of AI-VLab requires strict adherence to ethical standards and data governance policies. Since AI-driven experimentation involves collecting and analysing student data, institutions must implement safeguards for privacy, transparency, and algorithmic fairness. Clear policies should address bias mitigation, data ownership, and predictive analytics use (Caccavale *et al.*, 2022; Skulmowski, 2023). These ethical imperatives build user trust and align AI-VLab practices with international standards for responsible AI in education (Kayal, 2024).

iii. Faculty Training and Curriculum Integration: The successful integration of AI-VLab depends on faculty competence and readiness. Continuous professional development is essential to equip educators with skills to utilize AI tools, interpret data analytics, and guide students through adaptive learning environments. Curriculum alignment is vital as the AI applications must be embedded within pedagogical goals rather than treated as stand-alone innovations (Eden *et al.*, 2024; Long *et al.*, 2025). By integrating AI into the science curriculum, faculty can foster inquiry, experimentation, and data-informed reflection, enhancing both teaching and learning outcomes.

Advanced artificial intelligence systems may not achieve significant educational outcomes in the absence of supportive ethical and institutional frameworks. Consequently, Level 5 ensures that the AI-VLab framework remains firmly rooted in institutional preparedness, equitable access, and ethical integrity, thereby anchoring innovation in practices that are human-centred, inclusive, and sustainable (Tong, 2024; Kayal, 2024).

Assessment and Continuous Improvement (Level 6)

The final stage of the AI-VLab Framework underscores the significance of ongoing assessment and continuous enhancement to ensure that AI-integrated virtual laboratories remain effective, relevant, and pedagogically responsive to the evolving demands of science education (Alharbi, 2024). Continuous evaluation establishes a feedback loop through which insights from implementation, user experiences, and educational outcomes inform the iterative refinement of both the technological and pedagogical dimensions of the system. This adaptive layer promotes evidence-based decision-making by incorporating both quantitative and qualitative assessment data to measure learner engagement, instructional effectiveness, and system efficiency. Through this cyclical process, the AI-VLab evolves as a dynamic learning ecosystem, consistently aligning with curricular goals, user expectations, and technological advancements.

- *Student and Faculty Feedback systems:* Effective AI-VLab must embed mechanisms for continuous assessment and improvement, ensuring learning outcomes and system usability evolve over time. These mechanisms should leverage automated analytics, feedback loops, and AI-driven assessments to monitor student understanding in real time (Sajja *et al.*, 2025). Through these tools, educators can track knowledge retention, conceptual mastery, and problem-solving skills, enabling timely interventions. The design and implementation of these assessment systems should be informed by technology acceptance models like

TAM or UTAUT. By prioritizing perceived usefulness, ease of use (TAM), performance expectancy, effort expectancy, and facilitating conditions (UTAUT), the framework ensures educators and learners readily adopt VLab tools. This alignment enhances user experience and enables iterative refinement, where data-driven insights inform updates to content, design, and AI functionality ensuring effectiveness in science education.

- *AI Model Calibration:* Continuous monitoring of AI algorithms ensures that biases are minimized, predictions remain accurate, and automated feedback remains reliable. This can be done by well-trained technicians or faculty members. A regular updates and refinements to AI-driven functionalities can help optimize experiment simulations, data analysis tools, and collaboration frameworks, improving overall learning experiences (Jumreornvong *et al.*, 2025)
- *Curriculum Alignment and Policy Review:* To sustain the academic relevance of AI-VLab, periodic curriculum alignment reviews are necessary to assess their compatibility with educational standards, faculty expectations, and institutional objectives. AI-powered labs should continuously evolve to support emerging pedagogical approaches, national curriculum frameworks, and competency-based learning outcomes. Moreover, ethical considerations surrounding AI governance, data privacy, and security policies must be regularly revised (Johnson *et al.*, 2020) to safeguard responsible AI implementation. Establishing transparent and ethical AI guidelines ensures that VLab uphold student data protection, algorithmic accountability, and fair access to digital learning tools.

By integrating assessment and continuous improvement into the framework, AI-driven VLab develop into intelligent, adaptive, and student-centred ecosystems that advance scientific discovery within Colleges of Education.

Final presentation of the proposed AI-VLab framework

The AI-VLab Framework synthesizes levels into an integrated conceptual model showing their hierarchical structure and interconnections. The framework integrates Artificial Intelligence into Virtual Laboratories (VLab) to enhance scientific discovery and pedagogical innovation within Colleges of Education (CoEs). The "Users and Competence" level represents pre-service teachers in Ghana, guided by National Teachers' Standards (NTS) and National Teacher Education Curriculum Framework (NTECEF). Curriculum and pedagogical alignment layers ensure AI integration supports institutional learning outcomes and science education objectives. The AI-integrated VLab environments, including Virtual Reality (VR), 3D and 2D simulations, online platforms, and device-based laboratories form the technological layer, providing experiential learning opportunities adaptable to infrastructure and user constraints. The framework's theoretical foundations, Constructivist Learning Theory and the Technological Pedagogical Content Knowledge (TPACK) Model, justify the pedagogical design of AI-enhanced virtual labs, supporting learning through simulation and reflection. Cross-cutting principles ensure equitable access, data privacy, and fairness in AI deployment. The framework includes an assessment layer, creating feedback for refining instruction, technological performance, and policy alignment.

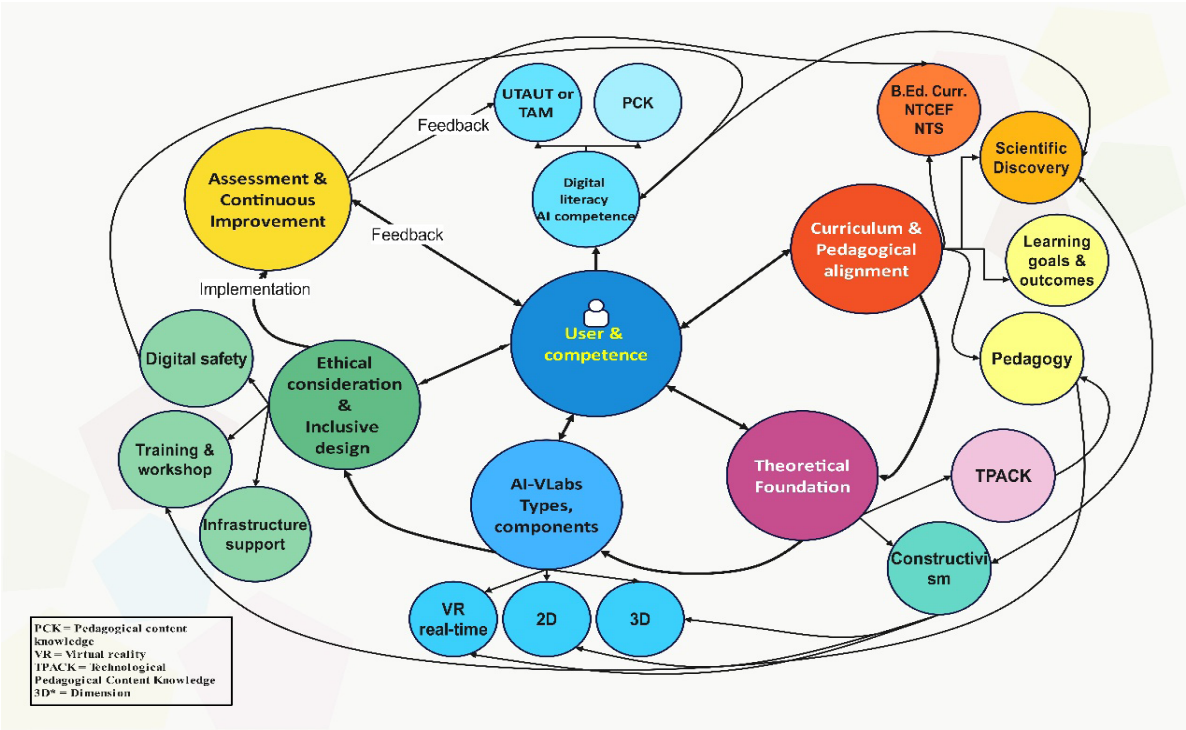

Figure 3: *A graphical representation of the proposed AI-VLab framework*

(Source: Authors' own creation)

Suggested steps for Continuous Assessment and Improvement of the Framework

It is important to conduct periodic assessment of the impact of the framework thus the need to improve where necessary. The authors propose these steps to help evaluate the framework and its impact. These suggested steps can begin from setting up a baseline for outcomes or goals to establishing a feedback loop that will help institutionalise this means of assessment process.

Step 1 - Establishing key performance indicators (KPIs): Establishing clear learning objectives and key performance indicators, such as conceptual understanding, problem-solving, and user engagement, is essential. Institutions should also define their goals for AI integration, like improving student inquiry or enhancing digital competence, while using pre-implementation data to set a baseline for future comparisons.

Step 2 - Develop Assessment Instruments and Tools for regular feedback collection: To ensure continuous improvement, institutions should implement student and faculty surveys to assess usability and effectiveness, gather real-time feedback through AI-driven analytics tracking learning progress and engagement, and conduct focus group discussions with educators to address challenges in implementation. These tools can be developed from adoption frameworks like UTAUT, TAM etc. to put the feedback into proper context

Step 3 - Analysis, Optimization of AI Model and System Calibration: Once user feedback is established, educators can focus on calibrating adopted AI models or tools. Mechanisms to ensure minimal bias detection can be implemented. This refinement improves algorithm and

prediction accuracy for personalized feedback. When users change, learning settings should adapt to accommodate diverse learner needs and align AI functionalities with curriculum standards. This ensures the technology remains effective, inclusive, and pedagogically relevant.

Step 4 - Organisation of periodic professional development sessions: To ensure effective continuous improvement in the integration of AI tools, institutions should conduct PD sessions that are specifically designed AI competency building for educators and establishing peer-led faculty collaboration networks to share best practices. Doing this can encourage faculty-led AI research initiatives involving educators, IT staff, and curriculum experts to foster innovation. These efforts can help identify areas requiring refinement, thereby enhancing the overall application of AI in various institutions.

Step 5 - Implement Iterative Improvements and sustain feedback roadmap: Assessment findings should directly inform refinements to AI functionalities and enhance instructional design, improving learner outcomes. Effective practices can be scaled across Colleges of Education, ensuring consistency and quality. For sustained progress, Colleges can establish regular reviews (termly or annually) and broaden stakeholder involvement, including student-teachers and practicum supervisors. These insights can guide curriculum updates and policy decisions, reinforcing a continuous feedback loop for impact.

(Johnson *et al.*, 2020 ; Sajja, *et al.*, 2025)

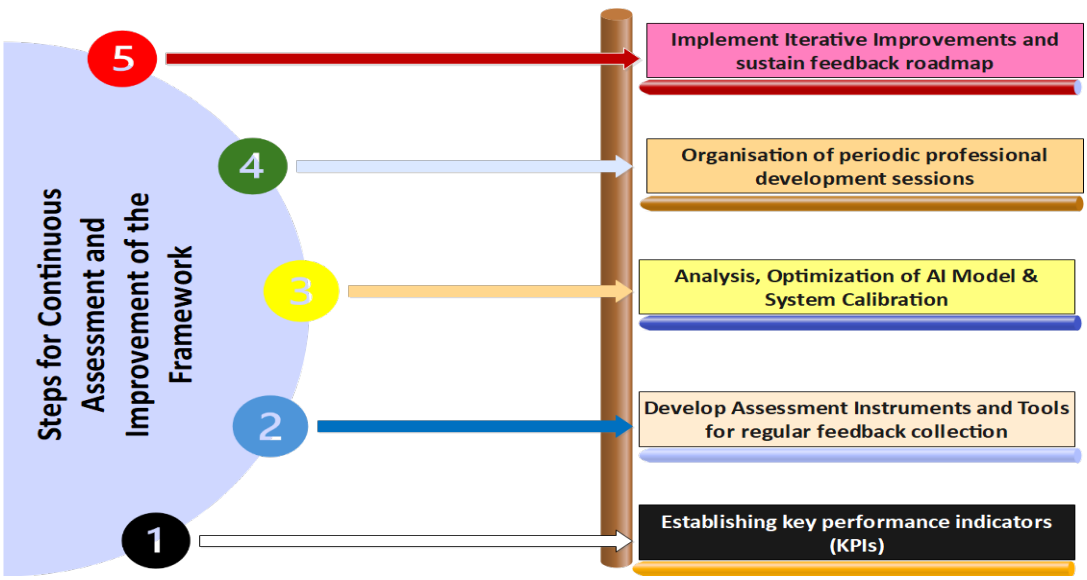

Figure 4: *Graphical representation of the steps involved in assessment and continuous improvement of the AI-VLab framework stage.*

(Source: Authors' own creation)

IMPLICATIONS FOR POLICY, PEDAGOGY, AND TECHNOLOGY ADOPTION

The proposed AI-VLab Framework offers significant implications for educational policy, pedagogical innovation, and technology adoption within Colleges of Education and similar e-learning environments.

Policy Implications: The framework provides a foundation for developing context-responsive AI integration policies aligned with national teacher education standards, including the National Teacher Education Curriculum Framework (NTCEF) and National Teachers' Standards (NTS). Policymakers should incorporate AI literacy and digital competence benchmarks into teacher training regulations, accreditation frameworks, and professional development schemes. Institutional policies must address ethical AI governance, ensuring fairness, transparency, and data protection in AI-driven learning environments. Investment in digital infrastructure and equitable access is crucial to bridge the rural-urban digital divide and promote inclusive participation across Colleges of Education.

Pedagogical Implications: The AI-VLab Framework promotes inquiry-based, constructivist, and adaptive learning, where pre-service teachers use AI-supported simulations to explore scientific phenomena. This redefines teachers as facilitators and co-investigators, promoting reflective, data-informed instructional practice. Integrating AI-VLab within B.Ed. science curriculum enhances personalized learning, feedback, and formative assessment, fostering cognitive and metacognitive growth. Faculty training programs should be strengthened to help educators design and implement AI-enhanced laboratory experiences aligned with pedagogical goals.

Technology Adoption Implications: The framework emphasizes institutional readiness, scalability, and user-centred design for technology adoption. Adoption strategies should align with UTAUT and TAM models, as user perceptions of usefulness, ease of use, and institutional support influence technology uptake. AI-driven virtual lab integration should be phased, starting with pilots that enable refinement based on user feedback. Sustainable adoption requires AI-pedagogy guidelines, collaboration between educators and technologists, and monitoring of system performance to ensure innovations remain pedagogically meaningful and contextually relevant.

CONCLUSION AND FURTHER RESEARCH

This paper proposes the AI-VLab framework as a conceptual model for integrating AI into VLab, specifically within Colleges of Education context. Stemming from the increasing demand for innovative science education practices and the limitations of traditional laboratory access, the framework responds to the need for inclusive, and contextually relevant solutions. The AI-VLab framework is grounded by its design in pedagogical theory and aligning AI functionalities with learner autonomy, assessment, and instructional feedback. It provides a practical roadmap for enhancing scientific discovery and self-learning in teacher education through AI-driven virtual laboratories that support both pre-service teacher training engagement. Further research will involve piloting and refining the AI-VLab framework across selected Colleges of Education. This includes empirical testing of its impact on learner outcomes, integration with pedagogical models such as TPACK and UTAUT, and development of adaptive learning capabilities. Future studies will explore the framework's potential for collaborative learning,

accessibility, and ethical data use in AI personalization. These steps will help establish a robust and scalable model for AI integration in virtual science education.

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THE ROLE OF GENERATIVE AI IN BUILT ENVIRONMENT RESEARCH: A SYSTEMATIC LITERATURE REVIEW

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Article History
Received 5 October 2025
Accepted 23 January 2026

Abstract

As a complex and interrelated domain, the emergence of generative AI (GenAI) presents transformative potential for built environment research. Traditional research methodologies in this field have remained static, creating a need for innovative approaches. This study systematically reviews the applications of GenAI in built environment research to identify current applications, knowledge gaps, and future research directions. The study follows the PRISMA framework to carefully analyse 21 peer-reviewed publications from Scopus and Web of Science databases (2022-2025). Bibliometric mapping and thematic synthesis were employed to examine publication patterns, collaboration networks, and research themes. Findings reveal that GenAI is reshaping research practices through applications in design generation, multimodal data analysis, human-AI collaboration frameworks, decision support systems, and educational transformation. China, the United States, and the United Arab Emirates demonstrated the strongest collaborative efforts. However, significant gaps exist, including limited AI-human perception alignment, insufficient domain-specific model development, scalability constraints, and inadequate validation frameworks. Critically, the study identified the absence of comprehensive ethical guidelines as a major obstruction to realizing GenAI's full potential. Future research should focus on domain-specific models, validation frameworks, and ethical governance.

Keywords: Built Environment, ChatGPT, Generative AI, Large Language Models, Research Methodology, Systematic Literature Review

INTRODUCTION

The built environment research domain has inherent complexities with methods historically remaining static for years (Thampanichwat *et al.*, 2025; Durmus *et al.*, 2024). These traditional research methodologies are based on time-consuming manual data collection, extensive data analysis techniques and little inter-disciplinary collaboration (Garcia, 2025). The advent of artificial intelligence technologies, specifically GenAI, presents innovative approaches and methodologies in all fields (Aly *et al.*, 2025). Recent advances in GenAI models, such as large language models like ChatGPT, Claude AI and Google Gemini, have further provided perspectives of the opportunities presented by these advanced technologies (Tupayachi *et al.*, 2024). For example, ChatGPT was launched publicly in November of 2022, attracting initial interest reaching 100,000,000 users in two months, indicating remarkable prospects (Pereira *et al.*, 2024). This characteristic is particularly relevant to built environment research, which requires integration of technical, spatial, and social considerations. However, the Architecture, Engineering and Construction (AEC) sector has been noted for being a late adopter of AI technologies, relative to other industries (Onatayo *et al.*, 2024). Notwithstanding the dominance of traditional processes within these domains, there is the need for more innovative approaches given its dynamic nature, where codes, materials and mechanisms require flexibility (Durmus *et al.*, 2024). Studies such as Cao *et al.* (2024) opined that researchers in the domain have historically relied on empirical observation, physical modelling, expert opinion and traditional analytical paradigms. While such approaches have their own promises, the limited nature that is not able to meet current and future demands has been a concern. GenAI technologies have become game changers, disrupting such paradigms. For example, GenAI technologies such as generative adversarial networks and variational autoencoders have been extensively employed in architectural image generation. Recent studies also show that the development of large visual models such as Stable Diffusion, DALL-E 2, and Midjourney assists architects and researchers in increasingly generating creative designs (Li *et al.*, 2025; Belaroussi, 2025). Also, GenAI has demonstrated transformative potential in improving operational workflows in the built environment. This transformation is demonstrated by professional adoption statistics from the Royal Institute of British Architects. This professional adoption creates new opportunities and imperatives for built environment researchers. Most architects in the UK are integrating AI into their professional practices (Stewart *et al.*, 2020). Stewart *et al.* (2020) further reported that testimonies from these professionals reinforce the operational efficiency of GenAI. Some studies have demonstrated through experiment a significant reduction of 66% query times and an increase in user satisfaction of 21% compared to traditional systems (Zhu *et al.*, 2024). For built environment researchers managing vast literature databases, building codes, material specifications, and case study repositories, such efficiency gains could fundamentally alter research workflows. The applications of GenAI in geomatics engineering also show remarkable improvement. A study by Taktak (2025) reveals that ChatGPT is enhancing the capacity to process large datasets and also reducing data analysis time by approximately 40%. Given the risky nature of built environment operations, achieving accuracy is key. AI is known for its capabilities of achieving higher accuracy. Stable Diffusion technology, for instance, has been integrated into a corrosion detection system demonstrating an accuracy rate of 90% (Ramos *et al.*, 2025). These potentials are also proven in construction management applications. For example, ChatGPT supports project planning and scheduling with a 30% reduction in planning time and 25% increase in resource utilization efficiency (Taktak, 2025).

While the potentials of GenAI show significant contribution, adoption remains low. This slow adoption has been attributed to challenges faced by researchers in adopting the technology. Studies such as those by Onatayo *et al.* (2024) and Sukkar *et al.* (2024) emphasize a critical challenge of fragmentation resulting in the absence of a comprehensive understanding of methodological implications and the transformative potentials presented by these technologies. According to Wang *et al.* (2022), this fragmentation is seen in isolated research applications with limited frameworks guiding the implementation. While existing reviews have examined AI applications in built environment practice (Onatayo *et al.*, 2024) or general technology adoption patterns (Wang *et al.*, 2022), this study addresses a distinct gap by focusing on how GenAI transforms research methodology rather than professional practice. The integration of bibliometric analysis with thematic synthesis provides both structural collaboration insights and contextual application understanding. Rather than cataloguing applications, this review systematically identifies methodological implications and knowledge gaps to advance built environment scholarship. As a growing field, such fragmentation demands a targeted systematic literature review positioned to map the applications and the methodological innovations. Hence, this study aims to systematically review the role of Generative AI in built environmental research. The specific questions it seeks to answer are: What is the current state of the application of generative AI in built environmental research? What are the main areas of research in the domain? What are the gaps in the existing body of knowledge? And what are the future research directions?

THEORETICAL FRAMEWORK

Understanding how GenAI integrates into built environment research requires a clear theoretical lens. In view of that, this study adopts the Technology-Organization-Environment (TOE) framework (Tornatzky and Fleischer, 1990) and Rogers' Diffusion of Innovations theory (Rogers, 2003) to contextualize GenAI adoption patterns. The TOE framework examines technology adoption across three dimensions. At the technological level, GenAI offers natural language processing, generative design functions, and multimodal data analysis. These capabilities determine how well GenAI fits-built environment research tasks. Compatibility with existing workflows and perceived complexity influence adoption decisions. At the organizational level, institutional research culture, computational resources, researcher expertise, and collaborative networks shape integration capacity. The environmental dimension includes regulatory frameworks, professional standards, funding priorities, and academic publishing pressures.

Rogers' Diffusion of Innovations theory explains how GenAI adoption progresses through research communities (Rogers, 2003). Five innovation characteristics influence adoption rates. Relative advantage measures improvements over traditional methods. Compatibility assesses alignment with existing research values. Complexity relates to ease of use. Trialability allows experimentation before commitment. Observability refers to how visible results are to others. Early adopters in built environment research demonstrate GenAI applications and create outcomes that influence later adopters. These frameworks guide the interpretation of the systematic review findings. This theoretical grounding moves the analysis beyond cataloguing applications. It enables critical examination of adoption dynamics, knowledge gaps, and strategic priorities for the field.

RESEARCH METHODOLOGY

To achieve the objectives, the study employed a mixed research methods approach, combining bibliometric and systematic review methods. It therefore follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines. The PRISMA approach was used due to its qualities of transparency, accuracy, reliability and replicability.

Stage 1: Search Strategy and Article Retrieval

Before the literature search was conducted, a set of carefully selected search strings was developed based on the study's objectives and scope. The Scopus and Web of Science databases were used due to: (1) their high score performance on accuracy in retrieving journal articles; (2) the wider coverage of publications in the field essential for this study; and (3) proven by several similar built environment review studies (Pittri *et al.*, 2025; Amudjie *et al.*, 2025). The search was conducted in March 2025, focusing on publications from 2022 to 2025 to capture contemporary developments in generative AI technologies within built environment research contexts. This timeframe was selected not only for recency but because it represents a clear technological and disciplinary inflection point in the evolution of generative AI, including cloud-based collaboration, digital-twin integration, and automation strategies stabilized and embedded into mainstream construction practices. Research outputs after 2022, therefore, represent the first sustained body of work integrating generative AI within emerging digital-construction ecosystems (Memon *et al.*, 2025).

Search strings applied:

Incorporating well-known keywords in a study is critical to enhancing the validity and reliability of the data (Amudjie *et al.*, 2025). The keywords were broken into three parts. In the first portion, the keywords used are ("Generative AI" OR "ChatGPT" OR "GPT-4" OR "DALL-E" OR "Midjourney" OR "Stable Diffusion" OR "Claude" OR "Gemini" OR "Spacemaker" OR "TestFit"), the second section used these keywords ("Built Environment" OR "Architecture" OR "Urban Planning" OR "Construction Research" OR "Building Design"), and the third section used ("Research" OR "Research Method" OR "Academic Study" OR "Investigation" OR "Analysis" OR "Evaluation").

Selection Criteria:

The study applied predefined inclusion and exclusion criteria to ensure systematic selection of relevant publications. Publications were included if they were peer-reviewed journal articles or conference proceedings from established academic conferences, published between 2022 and 2025, and written in English. Articles needed to explicitly discuss GenAI applications such as ChatGPT, GPT-4, DALL-E, Midjourney, Stable Diffusion, Claude, Gemini, or similar generative AI technologies. The focus had to be on built environment contexts, including architecture, construction, urban planning, or building design, with specific attention to how GenAI is applied in research processes or methodologies.

Publications were excluded if they were editorial notes, opinion pieces, or commentaries without empirical or analytical content. Review papers and book chapters were also excluded. Papers that mentioned AI only tangentially without substantive GenAI analysis were removed, as were duplicate publications and non-English publications. Studies focusing exclusively on traditional AI or machine learning without generative components did not meet the inclusion threshold.

The initial, unfiltered outcome of the search revealed 1896 documents (1,011 from Scopus and 885 from Web of Science). These papers were peer-reviewed journal papers or conference proceedings in English with a specific discussion of GenAI applications in the built environment. Papers without these foci were excluded. After this initial screening, 712 articles satisfied the inclusion criteria. Removal of duplicates eliminated 221 documents, leaving a total of 491 unique publications. A comprehensive title, abstract, and keywords screening was conducted to assess relevance to the research objectives. This screening led to 21 articles for detailed analysis. The screening systematically applied the predefined inclusion and exclusion criteria to ensure only studies with direct relevance to GenAI applications in built environment research were retained.

2 Stage 2: Analysis Framework

A science mapping analysis was conducted to gain comprehensive insight into the publication and knowledge in the field. Among the available science mapping tools, such as CoPalRed, VOSviewer, BibExcel, CiteSpace, Gephi, and IN-SPIRE, VOSviewer was utilized because of its graphic-enhanced features and ability to handle large datasets. The bibliometric data were analysed in the initial stage to determine the frequency of publication based on year, geographic distribution, leading authors, and keywords. As explained by Hsieh and Shannon (2005), content analysis is an approach that aims at identifying texts, words, statements and phrases used as text data for data analysis. For this study, the content analysis was conducted on the 21 selected papers by coding each paper's objectives, methodologies, and key findings. It also identified recurring themes on GenAI applications in built environment research. The analysis also examined the key challenges and opportunities associated with GenAI.

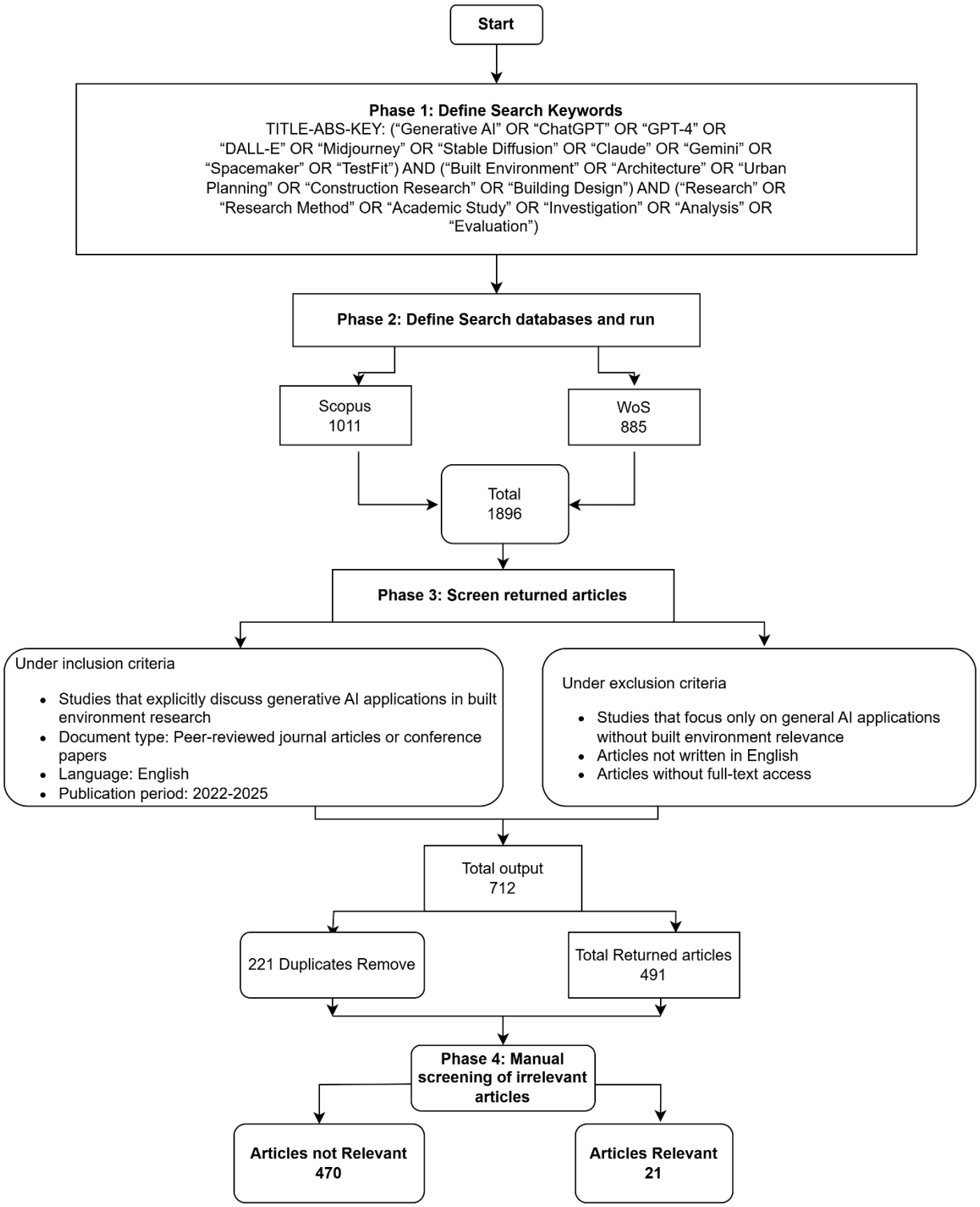

Figure 1: *PRISMA-based SLR flow diagram*

(Source: Author's Construct, 2025)

RESULTS

Current status of generative AI application in built environment research

Mapping of the Co-occurrence of keywords

Keywords network analysis ensures a coherent illustration of a specified sphere of knowledge, ensures a comprehensive understanding of topics, and the cognitive inter-relationships between these topics (Babalola *et al.*, 2023). For this study, the VOSviewer software was used to map the co-occurrence of keywords. In VOSviewer, the circles and labels display items in the visualization network while the distance between each item indicates the strength of their relationships. Consequently, the greater the distance between any two specified sites within the network, the lower the correlation between the associated items, and vice versa. While there are no standard rules for setting the frequency of the occurrence of the keywords, known best practices from construction studies were adopted in this study. Consequently, using the full counting method with co-occurrence as the basis of analysis, the minimum keyword occurrence was set to 2. Out of the total keywords identified, 12 keywords co-occurred. Figure 2 shows a network visualization map of the co-occurring keyword clusters. The size of the circles show how frequently it appeared as an author keyword. Figure 2, shows that the keywords that have distinctly larger nodes include architectural design, artificial intelligence, and large language models.

Keywords with the highest occurrences and total link strength are architectural design (7 occurrences, total link strength = 12), artificial intelligence (7 occurrences, total link strength = 13), and large language models (5 occurrences, total link strength = 10). ChatGPT shows 4 occurrences with total link strength = 11, while generative AI appears 4 times with total link strength = 2. The visualization demonstrates that architectural design and artificial intelligence form the core research focus. The dominance of architectural design reflects the field's early adoption focus on visual and creative applications, where GenAI tools like Midjourney and DALL-E show immediate impact. However, the weak linkage of generative AI (total link strength = 2) to other keywords suggests fragmented research without strong thematic connections. The notable absence of ethics-related keywords indicates a gap in critical discourse around responsible AI use in built environment research.

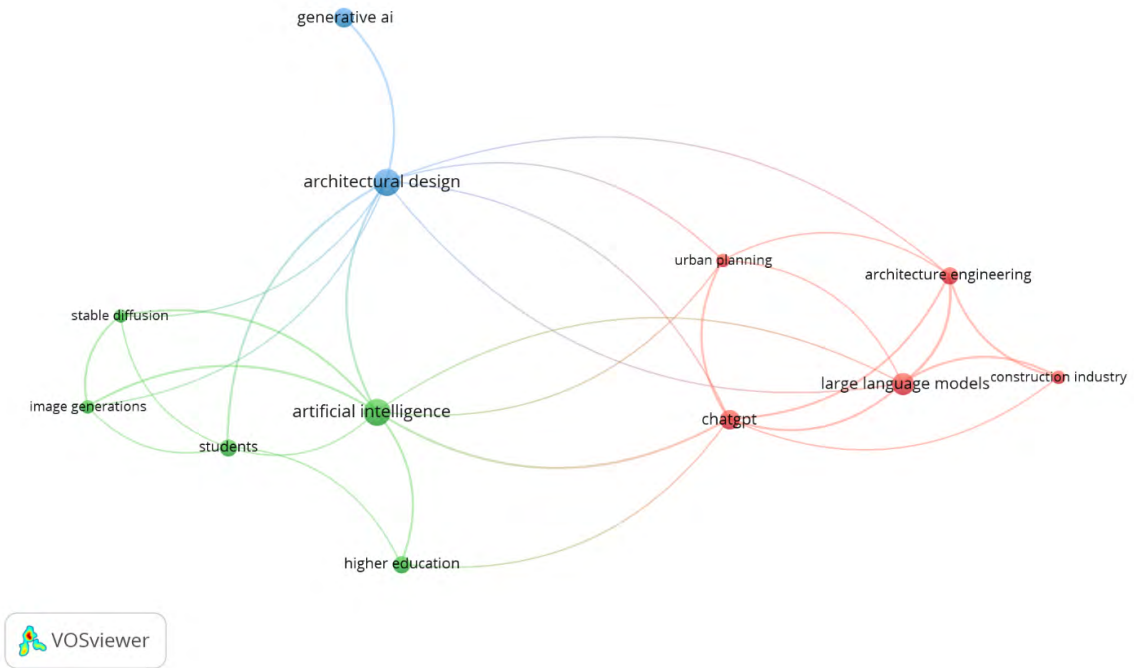

Figure 2. Network of Co-occurrence of Keywords

(Source: Author's Construct, 2025)

Mapping of co-authorship

Collaborative efforts among researchers and institutions facilitate knowledge sharing, innovations and joint research activities (Babalola *et al.*, 2023). Hence, it is essential to examine the co-authorship patterns of authors, which helps in identifying key research collaborations in the domain. As shown in Figure 3, VOSviewer was employed to generate a network visualization of co-authorship. The analysis type was configured as "co-authorship", and the unit of analysis was specified as "authors", while the counting approach adopted was "fractional counting." The minimum threshold of publications per author was established at 2. The network visualization presented in Figure 3 shows limited collaborative linkages among researchers. This observation suggests that generative AI in built environment research is an emerging domain with dispersed research activities. The findings show that individual research teams are investigating applications independently. However, as a growing and important domain, there is the need for strong collaborative efforts.

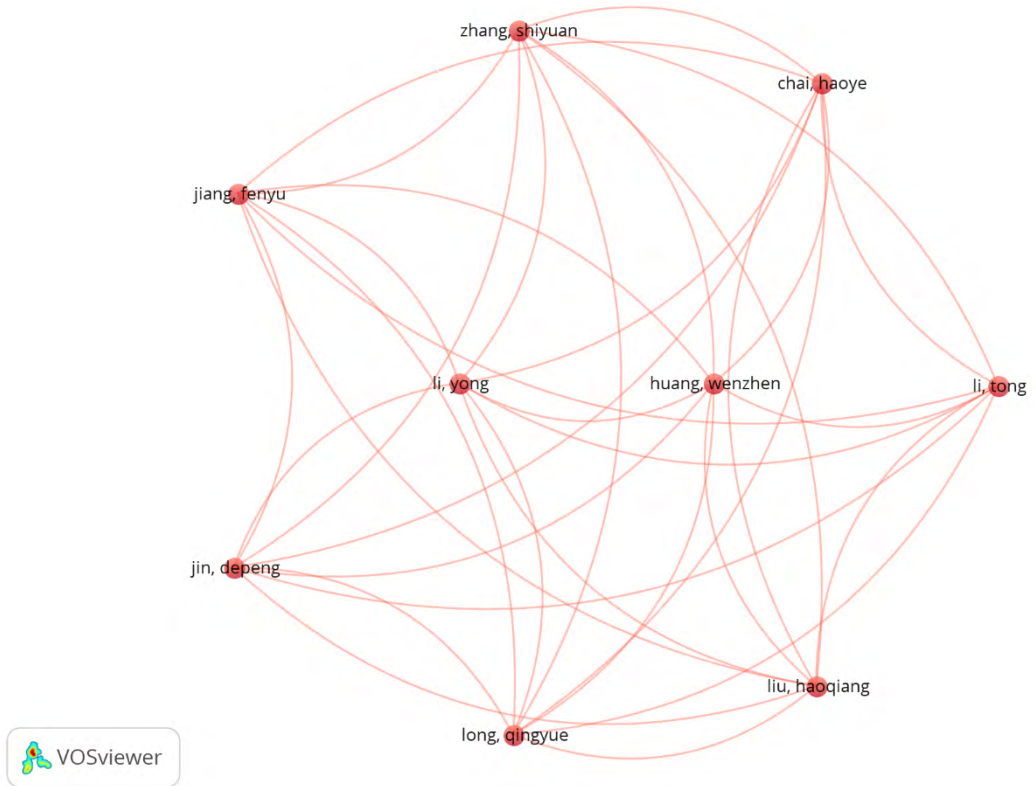

Figure 3: *Network of co-authorship*

(Source: Author's Construct, 2025)

Mapping of collaborations by country

In line with the earlier descriptions of keywords and authors' network analyses, the collaboration network of countries within relevant research domains aids in identifying active countries. Hence, VOSviewer was again employed to identify the countries that are most prominent in producing studies that focus on generative AI applications in built environment research. Similarly, the type of analysis chosen was "co-authorship" with the unit of analysis configured as "countries", and the counting approach was "fractional counting." In addition, the minimum threshold of documents per country was established at 1, while the minimum threshold of citations per country had a default setting of 0. The total number of countries identified by VOSviewer software was 21, with all satisfying the thresholds. The largest set of connected items was, however, 21 items as displayed in Figure 4, which illustrates the research-active countries in generative AI for built environment research. As observed in Figure 4, larger nodes indicate China, United States, and United Arab Emirates. The most research-active countries are China (5 documents, total link strength = 2), United States (4 documents, total link strength = 6), and United Arab Emirates (2 documents, total link strength = 0). It can also be observed from Figure 4 that the analysis shows a globally distributed but relatively sparse research landscape. China dominates in publication output, while the United States exhibits stronger international collaborative connections, establishing it as a central connector in the

global research network. The UAE's substantial citation count (183) with limited collaboration indicates focused high-impact research with restricted knowledge dissemination.

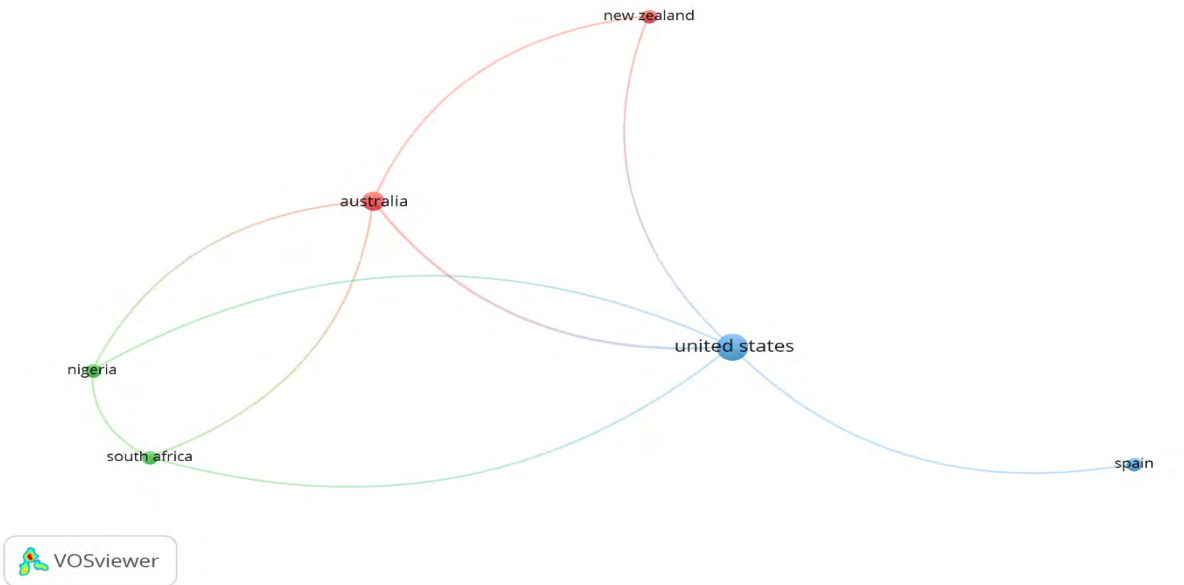

Figure 4: *Network of Collaborations by Country*

(Source: Author's Construct, 2025)

Distribution of publications by year

In this study, 21 journal articles were used for content analysis as distributed in Figure 5. Figure 5 shows the annual publication trend of articles related to generative AI applications in built environment research. The articles were published from 2022 to 2025. The figure clearly shows a significant overall upward trend in the number of published articles on GenAI applications in built environment research from 2023 to 2025. This increase in number of publications could be attributed to the advancement of GenAI technologies. Also, there is a growing interest by both practitioners and researchers in this field. For instance, the public release of ChatGPT in November 2022 promoted the demand for AI-assisted research methodologies. The analysis also shows a significant increase in papers in the year 2024. This pattern indicates rapid recognition by built environment researchers of GenAI's transformative potential. Hence, it can be projected that future research methodologies will be greatly shaped by the transformative potentials of GenAI.

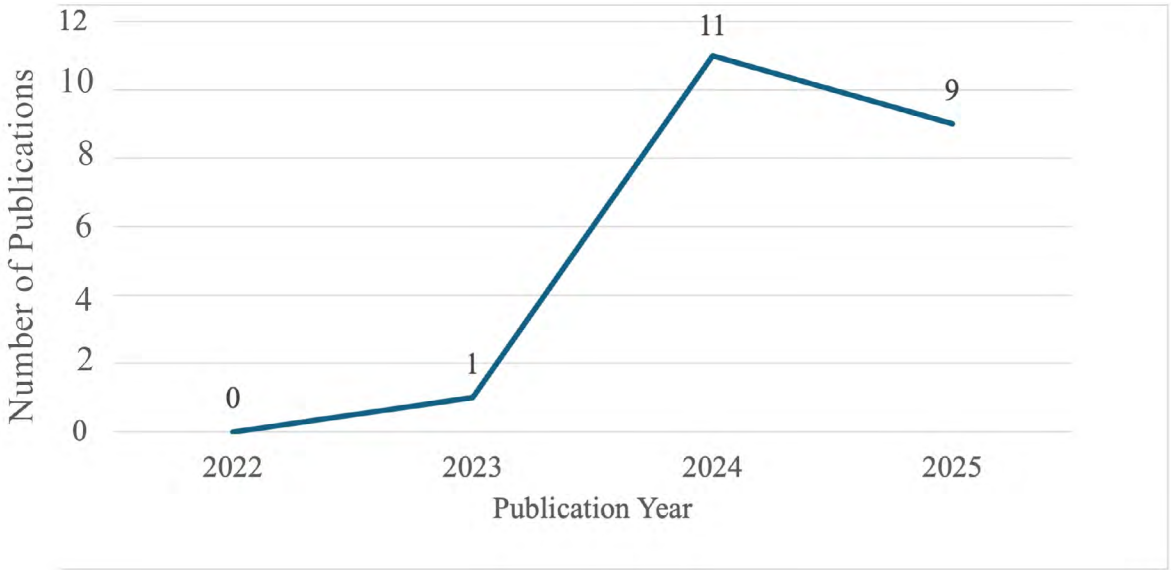

Figure 5: *Distribution of publications by year*

(Source: Author's Construct, 2025)

DISCUSSIONS

The Main Areas of Research in the Domain

The built environment research involves researchers who approach their object of study from diverse disciplinary and methodological perspectives. Scholars within the field conduct research that requires theories and methodological tools that cut across the disciplines of arts, statistics, philosophy, etc. (Knight *et al.*, 2009). The domain has long relied on conventional research methodologies. However, built environment professionals and researchers have seen the need to transition from traditional design methods to more modernized, advanced research approaches. The review identified five main thematic areas where GenAI is transforming built environment research: design generation and visualization, multimodal data analysis, educational transformation, decision support systems, and human-AI collaboration frameworks. These themes align with the bibliometric findings presented earlier. The dominance of "architectural design" in keyword co-occurrence (7 occurrences) corresponds with the substantial focus on design generation applications in the reviewed studies. Similarly, the strong presence of "large language models" as a keyword reflects the emphasis on multimodal data analysis and educational applications discussed below. The sparse co-authorship network observed in Section 4.1.2 is also evident in the content analysis, where most studies approach GenAI applications independently with limited cross-domain integration.

Design Generation and Visualization

The review identified that GenAI is significantly transforming design generation and visualization. This transition has been emphasized by Xu and Huang (2024) regarding how Midjourney Intelligent Drawing Software influences architectural design education. Midjourney (v.1.4.10), for instance, uses advanced image generation algorithms to facilitate complex image creation by providing simple text descriptions. From a comparative analysis done by Xu and Huang (2024) of changes in students' design works, Midjourney improves

design by enhancing visual effects, increasing design elements, and providing more spatial processing capabilities. Such capabilities can hardly be achieved using traditional methods. Cao *et al.* (2024) also showed how GenAI, like Stable Diffusion, enables higher possibilities in design exploration, elaboration, and visualization in the earlier design stages. What is more important is how these design innovations are contributing to the methodological shifts in architectural practice. For example, a study by Sukkar *et al.* (2024) opened a compelling discourse on the very evolution of Islamic architecture through modern technology. The discourse on Postmodern Islamic Architecture (PMIA) and Artificial Intelligence Islamic Architecture (AIIA) signals a paradigm shift in architectural methodologies. Scholars are leveraging AI tools and computational approaches to advance design, preservation, and understanding of architectural elements. However, Sukkar *et al.* (2024) also revealed that most GenAI models rely on general training datasets that lack region-specific architectural traditions, raising concerns about cultural sensitivity and contextual appropriateness of AI-generated designs.

Multimodal Data Analysis

Ohene *et al.* (2024) emphasized that the AEC industry produces huge heterogeneous data. More critical are the projections that this volume is expected to increase due to the proliferation of sensor networks and IoT technologies. These data sources include data from building information models (BIM), sensor networks, geographic information systems (GIS), occupancy data, energy metrics, climate data, etc. These heterogeneous data sources require comprehensive integration. Traditional analytics has over the years proven incapable of handling these complexities. Traditional analytics cannot handle the multimode nature of information generated by the industry practices. Researchers now require systems that possess the ability to analyse numeric, spatial, textual, and visual data together. Unlike most industries, the AEC industry relies on temporal data but requires real-time analytic capability. This presents considerable difficulties.

These complexities have ushered researchers to explore complex analytics such as knowledge extraction and ontology generation. The pursuit is demonstrated by Tupayachi *et al.* (2024) with the purpose of advancing operations research. The study used pre-trained Large Language Models (LLMs) to create knowledge representations. This demonstrates that improving data and metadata modelling and data integration, and simulation coupling significantly advances the built environment research frontier. Researchers have illustrated these analytical capabilities in construction management practices and geomatics engineering. A study by Taktak (2025), through analysis of case studies, provided in-depth insight into how the use of ChatGPT allowed for processing and interpreting larger datasets. The study found ChatGPT facilitates timely data analysis by research with about a 40% reduction in analysis time. Despite these advances, Tupayachi *et al.* (2024) acknowledged the potential for LLMs to hallucinate, negatively impacting the reliability and accuracy of ontologies produced. This reliability concern underscores the need for validation frameworks in AI-assisted data analysis.

Educational Transformation

This review also identified the transformative role of GenAI in built environment education. According to Abril *et al.* (2024), LLMs like ChatGPT are improving critical thinking in construction management students. Dempere *et al.* (2023) also outline how GenAI is serving as research assistance, automated grading, and enhanced human-computer interaction.

Wang *et al.* (2022), however, argue that there is the need to keep abreast of the technological developments within the field. Yet concerns exist about academic integrity and over-reliance on AI tools. Kim *et al.* (2025) identified a lack of understanding of AI as a limitation within academic research, suggesting students may use these tools without comprehending their capabilities or constraints.

Decision Support Systems and Technical Applications

The research domain also has a number of technical contexts showing the ability for AI to adapt to the challenges of the built environment. For example, Durmus *et al.* (2024) discusses "AI-in-the-loop" models that can promote decision support for dynamic building environments in a fire safety planning setting. Pugliese *et al.* (2024) also explain how feedback to LLMs can be used for dynamic production parameter adjustment/debugging errors and improving productivity in additive manufacturing. However, Durmus *et al.* (2024) noted challenges that both expert systems and LLMs face, including implementation costs. Pugliese *et al.* (2024) observed that some open-source pre-trained models were not fine-tuned for specific sectors, limiting their immediate applicability.

Human-AI Collaboration in Research Practices

These transformations in research methodologies represent a meta-level domain that exemplifies AI's ability to disrupt scholarly practices. However, Garcia (2023) explains that the acceptance of technology may take different forms than the acceptance of traditional tools. The study, for instance, elucidates that researchers weigh trusting beliefs and the compatibility of a technology to a task first. Pereira *et al.* (2024) elucidate that AI is informing the structuring and presentation of knowledge on certain topics, data mining, and referencing and consulting sources. These applications indicate GenAI is reshaping fundamental research tasks, yet questions remain about the appropriate boundaries of human-AI collaboration and maintaining research integrity when using these tools.

The Gaps in the Existing Body of Knowledge

Even though the review shows progressiveness in the use of generative AI in built environment research, several gaps currently hinder deep understanding and applications. There is a crucial lack of domain-specific theoretical frameworks (Belaroussi, 2025). As an emerging field, there is a general lack of theoretical frameworks across industries. It is, however, important to note that without domain-specific frameworks, there will be no clear understanding of what the future actually holds (Wang *et al.*, 2022). Some studies also found the results of GenAI in research as not reliable or valid (Thampanichwat *et al.*, 2025). These concerns undermine the confidence of professionals in applying generative AI. Tupayachi *et al.* (2024) also acknowledge the potential for LLMs to hallucinate. These negatively impact the reliability and accuracy of the ontologies produced. Kim *et al.* (2025) identified the lack of understanding of AI as a limitation within academic research. According to Pugliese *et al.* (2024), reliability issues intersect with technical limitations. Pugliese *et al.* (2024) further observe that some open-source versions of pre-trained models were simply not fine-tuned for certain sectors. The concern of validating the accuracy and reliability of AI ontologies becomes urgent when considering the observations of Durmus *et al.* (2024) about challenges that both expert systems and LLMs face and the costs involved. The failure to recognize cultural and contextual issues relating to AI in the built environment, to a great extent, limits its application. Sukkar *et al.* (2024) affirms that the underlying reason for this is greatly due to the general nature

of the training data used for GenAI models. The training data is broadly based and does not account for cultural or regional aspects. The implications of the lack of cultural aspects go beyond academia. For example, Aly *et al.* (2025) show that general-purpose applications are simply not culturally specific enough or sensitive to context or to the depth of understanding to address complex architectural problems. GenAI application is capable of ameliorating these defects in a common platform usage opportunity. GenAI can be used, for example, as a platform of analysis for common forms of data representation and as a model of analysis. Developments such as this have the potential for great improvement in decision support systems. Unfortunately, studies show a challenging fragmentation of the implementation of GenAI. Instead of using the possibilities of GenAI for an interdisciplinary collaborative effort, most models are utilized for a discipline-specific application. Onatayo *et al.* (2024) noted that most of the studies are undertaken on specific applications that produce little measurable impact. Dempere *et al.* (2023) also studied the effects of AI chatbots on higher educational institutions, but acknowledged that the study did not take into consideration the possible effects and implications of implementation.

Future Research Directions

The review has identified areas where GenAI is being applied in built environment research, and has also provided insight into the gaps in knowledge. This section therefore synthesizes and gives directions for future research to realize the full potential of GenAI. The findings shows that efforts should be directed towards addressing gaps while paying close attention to the dynamics that emerges. Given the culturally sensitive nature of the domain, while models rely on general training data, studies should focus on how to develop targeted models. For example, Sukkar *et al.* (2024) rightly points to the need for the training data to be reflective of the diversity of Islamic architectural traditions from different regions and historical periods. Some researchers are also of the opinion that this specialization should go beyond culture (Abril *et al.*, 2024). Li *et al.* (2025) for instance, envisioned human-enabled Artificial General Intelligence; native networks which have human characteristics like reasoning, planning, perceptions, and common sense which could be tailored for built environments. Comprehensive validation frameworks are needed because it improves professional confidence. Tupayachi *et al.* (2024) also calls for employing fine-tuning practices to direct LLMs to generate more specialized ontologies. The study further recommended the development of software modules and codes that advances urban decision support system. This review identified challenges of consistency, reliability, and adaptability; hence, the need for evaluation metrics. These evaluations metrics are also expected to go beyond just technical accuracy to the consideration of professional applicability and safety implications.

As an emerging practice, research on educational and skills development requires systematic intention to prepare professionals for the responsible use of AI. Kim *et al.* (2025) recommends exploring how to develop both higher-order thinking skills for students and AI, while Abril *et al.* (2024) show examples of implementations using AI as a tool in construction management education. From the view of Onatayo *et al.* (2024), this transformation in education needs to address essential imperatives for up-skilling, developing a robust framework for AI use in higher education to enhance AI literacy and foundational skills. Future research could further explore how the findings of Xu and Huang (2024) on Midjourney could inform developing curricula for AI integration in higher education. As fragmentation remains a major challenge, studies point to interdisciplinary collaborations as strategic solution (Pereira *et al.*, 2024; Sanchez *et al.*, 2024). Research directions for developing ethical and governance

frameworks must be prioritized to address the concerns of stakeholders. Tang *et al.* (2024) advocate for standard transparency requirements. Similarly, Garcia (2025) call for exploring misinformation analysis regarding AI-generated outputs that produced synthetic information that are factually incorrect.

CONCLUSION

This study provided a state-of-the-art SLR review to identify the role of GenAI in built environment research. It also makes a case for its future need. Following the PRISMA guidelines, a bibliometric and content analysis was conducted on 21 carefully selected papers. The study identified that the built environment research domain is gradually transitioning to technologically advanced methodologies. GenAI is drastically transforming design creation, data processing and analysis, decision-making support, and educational innovation. Such a transformation presents considerable benefits to addressing the complex-built environment challenges. Despite these advancements, there are significant barriers that still impede AI from reaching its full potential in this area. The research found seven main knowledge gaps: lack of clarities on the relationship between the outputs of AI and human professional judgement; the absence of appropriate AI models designed for built environment applications; issues of real-time data processing; limitations of scaling for larger projects; challenges of inputting domain knowledge into AI systems; lack of trusted validation processes; and privacy and ethical challenges. Most of the current research efforts remain isolated, failing to create the theoretical foundations or connections across disciplines, hence, limiting the understanding of the impact of AI in built environment fields. The study however identified eight research areas that need to be prioritized to advance the field. Among these, developing validation frameworks and ethical guidelines are foundational priorities, as they underpin the responsible implementation of all other GenAI applications. Building domain-specific models and fostering interdisciplinary collaboration are secondary priorities that depend on these ethical and quality assurance foundations. Researchers should develop AI models for built environment applications, develop methods for testing quality and reliability, improve collaboration between humans and AI; develop frameworks for cross-disciplinary collaboration, reform educational programs and training; create ethical guidelines and governance structures; develop technological infrastructure; and longitudinal studies examining the impacts of AI over time. Prioritizing these areas appropriately will require dedicated collaborative efforts from universities, professional associations and regulators to develop AI technologies that meet the professional requirements while addressing the broader social implications.

The implications of the findings are important for both academic research and professional practice. Researchers are provided with a detailed understanding of AI applications, new methodological approaches and areas that require further studies. Professionals are provided with insight concerning new tools and methods that could improve their work practices, as well as guidance about the importance of developing AI skills to support their professional capabilities. The study emphasizes the need for educational institutions to enhance their educational programs and educational approaches to prepare students and professionals for future workplaces. However, this review has limitations that should be acknowledged. The relatively small sample size reflects the emerging nature of GenAI in built environment research but limits generalizability. The focus on English-only publications from Scopus and Web of Science may introduce geographic and language bias. The temporal scope (2022-2025) ensures currency but may exclude earlier foundational work. However, the main issues

require urgent attention. The rapid rate at which AI is developing means that the findings of this research will need constant revisions to maintain usefulness and accuracy.

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Designing Inclusive Learning Environments: Application of Universal Design for Learning to Enhance Visual Arts Education for Students with Learning Disabilities

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Article History
Received 5 Nov. 2025
Accepted 23 January 2026

Abstract

Universal Design for Learning (UDL) represents a transformative framework for inclusive education, moving beyond accommodation to promote equitable and engaging learning for all students. In Ghana's mainstream Senior High Schools (SHS), however, students with learning disabilities (LDs) continue to experience marginalisation due to limited teacher preparedness, negative perceptions, and insufficient adaptive instructional strategies. This study explored how the application of UDL principles enhances teaching and learning experiences in Visual Arts education for students with learning disabilities in a co-educational public SHS in the Ashanti Region. A convergent parallel mixed-methods design was employed, using questionnaires, focus group discussion and classroom observations to gather data from a purposive and convenience sample of 100 second-year Visual Arts students. Findings revealed three student categories; normative (56%), students with LDs (31%), and those with special educational needs and disabilities (13%) whose LDs emanated thematically from environmental barriers to learning, unsupportive institutional response and teacher-student variables, and emotional and cognitive manifestations of learning struggles. Students highly valued the UDL principles of multiple means of representation (M = 4.29, 85.8%), engagement (M = 4.23, 86.4%), and action and expression (M = 4.28, 85.6%). Strong positive correlations were observed between UDL principles and student engagement and participation, indicating that UDL significantly predicts improved learning outcomes ($R = .96$, $F(1,98) = 1054$, $p < .001$) with a large effect size ($R^2 = .971$). The study underscores the potential of UDL as a pedagogical model for designing inclusive learning environments that foster academic success and participation among students with learning disabilities in Visual Arts education.

Keywords: inclusive learning environment, universal design for learning, learning disabilities, special educational needs and disabilities, visual arts students, mainstream senior high school

INTRODUCTION

In a rapidly diversifying global education landscape, the pursuit of inclusive education has emerged as both a moral and pedagogical imperative. Central to this movement is Universal

Design for Learning (UDL), a transformative educational framework that challenges the traditional "one-size-fits-all" model of teaching. UDL promotes flexible curriculum design that accommodates the full spectrum of learner variability and ensures equitable access, participation, and progress for all students, especially those with learning disabilities (LDs) (King-Sears *et al.*, 2023). Through its three core principles: multiple means of engagement, representation, and expression, UDL provides a scaffolded structure that fosters meaningful learning experiences (Syre-Hager, 2022; Niad *et al.*, 2021).

Emerging studies within Ghana highlight the promise of UDL in reimagining inclusive education. Study by Adom *et al.* (2023) in visual arts education has demonstrated how UDL principles can democratize access to content and foster active learning. Additionally, Niad *et al.* (2021) provide technical guidance for educators to implement UDL strategies effectively, particularly for learners with difficulties. Likewise, Nantwi *et al.* (2023) demonstrate that art teachers who applied UDL strategies improved classroom inclusivity. These findings align with international evidence that confirms the adaptability of UDL across cultural and educational settings (Almumen, 2020). Regardless of the positive examples of UDL, this framework remains isolated and has not translated into widespread practice within the Visual Arts domain, where creativity, diversity, and individualised expression are core but frequently constrained by rigid instructional models (Adom, 2022).

Although the Global Initiative for Inclusive ICT (2020) reported UDL implementation in SHSs in the Upper West, Upper East, North East, and Northern regions, these efforts were confined to students in special schools, not in mainstream SHS settings or visual arts students with LDs. Again, Adom (2022) reflects on his UDL practice as an SHS visual art teacher but is silent on students with LDs. Thus, sparse studies of UDL as inclusive strategies in mainstream classrooms where neurodiverse learners and learner variability are co-instructed with their peers (Celestini, 2022), highlights a critical research gap that could extend to harnessing stories of lived experiences and support needs of Visual Arts students with learning disabilities in educational practice. Hence, nowhere is UDL more pressing than in mainstream SHS visual arts classrooms, where students with LDs often face exclusion caused by inadequate teacher preparedness, stigmatising attitudes, and a lack of differentiated instructional tools (Opoku, 2022).

Despite the acknowledged benefits and localized application of UDL in Ghana's education, its implementation remains isolated and has not translated into widespread practice within mainstream SHS visual arts classrooms, especially for students with LDs. Furthermore, the specific lived experiences and support needs of Visual Arts students with LDs in mainstream settings constitute a critical research gap. The primary aim of this study is to examine how the UDL framework can inform the design of inclusive learning environments to enhance the educational prospects of students with LDs in mainstream SHS visual arts classrooms in Ghana. To achieve this aim, the study pursued the following specific objectives: to explore the lived experiences and support needs of Visual Arts students with LDs in mainstream SHS settings; to apply the principles of UDL to develop context-driven guidelines for designing inclusive visual arts learning environments; and to evaluate the potential impact of UDL-informed instructional practices on enhancing participation and engagement for students with LDs.

The subsequent sections of this paper are structured to first provide a detailed review of the literature on UDL and its application as an inclusive education practice, and learning disabilities and its identification criteria among visual arts students. Following the literature review, the methodology section details the convergent parallel design, data collection instruments, sampling procedure, and analytical approach employed in the study. The findings section then presents the empirical data collected through questionnaires, observations and focus group discussion, organised according to the study's specific objectives. Finally, the discussion interprets these findings in relation to existing literature, followed by the conclusion, which summarizes the study's main contributions, outlines the developed UDL-informed guidelines, and provides recommendations for future research and practice.

LITERATURE REVIEW

UDL Framework and Its Core Components

Universal Design for Learning (UDL) is an educational framework grounded in cognitive neuroscience that aims to make learning accessible and effective for all learners, particularly those with disabilities. Developed by CAST, UDL emphasises flexible curriculum design to accommodate learner variability (CAST, 2024). The framework revolves around three core principles: Multiple Means of Engagement, Representation, and Action and Expression, each addressing the why, what, and how of learning (Rao *et al.*, 2023). Recent studies affirm UDL's growing relevance in inclusive education. Levey (2023) explains that UDL promotes educational equity through anticipation of diverse learning needs. This is especially relevant in visual arts classrooms, where traditional methods can hinder creative expression among students with learning disabilities. UDL enables such classrooms to evolve into inclusive environments that support different ways of engaging, perceiving, and expressing knowledge.

Multiple Means of Representation

This principle focuses on presenting information in various formats to aid perception and comprehension. Students with LDs often struggle with decoding language, interpreting symbols, or understanding abstract concepts, which are key in visual arts education (CAST, 2024). Nave (2021) notes that integrating visual diagrams, videos, and interactive simulations supports understanding of complex ideas. Hence, the use of Videos, PowerPoint presentations, and Printouts can be used to make lessons more tangible and reduce cognitive load. Almeqdad *et al.* (2023) affirm that UDL's representation strategies enhance academic performance, especially for students with diverse learning needs. In visual arts classrooms, layered scaffolds, step-by-step visuals, or symbol-supported instructions can increase content accessibility.

Multiple Means of Engagement

This principle addresses how learners get involved and stay motivated. For students with LDs, sustaining attention in traditional classrooms is often challenging (CAST, 2024). UDL suggests providing choice, autonomy, and emotional support to maintain engagement. Saunders and Wong (2023) and Adler and Kletenik (2025) argue that allowing choice in content, tools, and assessment boosts intrinsic motivation. In visual arts, this could mean choosing materials or themes based on interest and increasing emotional investment. Moleko (2021) adds that adaptive strategies like gamification and peer collaboration benefit students with attention difficulties. UDL also builds community and encourages self-regulation, which tends to reduce

anxiety and frustration (Owiny & Hartmann, 2020). These strategies support both academic achievement and emotional well-being.

Multiple Means of Action and Expression

This principle concerns how learners demonstrate their knowledge. Students with LDs may have difficulties with motor coordination, organisation, or expressive language, which can impact art assessments (CAST, 2024). Multiple Means of Action and Expression ensures that students, particularly those with LDs, have flexible options to navigate the learning environment and demonstrate knowledge (Rao *et al.,* 2023). This requires providing varied assessment methods in visual arts, such as oral presentations, digital portfolios, exhibitions, video submissions, or performance-based tasks, rather than relying on a single format (Kärpänen *et al.,* 2024), thereby supporting the development of Personalized Learning Paths based on individual strengths (Abaa, 2025). Sewell *et al.* (2022) have framed UDL as an inclusive practice aligned with educational psychology, which enables student agency. Experiential and project-based learning methodologies aligned with UDL framework inherently support and fosters students' metacognition and independence to learn (Leighton, 2023). Through experience-based applications, UDL again serves as an effective mechanism for overcoming typical barriers to learning and actively promotes self-regulation and goal-setting, a core component of metacognition (Mackey *et al.,* 2023). Furthermore, these active learning approaches, with the integration visual thinking strategies, simultaneously lead to deeper participation and comprehension in the classroom (Flood *et al.,* 2025).

Learning Disabilities

Learning disabilities (LDs) are neuro-developmental disorders that interfere with acquiring, organising, retaining, or using verbal or non-verbal information. They manifest in difficulties with listening, speaking, reading, writing, spelling, or performing mathematical tasks (U.S. DoE, 2025). This definition reflects the broad and heterogeneous nature of LDs, which can impact visual arts students' academic and creative performance.

Identification Methods and Challenges

The identification of LDs remains inconsistent due to the historical shift between the Cognitive Discrepancy Model and the Response-to-Intervention (RTI) approach, alongside limited teacher training, an issue impacting teacher preparedness for this essential classification shift (Hogan, 2025). While the multi-tiered RTI/MTSS model is a prevalent framework for screening and intervention in academic areas (Keles *et al.,* 2025; Al Otaiba *et al.,* 2025), the application remains inconsistent, often delaying or preventing accurate identification, especially for highly creative students who mask their difficulties. To ensure inclusive education and tailored support (Walton & Engelbrecht, 2024; Rothstein & Johnson, 2025), a comprehensive, interdisciplinary collaboration involving educators, specialists, and counsellors is essential; for visual arts students, this means supplementing standardized tools with rich qualitative data from behavioural observations, functional assessments, teacher reports, and portfolio assessments, aligning with the UDL value of promoting instruction based on individual strengths.

International and Inclusive Perspectives

Globally, identification frameworks are shifting toward more inclusive, culturally responsive systems. Lien (2025) proposes a systems-theoretical approach that decolonises Special

Educational Needs and Disabilities (SEND), urging recognition of how social structures influence diagnosis and access. Alghrani *et al.* (2024) highlight a crisis in SEND assessments, advocating for early intervention, family involvement, and well-trained assessors aligned with UDL. The NC DPI Exceptional Children Division (2021) stresses documentation and individualised plans to guide support. These enable educators to apply UDL strategies like varied expression and targeted feedback. The Middlesbrough Council (2021) emphasises inclusive policies backed by professional development. However, without systemic commitment, even strong UDL designs may fall short in supporting students with LDs in the arts.

Learning Disabilities Identification Based on Academic Benchmark

In Ghana, students complete junior high school (JHS) by age 14 and transition into SHS between ages 15-18 (MoE, 2018a). Placement is determined by the Computerised Selection and Placement System (CSSPS), which works with BECE results, school choices, and a deferred acceptance algorithm (Babah *et al.*, 2020). Aggregates 6-15 enter Category A, 10-25 go to Category B, while 10-30 go to Category C schools (Kankam *et al.*, 2025). Due to systemic perceptions shaped by identity and system justification theories (Baidoo-Anu *et al.*, 2022), low-performing students are often assigned to pursue visual arts, regardless of interest (Kankam *et al.*, 2023), leading to discrimination, especially in core subjects (Kankam *et al.*, 2025). Interestingly, Kankam (2023) identified a strong positive correlation between underperformance and learning disabilities. Guided by IDEA 2004 (U.S. DoE, 2025), NC DPI (2021), Government of New Brunswick (2003), and category benchmarks (Kankam *et al.*, 2023), students who scored 10-25 were normative, 26-30 were labelled as learning disabled, and those placed in visual arts despite falling below all categories were identified as having SEND (Lien, 2025). Teaching these students is demanding and time-intensive.

RESEARCH METHODOLOGY

Setting, Design, and Sample

Guided by the pragmatism paradigm, this study employed a mixed-methods approach using a convergent parallel design to collect and analyse quantitative and qualitative data concurrently but separately (Terrell, 2022). This allowed for the triangulation of quantitative data (obtained through the UDL 36-item scale) with qualitative data (through focus group discussion and observations) to achieve a more comprehensive, and in-depth understanding of designing inclusive visual arts environments for students with LDs than single-method approaches would yield. The study was conducted at Juaben Senior High School (SHS), a co-educational public school in the Ashanti Region of Ghana, from 17th February to 28th May 2025 (15 weeks). The school was strategically selected as a case for this study because its designation as a Category B school (Kankam *et al.,* 2025), which enrolls students with average or below-average academic performance, provides an ideal setting to validate the established correlation between the prevalence of LDs and lower academic performance (Kankam, 2023), consistent with system justification theory (Baidoo-Anu *et al.*, 2022). Furthermore, using this specific site was necessitated by the study's longitudinal design, which required monitoring two separate student cohorts (2022-2023 and 2024-2025) within the same school to establish a trend in LD identification and effectively test the educational intervention based on the UDL framework. Only Form 2 Visual Arts students were considered in this study since the analysis was strictly confined to the first stage of the longitudinal study involving this specific cohort group. The study utilized a total enumeration (census) approach (Nanjundeswaraswamy & Divakar, 2021) targeting the accessible population of Form 2 Visual Arts students (N=114), with

the final sample of n=100 representing the maximum accessible participants after excluding the 14 students who did not complete the initial two phases of the study model. Convenience sampling was used due to the researchers' access and facilitation role during regular student classroom practice, while purposive sampling ensured the selection of the precise target population (Form 2 Visual Arts students) involved in the distinct practical approaches and instructional content of visual arts education. Form 3 Visual Arts students were used for piloting between 13th and 31st January 2025 for this specific cohort study. While sharing similar characteristics, they had not yet been taught the specific Form 2 syllabus content embedded in the research instrument, thus preventing curriculum sensitization among the main Form 2 sample. Hence, the entire available Form 3 students (n=85) were included in the pilot study to maximize data for instrument validation and were subsequently excluded from the main study to maintain the integrity of the Form 2 sample and prevent contamination of the actual research results.

Procedures and Ethics

Permission to undertake the study was granted by the EIST Department, KNUST (EIST/S/3) and the Ghana Education Service (Ref: T.J14/90/22). The study followed ethical standards regarding voluntary participation, informed consent, anonymity, and confidentiality (Alipour *et al.*, 2023; Nii Laryeafio & Ogbewe, 2023). Participants were informed about the study's purpose and could withdraw at any time without penalty. Written consent was obtained from all students, with additional parental consent for minors. Data were securely stored and accessible only to the research team. Photographs were used only with explicit permission. To maintain ethical integrity, pseudonyms were assigned to all participants, and no identifying information appeared in reports or publications.

Measurements

Quantitative data were collected using the CAST (2024) Universal Design for Learning (UDL) 36-item scale, which measured three constructs: representation (12 items), engagement (13 items), and action and expression (11 items). Items were rated on a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree) and took approximately 35-40 minutes to complete. Pilot testing established instrument reliability with a Cronbach's alpha of 0.805 (Malapane & Ndlovu, 2024). Qualitative data were collected via two forms: Focus Group Discussion (FGD) with eight participants, and non-participant observation supplemented by field notes. The selection of eight participants is justified by empirical guidelines for FGDs, promoting rich data generation while ensuring manageability and informational saturation (Hennink & Kaiser, 2022; Wutich *et al.,* 2024). The FGD lasted approximately 62 minutes, aligning with the optimal timeframe necessary to explore complex issues in depth without compromising participant focus (Hennink & Kaiser, 2022).

Data Collection and Analysis

Quantitative data, collected via Google Forms, were exported in CSV format, cleaned using Microsoft Excel (2016), and analysed using Jamovi (2.6.44). Descriptive statistics summarized students' perceptions, while Pearson's correlation and multiple regression analyses tested relationships between UDL principles and learning outcomes ($p<.001$). Qualitative data from the FGD specifically explored students' lived experiences, categorized into three themes: Environmental Barriers to Learning, Unsupportive Institutional Response, and Emotional and Behavioural Manifestations of Struggle. Data from the classroom observations documented

student engagement during practical Visual Arts lessons designed around the three UDL principles. The qualitative data analysis employed Braun and Clarke's Thematic Analysis (2021; 2006). This process systematically involved six procedural phases: familiarization, generating initial codes, searching for themes, reviewing and refining themes, defining and naming the themes, and producing the final report. To ensure trustworthiness and minimize bias, the criteria of credibility, transferability, dependability, and confirmability were upheld (Ahmed, 2024; Haq *et al.,* 2023). Finally, quantitative and qualitative findings were triangulated and interpreted according to the study's objectives (Schlunegger *et al.,* 2024).

FINDINGS AND DISCUSSIONS

Study Participants

Age and Gender

Table 1 indicates the age and gender of the sampled visual arts students, with the majority (66%) being male, while age-wise, 89% were between 15 and 18 years old. Details on age and gender are presented in Table I.

Table I: *Age and Gender of Participants*

Class/Form	Gender	Age	Frequency	% of Total	Total
SHS2	Female	<15	1	1.0 %	
		15-18	30	30.0 %	
		19-22	3	3.0 %	34 (34%)
	Male	<15	4	4.0 %	
		15-18	59	59.0 %	
		19-22	3	3.0 %	66 (66%)

Source: Field Data, 2025

BECE Aggregate Scores of Students

The Ministry of Education (MoE) and Ghana Education Service (GES) are saddled with social identity and system justification theories, and as such, students with lower scores are often assigned to the visual arts programme irrespective of their interests or strengths (Kankam *et al.*, 2023). On that premise, the study sought to ascertain the BECE aggregate scores of the sampled visual arts students. Figure 1 indicates aggregate 15-18 (8%) as upper-performance students, and aggregate 19-25 (48%) as lower-to-mid performance students. This implies that the sampled students' performance was skewed towards the lower end of category B schools' grade criteria. However, aggregates 26-40 (44%) were deemed as 'underperforming or academically weak' students and were also recorded (Kankam *et al.*, 2023). Details of the aggregate distributions are illustrated in Figure 1.

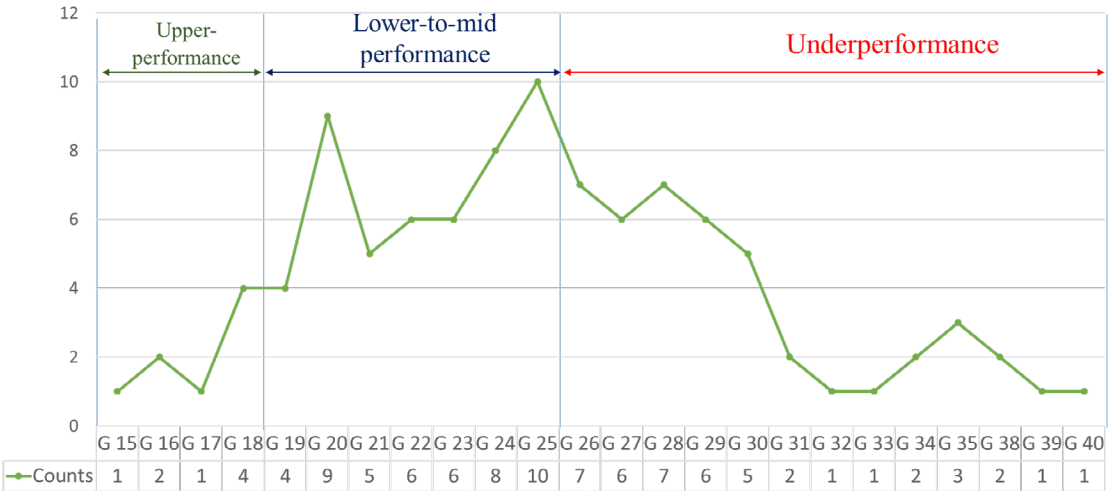

Figure. 1: *BECE Aggregates of Visual Arts Students*

(Source: Field Data, 2025)

Categorisation of Students Based on BECE Aggregates

Based on IDEA 2004 (US Department of Education, 2025), Specific Learning Disability Fact Sheet #4 (NC DPI Exceptional Children Division, 2021), Learning Disability Identification Manual (Government of New Brunswick, 2003), and the aggregate criteria for category B SHSs (Kankam *et al.*, 2023), the sampled visual arts students were categorized into three groups with normative students (56%) being dominant. Table II presents the detailed distribution of the groupings.

Table II: *Categorisation of Students Based on BECE Aggregates*

LD Category	BECE Aggregates	Frequency	% of Total
Normative Students	Aggregate 25 and below	56	56.0 %
Students with LD	Aggregate 26-30	31	31.0 %
Students with SEND	Aggregate 31 and above	13	13.0 %
Total		100	100.0%

**Note: Based on Specific Learning Disabilities Policy Fact Sheet #4 (NC DPI ECD, 2021), IDEA 2004 (US DoE, 2025*

(Source: Field Data, 2025)

Identification of Students' Learning Disabilities

Guided by the Learning Disability Identification Manual (Government of New Brunswick, 2003), the sampled students manifested varied forms of learning disabilities spread across the three categorised groups. Table III indicates that the majority (63%) manifested more than one form of learning disability, with the normative students being the worst casualty (56%). The details of the data distribution are shown in Table III.

Table III: *Students' Manifestation of Learning Disabilities*

Specific Learning Disability	Normative Student	Student with LD	Student with SEND	Total
1 Form of Learning Disability	20	11	6	37
2 Forms of Learning Disabilities	22	10	4	36
Multiple Forms of Learning Disabilities	14	10	3	27
Total	56	31	13	100

**Specific Learning Disabilities:* *Attention; Auditory; Language; Math; Memory; Organization; Reading; Spatial; Visual; Written*

(Source: Field Data, 2025)

Lived Experiences and Support Needs of Visual Arts Students with LDs

The focus group discussion reveals three dominant themes that illustrate the challenges contributing to students' academic struggles and lived experiences: Environmental Barriers to Learning, Unsupportive Institutional Response, and Emotional and Behavioural Manifestations of Struggle. These three derived themes effectively categorise and summarise the specific challenges and difficulties students with LDs described during the focus group discussion.

Theme 1: Environmental Barriers to Learning

This theme (see Table IV) encompasses the external, structural, and relational factors originating from the school, classroom, and home that impede effective learning for students with LDs.

Table IV: *Environmental Barriers to Learning*

Sub-Theme	Qualitative Comment	Participant
Deficiencies in Instructional Capacity	"Poor teaching methods," "Lack of good teachers," and "Poor professional competence of teachers."	P1, P2, P4, P5, P6, P7, P8
Inadequate Resources & Infrastructure	"Inadequate infrastructure" and "Lack of adequate teaching and learning resources."	P1, P4, P5, P7
Unconducive Home Learning Environment	"Lack of parental support for learning," "Overloaded house whole chores," and the mother's words keep ringing 'Put the book away' whenever I pick a book to learn.	P3, P2, P5

Field Data, 2025

This theme (Table IV) emphasizes that students' academic struggles are primarily rooted in external systemic failures, encompassing infrastructural deficits, critically inadequate teaching and learning resources, and a widespread deficiency in teachers' professional competence and methods. Furthermore, the data highlights that the home environment is often unsupportive, characterized by a lack of parental involvement and overwhelming household chore demands,

creating a persistent conflict between academic requirements and domestic responsibilities which aligns with Kankam *et al.'s* (2023) study.

Theme 2: Unsupportive Institutional Response and Teacher-Student Variables

This theme (see Table V) captures the students' perception of the school administration and teachers' failure to recognize, monitor, and effectively address their academic struggles.

Table V: *Unsupportive Institutional Response*

Sub-Theme	Qualitative Comment	Participant
Lack of Monitoring and Accountability	"No monitoring and supervision of teachers" and "Lack of monitoring of students' learning progress."	P2, P5, P6, P8
Knee-Jerk Reactions to Supervision	"There was a mostly knee-jerk reaction from teachers during supervision," and teachers sometimes tell us to "act serious" and behave well in the presence of supervisors.	P1, P7
Fear and Unconducive Relationship	"An unconducive teacher-student variable couldn't allow it," and "We were even afraid to report the teachers to the authorities."	P3, P6, P8

Field Data, 2025

The findings under this theme (Table V) indicate a profound breakdown in the support system (Baidoo-Anu *et al.,* 2022), marked by a perceived absence of effective institutional monitoring and accountability for teachers (Kankam *et al.*, 2023). Students consistently reported that the institutional response to their learning struggles was neglectful or performative, characterized by *"knee-jerk reactions"* during supervision. Critically, the prevalence of an *"unconducive teacher-student variable"* fosters fear and silence, actively discouraging students from reporting poor teaching or seeking necessary assistance.

Theme 3: Emotional and Cognitive Manifestations of Learning Struggles

This theme (see Table VI) reflects the internal cognitive difficulties (attention, memory, specific skill deficits) and the associated negative emotional consequences experienced by the students.

Table VI: *Emotional and Cognitive Manifestations*

Sub-Theme	Qualitative Comment	Participant
Specific Academic Deficits	"I struggle to do practical work. My artistic ability is nothing to write home about due to inadequate exposure to practical lessons." / "Math is like two parallel lines to me. I struggle and I can't cope at all."	P1, P7 / P1, P2, P3, P5, P7, P8
Cognitive/Attention Difficulties	"Easily distracted," "Forgetful in-class lessons," "Fails to pay attention," "Does not follow through on instructions," and "Reluctant to engage in a task that requires sustained mental effort."	P2, P5, P6, P7, P8
Negative Emotional Impact and Shame	"I feel sad and wonder why all my friends can cope with academics but am not able to do the same." / "The pain of not coping with academic work is unbearable." / "It makes you feel shy to mingle with them."	P2, P3, P5, P6, P7, P8
Desire to Quit vs. Persistence	"I feel like quitting school at some point," and "I wish I could quit schooling." Conversely: "I know am struggling to cope with academics but I won't quit. I will keep on trying."	P2, P3, P6, P7 / P1, P5, P8

Field Data, 2025

This theme (Table VI) demonstrates the internal consequences of the external barriers, revealing specific academic deficits, particularly in practical Visual Arts work and Mathematics, compounded by widespread cognitive issues such as forgetfulness and difficulty sustaining attention (Kankam, 2022). The realization of these struggles manifests as intense negative emotional distress, including feelings of sadness, pain, shame, and a sense of hopelessness, frequently leading students to contemplate quitting school for a trade, despite some expressing a determination to persist.

Hence, the three themes served as a strong empirical basis for understanding the LDs experienced by the students, as they align with the recognised diagnostic and contextual factors that define and categorise LDs (Keles *et al.,* 2025; Al Otaiba *et al.,* 2025). Furthermore, the themes provide direct and actionable suggestions for implementing the Universal Design for Learning (UDL) framework in the classroom.

Students' Perception of UDL Usage in Teaching and Learning

Owing to the manifestation of learning disabilities among the sampled visual arts students, UDL principles were adapted as a teaching and learning methodology. The CAST (2024) UDL 36-item scale was used to elicit the students' responses on the perceived value of UDL in teaching and learning. Their responses were summarised using statistical metrics: mean, median, and standard deviation. The statistical mean of the scale is 2.5 for Likert scale 1-2-3-4-5 (1 = strongly disagree; 2 = disagree; 3 = neutral; 4 = agree; 5 = strongly agree). Results above 2.5 were deemed favourable and positive toward UDL usage under the three core principles of multiple means of representation, engagement, and action and expression.

Teaching and Learning Sessions Using UDL Principles

During the study period, various aspects of UDL principles were applied to enhance the teaching and learning of the sampled visual arts students with LDs. Under multiple means of representation, Plate 1-3 illustrate how accessible materials such as PowerPoint presentations, videos, and printed handouts were used to support learning from varied perspectives.

Plate 1 – 3

Plate 1: PowerPoint Presentation

Plate 2: Video Presentation

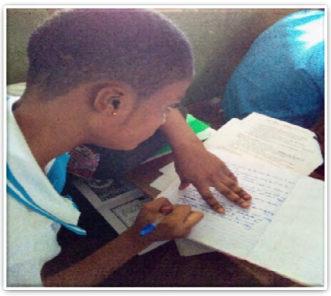

Plate 3: Printable Material

(Source: Field Data, 2025 – Multiple Means of Representation)

On multiple means of engagement, field trips to a nearby wood sawmill (at Juaben), project-based learning (both individual and group work), experiential learning and personalised learning approaches were employed to optimise the learning experience and spark joy and playfulness in the learning process. Plates 4-7 illustrate how the students were engaged in varied approaches under the guiding principle of UDL.

Plates 4 – 7

Plate 4: Sawmill field trip

Plate 5: Project-based learning (Teamwork & Collaboration)

Plate 6: Experiential learning

Plate 7: Personalized learning

(Source: Field Data, 2025 – Multiple Means of Engagement)

On multiple means of action and expression, the students were allowed to express learning in flexible ways. Plates 8-10 illustrate how oral presentations and exhibitions (individual and groups) were employed to support the students to explore, experiment, practice, and develop confidence in their learning process.

Plate 8 – 10

Plate 8: Oral presentation

Plate 9: Individual exhibition

Plate 10: Group Exhibition

(Source: Field Data, 2025 – Multiple Means of Action and Expression)

Perception of UDL as a Teaching Methodology

UDL promotes a proactive and flexible teaching methodology that accommodates variability and ensures equitable access, participation, and progress for all students (Adom *et al.*, 2023; King-Sears *et al.*, 2023). Hence, the CAST (2024) questionnaire was administered to ascertain the students' perception and value of UDL as a teaching methodology. Data shown in Table VII indicates the following results: multiple means of representation (mean=4.29 or 85.8%), multiple means of engagement (mean=4.23 or 86.4%), and multiple means of action and expression (mean=4.28 or 85.6%). Details of the various variables under the three core principles of UDL are presented in Table VII.

Table VII: *Perception and Value of UDL*

Multiple Means of Representation	N	Mean	Median	SD	Min	Max
Perception	100	4.24	4.3	0.326	3.7	5
Language & Symbols	100	4.3	4.3	0.281	3.6	5
Building Knowledge	100	4.32	4.2	0.289	3.8	5
Average Score	100	4.29	4.3	0.214	3.8	4.9

Multiple Means of Engagement	N	Mean	Median	SD	Min	Max
Interest & Identity	100	4.37	4.5	0.317	3.5	5
Effort & Persistence	100	4.33	4.4	0.272	3.6	5
Emotional Capacity	100	4.25	4.2	0.272	3.8	5
Average Score	100	4.32	4.3	0.211	3.8	4.9

Multiple Means of Action and Expression	N	Mean	Median	SD	Min	Maxi
Interaction	100	4.26	4	0.337	3.5	5
Expression and Communication	100	4.3	4.2	0.286	4	5
Executive Function	100	4.28	4.2	0.253	3.8	4.8
Average Score	100	4.28	4.3	0.204	3.8	4.9

(Source: Field Data, 2025)

How UDL Shapes Education of Students with Learning Disabilities

Correlation and regression analyses were conducted to ascertain the relationships and impact of UDL on the students' learning outcomes. In Table VIII, the results show a significantly positive and strong correlation between UDL principles and students' varied forms of representation (r (98) = 0.73, "p <.001"); engagement (r (98) = 0.75, "p <.001"); and action and expression r (98) = 0.71, "p <.001"). These results as presented in Table IX to indicate that UDL principles positively and significantly predict students with learning disabilities' learning outcomes through multiple means of representation, engagement, and action and expression, R = .96, F (1, 98) = 1054, "p <.001 with a large effect size (R = .971).

Table VIII: *How UDL Shapes the Education of Students with LDs*

Variables		Representation	Engagement	Action & Expression	UDL Principles
UDL Principles	Pearson's r	0.732***	0.749***	0.705***	—
	df	98	98	98	—
	p-value	< .001	< .001	< .001	—

Note. * p < .05, ** p < .01, *** p < .001

Table IX: *Impact of UDL on Students with Learning Disabilities*

			Overall Model Test			
Model	**R**	**R^2**	**F**	**df1**	**df2**	**p**
1	0.985	0.971	1054	3	96	< .001

Note. Models estimated using a sample size of N=100

(Source: Field Data, 2025)

DISCUSSION

The discussion is structured according to the study's objectives, beginning with the context of the participants, followed by an analysis of the lived experiences, and concluding with a critical review of the UDL framework's application and impact.

Demographic Context and Learning Disabilities Stereotypes

Analysis of participant demographics confirmed that while most students fell within the typical SHS age range (15-18 years), the BECE aggregate scores highlighted a persistent, systemic bias: Visual Arts program absorbs students deemed "marginal performers" (aggregates 15-25) or those categorized as 'learning disabled' (aggregates 26-30) or 'students with SEND' (aggregates 31-40) (Kankam, 2023; Lien, 2025; Alghrani *et al.*, 2024). This reinforces the stereotype of visual arts as a "last resort" for underperforming students (Kankam *et al.*, 2023), aligning with arguments regarding systemic bias and academic misplacement that often ignore students' core strengths and interests (Baidoo-Anu *et al.*, 2022). Given that underperformance is commonly linked to LDs, a neurodevelopmental disorder affecting both academic and creative performance (U.S. DoE, 2025), this placement context underscores the urgent need for tailored instructional support.

Lived Experiences and Support Needs of Visual Arts Students with LDs

The three derived themes: environmental barriers to learning, unsupportive institutional response, and emotional and cognitive manifestations of struggle, collectively confirm that students' academic difficulties stem from a combination of intrinsic LD symptoms and extrinsic instructional and environmental deficits.

Environmental barriers to learning (poor teaching, lack of resources, unsupportive homes) are not the LDs themselves, but they act as powerful contributing factors that prevent early identification, mask students' potential strengths, and preclude necessary foundational support. This situation is compounded by unsupportive institutional response, where the failure of the institutional system to utilise evidence-based practices like Response-to-Intervention (RTI) or Multi-Tiered Systems of Support (MTSS), evidenced by the lack of monitoring and unconducive teacher-student relationships, creates a risk-prone environment where LDs go undiagnosed or untreated (Keles *et al.*, 2025; Al Otaiba *et al.*, 2025). Furthermore, emotional and cognitive manifestations of struggle directly reflect the core symptoms of LDs, including specific skill deficits (in math and practical art tasks) and Executive Functioning weaknesses (distractibility and forgetfulness), with the associated emotional distress (shame, anxiety, desire to quit) being a well-documented consequence of coping with unsupported LDs.

Students' Perception and Application of UDL

The study aimed to ascertain the perceived value of UDL in shaping education for students with LDs, revealing significant positive outcomes rooted in cognitive neuroscience (CAST, 2024; Rao *et al.*, 2023). Hence, the application of UDL's three core principles directly addressed the barriers identified in students' lived experiences.

With multiple means of representation, the "poor teaching methods" and "lack of resources" was addressed through the use of multimodal formats: PowerPoint presentations, videos, and printed materials. This enhanced accessibility, consistent with findings that multimodal representation improves comprehension and cognitive efficiency (Almeqdad *et al.*, 2023;

Finnegan & Dieker, 2019). Thus teachers' use of UDL-oriented representation fosters inclusion and improved learning outcomes (Tierney, 2024; Matthews *et al.*, 2023; Seth, 2023).

On multiple means of engagement, the utilisation of interactive and experiential tasks in the form of field trips, project work, and personalised activities, directly countered the "unconducive teacher-student variable" and lack of support. These methods enhanced students' autonomy and intrinsic motivation (Adler & Kletenik, 2025; Saunders & Wong, 2023), aligning with UDL-oriented approaches that position engagement as an essential instructional and design strategy for interactive learning environments (Mistry *et al.*, 2025; Seo & Richard, 2021; Sewell *et al.*, 2022).

The application of multiple means of action and expression helped to mitigate the core cognitive deficits and specific skill struggles of students as it provided flexible assessment pathways through oral presentations, exhibitions, and individualised project works, which supports the development of personalised learning paths based on individual strengths (Abaa, 2025). This aligns with the view that varied assessment options empower learners (Mackey *et al.*, 2023) and that experiential and project-based learning methodologies inherently foster students' metacognition, independence, self-regulation, and goal-setting (Leighton, 2023; Mackey *et al.*, 2023). Furthermore, the use of visual thinking strategies in these active learning approaches simultaneously led to deeper participation and comprehension (Flood *et al.*, 2025).

As such, the study's outcomes suggest that UDL functions as a robust instructional design methodology for interactive learning environments that promotes inclusion through flexibility and learner autonomy (Haji, 2025). This design orientation encourages a shift from product-centred assessment to process-oriented learning in visual arts education, where the students' creative journey becomes evidence of understanding (Triana & Supena, 2023). The adaptability of UDL, whether integrated into digital frameworks (Yuwono *et al.*, 2023; Bray *et al.*, 2024) or low-tech, action-oriented tasks, highlights its capacity to bridge accessibility gaps (Abaa, 2025; Kearney, 2022).

How UDL Shapes Education of Students with Learning Disabilities

The quantitative analyses confirmed the positive impact of UDL. Correlation analysis revealed that increased use of UDL strategies enhanced engagement, comprehension, and expressive outcomes among students with LDs, confirming Rao *et al.*'s (2023) position that UDL successfully reduces instructional barriers and addresses learner variability. Regression analysis further verified UDL's predictive capacity, affirming its neuroscientific foundation by addressing the "what," "why," and "how" of learning (CAST, 2024). Representation supports content access, engagement fosters motivation, and expression ensures deeper participation and comprehension, ultimately promoting self-regulation and independence (Mackey *et al.*, 2023). This study contributes to the debate on UDL's universal applicability, revealing that while its neuroscientific basis is robust, its successful implementation requires contextual adaptation to address systemic inequities and align with local inclusive education frameworks (Anastasiou *et al.*, 2025; Cioè□Peña, 2022; MoE, 2018b; 2015).

Implications for Policy, Pedagogy, and Practice

At the policy level, the findings align with the Global Partnership for Education's (2025; 2023) call for equitable and inclusive educational systems that leave no learner behind. Ghana's

Coordinated Programme of Economic and Social Development Policies (2021-2025) and Pre-Tertiary Education Act (2020) already prioritise inclusive learning (Republic of Ghana, 2022; 2020), yet the absence of explicit categorisation guidelines of LDs under childhood vulnerabilities (GSS 2022) and persons with difficulty in performing activities (GSS, 2024) hamper LDs identification and implementation UDL as methodology to address the learning needs of such students. Integrating UDL into Ghana's Education Strategic Plan and teacher education curricula (MoE, 2018b) would strengthen compliance with SDG 4 (United Nations Ghana, 2019) and the Continental Education Strategy for Africa (African Union, 2021).

Pedagogically, the need to equip educators with professional development in UDL-based instructional design is essential (Haji, 2025; Seth, 2023) as UDL promotes adaptive lesson plan that combines representation, engagement, and expression.

CONCLUSION, AND FURTHER RESEARCH

This study set out to explore how Universal Design for Learning (UDL) shapes the educational experience of students with learning disabilities in the visual arts classroom. Rooted in inclusive educational theory and grounded in empirical field data, the study employed a mixed-methods approach to examine the impact of UDL principles on learning outcomes. Through classroom observations, visual documentation, and statistical analyses, the findings revealed that the integration of UDL principles fostered a more inclusive environment, which significantly improved students' learning outcomes and participation. These insights are valuable for visual arts educators, curriculum designers, and inclusive education policymakers to better address learner diversity and promote equitable access to the arts. The study therefore recommends a UDL Implementation Framework for Visual Arts Education, comprising: policy integration that aligns national inclusive education frameworks with UDL principles; teacher capacity building embedding UDL in pre-service and in-service training; interactive learning environments that promotes digital tools, and art-based simulations; and assessment diversification that employs flexible formats for students to demonstrate their creativity and understanding. These recommendations echo the global movement toward instructional equity (Sánchez *et al.*, 2023; World Bank, 2018) and reaffirm UDL's potential to redefine visual arts education as an inclusive, interactive, and empowering space for all learners especially those with learning disabilities.

Further research could make a comparative analysis of the effectiveness of UDL across disciplines such as science or mathematics. Longitudinal studies may also investigate how sustained UDL practices affect academic growth and emotional well-being. Additionally, the inclusion of teacher and parent perspectives could further broaden the understanding and implementation challenges of UDL, and the systemic support needs to accommodate students with LDs.

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DIGITAL PEDAGOGIES FOR INCLUSIVE AND CONTEXTUALISED CORE MATHEMATICS EDUCATION IN PRE-TERTIARY TVET: EVIDENCE FROM GHANA

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Article History
Received 5 November 2025
Accepted 23 January 2026

Abstract

Core Mathematics remains a persistent challenge in Ghana's pre-tertiary Technical and Vocational Education and Training (TVET) institutions, particularly in rural and under-resourced contexts. This study examines how digital tools can be leveraged to support inclusive and contextually meaningful mathematics instruction in such settings. An explanatory sequential mixed-methods design was employed, drawing on survey data from 137 mathematics facilitators across six regions, Core Mathematics exit examination results from nine TVET institutions, and focus group discussions. Quantitative results revealed significant achievement disparities among urban, peri-urban, and rural schools ($H = 21.58$, $p = 0.00576$), alongside severe infrastructural deficits, with only 2% of deprived institutions having functional ICT laboratories. Most facilitators reported unreliable electricity and limited internet connectivity as major barriers, while qualitative findings showed that many digital tools lacked vocational and cultural relevance. Nevertheless, facilitators who effectively integrated technology with pedagogy achieved higher learner gains ($\beta = 0.47$, $p = 0.02$). These findings suggest that successful digital integration depends less on technological sophistication than on pedagogical adaptation to infrastructural and contextual realities. The study extends the TPACK framework by introducing Infrastructural Pedagogical Knowledge (IPK) and concludes that sustainable digital transformation in TVET mathematics requires context-sensitive pedagogy, resilient infrastructure, and equity-driven policy alignment.

Keywords: Digital inclusion, TVET mathematics, Curriculum alignment, Infrastructural pedagogy, Gender equity, Contextualized instruction.

INTRODUCTION

The global educational landscape is undergoing a profound transformation, driven by the imperative to integrate digital technologies not as supplementary tools but as core enablers of pedagogical innovation, equity, and relevance (Eden *et al.*, 2024; Richter *et al.*, 2025). This digital shift is particularly critical within Technical and Vocational Education and Training (TVET), which is tasked with equipping learners with the analytical, problem-solving, and practical competencies required for a rapidly evolving workforce (UNESCO, 2025a). In Ghana, Core Mathematics serves as a foundational pillar in the pre-tertiary TVET curriculum, essential for developing the cognitive skills necessary for technical trades and further academic pursuits. Despite its importance, Core Mathematics remains a persistent and significant barrier to learner achievement and progression, a challenge acutely felt in under-resourced and rural educational settings (Boafo, 2017; Fokuo *et al.*, 2022; Frempong & Asare-Bediako, 2016).

Recognising this, the Ghanaian government has initiated multiple reforms, including curriculum standardisation and the rollout of ICT-in-education policies, to revitalise the pre-tertiary TVET sector in alignment with national industrialisation goals (Donani *et al.*, 2021). However, empirical evidence suggests a stark disconnect between policy intent and classroom reality. Mathematics instruction continues to be predominantly traditional, decontextualised from learners' vocational and cultural realities, and heavily facilitator-centred (Atteh, 2023; Gyaase *et al.*, 2020). Consequently, digital tools—which hold demonstrable promise for enhancing interactivity, personalising instruction, and rendering abstract mathematical concepts more tangible—have failed to achieve widespread or pedagogically meaningful integration (Buabeng *et al.*, 2024; Fleury, 2023).

The specific problem this study addresses is the ineffective, inequitable, and insufficiently contextualised integration of digital tools in Core Mathematics instruction across Ghana's diverse pre-tertiary TVET institutions. While the potential of educational technology is widely acknowledged, its transformative capacity remains largely unrealised due to a confluence of infrastructural deficits, inadequate facilitator preparedness, and a critical lack of culturally and vocationally relevant digital content (Anlimachie, 2016; Spoto *et al.*, 2022). Recent scholarship underscores that many technology integration models, often developed in the Global North, implicitly assume a baseline of reliable infrastructure, thereby creating a conceptual blind spot when applied to contexts in the Global South (Imaduddin & Firdaus, 2025; Jukes *et al.*, 2021; Ntorukiri *et al.*, 2022). This oversight is compounded by a research focus that frequently isolates technological access from the pedagogical and socio-cultural dimensions of its use, failing to account for their dynamic interplay (Ulviani, 2025).

Globally, evidence attests to the efficacy of digital tools in enhancing mathematics learning, particularly when they are adaptive and contextually grounded. Studies in vocational education have shown that interactive platforms can significantly improve conceptual understanding (Zwart *et al.*, 2017), while research in Ghana has demonstrated that AI-powered tutors like Rori can lead to substantial gains in learner achievement (Henkel *et al.*, 2024). Furthermore, scholars like Eden *et al.* (2024) and Asgarov & Badalova (2024) compellingly argue that inclusive digital systems are vital for bridging socio-economic learning gaps, especially in transitional educational systems. However, these successes are often documented in pilot projects or relatively well-resourced environments. In contrast, the Ghanaian context is characterised by infrastructural and socio-cultural barriers, including unreliable electricity,

profound internet connectivity issues, and gendered access to technology, that systematically marginalise learners in rural and deprived areas, thereby exacerbating existing educational inequities (Ghana News Agency, 2025; UNESCO, 2025b).

This study therefore contends that without an intentional design, localisation, and implementation strategy that is acutely aware of pedagogical imperatives and infrastructural constraints, digital tools risk perpetuating or even amplifying existing disparities rather than mitigating them. The study is theoretically anchored in the Technological Pedagogical Content Knowledge (TPACK) framework by Koehler and Mishra (2009), which posits that effective technology integration emerges from the synergistic interplay of content, pedagogical, and technological knowledge. While TPACK provides a robust foundation, its application in low-resource contexts like Ghana reveals a critical limitation: its insufficient attention to the material conditions that enable or constrain digital pedagogy.

To address this gap, the present study extends the TPACK framework by introducing the construct of *Infrastructural Pedagogical Knowledge (IPK)*. IPK is defined as the educator's competence to dynamically adapt both pedagogy and technology use to prevailing infrastructural constraints, such as power outages, limited connectivity, and device scarcity. This extension acknowledges that in under-resourced pre-tertiary TVET settings, effective digital instruction is contingent not only on a facilitator's technological and pedagogical knowledge but also on their capacity for resilience, improvisation, and contextual adaptation.

Guided by this refined theoretical lens, the study employs an explanatory sequential mixed-methods design to investigate four core research questions:

1. What is the state of digital tools availability and usage in Core Mathematics instruction in Ghanaian pre-tertiary TVET institutions?
2. How do facilitators perceive the inclusivity and contextualisation of existing digital Core Mathematics instruction?
3. Is there a statistically significant difference in the mean mathematics achievement of urban, peri-urban, and rural pre-tertiary TVET institutions in Core Mathematics exit examinations?
4. What strategies can be employed to effectively use digital tools in creating inclusive and contextualised mathematics instruction that improves learner engagement and performance?

By exploring these questions, this study aims to contribute context-specific empirical evidence and propose a more nuanced, actionable framework for achieving sustainable and equitable digital transformation in Core Mathematics education within Ghana's pre-tertiary TVET sector and similar settings elsewhere.

LITERATURE REVIEW

Theoretical Framework: Technological Pedagogical Content Knowledge (TPACK)

This study is anchored in the Technological Pedagogical Content Knowledge (TPACK) framework developed by Koehler and Mishra (2009), which emphasizes the interconnectedness of content knowledge (CK), pedagogical knowledge (PK), and technological knowledge (TK). While the TPACK framework has been widely adopted across diverse educational contexts, it has also

been critiqued for its implicit assumption of adequate infrastructure and technological access (Anjarani, 2020; Harris *et al.*, 2017; Mondal, 2025; Oktaviani & Utami, 2024). Developed within relatively well-resourced educational environments, the model tends to overlook the contextual realities of under-resourced settings where stable electricity, reliable internet, and sufficient digital devices cannot be taken for granted. This limitation creates a conceptual blind spot when applying TPACK to developing countries, particularly in sub-Saharan Africa, where infrastructural constraints significantly shape how teachers can enact technological pedagogy. As such, the framework requires contextual adaptation to reflect the additional competencies educators must develop to navigate these challenges effectively. In the context of pre-tertiary TVET in Ghana, TPACK provides a conceptual foundation for understanding how facilitators integrate digital tools into mathematics instruction. However, the current study extends the model by proposing "infrastructural pedagogical knowledge", which is defined as the competence to adapt pedagogy and technology to infrastructural constraints; a dimension necessary for educators operating in digital-resource-constrained environments. This adaptation acknowledges that effective integration of digital tools in under-resourced pre-tertiary TVET settings requires not only technological fluency but also creativity and improvisation to overcome infrastructural deficits.

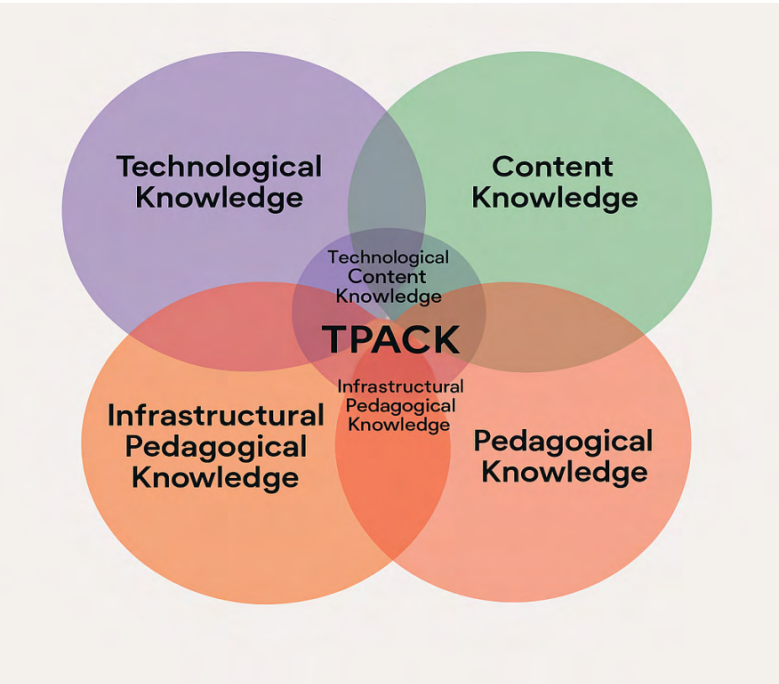

Figure 1: *Revised TPACK framework with Infrastructural Pedagogical Knowledge*

Global Promising Practices in Digital Mathematics Education

Across diverse global contexts, research consistently highlights the potential of digital technologies to enhance the teaching and learning of mathematics, particularly when such tools are pedagogically grounded and responsive to learners' needs. In Europe, Zwart *et al.* (2017), drawing on evidence from vocational education settings in the Netherlands, demonstrated that interactive digital platforms significantly improve learners' conceptual understanding when aligned with task-specific and learner-centered instructional designs. Similar findings have been reported in Germany and Finland, where adaptive digital environments have been

shown to support problem-solving skills and mathematical reasoning in vocational and upper-secondary education (OECD, 2020; Henning & Keune, 2021).

In North America, studies from the United States and Canada indicate that blended and technology-mediated mathematics instruction can enhance learner engagement and achievement, particularly when digital tools are integrated with formative assessment and scaffolding strategies (Means *et al.*, 2014; Borba *et al.*, 2018). In East Asia, countries such as South Korea and Singapore have leveraged national digital education strategies to embed intelligent tutoring systems and dynamic visualization tools into mathematics curricula, yielding measurable gains in learner performance and equity (Ng & Lee, 2020; Kwon *et al.*, 2022).

Within low- and middle-income contexts, evidence from Sub-Saharan Africa and South Asia presents a more nuanced picture. In Kenya and Rwanda, mobile-based mathematics applications have improved access and learner participation in resource-constrained schools, particularly where offline functionality is prioritized (Trucano, 2016; Mtebe & Raphael, 2018). In India, large-scale initiatives such as DIKSHA have demonstrated that low-bandwidth digital resources can support mathematics learning at scale when aligned with local curricula (Kumar *et al.*, 2021).

In Ghana, Henkel *et al.* (2024) documented the effectiveness of an AI-driven mathematics tutor, reporting substantial learning gains among participating students. While this study highlights local potential, its scalability across rural pre-tertiary TVET institutions remains limited, given that only 2% of deprived schools possess functional ICT laboratories. This infrastructural constraint mirrors challenges observed in other low-resource settings, where access, sustainability, and contextual relevance shape the success of digital interventions.

Collectively, global evidence emphasizes inclusivity and adaptability. Eden *et al.* (2024), drawing on multi-country data, advocate for equity-oriented digital systems that reduce socio-economic disparities, while Asgarov and Badalova (2024), focusing on post-transition economies in Eastern Europe and Central Asia, stress the importance of flexible digital pedagogies. However, the Ghanaian experience reveals a critical gap: many available digital tools lack cultural and vocational relevance, limiting their capacity to bridge mathematical theory and workplace practice. This underscores the need for context-sensitive digital mathematics education models that align technological innovation with local realities.

Challenges in Digital Integration: The Ghanaian Experience

While Ghana has invested in ICT policy and TVET reform (Donani *et al.*, 2021), substantial challenges hinder the meaningful integration of the promising digital tools highlighted in global research. Gyaase *et al.* (2020) note that implementation is often hampered by the very infrastructural deficits that global models frequently take for granted. The promising practices of AI tutors and interactive platforms are thus neutralized by the reality that only 2% of deprived schools have functional ICT labs (The Business & Financial Times, 2025; African Education Watch, 2025), and frequent power outages restrict the use of even basic digital resources. Socio-cultural barriers compound these technical challenges. Gender disparities, for example, continue to limit female learners' access to technology (UNESCO, 2025a), undermining the inclusive potential of digital education. Furthermore, while global literature emphasizes localization, the Ghanaian context reveals a critical misalignment: most

digital tools fail to reflect local knowledge systems or vocational realities, and lack support for local languages. The study supports these observations by showing that, despite moderate usage of digital tools by facilitators, the lack of contextual and inclusive content rendered these tools pedagogically ineffective. The perception data from the respondents, especially the low scores on the relevance of digital content and its ability to bridge theory and practice, confirms a widespread disconnect between global digital innovation and the pedagogical and infrastructural realities of vocational education in Ghana.

Gaps and Limitations in Current Literature

Existing literature consistently highlights the potential of digital tools to enhance mathematics education when thoughtfully integrated into pedagogy and adapted to learners' contexts. Evidence suggests that technology can improve learner engagement, conceptual understanding, and academic performance, especially in TVET settings where applied, interactive learning is critical (Henkel *et al.*, 2024; Zwart *et al.*, 2017). Moreover, there is increasing recognition of the need for inclusive digital design and content localization to bridge socio-economic and geographical divides (Eden *et al.*, 2024; Asgarov & Badalova, 2024). In Africa, studies from countries such as Nigeria, Kenya, and Uganda reveal common structural challenges in integrating digital tools into TVET education. Ogudo *et al.* (2024) identify persistent infrastructural deficits in Nigeria, notably unreliable electricity and poor internet access. In Kenya, Marangu *et al.* (2022) report that despite supportive digital learning policies, TVET facilitators often lack adequate training and support. Similarly, Muinda *et al.* (2024) highlight Uganda's efforts to enhance digital capacity but note that high student–computer ratios and non-contextualised content hinder effective implementation. These findings point to the importance of context-responsive strategies rather than uncritical adoption of global models. Despite these insights, several key gaps remain. Much of the research is based on pilot projects or relatively well-resourced institutions, resulting in limited empirical evidence from under-resourced or rural pre-tertiary TVET settings in sub-Saharan Africa. This raises concerns about the generalizability of current best practices. Additionally, few studies explore digital integration holistically by considering infrastructure, pedagogy, and equity in tandem. Critical contextual factors such as unreliable power, limited internet, and linguistic mismatches are often underexplored, as are the perspectives of facilitators and learners regarding inclusivity and relevance. This study addresses these gaps by providing a context-specific analysis of digital integration in Ghanaian pre-tertiary TVET mathematics classrooms. It incorporates both quantitative and qualitative insights, emphasizing the lived experiences of teachers and learners. By situating Ghana's experiences alongside those of Nigeria, Kenya, and Uganda, the study introduces the concept of *infrastructural pedagogical knowledge*, a framework that highlights resilience and improvisation as essential competencies for digital teaching in low-resource environments. While TPACK-XL (Saad *et al.*, 2012) addresses leadership, our construct focuses on resource constraints, this dimension extends the TPACK framework, offering a more nuanced lens for educational technology research across sub-Saharan Africa.

Contribution to the Field and Theoretical Advancement

This study contributes both practically and theoretically to the discourse on digital pedagogy in developing contexts. Practically, it offers actionable insights for policymakers, suggesting the urgent need for localized digital content, targeted facilitator training, and infrastructure investment. Theoretically, it refines the TPACK model by introducing the concept of infrastructural pedagogical knowledge, underscoring the need for adaptability and innovation

among educators in under-resourced environments. In highlighting how facilitators improvise with offline tools and adjust pedagogy based on infrastructural realities, the study provides a model for scalable, equitable digital transformation. These insights are critical not just for Ghana but also for other countries grappling with similar digital divides in education.

RESEARCH METHODOLOGY

Research Approach and Method

The current study employed a mixed-methods approach using an explanatory sequential design, which involved two distinct phases: an initial quantitative phase followed by a qualitative phase. The rationale for this approach lies in its capacity to provide both breadth and depth of understanding (Creswell & Creswell, 2018). The quantitative phase was used to examine the availability and usage of digital tools, facilitators' perceptions, and learner performance data in Core Mathematics across selected pre-tertiary TVET institutions in Ghana. Following this, the qualitative phase explored in greater depth the patterns and anomalies identified in the quantitative data. The mixed-methods strategy was selected to combine the strengths of both quantitative and qualitative methodologies while addressing their respective limitations. According to Creswell and Plano Clark (2018), such integration enhances the validity and reliability of findings by allowing one method to inform or clarify the results of the other. In this study, descriptive and inferential statistics were applied to the quantitative data collected via questionnaires and learners' Core Mathematics exit examination results. The qualitative component involved thematic analysis of focus group discussions, which provided nuanced insights into facilitators' strategies, challenges, and contextual experiences regarding the use of digital tools in instruction. Despite acknowledged limitations of the mixed-methods approach, such as potential methodological complexity and resource intensiveness, it was deemed suitable for addressing the multifaceted nature of digital tool integration within Ghana's diverse pre-tertiary TVET educational landscape. The approach enabled the researchers to move beyond surface-level trends to uncover underlying dynamics that influence inclusive and contextually relevant mathematics teaching.

Population

The population for this study included all the two-hundred and thirteen (213) Core Mathematics facilitators from selected pre-tertiary TVET institutions across six regions in Ghana. The six regions were chosen using purposive sampling to ensure geographical, socio-economic, and educational diversity.

Sample and Sampling Techniques

The study employed a stratified and purposive sampling strategy to ensure representativeness and minimize sampling error. Using the Cochran formula (Cochran, 1977) with a 5% margin of error and a 95% confidence interval, a sample size of 137 mathematics facilitators was determined to be statistically adequate for inferential analysis. This sample size was considered sufficient to reflect the diversity of Ghana's pre-tertiary TVET sector while maintaining statistical power. To reduce sampling error, which is an inherent limitation in probability sampling (Irwin *et al.*, 2019), the sampling process incorporated stratification based on geographical location, specifically urban, peri-urban, and rural classifications (Yu *et al.*, 2024). All participating institutions were grouped into these three strata. From each stratum,

three institutions were randomly selected, making a total of nine (9) schools. This approach was adopted to reduce bias and enhance the representativeness of the institutional sample.

In selecting the schools, efforts were made to reflect vocational heterogeneity by drawing institutions from agro-industrial, coastal, and mining economies. Furthermore, to account for regional variation, schools were purposively selected from six geographically and socio-economically diverse regions across Ghana namely Greater Accra, Ashanti, Bono East, Western, Volta, and Northern regions, This ensured that the sample captured variations in infrastructural development, digital access, and educational investment, offering a nuanced picture of the national pre-tertiary TVET landscape. Finally, 137 mathematics facilitators were randomly sampled from these schools. This ensured that the individual-level data collected was representative across the different geographical strata and institutional contexts, providing a solid foundation for generalizing findings across Ghana's pre-tertiary TVET system.

Data Collection Instruments

Two primary instruments, tailored to the research questions, were used to gather data for the study. First, a structured questionnaire was administered to Core Mathematics facilitators to assess the availability and usage of digital tools, as well as their perceptions regarding inclusivity and contextualization of instruction. This questionnaire consisted of closed-ended items and was designed to elicit quantitative data for statistical analysis. A 5-point Likert scale ranging from 1 (Strongly disagree) to 5(Strongly agree) was used to measure the key constructs such as availability, usage, perceived relevance, and self-efficacy. Furthermore, a focus group interview guide was employed to collect qualitative data from selected mathematics facilitators. This interview was conducted to gain deeper insights into the strategies, experiences, and challenges associated with using digital tools to create inclusive and contextualized learning environments. All instruments were developed with reference to established tools from similar studies (e.g., Buabeng-Andoh, 2012; Agyei & Voogt, 2011) and adapted to the Ghanaian pre-tertiary TVET context to ensure relevance and appropriateness.

Validity and Reliability of Instruments

The content validity of the questionnaire and test instrument was established through expert review by professionals in mathematics education and educational technology. A pilot study was conducted in a comparable institution with three mathematics facilitators, and Cronbach's alpha was used to measure internal consistency reliability of the questionnaire, achieving a coefficient of 0.81, which indicates good reliability (Taber, 2018). Validity of the qualitative instrument was ensured through peer review, and expert validation.

Data Collection, Processing, and Analysis Procedure

Data collection was conducted over six weeks, beginning with ethical clearance and institutional approvals. Questionnaires were administered to facilitators, and learner performance data from 2011 to 2020 exit examinations were gathered from participating institutions. In the final week, focus group discussions were conducted using a semi-structured guide and audio recorded with participants' consent. Quantitative data were coded and analysed using SPSS version 23. Descriptive statistics such as means and standard deviations were computed. A boxplot revealed a violation of normality ($H=21.58$, $df=2$, $p=0.00576$); thus, the Kruskal-Wallis' test was employed to compare group perception scores across urban, peri-urban, and rural settings for the first three research questions. The fourth research question was

addressed through qualitative data from the focus groups, which were transcribed verbatim and analysed thematically using Braun and Clarke's (2006) six-step framework.

Trustworthiness of Qualitative Data

To ensure the credibility and trustworthiness of the qualitative findings, the study adhered to credibility and dependability from the four criteria by Lincoln and Guba (1985). Credibility was enhanced through triangulation by integrating qualitative focus group data with quantitative survey and performance data. Member checks were conducted during the focus group discussions by summarizing participants' statements for confirmation and clarification. Dependability was addressed by maintaining a clear audit trail of the research process, including documented procedures for data collection, coding, and analysis. Thematic analysis followed Braun and Clarke's (2006) six-step framework to ensure consistency.

Ethical Considerations

The study adhered to ethical standards for research involving human subjects in accordance to the dictates of the clearance obtained from the institutional review board with reference number HuSSREC/AP/57/VOL. 3. Participants were briefed on the purpose and procedures of the study and gave informed consent before participation. Participant anonymity was maintained by anonymizing survey responses, and data were stored on password-protected servers. They were further assured that the data were solely meant for research purposes.

Limitations of the Study

While this study provides valuable insights into digital pedagogy in Ghanaian pre-tertiary TVET, its findings must be interpreted in light of certain limitations. First, the research employed a cross-sectional design, capturing data at a single point in time. This design offers a snapshot of the relationships between variables but cannot establish causality or trace the long-term evolution of facilitators' digital competencies and learner outcomes. Second, a significant portion of the data, particularly regarding perceptions, usage, and barriers, was self-reported by facilitators. Such data, while insightful, is susceptible to social desirability bias and potential inaccuracies in recall or self-assessment. Finally, the study focused exclusively on Core Mathematics. Although mathematics is a foundational subject, the challenges and strategies for digital integration may differ in other pre-tertiary TVET subjects that are more practical or workshop-based (e.g., technical drawing or specific trades). Consequently, the generalizability of the findings to the entire pre-tertiary TVET curriculum should be approached with caution. Future longitudinal studies incorporating direct observation and encompassing a broader range of pre-tertiary TVET subjects would help to strengthen and extend these findings.

Researcher Positionality

Researcher positionality is an important consideration in mixed-methods educational research, particularly when studies engage with issues of pedagogy, equity, and contextual realities (Creswell & Poth, 2018). This subsection outlines the professional background of the researcher and reflects on how this positioning may have shaped the research process and interpretation of findings.

The lead researcher is a mathematics educator with over twenty years of teaching experience across primary, junior high, senior high, and pre-tertiary TVET institutions in Ghana, as

well as experience in university-level teacher education. This prolonged engagement with mathematics education provided strong contextual insight into curriculum implementation, assessment practices, and the infrastructural and pedagogical challenges faced by facilitators, especially in under-resourced TVET settings.

While this professional familiarity strengthened the study's contextual sensitivity and facilitated meaningful engagement with participants, it also carried the potential risk of interpretive bias, particularly during qualitative analysis. To address this, deliberate reflexive and methodological safeguards were employed. The explanatory sequential mixed-methods design ensured that qualitative interpretations were anchored in previously analysed quantitative results (Creswell & Plano Clark, 2018). In addition, open-ended interview questions were used to foreground participants' voices, and member checking was conducted during focus group discussions to confirm accuracy of interpretations (Lincoln & Guba, 1985).

Peer debriefing with colleagues in mathematics education further supported analytical rigor, while ongoing reflexivity helped prevent the normalisation of systemic challenges such as infrastructural constraints and gender disparities. By acknowledging and managing positional influences transparently, the researcher's insider status functioned as an analytical resource rather than a limitation, thereby enhancing the credibility, trustworthiness, and contextual validity of the study (Patton, 2015).

FINDINGS AND DISCUSSION

The discussion draws directly from the theoretical lens of the TPACK framework, alongside empirical evidence from global and local literature, to unpack the complex interactions among infrastructure, pedagogy, and learner outcomes.

Demographics

The demographic profile of the participating mathematics facilitators, predominantly male (83.21%) with moderate teaching experience (61.31% having 1-10 years) and a majority holding a B.Ed. (55.47%), provides a crucial context for interpreting the study's findings. While these statistics offer a snapshot of the teaching force, the significant gender imbalance among educators, coupled with later findings regarding gender disparities in learner access to digital tools (male learners accessing mobile practice apps 1.7 times more frequently), underscores a broader systemic challenge. This aligns with UNESCO's observations (2025a, 2025b) regarding the persistent digital gender gap in sub-Saharan Africa, where socio-cultural norms and economic barriers disproportionately affect girls' engagement with technology. Understanding the characteristics of the teaching body is essential for designing targeted professional development initiatives that address not only technological skills but also gender-responsive pedagogy, as advocated by UNESCO (2025a).

The significant gender imbalance among the teaching force, with male facilitators constituting 83.21% of the sample, has profound implications for both classroom culture and the observed gender gap in learner access. A predominantly male facilitator body may inadvertently perpetuate a classroom environment that is less attuned to the specific learning preferences and socio-cultural barriers faced by female learners. This dynamic can reinforce implicit biases and contribute to the findings that male learners accessed mobile practice apps 1.7 times more frequently than their female counterparts. The lack of female role models in mathematics instruction may further dissuade girls from engaging confidently with technology and STEM

subjects, thereby reinforcing the very digital gender gap that inclusive policies seek to close. Addressing this representation gap is therefore not merely an equity issue but a critical pedagogical strategy for creating more inclusive and effective digital learning environments.

Digital Tools Availability and Usage in Core Mathematics Instruction

The data revealed a pervasive inadequacy in digital infrastructure across surveyed institutions, especially in rural areas. Facilitators rated infrastructure availability poorly (mean score = 3.94), echoing national reports that only 2% of deprived basic schools have functional ICT labs (Africa Education Watch, 2025). Unreliable electricity and limited access to internet connectivity were cited by over 85% of facilitators as significant constraints, a finding consistent with Gyaase *et al.* (2020), who noted that digital integration in Ghanaian classrooms remains largely aspirational due to infrastructural deficits. This stark reality limits the implementation of promising digital tools such as GeoGebra or AI-driven tutors like Rori (Henkel *et al.*, 2024), whose effectiveness presuppose stable access to devices and connectivity. The mismatch between national ICT policies and ground-level realities demonstrates a key issue raised in the literature: policy intent does not translate into pedagogical transformation without robust infrastructural support.

Perception of Inclusivity and Contextualization of Core Mathematics Instruction

A critical issue emerging from both the literature and the current data is the poor localization and inclusivity of digital tools. Facilitators overwhelmingly disagreed that digital resources supported diverse learning needs (score = 3.56) or reflected local realities (score = 3.83). Most notably, the lowest score (1.72) was recorded for the perception that tools helped bridge theory and practice, a central mandate of pre-tertiary TVET education. This finding parallels Eden *et al.* (2024) and Asgarov & Badalova (2024), who emphasized that without cultural and local relevance, digital interventions are unlikely to promote equity and engagement. The results also corroborate Almeda (2023), who noted the importance of embedding indigenous knowledge and vocational relevance into instructional materials. The absence of tools in local languages and the lack of vocationally anchored digital simulations are significant barriers to contextualization.

Disparities in Mathematics Achievement Across Geographical Locations

Table I: *Summary of Mathematics Achievement*

School Type	Average Pass Rate (%) by School type	Std. Dev. by School	Average Score by Geographical location	Standard Deviation
Urban				
School A	50.87	9.48	49.50	7.36
School B	49.02	7.17		
School C	48.60	3.32		
Peri-urban				
School A	41.11	6.38	43.61	5.99

School Type	Average Pass Rate (%) by School type	Std. Dev. by School	Average Score by Geographical location	Standard Deviation
School B	43.82	9.65		
School C	45.91	4.46		
Rural				
School A	40.03	3.70	41.85	4.63
School B	44.29	4.62		
School C	41.22	7.09		

The Kruskal-Wallis' test confirmed a statistically significant difference in Core Mathematics exit examination pass rates among urban, peri-urban, and rural pre-tertiary TVET institutions ($H=21.58$, $p=0.00576$), with a specific significant difference between Urban School C and Rural School A ($p=0.02098$), serves as empirical evidence of the profound impact of the digital divide on educational equity. This finding is not an isolated anomaly but is strongly supported by a growing body of literature. Research on school electrification in Ghana has demonstrated that access to electricity is a crucial mediating factor for improving academic performance in deprived districts, with Adamba (2017) reporting a 37.5% increase in mathematics pass rates due to rural electrification (Adamba, 2018). Beyond Ghana, studies in Senegal (Magbonde *et al.*, 2025) and among BRICS countries (Akram, 2022) consistently link improved access to electricity with enhanced educational outcomes, including increased school attendance and study duration. This highlights fundamental infrastructural disparities, such as reliable electricity and internet access, are not merely inconveniences but direct determinants of academic success, perpetuating educational inequities across geographical divides.

Strategies for Effective Digital Tool Integration and Persistent Challenges

Table II: *Summary of actionable strategies*

Challenge	Short-term Solution	Long-term Policy
Electricity outage	Offline apps + Solar-powered devices	National school electrification program
Gender gap	Female-only tech labs + mentorship	Gender quotas in STEM teacher recruitment

The focus group interviews revealed both the promise and the challenges of using digital tools in Ghanaian pre-tertiary TVET education. Facilitators praised tools like *GeoGebra* for transforming pedagogy by promoting collaboration and deeper conceptual understanding, supporting prior findings on the benefits of interactive and AI-enhanced learning tools. However, significant challenges hinder effective implementation, especially in rural areas. While many facilitators (63%) attempted to contextualize digital content, they struggled with poor infrastructure, with 92% citing unreliable electricity and 85% noting a lack of local language support in digital tools. These issues align with the broader digital divide in Ghana, where limited connectivity and high costs obstruct rural digital integration. Equity concerns

also emerged, highlighting a "digital readiness gap" shaped by cognitive, infrastructural, and socio-cultural factors. Low prior exposure to technology increased cognitive burden among 41% of learners, emphasizing the need for foundational digital literacy. Disparities between urban (89%) and rural (33%) internet access directly affect learning outcomes. Additionally, gender inequalities persist: male learners accessed mobile learning apps 1.7 times more than females, a trend reflecting broader barriers faced by girls in accessing technology, with serious consequences for their future in STEM and economic empowerment.

To bridge the gender gap in mathematics education, particularly in Technical and Vocational Education and Training (TVET), gender-sensitive interventions must be prioritized through deliberate policy actions. One key strategy is the targeted recruitment and training of female mathematics facilitators who can serve as role models and help reduce implicit gender bias in instruction. Ensuring equitable access to technology is also essential; this can be achieved through the provision of subsidized or free digital devices to female learners, especially in rural areas, alongside community sensitization efforts to overcome cultural resistance. Additionally, developing digital content in local languages that incorporates gender-inclusive scenarios will enhance relevance and engagement for female learners. Teacher professional development should also be strengthened to include gender-responsive pedagogy and effective strategies for equitable digital engagement. Finally, partnerships with organizations such as UNESCO and Girls in ICT can support the launch of after-school digital literacy programs tailored for girls in pre-tertiary TVET institutions, fostering a more inclusive and empowering learning environment.

These interventions align with the global call to close the gender digital divide (UNESCO, 2025a) and enhance the inclusive potential of digital learning tools in STEM education for all learners.Top of FormBottom of Form

Synthesis with Theoretical Framework: Extending TPACK for Real-World Constraints

The TPACK model (Koehler & Mishra, 2009) provided a valuable lens to interpret the observed variations in implementation success. The finding that facilitators with integrated technological-pedagogical knowledge achieved significantly higher learner gains ($\beta=0.47$, $p=0.02$) strongly reinforces the framework's core tenet: effective technology integration requires a synergistic understanding of content, pedagogy, and technology. This aligns with broader literature emphasizing that digital competence extends beyond technical proficiency to encompass the thoughtful application of technology to enhance learning (Nadapdap, 2025).

However, this study's data compellingly argues that the standard TPACK model is necessary but not *sufficient* for understanding effective digital pedagogy in resource-constrained environments. The model's implicit assumption of adequate infrastructure creates a critical blind spot. Our findings reveal that in the Ghanaian pre-tertiary TVET context, a facilitator›s knowledge exists in dynamic tension with material reality. It is not enough to know *that* GeoGebra can illustrate a function (TK); effectiveness depends on knowing *how* to operationalize it when the school›s only projector fails. This is where the proposed construct of Infrastructural Pedagogical Knowledge (IPK) fundamentally extends and changes the model.

IPK represents a paradigm shift from what is ideally possible to what is contextually feasible. It is the competence that enables a facilitator to dynamically adapt the other TPACK domains under constraint. For instance:

A facilitator with high IPK does not just know GeoGebra [TK] but knows how to download its offline version onto a personal smartphone and design a collaborative, small-group activity around that single device when the computer lab is unavailable [IPK].

They do not just understand that Khan Academy offers personalized learning paths [TPK], but they proactively download lessons via Kolibri during sporadic internet access and integrate them into a peer-to-peer teaching model for a classroom with only two functional laptops [IPK].

They contextualize a mathematics problem on percentages not just with a generic example [CK], but by linking it to a local vocation, such as calculating fabric waste in tailoring, using a physical chalkboard when digital simulations are inaccessible [IPK].

The significant correlation between such improvisational strategies and rural learner outcomes ($r=0.58$) underscores that IPK is not a peripheral skill but a central determinant of success. It transforms the TPACK framework from a static Venn diagram of ideal knowledge domains into a dynamic, resilient practice of *orchestration under constraint*. This adaptation is crucial for educational technology research and practice in developing countries, as it formally acknowledges that resourcefulness, flexibility, and contextual pragmatism are not optional extras but core components of professional competence. By integrating IPK, the model becomes a more authentic and powerful tool for preparing and supporting educators to achieve digital transformation in the face of adversity.

CONCLUSION

This study examined the potential of digital tools to promote inclusive and contextually grounded Core Mathematics instruction in Ghana's pre-tertiary Technical and Vocational Education and Training (TVET) institutions. Using an explanatory sequential mixed-methods design, the study integrated quantitative achievement data with facilitators' perspectives to generate a comprehensive understanding of how digital pedagogy operates within resource-constrained educational environments.

The findings reveal that access to and effective use of digital tools remain severely limited, particularly in rural and peri-urban TVET institutions. With only a small fraction of deprived schools possessing functional ICT laboratories and the majority of facilitators reporting unreliable electricity and poor internet connectivity, infrastructural constraints continue to undermine the implementation of digital mathematics instruction. These deficits significantly restrict the pedagogical use of widely promoted tools such as dynamic mathematics software and AI-driven platforms, despite their demonstrated potential in more resourced contexts.

Beyond access, the study highlights a critical misalignment between existing digital resources and the inclusive, practice-oriented goals of TVET mathematics education. Facilitators expressed low confidence in the cultural and vocational relevance of available tools, noting their limited capacity to connect mathematical concepts to workplace applications. This

disconnect reinforces the need for localized, inclusive, and vocation-specific digital content that reflects learners' lived experiences and occupational pathways.

Achievement data further underscore the consequences of these inequities, revealing significant disparities in Core Mathematics performance across urban, peri-urban, and rural institutions. These differences mirror broader socio-economic and infrastructural inequalities, confirming that access to digital learning environments plays a central role in shaping educational outcomes.

Importantly, the study demonstrates that when facilitators possess strong technological and pedagogical integration skills and adapt digital resources to contextual realities, learner engagement and achievement improve. In response, the study advances Infrastructural Pedagogical Knowledge (IPK) as an extension of the TPACK framework, emphasizing educators' capacity to align pedagogy and technology use with infrastructural constraints. The resulting TPACK–IPK model provides a context-sensitive framework for guiding sustainable digital mathematics instruction in low-resource settings.

Digital tools hold considerable promise for transforming Core Mathematics teaching in Ghana's pre-tertiary TVET institutions; however, this potential is constrained by persistent infrastructural, pedagogical, and socio-cultural challenges. Addressing these challenges requires an ecosystemic approach that brings together government agencies, the private sector, and community stakeholders. Strategic investments in basic infrastructure, localized digital content development, continuous professional capacity building, and gender-responsive inclusion initiatives are critical to ensuring that digital transformation in TVET mathematics education is inclusive, equitable, and firmly grounded in local contexts.

Overall, the study concludes that meaningful digital transformation in pre-tertiary TVET mathematics extends beyond the provision of technologies to encompass infrastructural resilience, pedagogical adaptability, and equity-driven policy alignment, without which digital innovation risks reinforcing, rather than reducing, existing educational inequalities.

CONTRIBUTIONS AND IMPLICATIONS

This study makes three key contributions, namely theoretical, practical, and methodological, that collectively advance understanding and practice in digital pedagogy within resource-constrained pre-tertiary TVET environments.

Theoretical Contribution

The study extends the Technological Pedagogical Content Knowledge (TPACK) framework by introducing the construct of Infrastructural Pedagogical Knowledge (IPK), defined as the educator's capacity to adapt pedagogy and technology use to infrastructural constraints. IPK acknowledges that effective digital teaching in under-resourced contexts depends not only on mastery of content, pedagogy, and technology, but also on adaptability, creativity, and resilience in the face of infrastructural limitations such as unreliable electricity and poor connectivity. This theoretical refinement addresses a major blind spot in the standard TPACK model, which assumes adequate technological access and overlooks the contextual challenges that shape digital teaching in developing countries.

Practical Contribution

Practically, the study contributes actionable strategies and frameworks that bridge the gap between digital innovation and local realities. It proposes the TPACK-IPK Integration Cycle, a structured model that guides teachers in designing lessons that are pedagogically sound, technologically feasible, and contextually meaningful. The study also recommends systemic interventions such as a National Framework for Contextualized Digital Pedagogy (NF-CDP), the creation of Regional Digital Equity Hubs, and gender-responsive digital inclusion policies. These initiatives collectively promote sustainable and equitable digital transformation across Ghana's pre-tertiary TVET institutions by linking pedagogy, infrastructure, and policy.

Methodological Contribution

Methodologically, the study demonstrates the utility of an explanatory sequential mixed-methods design in exploring complex educational challenges at the intersection of technology, pedagogy, and infrastructure. By integrating quantitative analyses of digital access and achievement with qualitative insights from facilitator experiences, the study provides a nuanced understanding of how contextual and pedagogical factors interact to influence outcomes. This design serves as a methodological blueprint for future research examining digital integration in low-resource educational environments.

Together, these contributions establish a multidimensional framework for advancing inclusive, contextually relevant, and equitable digital pedagogy in Ghana's pre-tertiary TVET system and comparable settings.

RECOMMENDATIONS AND FRAMEWORKS FOR PRACTICE

The findings of this study necessitate a coordinated, multi-level approach to bridge the gap between digital potential and classroom reality in Ghana's pre-tertiary TVET sector. The recommendations that follow are structured to inform national policy, institutional strategy, and classroom practice, collectively forming a coherent framework for action.

At the national policy level, a decisive step is the development of a National Framework for Contextualized Digital Pedagogy (NF-CDP) by the Ministry of Education and the Commission for Technical and Vocational Education and Training (CTVET). This framework must establish mandatory standards ensuring that digital learning resources are not only offline-compatible but also localized to reflect Ghanaian vocational contexts and available in major local languages. Furthermore, it should embed accessibility standards for learners with disabilities and enforce gender-sensitive design to counteract the disparities identified in this study. Concurrently, the concept of Infrastructural Pedagogical Knowledge (IPK) must be institutionalized within national teacher education and certification frameworks. By integrating IPK into the curricula of the National Teaching Council (NTC) and CTVET, educators will be formally prepared and assessed on their ability to adapt pedagogy creatively amidst infrastructural constraints, moving beyond an idealised view of technology integration. To directly address the persistent gender gap, a gender-responsive digital inclusion policy is imperative. This should include practical interventions such as providing subsidised digital devices for female learners in rural areas, establishing female-focused ICT mentorship labs, and collaborating with organisations like UNESCO and Girls in ICT Ghana to strengthen mentorship and role-modeling programs.

At the institutional and infrastructural level, the establishment of Regional Digital Equity Hubs is recommended to decentralise support and resources. These hubs, ideally solar-powered and connected to broadband, would serve as centres for professional development, host offline digital content libraries, and provide technical maintenance support for clusters of schools in underserved areas. To address the critical infrastructure deficits, institutions must proactively foster Public-Private Partnerships (PPPs) with telecom companies, renewable energy providers, and non-governmental organisations. Such collaborations are vital for achieving sustainable school electrification, installing community Wi-Fi, and provisioning solar-powered classrooms, thereby creating the enabling environment for digital tools to thrive beyond short-term donor projects.

For mathematics facilitators at the classroom level, this study proposes the TPACK-IPK Integration Cycle, a practical five-step model for lesson design. This cycle begins with identifying the core content objective, followed by selecting an appropriate pedagogy. The third step involves choosing a suitable digital tool, which is then critically adapted in the fourth step through the lens of IPK—planning for offline or low-tech alternatives in anticipation of infrastructural failures. The final step requires contextualizing the content by linking mathematical concepts to local vocational experiences. To sustain this practice, schools should encourage the formation of Communities of Practice, where facilitators can engage in peer mentoring, share locally developed resources, and collaboratively solve technological challenges through platforms like WhatsApp or Telegram.

To ensure sustainability, the recommended interventions should be implemented through phased and iterative processes that incorporate continuous monitoring, evaluation, and evidence-informed refinement. Investments in infrastructure, localized digital content, and professional capacity building should be accompanied by systematic data collection on implementation outcomes, learner experiences, and equity effects, particularly in rural and deprived TVET institutions. Such feedback loops would enable policymakers, institutions, and practitioners to adapt digital strategies in response to contextual realities and emerging challenges, ensuring that digital transformation remains responsive rather than prescriptive. In this way, recommendations are not treated as endpoints but as evolving practices that generate new evidence to inform subsequent cycles of research, policy, and pedagogical innovation.

In conclusion, the holistic TPACK-IPK Implementation Model synthesizes these recommendations. It posits that effective digital teaching emerges not from technological proficiency alone, but from the dynamic interplay of Content Knowledge, Pedagogical Knowledge, Technological Knowledge, and the critical, context-aware dimension of Infrastructural Pedagogical Knowledge. When this model is operationalized within supportive policy and institutional structures, it provides a robust roadmap for transforming Ghana's pre-tertiary TVET mathematics classrooms into spaces of digital inclusion, contextual relevance, and equitable learning outcomes.

ACKNOWLEDGEMENT

The researchers acknowledge the crucial contributions of the principals for providing learner performance data, which was essential for the quantitative phase, and the mathematics facilitators for sharing their experiences and insights, which enriched the study’s findings.

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Effect of technostress on university students' academic productivity during the COVID-19 Pandemic

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Article History
Received 27 November 2025
Accepted 26 February 2026

ABSTRACT

The closure of universities during the COVID-19 pandemic prompted the adoption of Emergency Remote Teaching (ERT) by universities to minimize the impact of the disruption on the academic calendar. Although beneficial, ERT which hinges on the use of ICTs and online learning, has a negative consequence; technostress. Through a descriptive correlational study, using a convenience sample of 385 students, this study examines the effect of technostress on the academic productivity of students at the University of Education, Winneba (UEW), during the COVID-19 pandemic. Data was collected using a structured questionnaire adapted from Abd Aziz and Abu Yazid (2021), and analyzed using descriptive statistics and correlation techniques with the aid of SPSS and SmartPLS software. The study revealed a moderate level of technostress among students of UEW. Based on the demographic characteristics, results showed that students experienced same levels of techno-stress. Further, technostress had a negative but statistically insignificant effect on academic productivity ($\beta = -0.197$, $p = 0.268$), suggesting that overall technostress does not directly predict changes in academic productivity in this sample. Although the technostress level was moderate, it is recommended that the university explore ways to reduce technostress and help improve ICT skills to minimize the effects of technostress among students.

Keywords: ICT, Technostress, COVID-19, University Students

INTRODUCTION

Many governments worldwide ordered the closure of all educational institutions during the COVID-19 pandemic. Educational institutions stopped operating because they had to shield their students from the widespread infection of the virus (Quinn, 2020). To prevent the pandemic's detrimental effects on education, governments across the world launched a crisis response initiative by modifying the schools' academic calendar and curricula, providing physical and technological resources, and setting guidelines for how education should be delivered and accessed (Agormedah *et al.*, 2020; Muthuprasad *et al.*, 2021). For example, schools in the Philippines were compelled to integrate online learning at all grade levels to make schooling flexible (Cacho *et al.*, 2022). By April 2020, 191 nations had imposed

nationwide lockdowns and closed educational institutions. Although the closure of educational institutions tremendously impacted the vast number of students, implementing lockdowns and social or physical distancing were the only proven and effective measures to break the chain of transmission of the COVID-19 virus (Muthuprasad *et al.*, 2021).

In Ghana, the government took pragmatic measures, including locking down certain cities with recorded cases of the disease to prevent the virus from spreading further and closing down all schools till January 15, 2021. During this profound paradigm shift, universities had to explore how to keep teaching and learning going while adhering to government directives (Essel *et al.*, 2021). This introduced emergency remote teaching (ERT); a brief change in instructional delivery to a different medium, such as online, in the event of a crisis (Hodges *et al.*, 2020) in universities, inspiring new instances of educational innovation by using digital technology (Muthuprasad *et al.,* 2021).

Emergency remote teaching (ERT) entails the use of entirely remote teaching solutions for instruction or education that would ordinarily be offered face-to-face or as blended or hybrid courses, with the aim of returning to that format after the crisis or emergency has passed (Hodges *et al.*, 2020). Some scholars distinguish between ERT and online learning because they believe that the major goal of ERT is to give temporary access to teaching and instructional aids in a way that is easy to set up and reliable during an emergency or crisis, rather than to re-create a comprehensive educational environment that provides high-quality online learning (Penado-Abilleira *et al.*, 2021). ERT, according to Sangrà *et al.* (2012), varies significantly from online learning in that it reflects an unanticipated and abrupt transition from traditional brick-and-mortar classes to a distance system of education (Aguliera & Nightengale-Lee, 2020).

However, it is instructive to recognize that ERT cannot take place without the online engagement between instructors or facilitators and learners or students. Therefore, this study focuses on students' experiences with online learning to examine their technostress levels. Although it had not been widely used in Ghanaian institutions before the COVID-19 lockdown, ERT became a necessary and popular alternative, and its adoption dramatically boosted the use of information and communication technologies (ICTs) in modern education around the world, setting ICT usage as the standard (Essel *et al.*, 2020; Upadhyaya & Vrinda, 2021). The shift from in-person teaching to ERT saturated the learning environment with innovative digital technologies such as intelligent tutoring systems (ITS), learning analytics, and a variety of learning applications that supported distance and blended learning, but these technologies were new and unfamiliar to most students (McGuinness & Vlachopoulos, 2019). For instance, through the ITS, online learning became feasible for universities to make high-quality curricular resources available to students to study at home, and the ITS served as a platform-based application where academics could instruct without in-person instruction (Cao *et al.*, 2021). Zoom, University Learning Management System (LMS), Microsoft Teams, Blackboard, Google Meet, and Google Classroom were the popular and frequently used e-learning platforms among the various computer and web-based applications that were used in universities to support teaching and learning during the pandemic (Fuady *et al.*, 2021).

ICTs assist students by improving performance, saving institutional resources and time, increasing student happiness (Barbuto *et al.*, 2020), providing convenience and flexibility, and extending access to high-quality learning support (Wang *et al.*, 2020). As a result of the

ICTs, distance and time were no longer barriers, allowing educators and students to save on travel time, avoid conserving resources and, most importantly, avoid the potential risk of contracting the COVID-19 disease (Cao *et al.*, 2021) thereby aiding students' learning processes. Further, Purwati and Khairunisa (2022) found that students had a positive perception of using applications for online learning, and they stated that their knowledge and understanding of using ICT for educational purposes had improved.

Despite the benefits of using ICT, there is a rising concern about the harmful impact of technology on students (Essel *et al.*, 2021). Technology can induce stress (technostress) in its users (Salanova *et al.*, 2013), and university students may be more susceptible to technology-induced stress due to the increasing use of sophisticated technology in education (Salem, 2018). ICTs have a dark side, but it is widely assumed that university students are tech-savvy and unaffected by technology-induced stress, their psychological and cognitive responses to new applications, features, and workflows are overlooked (Qi, 2019). Students may experience negative consequences or have anticipated interactions with ICTs as conditions and expectations change with requests for more time and effort, time management biases, and calls for a more self-regulated learning (Jung, 2013).

Technostress is described as stress and negative feelings caused by ICT (Essel *et al.*, 2021). It is an inverse psychological condition linked to the use or potential threat of ICTs, characterized by a sense of an imbalance between resources and demands associated with ICT use, resulting in increased psychophysiological activation and the development of negative attitudes toward ICTs (Salanova, 2003). It is an adaptable problem caused by students' incapacity to deal well with growing digital technology (Penado-Abilleira *et al.*, 2020), or a maladaptation situation created by students' lack of ability to survive in a constantly changing technological world (Jena, 2015). As a result, technostress develops when ICT core competencies required in an institution exceed students' level of knowledge in ICT, or when technological expectations exceed students' capabilities or capacity to meet them (Penado-Abilleira *et al.*, 2020). Aside from that, Ayyagari *et al.* (2011) identified usability, intrusiveness, and dynamism as the three technological traits linked to workplace stress.

Research has shown that ICTs can induce stress in their users (Fitzgerald, 2021), thereby negatively affecting their physical and mental health and productivity. Students are therefore susceptible to stress due to the increasing level of digitalization in higher institutions. The use of ICTs in online learning and their resultant technostress in universities may vary based on institutional characteristics like vision/mission, programmes/courses of study, and digital infrastructure. Although the level of digitalization may vary across institutions based on programmes of study, visions and missions, infrastructural capacities among others, technology-induced stress among students can lead to decreased learning commitment, burnout, deficient performance, and plans to stop using technology. While Adam *et al.*, (2017) examined technostress in the organizational setting, Essel *et al.*, (2021) focused on the phenomenon in an educational environment; the Kwame Nkrumah University of Science and Technology, (KNUST) Kumasi, but did not take into account new developments and advancements in the technology of contemporary times (Salem, 2018), especially those that emerged during the COVID-19 pandemic. Whereas KNUST is older (established in 1961) and a science and technology institution, comparatively, UEW is a relatively new institution (established in 1992) with a focus on advancing education. These differences make studying

technostress among UEW students interesting, as it brings to the fore the perspective from newer universities, offering education-related programmes.

The University of Education, Winneba (UEW) adopted a blended or hybrid approach (combining face-to-face and online modes) to teaching and learning during the 2020/2021 academic year, like other institutions of higher education, thereby increasing the level of digitalization across the sector. Because ICT use and online learning of this magnitude have never occurred on this scale in the educational space during that period, it is unclear how students from various institutions perceive and experience the influx of new technologies and online learning, and how that improves their performance. Therefore, this study sought to fill that gap. It is imperative to constantly examine the situation to fully comprehend how the use of ICT affects academic productivity, hence, the need to investigate technology-related stress (technostress) and students' academic productivity during the COVID-19 pandemic. The objective of the study was to assess the effect of technostress on students' academic productivity at the University of Education, Winneba, in the Central Region of Ghana.

LITERATURE REVIEW

Technostress, as described by Brod (1984), causes people to feel anxious, reluctant, and even afraid of using ICT. Amin *et al.* (2012) found that modern technologies cause technology-related stress, which in effect causes anxiety and trauma in those who use them. Nightmares, headaches, and irritation are all symptoms and physiological effects of technostress when using ICT or completely refusing to use any form of ICT. The effects of technostress on people who use ICT are far-reaching; hence, it is frequently necessary to explore the negative sides of technology, such as technology-induced stress, which can have a detrimental impact on performance and productivity.

Transactional Model of Stress and Coping

Based on several empirical investigations by Richard Lazarus on the nexus of physiology and psychology in the 1960s and 1970s, Lazarus and Folkman (1984) presented a seminal theory: Transactional Model of Stress to explain human stress reactions. The major characteristic of this Transactional Model of Stress, the background context of this study, is that stress is not solely conceptualized as a biological phenomenon, but as a complex construct that results from the interplay between an individual and the environment (hence, the term "transactional"). In particular, the theory states that stress (1) emerges from an imbalance between demands from the environment and an individual's resources, and (2) is subject to the meaning of a stimulus to the perceiver, implying that the same stimulus may affect the stress of different individuals differently.

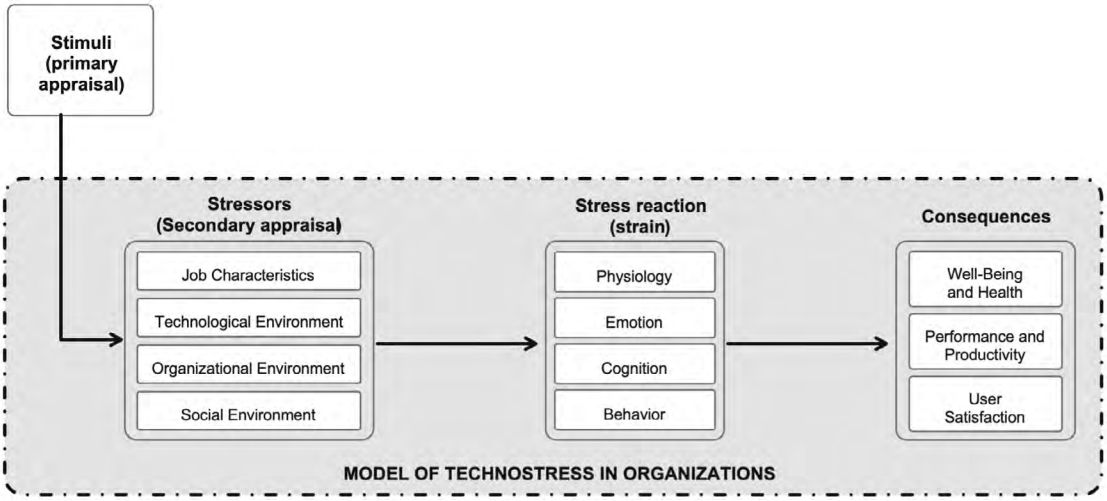

Figure 1: *Model of technostress in organisations*

(Source: Adam et al. (2017))

According to the seminal stress theory by Lazarus and Folkman (1984), the underlying rationale is that when faced with stimuli (see Figure 1 above and Figure 2 below), an individual evaluates whether they are irrelevant, benign-positive, or stressful (primary appraisal). In the latter case, another evaluation process (secondary appraisal) takes place where the individual assesses whether he/she can cope with the stimulus (stressor) by using the available resources (e.g., institutional, personal, and social). Two outcomes are possible: the resources are either sufficient or they are not. In the latter case, stress reactions are possible on four levels: physiology, emotion, cognition, and behaviour. Next, to mitigate these stress reactions, an individual applies different coping strategies, which can be either problem-focused or emotion-focused. The former strategy has the goal to actively change the person-environment realities related to a stressful situation (e.g., by increasing the amount or quality of resources), while the latter seeks to reduce negative feelings by changing the primary and/or secondary appraisal of a given stressful situation.

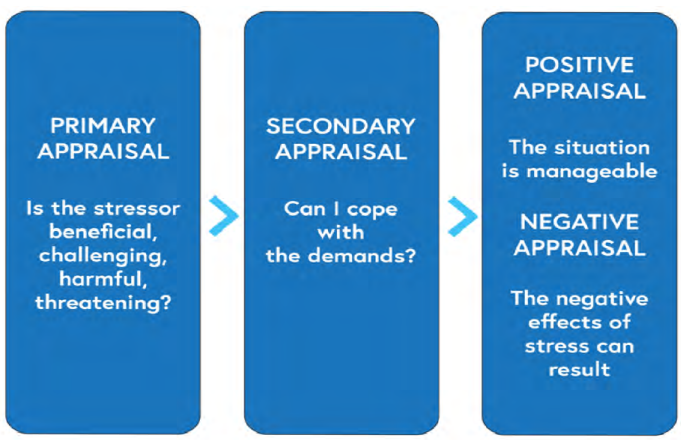

Figure 2: *Transactional model of stress and coping*

(Source: Lazarus and Folkman (1984))

Applying the rationale of the Transactional Model of Stress in educational settings, we find that stress is generated as a dynamic process that is triggered by a set of acute and chronic stressors (i.e., stress-creating factors and conditions), and involves individual stress reactions which, in turn, have several consequences on wellbeing and health, performance and productivity, and user satisfaction. This dynamic process includes conscious changes in perception; however, there are also unconscious changes in body physiology that usually set in before conscious stress perception. This includes, for example, the release of the stress hormone adrenaline.

Importantly, there is more to the cognitive side than perception alone; users can cognitively intervene at an earlier stage of the process. As explained by Lazarus and Folkman (1984), the elicitation of stress is subject to the users' appraisal of the overall situation, availability of resources, and coping strategies. In this vein, users can apply, for example, information avoidance, stress management, and other coping strategies to mitigate the elicitation of stress and its negative consequences (Bostock *et al.*, 2011). Thus, the impact of stressors heavily depends on the users' capabilities and stress-coping strategies.

The Concept of Stress

The concept of stress has been discussed or studied in various fields hence a universal definition has been difficult to establish, as the meaning may differ depending on the scientific context in which it is used (Fitzgerald, 2021). Generally, stress refers to an over-stimulated situation that arises both physically and psychologically when the brain perceives external and/or internal circumstances as dangerous or harmful (Folkman, 1984). Stress can be caused by various factors but it is generally classified into traumatic events, continuous troubles, and problems in daily life (Hess & Copeland, 2006). The effect and intensity may differ from person to person and case by case. However, research has shown that prolonged exposure to stress can have severe effects and cause cognitive, emotional and behavioural problems (Schneiderman *et al.*, 2005). Additionally, excessive stress can cause health problems (Sapolsky, 2004). Eustress, distress, hyperstress and hypostress have been determined as four variations of stress that, if balanced well, can lessen the negative effects and lead to good health. Eustress is positive, often short-term, stress that emerges because of any activity involving the need for increased motivation and/or inspiration.

In contrast, distress is negative stress induced by changes in a routine that causes unpleasantness and unfamiliarity. Distress itself can be further divided into acute (intense, quick and short-term stress) and chronic (prolonged stress) types. Furthermore, hyperstress is induced by overwork when pushed beyond one's limits, which often has the consequence that smaller stressors trigger a bigger emotional response. The opposite is hypostress, which is induced by boredom or the lack of challenges and can cause restlessness and indifference. Stress is intrinsically neutral and varies in degree and effect depending on context and individual perception (Selye, 1983). In other words, the identical stressor can cause eustress or distress, but it is the individual discrepancies that induce either one of them (Hargrove *et al.*, 2013).

Technostress

The term 'technostress' was first introduced by Brod (1984), who defined it as a modern disease of adaptation caused by an inability to cope with the new computer world technologies in an unhealthy manner. Clark and Kalin (1996) countered that technostress is not a disease, but a negative psychological, behavioural and physiological impact caused, either directly or indirectly, by technology. Technostress creators are conceptualized as job demands that

require high physical, social, and cognitive skills, with an associated psychological cost. Technostress is also known as technophobia and computer anxiety because Brod (1984) argued that technostress can be felt in the form of technophobia, confusion, and fear, with the major symptom being anxiety. Tarafdar *et al.* (2007, p. 304) defined technostress as a "*problem of adaptation that an individual experiences when he or she is unable to cope with or get used to ICTs*". They proposed a multi-dimensional scale with five components: techno-overload, techno-invasion, techno-complexity, techno-insecurity, and techno-uncertainty.

Technostress has social, psychological, economic, and physiological consequences. The psychological effects on students may lead to a fall in academic performance, and this aversion may stand in the way of their academic achievement (Salem, 2018). A recent study of the phenomenon by Upadhyaya and Vrinda (2021) among private university students in India showed that technostress influenced students' academic productivity negatively, and in another study of technostress among postgraduate students in a management university in India, Sethi *et al.* (2021) showed that technostress and academic productivity are inversely related; therefore, technostress negatively affects academic productivity. Similarly, Essel *et al.* (2021) found that technostress has adverse effects on academic achievement and academic productivity. The psychological barrier to using computer technology induced by technostress might inhibit one from further learning (Wang *et al.*, 2008).

Students' everyday lives may be influenced by the educational environment and academic stress, which are regarded as possible factors that trigger psychopathological issues (Torales *et al.*, 2022), as the use of information and communication technology (ICT) in education is rapidly increasing, becoming an integral part of universities' learning environments. University students are required to be able to use computers, machines and the latest electronic devices, a range of ICTs, as they are expected to conduct technology-based work as part of their academic curriculum, such as using word processing applications, presentation software, searching the web, or using software that performs statistical analysis.

The concept of stress, as argued by Lazarus and Folkman (1984), is a result of an interaction between an individual and the environment. Based on their transactional model of stress, they explained stress and defined it as an individual psychological response to a situation, where the situation demands exceed the individual's situational capacity/resources or ability to cope with the situation. Using sociotechnical and role theory, Tarafdar *et al.* (2007) explained that these stressors are the conditions (creators) that originate from social or role (role stressor), technical or task (task stressor), or the use of ICTs (technology stressor). Adam *et al.* (2017) categorized stressors at the workplace into (1) job characteristics, (2) technological environment, (3) organizational environment, and (4) social environment; and stated that these stressor types can induce stress reactions in the users, both individually and collectively, but technology-related stressors exacerbate the others. Therefore, it is evident that ICT is one of the causes of stress from past research studies.

Universities across the world are currently actively modernizing their educational systems through the use of ICT. By utilizing technology-based learning, massively open online courses, and flipped classrooms, these universities began introducing and implementing blended learning. As a result of these new tools being introduced, it is anticipated that educators will go through a lot of change, particularly in their methods for educating students, which raises their stress levels (Li & Wang, 2021). However, the majority of researchers frequently ignore

how ICT-proposed instructional systems affect students' levels of technostress. Despite having grown up with technology, Generation Z students still have trouble adjusting to the many novel and remote learning environments that instructors use.

Technostress and Productivity

In the information systems (IS) discipline, productivity is often referred to as task productivity and defined as "the extent that an application improves the user's output per unit of time (Torkzadeh & Doll, 1999). Hysenbegasi *et al.* (2005) measured academic productivity using students' grade point average (GPA). Tarafdar *et al.* (2007) conceptualized productivity as increased work efficiency and output during work hours through mobile technologies as perceived by staff members. Tarafdar *et al.* (2007) found a negative impact of five technostress creators on productivity at the workplace. Lee *et al.* (2016) validated the inverse association of technostress from mobile communication on quality of life and employee productivity. Hung *et al.* (2011) found that 'ubiquitous technostress' or stress caused by the overuse of mobile phones at the workplace harms employees' productivity. Essel *et al.* (2021) found an inverse effect of technostress on students' academic productivity. Likewise, Upadhyaya and Vrinda (2021) found a negative impact of technostress on academic productivity. Based on the literature, the research model is presented in Figure 3 below, as researchers propose that technostress influences academic productivity.

Figure 3: *Research model*

(Source: Authors' construct)

Online Learning in Higher Educational Institutions during the COVID-19 Pandemic

Owing to the risk of COVID-19 transmission, higher education institutions were confronted with options of how to continue teaching while keeping faculty, staff, and students safe. On this account, many institutions authorised faculties to move their courses online or remotely to help thwart the spread of COVID-19. According to Golden (2020), although higher education institutions across the globe appeared to be engaged in online learning, they were in essence carrying out a provisional solution, one that would be more properly named "emergency remote teaching (ERT)". Hodges *et al.* (2020) indicated that well-designed online learning experiences are meaningfully different from courses offered online in response to a crisis or disaster. As such online education/learning is not the same as emergency remote teaching (Hodges *et al.*, 2020). That notwithstanding, ERT cannot take place without elements of online learning because the connection between teaching and learning remotely is mediated in an online environment.

According to Bozkurt and Sharma (2020), remote education refers to spatial distance and an obligation to use different strategies and approach the case with different Similarly, Hodges *et al.* (2020) indicate emergency remote teaching is a temporary shift of instructional delivery to

a substitute delivery mode due to catastrophic situations. It comprises the use of fully remote teaching solutions for instruction or education that would otherwise be delivered face-to-face or as blended or hybrid courses, which returns to the original format once the crisis or emergency has abated. The principal goal in these conditions is not to re-create and design a vigorous educational ecosystem but rather to offer impermanent access to teaching and learning and instructional supports in a manner that is quick to set up and is reliably available during the COVID-19 crisis.

Emergency remote teaching occurs outside of a physical classroom. ERT, which appears to be identical to e-learning, takes place online. Remote teaching is naturally facilitated through technology, such as video conferencing software, discussion boards or learning management systems. Both students and instructors interact via two-way communication technologies. Instructors are separated from their learners in time and distance. This type of teaching may be synchronous, where students watch instructors deliver their lectures live; or asynchronous, where students watch lecture recordings at a later point in time. Best practices for remote teaching include providing ongoing feedback, making assignment guidelines clear, and making effective use of online resources.

Teaching remotely obviously diminishes the number of interactions on campus, thereby significantly decreasing the rate of transmission of COVID-19. ERT can ensure that students continue learning through a variety of avenues, such as digital technologies, which can offer a wide set of capabilities for remote learning. It enables learners to extend learning outside the boundaries of traditional learning institutions through informal and enriched learning experiences using online communities on new platforms such as social media and other social platforms. It can essentially be as effective as face-to-face education when done right. When emergency remote learning is well-planned and structured, conducted in an appropriate learning management system and is in the hands of skilled lecturers, it can provide an equivalent learning experience to face-to-face teaching (Taylor-Guy & Chase, 2020). All higher educational institutions worldwide are seeking viable, blended and sustainable modes of online courses. Learning management systems (LMS), such as the University of Education's LMS Moodle, are designed to support online learning. These systems effectively organise learning resources, including multimedia resources that students can easily access. Students can engage in collaborative activities with their peers and lecturers through tools such as Zoom, WhatsApp, discussion boards and Wikis.

The call by higher education institutions to move instruction online enhanced the flexibility of teaching and learning anywhere and anytime; yet, it seems that the speed at which this move occurred was unprecedented and staggering. This abrupt substitution from in-person to emergency remote teaching has left academic faculty, staff and students with challenges. Thus, ERT introduces a change to both the people and the higher education institutions on a large scale. For example, educators have not been prepared to teach well with technology, let alone teach remotely with technology; hence, they struggled to figure out how to use digital tools, online resources, and apps to continue their teaching online. Similarly, higher education faculty have limited opportunities to learn how to teach with technology, including how to find, evaluate, adapt and use technology to enrich learning. As a result, the majority of educators were completely underprepared to design remote learning experiences with technology when states and districts started closing schools due to COVID-19 (Trust, 2020).

The shift to emergency remote teaching presented student-learning concerns, such as issues of equity, internet connection, personal learning devices, and student data accessibility; thus, the shift to ERT has illuminated and exacerbated the digital divide (Trust, 2020). Likewise, according to Taylor-Guy and Chase (2020), ERT hinders student cohesiveness, peer-to-peer and student-lecturer interaction beyond real-time video or chat interactions. This promotes student disengagement and dropout. Saavedra (2020) argued that developed countries are at an advantage when introducing emergency remote teaching, which may be invalid for some countries. For example, Adam (2020) indicated that it is only the advantaged who will gain from this online learning. The most vulnerable members and poorest of society were the hardest hit, both by the COVID-19 pandemic and the response (Guterres, 2020). It is evident that both developed and developing countries have already suffered from interludes to education, and for many, this is not a new narrative.

METHODOLOGY

Based on the objectives of the study, the research adopted a quantitative approach to investigate the issue. The sample size for this study was determined using the sample size determination formula by Cochran (1977), and in this case, we assume the student population is large, with a maximum variability of 0.5, a 95% confidence level and 5% level of precision. The formula is:

$$n_0 = \frac{Z^2 pq}{e^2}$$

According to Cochran (1977), is the sample size; is the Z-score of the α-level of significance for a 2-sided test, which is 1.96 for a 95% confidence level or 5% significance level; is the estimated proportion of an attribute that is present in the population, and in this case, because we do not know the variability in the proportion, we use 0.5, which is the maximum variability; is which is ; is the desired level of precision, which is 5%.

$$n_0 = \frac{(1.96)^2(0.5)(0.5)}{(0.05)^2}$$

$$n_0 = 385$$

Therefore, the sample size (*N*) used for the study is 385, which comprises students from the two streams of students in the university: undergraduate and graduate students. These students were recruited from the Winneba Campus using the non-probability convenience sampling technique. Non-probability convenience sampling was used primarily because of the time the study was conducted, which was during the COVID-19 pandemic era, and to lower the cost of data collection and was useful in exploratory studies like the current study.

The study adapted a survey questionnaire developed by Abd Aziz and Abu Yazid (2021), selecting four out of the five dimensions of the original scale to collect data for the study. The four dimensions selected were: *techno-overload, techno-complexity, techno-insecurity,* and *techno-uncertainty*. The questionnaire comprised a 22-item instrument divided among four main computer-related factors identified as causing stress (technostress creators). We found the questionnaire suitable for measuring technostress in the educational context, especially among students, given that it had been used in similar research in a University in Malaysia.

Also, because it did not have cultural or political underpinnings or nuances, we found it useful for our study and applicable in the Ghanaian context.

The four dimensions *techno-overload*, caused by an overload of information, had 9 items; *techno-complexity*, caused by the inability to deal with the complexity associated with technology, had 6 items; *techno-insecurity,* caused by technology-induced work insecurity, had 4 items; and *techno-uncertainty*, caused by the uncertainty associated with technology, had 3 items. All items were measured on a five-point Likert-scale The Cronbach's Alpha (α) was used to examine the reliability, and adequate reliability exists when the correlation coefficient is 0.70 or higher (Marczyk *et al.*, 2005). The data collected from the survey were analyzed using descriptive and inferential statistics with the help of Statistical Package for Social Sciences (SPSS) 26 software and SmartPLS software for structural modelling.

RESULTS AND DISCUSSION

Demographic Characteristics of Participants

The participants' demographic data collected include age, gender, academic level and knowledge in ICT. The ages of participants (students) were categorized into two age groups, which are below 25 years (18 – 24) and 25 years and above (25 – 52). From Table I, the results reveal that 185 (48.1%) of students fell between the ages of 18 and24 years and 200 (51.9%) between 25 and 52 years. This demographic data is important as it provides context and describes the population understudy to guide or direct the focus of intervention where necessary.

The results in Table I indicate that 242 (62.9%) of the participants studied were male students, and 143 (37.1%) were female students. Table I shows that the participants studied belong to two academic levels: undergraduate and postgraduate: 338 (87.8%) were undergraduates and 47 (12.2%) were postgraduate students. Table I gives information about participants' knowledge in ICT: 105 (27.3%) of participants indicated they have basic knowledge in ICT; 231 (60.0%) adjudged their knowledge in ICT as intermediate; and 49 (12.7%) have advanced knowledge in ICT.

Table I: *Demographic characteristics of participants (N= 385)*

Variable	M	SD	F	%
Age	25.90	5.175		
18 – 24			185	48.1
25 – 52			200	51.9
Gender				
Male			242	62.9
Female			143	37.1
Academic level				
Undergraduate			338	87.8
Postgraduate			47	12.2

Variable	M	SD	F	%
Knowledge in ICT				
Basic			105	27.3
Intermediate			231	60.0
Advance			49	12.7

Note: *N* = Total number of Participants; M = Mean; SD = Standard Deviation; F = Frequency; % = Percentage.

(Source: Authors' construct)

Level of Technostress among the Respondents

To measure the technostress levels among the students in this study, we examined the extent to which participants agreed and disagreed with the items of technostress constructs under each of the dimensions that measured students' technostress levels. The frequency table, mean, and standard deviations of each item of the technostress construct are presented as follows:

Table II: *Frequencies of participants' responses to items on the techno-stress scale and descriptive statistics of their responses (N= 385)*

Statements	SD F (%)	D F (%)	UD F (%)	A F (%)	SA F (%)	M	SD
Techno-overload							
TO1: I have to do more work than I can handle due to the implementation of online learning.	61 (15.8)	82 (21.3)	63 (16.4)	127 (33.0)	52 (13.5)	3.07	1.310
TO2: I have to work with very tight time schedules due to the implementation of online learning.	43 (11.2)	93 (24.2)	55 (14.3)	129 (33.5)	65 (16.9)	3.21	1.288
TO3: I have to change my study habits to adapt to online learning.	38 (9.9)	38 (9.9)	47 (12.2)	126 (32.7)	136 (35.3)	3.74	1.302
TO4: I have a higher workload because of the increased complexity of online learning.	62 (16.1)	105 (27.3)	68 (17.7)	96 (24.9)	54 (14.0)	2.94	1.314
TO5: I have less free time due to the implementation of online learning.	68 (17.7)	105 (27.3)	61 (15.8)	97 (25.2)	54 (14.0)	2.91	1.337
TO6: I have to be in touch with my work even during vacation because of online learning.	44 (11.4)	55 (14.3)	53 (13.8)	141 (36.6)	92 (23.9)	3.47	1.305

Statements	SD F (%)	D F (%)	UD F (%)	A F (%)	SA F (%)	M	SD
TO7: I have to work much faster due to the implementation of online learning.	39 (10.1)	54 (14.0)	64 (16.6)	133 (34.5)	95 (24.7)	3.50	1.279
TO8: I have to sacrifice my vacation and weekend time to keep current on the updates and new requirements of online learning.	58 (15.1)	86 (22.3)	52 (13.5)	118 (30.6)	71 (18.4)	3.15	1.361
TO9: I feel my personal life is being invaded by online learning.	110 (28.6)	90 (23.4)	73 (19.0)	59 (15.3)	53 (13.8)	2.62	1.394
Techno-complexity							
TC1: I often find online learning too complicated for me to understand it well.	76 (19.7)	106 (27.5)	68 (17.7)	76 (19.7)	59 (15.3)	2.83	1.361
TC2: I often find online learning too complicated for me to use it effectively.	80 (20.8)	130 (33.8)	52 (13.5)	78 (20.3)	45 (11.7)	2.68	1.320
TC3: The high complexity of online learning causes me to doubt its usefulness and practicality in education.	63 (16.4)	109 (28.3)	67 (17.4)	77 (20.0)	69 (17.9)	2.95	1.363
TC4: I do not have adequate knowledge of online learning to complete my homework satisfactorily.	111 (28.8)	117 (30.4)	45 (11.7)	83 (21.6)	29 (7.5)	2.49	1.309
TC5: I need to spend a considerable amount of time and effort to use online learning effectively.	39 (10.1)	90 (23.4)	53 (13.8)	130 (33.8)	73 (19.0)	3.28	1.289
TC6: I do not find enough time to study and upgrade my technology skills to meet the needs of online learning.	63 (16.4)	112 (29.1)	83 (21.6)	82 (21.3)	45 (11.7)	2.83	1.265
Techno-insecurity							
TIS1: I am threatened by peers who have more vital online learning skills.	89 (23.1)	119 (30.9)	60 (15.6)	72 (18.7)	45 (11.7)	2.65	1.330
TIS2: I do not share my knowledge regarding online learning with my peers for fear of being accused of cheating.	112 (29.1)	89 (23.1)	55 (14.3)	83 (21.6)	46 (11.9)	2.64	1.402

Statements	SD F (%)	D F (%)	UD F (%)	A F (%)	SA F (%)	M	SD
TIS3: I am threatened by peers who know more about online learning than I do.	98 (25.5)	115 (29.9)	58 (15.1)	65 (16.9)	49 (12.7)	2.62	1.361
TIS4: I am threatened by peers who quickly adapt to the online learning environment more than I do.	98 (25.5)	121 (31.4)	49 (12.7)	79 (20.5)	38 (9.9)	2.58	1.327
Techno-uncertainty							
TUC1: There are frequent upgrades in online learning that we use in our university.	60 (15.6)	84 (21.8)	71 (18.4)	104 (27.0)	66 (17.1)	3.08	1.340
TUC2: There are constant changes to the functionalities in online learning that we use in our university.	57 (14.8)	82 (21.3)	78 (20.3)	109 (28.3)	59 (15.3)	3.08	1.304
TUC3: Our university regularly replaces one teaching and learning method with another.	76 (19.7)	83 (21.6)	80 (20.8)	88 (22.9)	58 (15.1)	2.92	1.354

Note: *N* = Total number of Participants; SD = Strongly Disagree; D = Disagree; UD = Undecided; A = Agree; SA = Strongly Agree; M = Mean; SD = Standard Deviation; F = Frequency; % = Percentage; TO = Techno-overload; TC = Techno-complexity; TIS = Techno-insecurity; TUC = Techno-uncertainty.

(Source: Authors' construct)

From Table II, the evaluation items related to technostress reveal that, in general, the average obtained is moderate, indicating that the problem appears relevant to the population under study. For example, the highest mean is detected in the construct of techno-overload, which is M = 3.74 (TO3), followed by M = 3.50 (TO7) and M = 3.47 (TO6). The university students stated that they had to change their habits to adapt to online learning; work much faster due to the implementation of online learning; and work even during vacation because of online learning. The degree of discrepancy in the responses to these three items was SD = 1.302, SD = 1.279, and SD = 1.305, respectively. The results of the techno-uncertainty construct suggest that university students face stress due to frequent upgrades in online learning (M = 3.08, SD = 1.340) and constant changes to the functionalities in online learning (M = 3.08, SD = 1.304).

Similarly, university students reported facing some difficulties with the complexity of online learning. Among the items that compose the construct, what stands out is that they had to spend a lot of time and effort to use online learning effectively (M = 3.28, SD = 1.289). In contrast, the item with the lowest impact was the opinion that they do not have enough knowledge of online learning to complete their homework satisfactorily (M = 2.49, SD = 1.309). This contradicts the opinion of Li and Wang (2021), who claimed the younger generation (who

constitute almost half of the study population) is tech-savvy. Geographical location and time of data collection may have contributed to this contradiction.

Finally, the techno-insecurity construct presents the lowest mean among the four technostress constructs: the university students stated that they are threatened by peers with better online learning skills (M = 2.65, SD = 1.330). Another statement slightly considered is that university students do not share their knowledge regarding online learning with peers for fear of being accused of cheating (M = 2.64, SD = 1.402).

Table III: *Level of techno-stress*

Dimension	Mean	SD	Technostress level (*N*= 385)									
			Very Low		Low		Moderate		High		Very High	
			F	%	F	%	F	%	F	%	F	%
Techno-overload	3.178	0.743	16	4.2	73	19.0	136	35.3	127	33.0	33	8.6
Techno-complexity	2.843	0.900	41	10.6	115	29.9	129	33.5	70	18.2	30	7.8
Techno-insecurity	2.621	1.075	100	26.0	111	28.8	75	19.5	58	15.1	41	10.6
Techno-uncertainty	3.028	1.012	50	13.0	70	18.2	129	33.5	82	21.3	54	14.0
Overall	**2.92**	**0.681**										

Note: *N* = Total number of Participants; M = Mean; SD = Standard Deviation; F = Frequency; % = Percentage.

(Source: Authors' construct)

Table III above shows the overall level of technostress as well as the level for the four dimensions of technostress among students of UEW. While 3.1% (n = 12) of the respondents showed very low-level technostress, 31.2% (n = 120) demonstrated low-level technostress, 43.9% (n = 169) exhibited moderate-level technostress, 15.8% (n = 61) demonstrated high-level technostress, and 6.0% (n = 23) experienced very high-level technostress. With a mean score of M = 2.92 (SD = 0.681, range: 2.61 – 3.40), the findings indicate an overall moderate technostress level among the students of UEW. This suggests that the technostress experienced by students in UEW was not severe, and this finding aligns with previous studies (Upadhyaya & Vrinda, 2021), which found technostress levels to be moderate among students and staff members of the university.

Further, it suggests that students had a positive perception of the role of technology in improving their academic productivity, although they feel that using online learning contributes to some stress they experience. They might regard it as a new challenge, believing that online learning is there to help them continue learning anywhere and to help them effectively carry out their academic tasks with ease, especially during a global pandemic.

Table IV: *Technostress levels with factors*

Factor/ Dimension	Technostress level (*N*= 385)				
	Very Low	**Low**	**Moderate**	**High**	**Very High**
	M(SD)	**M(SD)**	**M(SD)**	**M(SD)**	**M(SD)**
Techno-overload			3.178(0.744)		
Techno-complexity			2.843(0.900)		
Techno-insecurity			2.621(1.075)		
Techno-uncertainty			3.028(1.012)		

Note: *N* = Total number of Participants; M = Mean; SD = Standard Deviation.

(Source: Authors' construct)

From Table IV above, all four dimensions of technostress were moderate among students, but students believed that techno-overload slightly contributed more to their stress levels, closely aligning with Upadhyaya and Vrinda (2021), who found technostress levels among university students in India to be high in terms of techno-overload. This could be due to higher levels of academic workload for students. Since the application of technology, in this case, online learning, generally pushes individuals to complete tasks in a shorter time frame, more than fifty percent of the participants moderately agreed that they had to work faster with tighter time schedules, do more work than they can handle, and change their study habits to adapt to online learning, among others. This finding supports the result of Gillespie *et al.* (2001), who reported that the introduction of new technologies increased the workload and stress among university staff. As a result of the high volumes of academic workload, the students may consistently be working for longer hours and always be online, which can further increase techno-overload. The university can explore ways in which the online learning platforms used can help their students and not add to their existing workload.

Communication was predominantly online during the pandemic, so students had to always be connected to ICT or smartphones for group discussions and to receive crucial learning materials for their classes. Therefore, students were multitasking, working under pressure to meet deadlines for assignments and interim assessments, while at the same time dealing with a lot of information coming from colleagues and lecturers teaching other courses. Wang *et al.* (2020) argued that expecting students to respond to people around them, notifications from social media and mobile marketing apps, and university-related reminders and information could lead to techno-overload. The way university students can avoid techno-overload is by developing appropriate coping strategies to manage the situations strategically.

Generally, techno-insecurity was minimal in explaining their technostress levels. The mean score (M = 2.621; SD = 1.075) indicated low levels of technostress experienced for this dimension compared to the other dimensions. From Table V, although techno-insecurity was quite low, it is still worth observing since, overall, it ranks moderate on the technostress levels rating scale. Whereas Qi (2019) and Maier *et al.* (2019) assert that university students are generally digital natives unafraid to learn new skills, especially skills that are related to ICT, and hence will be comfortable with the system, some students feel threatened that they will be left behind in their studies by their peers who are better than they are at online learning.

This explains why students may not like taking tests and examinations online, or performing online activities, as they feel that those who are ICT-savvy will outperform them. Students can overcome or minimize techno-insecurity by finding ways to continuously upgrade and acquire new knowledge and skills to keep up with technology, to appreciate new online learning platforms or applications adopted by the university and lecturers.

The effect of technostress level and academic productivity

To assess the effect of technostress on academic productivity, the structural model was assessed using SmartPLS. The results are illustrated in Table V

Table V: *Effect of techno-stress on academic productivity l (N= 385)*

	B	SD	*t*-Test	*p*-Values
Academic productivity <- Technostress	-0.197	0.177	1.109	0.268
Techno-overload <- Technostress	0.402	0.231	1.739	0.082
Techno-complexity <- Technostress	0.810	0.377	2.152	0.031*
Techno-insecurity <- Technostress	0.802	0.380	2.110	0.035*
Techno-uncertainty <- Technostress	-0.091	0.399	0.229	0.819
AP1 <- Academic productivity	0.846	0.251	3.373	0.001*
AP2 <- Academic productivity	0.899	0.265	3.387	0.001*
AP3 <- Academic productivity	0.738	0.224	3.291	0.001*
AP4 <- Academic productivity	0.691	0.237	2.917	0.004*
Model fit indices				
SRMR	0.123			
NFI	0.799			

Note: *N* = Total number of Participants; β = Beta Coefficient; SD = Standard Deviation; AP = Academic Productivity; Significance level (α) = 0.05, so relationships are significant at *P < 0.05.

(Source: Authors' construct)

Table V shows the results of the structural equation model (SEM). Standardized Root Mean Square Residual (SRMR) and Normed Fit Model (NFI) are popular goodness-of-fit measures in SEM using SmartPLS. Lower values of badness-of-fit measures of SRMR closer to zero indicate a good model (Kline, 2005). Hu and Bentler (1999) recommended a cut-off value of 0.08 for SRMR and 0.90 or above for NFI. Therefore, the model fit indices for SEM suggested by Hu and Bentler (1999), which include SRMR (0.123) and NFI (0.799), were found not to be within acceptable cut-off criteria. This means the researchers should consider working on the constructs to arrive at the acceptable cut-off criteria; however, some scholars have argued that SmartPLS is not good at estimating model fitness.

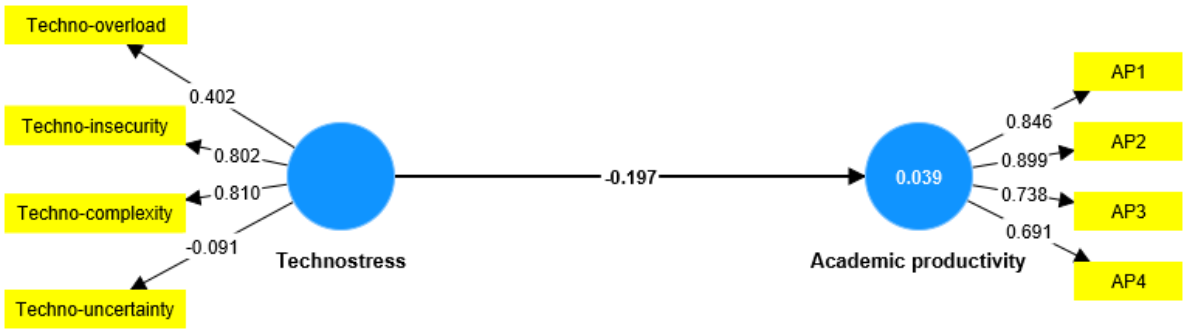

Figure 3: *Structural model*

(Source: Authors' construct)

The results of the SEM indicated that technostress has a negative but statistically insignificant effect on academic productivity (β = −0.197, p = 0.268), suggesting that overall technostress does not directly predict changes in academic productivity in this sample (Figure 3). The results were not consistent with past studies on technostress on different groups of users (Ayyagari *et al.*, 2011; Hung *et al.*, 2011; Lee *et al.*, 2016). This result could mean that students do not think their academic productivity has decreased because of online learning or that stress may affect other aspects of student life on campus, but not necessarily the student's academic productivity. Future research can therefore examine the other aspects of student life that technostress may affect. Although the results showed evidence of moderate technostress among the student population of the University of Education, Winneba, during COVID-19, students felt positive about the online learning platforms they used for lectures and academic work. The majority of students agreed that their academic productivity has increased, nonetheless.

Overall, among the four technostress dimensions that cause technology-related stress, technostress was induced by techno-complexity (*t*: 2.152, $p < 0.031$) and techno-insecurity (*t*: 2.110, $p < 0.035$), and among the two dimensions, techno-complexity (β = 0.810) was the highest contributor to technostress among the student population of UEW. This means that techno-complexity and techno-insecurity were the two dimensions that affected students' academic productivity. The contribution of the other two technostress dimensions, techno-overload (*t*: 1.739, $p > 0.082$) and techno-uncertainty (*t*: 0.229, $p > 0.819$), to technostress was statistically insignificant, which means that techno-overload and techno-uncertainty did not have any significant effect on academic productivity. Techno-uncertainty (β = -0.091) is negatively correlated to academic productivity.

Techno-complexity induced the highest technostress, probably because students lack knowledge about certain online learning platforms used in the university, such as the LMS, among other learning platforms that lecturers adopted, which only appeared during the COVID-19 pandemic. Qi (2019) stated that technology-based learning apps that are too difficult for students to understand are the main source of stress, and negatively affect academic productivity, or platforms to be used for online learning. Instead, the students are supposed to figure it out on their own. So, although there is a negative correlation between the moderate technostress levels found among students of UEW and their academic performance, the negative correlation was insignificant, suggesting that students believe that their technostress levels do not negatively affect their academic productivity.

CONCLUSION AND RECOMMENDATIONS

As the results indicate a higher impact of techno-overload and techno-uncertainty, the university must plan and schedule academic work in a manner that provides adequate time to complete the academic work, and keep students abreast with modifications, system updates and changes to online learning platforms used in the university and by lecturers. The university can mitigate the impact of techno-complexity by choosing user-friendly, familiar educational technology and providing adequate training for the students. They can further mitigate the effects of techno-insecurity by training all students on popular apps and computer software such as MS Word, Excel, PowerPoint, Zoom, and LMS, among others, so that students can develop confidence, overcome their fears, and not feel threatened by ICT and colleagues who have more advanced IT knowledge.

It was observed that male and female students experienced moderate technostress levels with the implementation of online learning during the COVID-19 pandemic. The results are inconsistent with the results of other technostress studies conducted on student populations (Broos, 2005; Qi, 2019). These studies found technostress levels to be higher in female students than in males. The fact that this study found no difference in technostress levels between male and female students does not suggest that male and female students were coping at the same level. The researchers recommend that the university take steps to further investigate and identify students who may be at risk and help them cope with technostress. As observed, older students, undergraduates, and students with basic ICT knowledge had higher levels of technostress in some dimensions. The university must identify and train students in basic ICT knowledge when admitted to the University to increase familiarity with technology to be used in their academic work.

The results indicated that technostress did not negatively impact on academic productivity which appears inconsistent with the previous studies conducted. This indicates that there could be other factors apart from technostress that impacts academic productivity within the context of ERT. Comparing the results of this study and previous studies, it is advisable that the University further examines the phenomenon to identify high-risk students and counsel them to help manage technostress. Results of such a study can improve students' perception of technology use and online learning, which can translate into good academic performance. If students are found to be experiencing higher levels of technostress, the university may assign such students to student mentors from their peer groups to increase their confidence in the use of technology.

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