



Artificial Intelligence Integration in Mathematics Instruction: Examining Barriers, Enablers, And Teacher Acceptance Among College of Education Lecturers in Ghana

Alexander Afari-Kissi¹, Bejamin Adu Obeng², Francis Ohene Boateng³, Jacob Arhin⁴

^{1,2,3}University of Skills Training and Entrepreneurial Development (USTED)

⁴Akrokerri College of Education

ARTICLE INFO	ABSTRACT
Published Online: 22 June 2026 Corresponding Author: Dr. Jacob Arhin KEYWORDS: Artificial intelligence, mathematics instruction, teacher acceptance, barriers, enabling factors, AI integration, Ghana.	Artificial intelligence (AI) is increasingly transforming educational practice by supporting personalized learning, intelligent tutoring, automated assessment, and data-driven instruction. However, the successful integration of AI in mathematics instruction depends largely on educators’ acceptance and readiness to adopt these technologies. This study examined the influence of barriers and enabling factors on lecturers’ acceptance of AI and investigated the effect of teacher acceptance on AI integration in mathematics instruction among Ghanaian Colleges of Education. Guided by the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), the study employed a quantitative cross-sectional survey design involving 230 mathematics lecturers. Data were analyzed using Structural Equation Modeling (SEM) with AMOS. The findings revealed that barriers negatively influenced teacher acceptance of AI ($\beta = -0.430, p < .001$), whereas enabling factors positively influenced teacher acceptance ($\beta = 0.469, p < .001$). Teacher acceptance was also found to significantly predict AI integration in mathematics instruction ($\beta = 0.665, p < .001$). The study concludes that reducing implementation barriers and strengthening enabling conditions are critical for promoting AI adoption in mathematics education. The findings provide practical implications for teacher education, institutional leadership, and educational policy aimed at fostering effective AI integration in Ghanaian Colleges of Education.

1.1 INTRODUCTION

Artificial intelligence (AI) has emerged as one of the most transformative technologies of the twenty-first century, influencing virtually every sector of society, including education (Sadiq et al., 2025; UNESCO, 2023). Advances in machine learning, natural language processing, learning analytics, and generative AI have created unprecedented opportunities for enhancing teaching and learning processes (Rodríguez-Ortiz et al., 2025). Within educational contexts, AI-powered technologies are increasingly being utilized to support personalized learning, automate routine instructional tasks, provide real-time feedback, and facilitate data-driven decision-making (UNESCO, 2023; Imamguluyev et al., 2024; Deepshikha, 2026). Consequently, educational institutions worldwide are exploring ways to integrate AI into

pedagogical practices to improve learning outcomes and prepare students for participation in an increasingly digital and knowledge-based society (Geng & Chen, 2026). The growing interest in AI has significant implications for mathematics education. Mathematics remains a foundational discipline that supports the development of logical reasoning, critical thinking, and problem-solving skills necessary for success in science, technology, engineering, and mathematics (STEM) fields (Aposika, 2026; Kotsis, 2025). Despite its importance, mathematics education continues to face persistent challenges, including low student achievement, limited learner engagement, diverse learning needs, and mathematics anxiety (UNESCO, 2023; Pushpanadham & Sarpong, 2024). These challenges have motivated educators and researchers to seek innovative approaches capable of

improving instructional effectiveness and student learning experiences. AI technologies offer promising possibilities in this regard through adaptive learning systems, intelligent tutoring platforms, automated assessment tools, and personalized instructional support (Sajja et al., 2024; Strielkowski et al., 2025). By tailoring instruction to individual learners' needs and providing immediate feedback, AI has the potential to enhance students' mathematical understanding and improve overall learning outcomes (Luong et al., 2025).

Existing research suggests that AI can contribute positively to mathematics instruction. Intelligent tutoring systems, for example, have been shown to improve students' conceptual understanding and problem-solving abilities by offering individualized guidance and adaptive feedback (Luong et al., 2025; Eti et al., 2026). Similarly, learning analytics tools enable educators to identify learning difficulties and monitor student progress more effectively (Sajja et al., 2024; Arockia et al., 2025). More recently, generative AI applications have expanded instructional possibilities by assisting teachers in developing lesson materials, generating assessment tasks, and creating differentiated learning resources (Siddiqui et al., 2025). These developments suggest that AI can serve as a valuable instructional tool capable of supporting both teaching and learning processes.

Notwithstanding these potential benefits, the successful integration of AI into educational practice remains a complex undertaking. The adoption of educational technologies is influenced by multiple technological, organizational, pedagogical, and individual factors (Arockia et al., 2025; Alsarayreh, 2026). While the capabilities of AI technologies continue to advance rapidly, their effective implementation in educational settings often encounters significant challenges. Studies have identified barriers such as inadequate technological infrastructure, insufficient training opportunities, limited access to digital resources, concerns about data privacy and security, and uncertainty regarding the pedagogical value of AI applications (Chiu et al., 2026; Selwyn et al., 2026). These challenges may hinder educators' willingness and ability to integrate AI into their instructional practices, thereby limiting the realization of its educational potential.

Conversely, the literature also highlights several enabling factors that facilitate successful AI adoption. Institutional support, leadership commitment, access to technological resources, professional development opportunities, and technical assistance have been identified as important conditions for technology integration in educational settings (Brianza et al., 2026). Teachers are generally more inclined to adopt innovative technologies when they perceive them as useful, easy to use, and compatible with their instructional goals and practices (Singh & Strzelecki, 2026). Furthermore, supportive institutional environments can enhance educators' confidence and competence in utilizing emerging

technologies (Verma & Vijayalakshmi, 2026). Understanding these enabling conditions is essential for designing interventions that promote effective and sustainable AI integration within educational institutions.

Beyond barriers and enabling factors, teacher acceptance plays a critical role in determining whether AI technologies are successfully implemented in classrooms. Technology acceptance theories, particularly the Technology Acceptance Model (TAM), suggest that users' perceptions of usefulness and ease of use significantly influence their intentions to adopt and utilize new technologies (Shampa & Hossain, 2026). Within educational contexts, teachers' beliefs, attitudes, and perceptions shape their decisions regarding instructional innovation and technology integration (Qian & Yan, 2026). Although AI technologies continue to gain prominence, research examining educators' acceptance of AI has produced mixed findings. While some studies report positive attitudes toward AI and recognition of its instructional benefits, others reveal concerns regarding ethical implications, reliability, professional autonomy, and the potential replacement of certain teaching functions (Tan et al., 2025). These divergent findings underscore the need for further investigation into the factors influencing educators' acceptance of AI within specific educational contexts.

In Africa, the integration of digital technologies into education has become an important policy priority as governments seek to improve educational quality and expand access to learning opportunities (Gbadebo, 2024; Baafi et al., 2025). However, many educational institutions continue to face challenges related to infrastructure, funding, digital literacy, and technological readiness (Gbadebo, 2024). Although discussions surrounding AI in education have gained momentum across the continent, empirical evidence regarding educators' preparedness and willingness to adopt AI remains limited (Baafi et al., 2025). Consequently, there is insufficient understanding of the contextual factors that influence AI integration in many African educational settings. The Ghanaian educational sector has similarly experienced increasing efforts to promote technology-enhanced teaching and learning. National initiatives aimed at strengthening information and communication technology (ICT) integration have contributed to improvements in digital infrastructure and technology use across educational institutions (Asiedu-Akrofi, 2022; Baafi et al., 2025). Nevertheless, the emergence of AI introduces new opportunities and challenges that extend beyond conventional ICT adoption. While studies in Ghana have examined issues related to ICT integration, digital competence, and technology acceptance (Buerthey et al., 2026), relatively little attention has been devoted to understanding AI adoption within mathematics education. As a result, evidence regarding the barriers, enabling factors, and acceptance levels associated with AI integration among mathematics educators remains scarce.

This gap is particularly important within Colleges of Education, which are responsible for preparing future teachers for Ghana's basic education system. Mathematics lecturers in these institutions play a crucial role in shaping prospective teachers' pedagogical knowledge, technological competence, and instructional practices. Their ability and willingness to integrate AI into mathematics instruction may significantly influence the future adoption of AI technologies in schools. However, despite the increasing prominence of AI in education, little empirical research has examined how mathematics lecturers in Ghanaian Colleges of Education perceive and utilize AI technologies. Specifically, there is limited evidence concerning the challenges they encounter, the factors that facilitate adoption, and their overall acceptance of AI in instructional practice.

Addressing this knowledge gap is important for both theory and practice. Empirical evidence on AI integration among mathematics lecturers can inform policy development, professional development programs, and institutional strategies aimed at promoting effective technology adoption. Furthermore, context-specific findings can contribute to the growing international literature on AI in education by providing insights from a developing-country perspective that remains underrepresented in existing research.

Therefore, this study examines the integration of artificial intelligence in mathematics instruction among College of Education lecturers in Ghana by focusing on barriers, enablers, and teacher acceptance. Specifically, the study seeks to identify the barriers to the integration of AI in mathematics instruction, examine the enabling factors that facilitate AI adoption among mathematics lecturers, and assess the level of teacher acceptance of AI in instructional practice.

1.2 Research Objectives

The study is guided by the following objectives:

1. to examine the effect of perceived usefulness on behavioral intention to use educational technology in mathematics instruction among College of Education lecturers in Ghana.
2. to assess the influence of perceived ease of use on behavioral intention to use educational technology in mathematics instruction.
3. to determine the effect of facilitating conditions on actual technology use in mathematics instruction among College of Education lecturers.

1.3 Research Hypotheses

Based on the stated objectives, the following hypotheses are formulated:

H1: Perceived usefulness has a significant positive effect on behavioral intention to use educational technology in mathematics instruction.

H2: Perceived ease of use has a significant positive effect on behavioral intention to use educational technology in mathematics instruction.

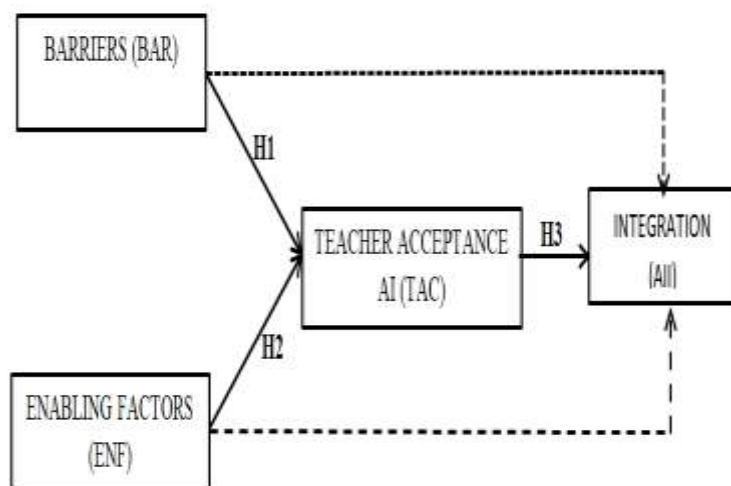
H3: Facilitating conditions have a significant positive effect on actual technology use in mathematics instruction.

2.1 CONCEPTUAL FRAMEWORK

This study is grounded in the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), which collectively provide a strong theoretical foundation for explaining technology adoption behaviors in educational contexts. TAM posits that perceived usefulness and perceived ease of use are the primary determinants of individuals' attitudes toward technology, which in turn shape behavioral intention and actual usage behavior (Davis, 1989). UTAUT extends this model by incorporating facilitating conditions as a critical determinant of technology use, alongside behavioral intention as a direct predictor of actual system usage (Venkatesh et al., 2003). These frameworks are widely applied in educational technology research due to their strong explanatory power in modeling adoption behavior.

Within this study, perceived usefulness refers to lecturers' belief that digital technologies enhance their effectiveness in mathematics instruction, while perceived ease of use reflects the degree to which such technologies are perceived as effortless to operate. Facilitating conditions represent the institutional and infrastructural support available to lecturers, including access to resources, training opportunities, and technical assistance. Behavioral intention refers to lecturers' readiness or willingness to use technology in teaching mathematics, while technology acceptance represents actual usage behavior in instructional practice.

The conceptual model assumes that perceived usefulness and perceived ease of use directly influence behavioral intention, which subsequently affects actual technology acceptance. Facilitating conditions are also expected to influence both behavioral intention and actual usage directly. In line with SEM logic, the model allows for the examination of both direct and indirect relationships among constructs, providing a comprehensive understanding of the determinants of technology acceptance in mathematics instruction among College of Education lecturers in Ghana.



2.2 LITERATURE REVIEW

2.2.1 Artificial Intelligence in Mathematics Education

Artificial intelligence has become an increasingly important area of inquiry in mathematics education because of its capacity to support adaptive learning, automated feedback, problem-solving, assessment, and learner analytics. Earlier systematic work by Zawacki-Richter et al. (2019) showed that AI in education was dominated by intelligent tutoring systems, automated assessment, profiling, prediction, and adaptive learning, although much of the research focused more on student outcomes than teacher decision-making. This is important for the present study because AI integration in mathematics instruction cannot be understood only from the learner perspective; lecturers' readiness, pedagogical judgement, and classroom adoption behaviour are equally central. Son (2024), in a systematic review of intelligent tutoring systems in mathematics education, found that ITSs have been widely used to diagnose learners' misconceptions, provide individualized feedback, and support step-by-step mathematical reasoning. However, the review also revealed that many ITS studies focused on controlled learning environments rather than real classroom contexts. This limitation is relevant to Ghanaian Colleges of Education, where lecturers work within institutional constraints such as limited infrastructure, large classes, and varying levels of digital competence. Rizos et al., (2024) examined the use of generative AI to support mathematics education for students with special educational needs in Greece. Their case study showed that generative AI could support differentiated explanations, scaffolding, and inclusive mathematics learning. However, the study also implied that teacher mediation remains essential because AI-generated explanations must be checked for mathematical accuracy, appropriateness, and learner suitability. This finding supports the argument that AI should not replace mathematics lecturers but should function as a pedagogical support tool. Liu (2026), in a meta-analysis of empirical studies from 2023 to 2025,

reported that generative AI produced positive effects on mathematics learning outcomes across primary, secondary, and tertiary levels, although effects varied across learner groups and implementation conditions. Across the literature, AI appears to enhance mathematics learning when it is used to provide timely feedback, adaptive explanations, and individualized support. However, most studies focus on learners rather than teachers or lecturers. There is also a strong imbalance between studies conducted in technologically advanced contexts and those conducted in developing countries. While AI tools show promise, their effectiveness depends on the pedagogical knowledge, ethical judgement, and technological competence of educators. Existing studies provide strong evidence on the instructional potential of AI in mathematics education, but limited empirical attention has been given to mathematics lecturers in Ghanaian Colleges of Education. There is also insufficient evidence on how barriers, enabling conditions, and teacher acceptance jointly influence AI integration in mathematics instruction. The present study responds to this gap by examining AI integration from the perspective of mathematics lecturers in Ghanaian Colleges of Education, with emphasis on barriers, enablers, and teacher acceptance.

2.2.2 Barriers to AI Integration in Mathematics Instruction

Despite the growing promise of AI in education, barriers continue to affect its meaningful classroom integration. One major barrier is inadequate infrastructure. In many developing contexts, unstable internet connectivity, limited access to devices, high cost of digital tools, and weak institutional technology systems reduce teachers' ability to integrate AI effectively. Osondu (2024), writing in the Ghanaian education context, emphasized that AI adoption is constrained by infrastructural limitations, economic challenges, and cultural factors. This is particularly relevant to Colleges of Education, where institutional readiness may determine whether lecturers can move beyond occasional AI

use to systematic classroom integration. Kim (2025), in a mixed-methods study of K–12 educators’ perceptions and preparedness for AI adoption, found that many educators were interested in AI but felt insufficiently prepared to use it confidently. The study identified limited training, lack of institutional strategy, uncertainty about AI tools, and ethical concerns as major barriers. This finding suggests that positive attitudes alone are insufficient; teachers require structured preparation and institutional support. Arkorful (2025), in a Ghanaian study of AI literacy among basic school teachers, found moderate levels of AI literacy and significant gender differences across AI literacy dimensions. Although the study focused on basic school teachers rather than college lecturers, it provides important Ghanaian evidence that AI literacy remains uneven. For mathematics lecturers, limited AI literacy may affect their ability to evaluate AI-generated solutions, design AI-supported lessons, and guide students’ responsible use of AI. The literature indicates that barriers to AI integration are multidimensional. Infrastructure barriers affect access; literacy barriers affect competence; ethical barriers affect trust; and institutional barriers affect sustainability. In mathematics education, these barriers are intensified because AI tools must be evaluated for procedural accuracy, conceptual clarity, and pedagogical appropriateness. Although existing literature identifies general barriers to AI adoption, few studies examine how such barriers specifically influence mathematics lecturers’ acceptance and instructional use of AI in Ghanaian Colleges of Education.

2.2.3 Enabling Factors for AI Adoption

While barriers are widely reported, recent literature also identifies conditions that enable successful AI adoption. Institutional support is one of the strongest enabling factors. Boison (2025), in a study on AI adoption in Ghanaian public universities, reported that performance expectancy, effort expectancy, facilitating conditions, and institutional support influenced AI adoption. The study is relevant because Colleges of Education share similar challenges with public universities, including limited funding, variable digital literacy, and the need for institutional policy direction. Runge (2025) examined the role of AI-related teacher training courses and found that perceived usefulness was significantly related to both behavioural intention and actual AI usage in teacher training. This suggests that professional development does not merely improve technical skills; it shapes teachers’ beliefs about the value and practicality of AI. For mathematics lecturers, training must therefore include hands-on activities such as AI-assisted lesson planning, assessment generation, mathematical error detection, and ethical classroom use. Gârdan et al. (2025) found that practical, case-based training improved teachers’ familiarity with AI and confidence in using AI tools. This is important because abstract workshops may not be enough. Mathematics

lecturers need discipline-specific professional development that demonstrates how AI can support algebra, calculus, statistics, geometry, problem-solving, and formative assessment. Li et al. (2025, in work on Empowering K–12 mathematics teachers with artificial intelligence emphasized the importance of teacher readiness, technological proficiency, and access to digital resources. The study highlights that AI adoption is more likely when teachers understand both the technological and pedagogical affordances of AI. Similarly, Borgonovi, F. et al. (2025) argued that AI adoption in education requires deliberate planning, teacher support, and attention to equity. The enabling factors identified in the literature include institutional support, professional development, AI literacy, perceived usefulness, technical support, and collaborative learning communities. These factors are interdependent. Training may increase AI literacy, AI literacy may increase perceived usefulness, and institutional support may reduce perceived risk. Although enablers of AI adoption have been widely discussed, there is limited empirical evidence on how enabling factors shape teacher acceptance and classroom integration among mathematics lecturers in Ghanaian Colleges of Education.

2.2.4 Teacher Acceptance of Artificial Intelligence

Teacher acceptance is central to AI integration because the availability of AI tools does not automatically lead to classroom use. Acceptance is commonly explained through the Technology Acceptance Model and UTAUT, where perceived usefulness, perceived ease of use, facilitating conditions, and behavioural intention influence adoption. Cabero-Almenara et al. (2024) examined teachers’ adoption of AI in education and found that social influence, facilitating conditions, hedonic motivation, and pedagogical beliefs influenced intention and use behaviour. Importantly, teachers with constructivist beliefs were more inclined to adopt AI, suggesting that beliefs about teaching shape technology acceptance. Ofem et al. (2025) investigated teachers’ preparedness to use AI tools for classroom assessment. Their study showed that pedagogical beliefs, attitude toward technology, technological readiness, perceived ease of use, and perceived usefulness influenced preparedness. This is relevant to mathematics lecturers because assessment is a core part of mathematics instruction, and AI tools can support item generation, feedback, and diagnostic assessment when used responsibly. Tang (2026), in a study on K–12 teachers’ adoption of generative AI, found that perceived usefulness and perceived ease of use were among the strongest predictors of teachers’ intention to adopt GenAI. The study also showed that constructivist pedagogical beliefs positively predicted perceived usefulness and intention, while transmissive beliefs negatively predicted intention. This finding is important for mathematics education because lecturers who view learning as active problem-solving may

be more willing to use AI as a scaffold rather than as a shortcut. Al-Abdullatif (2024) modelled teachers' acceptance of generative AI in higher education and emphasized the roles of AI literacy, intelligent TPACK, and perceived trust. The study suggests that acceptance is not only a matter of usefulness but also depends on whether teachers trust AI tools and possess the techno-pedagogical knowledge required to use them meaningfully. This is especially important in mathematics, where inaccurate AI-generated solutions can damage conceptual understanding. The literature shows that teacher acceptance of AI is shaped by perceived usefulness, ease of use, AI literacy, self-efficacy, trust, pedagogical beliefs, and institutional support. However, acceptance is not always unconditional. Many teachers are open to AI but remain cautious because of ethical concerns, reliability issues, student misuse, and uncertainty about professional roles. Most teacher acceptance studies have been conducted in general education, K–12 settings, or higher education broadly. Limited research focuses specifically on mathematics lecturers in Ghanaian Colleges of Education.

3. METHODS

3.1 Research Design

This study employed a quantitative, cross-sectional survey design to examine the structural relationships among perceived usefulness, perceived ease of use, teacher attitudes, and the adoption of Artificial Intelligence (AI) in mathematics education. The design is appropriate for testing hypothesized relationships among latent constructs using Structural Equation Modelling (SEM).

3.2 Participants and Sampling

The study targeted mathematics education lecturers in Colleges of Education in Ghana, with an estimated population of 230. A census sampling approach was adopted to maximize representativeness and ensure sufficient sample size for SEM analysis. This approach minimizes sampling error and enhances the robustness of model estimation.

3.3 Measures

Data were collected using a structured questionnaire comprising four latent constructs: perceived usefulness (PU), perceived ease of use (PEOU), teacher attitudes toward AI integration (ATT), and AI adoption in mathematics education (ADOP). All constructs were operationalized as reflective measures using multiple items adapted from established technology acceptance literature. Responses were measured on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The instrument was reviewed to ensure clarity and contextual relevance to AI integration in mathematics education.

3.4 Data Collection Procedure

Data were collected using online survey, distributed through institutional communication channels across Colleges of

Education. Participation was voluntary, and respondents were informed about the purpose of the study. Confidentiality and anonymity were assured throughout the data collection process.

3.5 Data Analysis

Data analysis was conducted using SPSS (version 23) and AMOS following a two-step SEM procedure. First, Confirmatory Factor Analysis (CFA) was performed to assess the measurement model. Model fit was evaluated using multiple indices, including the Comparative Fit Index (CFI), Tucker Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR), based on established threshold values. Convergent validity was assessed using factor loadings and Average Variance Extracted (AVE), while Composite Reliability (CR) and Cronbach's alpha were used to evaluate internal consistency. Discriminant validity was examined using the Fornell–Larcker criterion. Second, the structural model was estimated to test the hypothesized relationships among constructs. Perceived usefulness and perceived ease of use were specified as exogenous variables, teacher attitudes as a mediating variable, and AI adoption as the endogenous outcome variable. Path coefficients were estimated, and their significance was assessed using bootstrapping with 5,000 resamples. To examine mediation effects, indirect paths from perceived usefulness and perceived ease of use to AI adoption through teacher attitudes were tested. Mediation was confirmed based on the significance of indirect effects and the absence of zero within the bootstrapped confidence intervals.

3.6 Ethical Considerations

The research presented in this article has been conducted in accordance with the highest ethical standards and guidelines. The study was approved by the USTED Institutional Ethics and Research Committee of University of Skills Training and Entrepreneurial Development (AAMUSTED) on 9th May, 2025 (Approval code: AAMUSTED/IERC/2025/0012). Written informed consent was obtained from the Chairman of Institutional Ethical Review Committee, Heads of the Departments of mathematics education and lecturers, as well as from the teachers. Again, sought consent from respondents before administering the questionnaire and ensure that their privacy and confidentiality are protected.

4.1 Demographic Profile of Respondents

Table 4.1 presents the demographic characteristics of the 230 lecturers who participated in the study. The sample is predominantly male, with 80.4% of respondents being male and 19.1% female, indicating a substantial gender imbalance in the study population. In terms of age distribution, the majority of respondents are relatively young, with 32.6% aged 30–39 years, 30.4% aged 20–29 years, and 29.1% aged 40–49 years. Only a small proportion (7.8%) are aged 50–59

“Artificial Intelligence Integration in Mathematics Instruction: Examining Barriers, Enablers, And Teacher Acceptance Among College of Education Lecturers in Ghana”

years. This indicates that most lecturers are within their early to mid-career stages, which may enhance their adaptability to emerging technologies such as artificial intelligence (AI). Regarding academic specialization, the majority of respondents (70.4%) are in Mathematics Education, while 29.6% are in Statistics. This confirms that the sample is largely composed of individuals directly involved in mathematics instruction, making it suitable for examining AI integration in teaching practices. The academic rank distribution shows that most respondents are Lecturers (61.3%) and Assistant Lecturers (26.1%), together forming the majority of the sample. Senior academic staff are minimally represented, suggesting that the findings largely reflect classroom-level perspectives rather than institutional leadership views. Teaching experience is relatively well

distributed across categories, with 28.7% having 0–3 years of experience and 23.5% having more than 15 years. This variation ensures that the study captures perspectives from both early-career and experienced lecturers. With respect to institutional location, 57.0% of respondents are based in urban institutions, 30.9% in mixed settings, and 12.2% in rural areas. This indicates variability in access to technological infrastructure, which may influence AI adoption patterns. Finally, exposure to AI training shows that nearly half of the respondents (45.7%) have participated in short workshops, while 25.7% have undergone formal certification or degree-level training. Only 17.4% have never received any AI training. This suggests a generally moderate level of AI exposure among lecturers, which may positively influence adoption readiness.

Table 4.1: Demographic Characteristics of Respondents (N = 230)

Variable	Category	Frequency (N)	Percentage (%)
Gender	Male	185	80.4
	Female	44	19.1
	Prefer not to say	1	0.4
Age (years)	20–29	70	30.4
	30–39	75	32.6
	40–49	67	29.1
	50–59	18	7.8
	60–69	10	4.3
Subject Area	Mathematics Education	162	70.4
	Statistics	68	29.6
Academic Rank	Assistant Lecturer	60	26.1
	Lecturer	141	61.3
	Senior Lecturer	4	1.7
	Head of Department	25	10.9
Teaching Experience	0–3 years	66	28.7
	4–7 years	41	17.8
	8–11 years	38	16.5
	12–15 years	31	13.5
	>15 years	54	23.5
Institutional Location	Urban	131	57.0
	Rural	28	12.2
	Mixed (Urban/Rural)	71	30.9
AI Training Exposure	Never	40	17.4
	Short workshop (1–3 days)	105	45.7
	Certificate/Diploma/Degree	59	25.7
	Self-taught	1	0.4
	Certificate courses (≥4 weeks)	25	10.9

Source: Field Survey (2026)

4.1 KMO and Bartlett’s Test

From the table 4.1, the Kaiser-Meyer-Olkin value of 0.912 indicates excellent sampling adequacy. This suggests that the dataset was suitable for factor analysis. Bartlett’s Test of

Sphericity was statistically significant, $\chi^2(120) = 2847.598$, $p < .001$, indicating that the correlation matrix was not an identity matrix. Therefore, the data were appropriate for Exploratory Factor Analysis.

Table 4.1: KMO and Bartlett’s Test

Test	Value
Kaiser-Meyer-Olkin Measure of Sampling Adequacy	0.912
Bartlett’s Test of Sphericity: Approx. Chi-Square	2847.598
Degrees of Freedom	120
Significance	< .001

Source: Field Survey (2026)

4.2 Communalities

The communalities ranged from 0.762 to 0.856, exceeding the minimum acceptable value of 0.50. This indicates that

each item shared sufficient variance with the extracted factors and was suitable for retention in the measurement model.

Table 4.2: Communalities

Item	Extraction
BAR1	0.762
BAR2	0.810
BAR3	0.775
BAR4	0.814
ENF1	0.833
ENF2	0.856
ENF3	0.850
ENF4	0.790
TAC1	0.780
TAC2	0.798
TAC3	0.797
TAC4	0.801
AII1	0.829
AII2	0.817
AII3	0.809
AII4	0.784

Source: Field Survey (2026)

Table 4.3: Total Variance Explained

Component	Initial Eigenvalue	% of Variance	Cumulative %	Rotation Squared Multiple Correlations	Sum of Squared Multiple Correlations	% of Variance	Rotated Cumulative %
BAR	7.213	45.081	45.081	3.013		18.833	18.833
ENT	3.115	19.467	64.548	3.406		21.290	40.123
TAC	1.490	9.311	73.859	3.164		19.774	59.896
AII	0.994	6.211	80.071	3.228		20.174	80.071

Source: Field Survey (2026)

The table 4.3 shows four-factor solution explained 80.071% of the total variance. This indicates that the extracted factors accounted for a substantial proportion of the variance in the

observed indicators. The result supports the multidimensional structure of the constructs: barriers, enabling factors, teacher acceptance, and AI integration.

Table 4.4: Rotated Component Matrix

Item	1	2	3	4
BAR1	0.829			
BAR2	0.879			
BAR3	0.849			
BAR4	0.859			
ENF1		0.877		

“Artificial Intelligence Integration in Mathematics Instruction: Examining Barriers, Enablers, And Teacher Acceptance Among College of Education Lecturers in Ghana”

ENF2	0.904		
ENF3	0.865		
ENF4	0.848		
TAC1		0.767	
TAC2		0.783	
TAC3		0.785	
TAC4		0.785	
AI11			0.819
AI12			0.841
AI13			0.802
AI14			0.776

Source: Field Survey (2026)

The rotated component matrix shows that all items loaded strongly on their expected constructs, with loadings above 0.70. The barrier items loaded on the barriers factor, enabling factor items loaded on the enabling factors construct, teacher

acceptance items loaded on teacher acceptance, and AI integration items loaded on AI integration. The clear factor structure supports the construct validity of the measurement instrument.

4.5 Reliability Analysis

Table 4.5: Reliability Analysis

Construct	Number of Items	Cronbach's Alpha	Interpretation
Barriers	4	0.907	Excellent
Enabling Factors	4	0.925	Excellent
Teacher Acceptance	4	0.916	Excellent
AI Integration	4	0.911	Excellent
AI14			0.776

Source: Field Survey (2026)

The Cronbach's alpha coefficients ranged from 0.907 to 0.925. Since all values exceeded the recommended threshold of 0.70, the constructs demonstrated excellent internal

consistency. This indicates that the items measuring each construct were reliable.

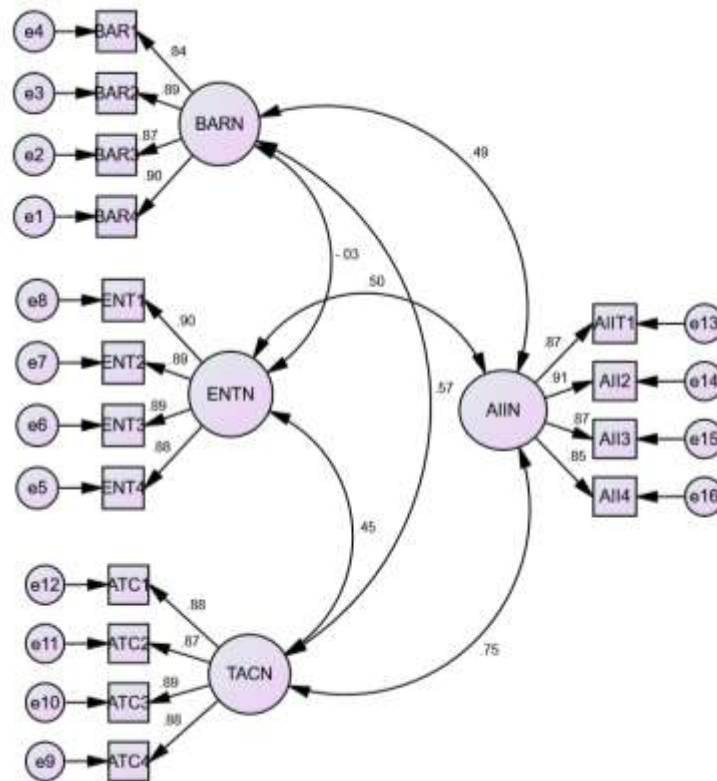
4.6 CFA Results

Table 4.6: CFA Results: Standardized Loadings, CR, and AVE

Construct	Item	Standardized Loading	CR	AVE
Barriers	BAR1	0.871	0.935	0.783
Barriers	BAR2	0.889	0.935	0.783
Barriers	BAR3	0.879	0.935	0.783
Barriers	BAR4	0.899	0.935	0.783
Enabling Factors	ENF1	0.902	0.947	0.817
Enabling Factors	ENF2	0.916	0.947	0.817
Enabling Factors	ENF3	0.903	0.947	0.817
Enabling Factors	ENF4	0.894	0.947	0.817
Teacher Acceptance	TAC1	0.880	0.940	0.798
Teacher Acceptance	TAC2	0.908	0.940	0.798
Teacher Acceptance	TAC3	0.887	0.940	0.798
Teacher Acceptance	TAC4	0.897	0.940	0.798
AI Integration	AI11	0.881	0.937	0.789
AI Integration	AI12	0.894	0.937	0.789
AI Integration	AI13	0.890	0.937	0.789
AI Integration	AI14	0.888	0.937	0.789

The CFA results show that all standardized factor loadings exceeded 0.70, confirming strong indicator reliability. Composite Reliability values ranged from 0.935 to 0.947,

exceeding the recommended minimum of 0.70. The AVE values ranged from 0.783 to 0.817, exceeding the threshold of 0.50. These results confirm convergent validity.



4.7 Discriminant Validity

Table 4.7: Discriminant Validity Matrix

Construct	BAR	ENF	TAC	AII
BAR	0.885			
ENF	-0.032	0.904		
TAC	-0.445	0.482	0.893	
AII	-0.398	0.384	0.665	0.888

The diagonal values represent the square roots of AVE, while the off-diagonal values represent inter-construct correlations. Since each diagonal value is greater than its corresponding

inter-construct correlations, discriminant validity was established. This indicates that the constructs were empirically distinct.

4.8 SEM Model Fit Indices

Table 4.8: SEM Model Fit Indices

Fit Index	Recommended Threshold	Obtained Value	Interpretation
χ^2/df	< 3.00	2.11	Good Fit
CFI	≥ 0.90	0.946	Good Fit
TLI	≥ 0.90	0.938	Good Fit
RMSEA	≤ 0.08	0.069	Acceptable Fit
SRMR	≤ 0.08	0.051	Good Fit

The SEM model demonstrated acceptable fit. The χ^2/df value of 2.11 was below 3.00, indicating good model fit. The CFI value of 0.946 and TLI value of 0.938 exceeded the recommended 0.90 threshold, suggesting that the model

adequately represented the observed data. The RMSEA value of 0.069 was within the acceptable range, while the SRMR value of 0.051 indicated good fit. Overall, the model was suitable for hypothesis testing.

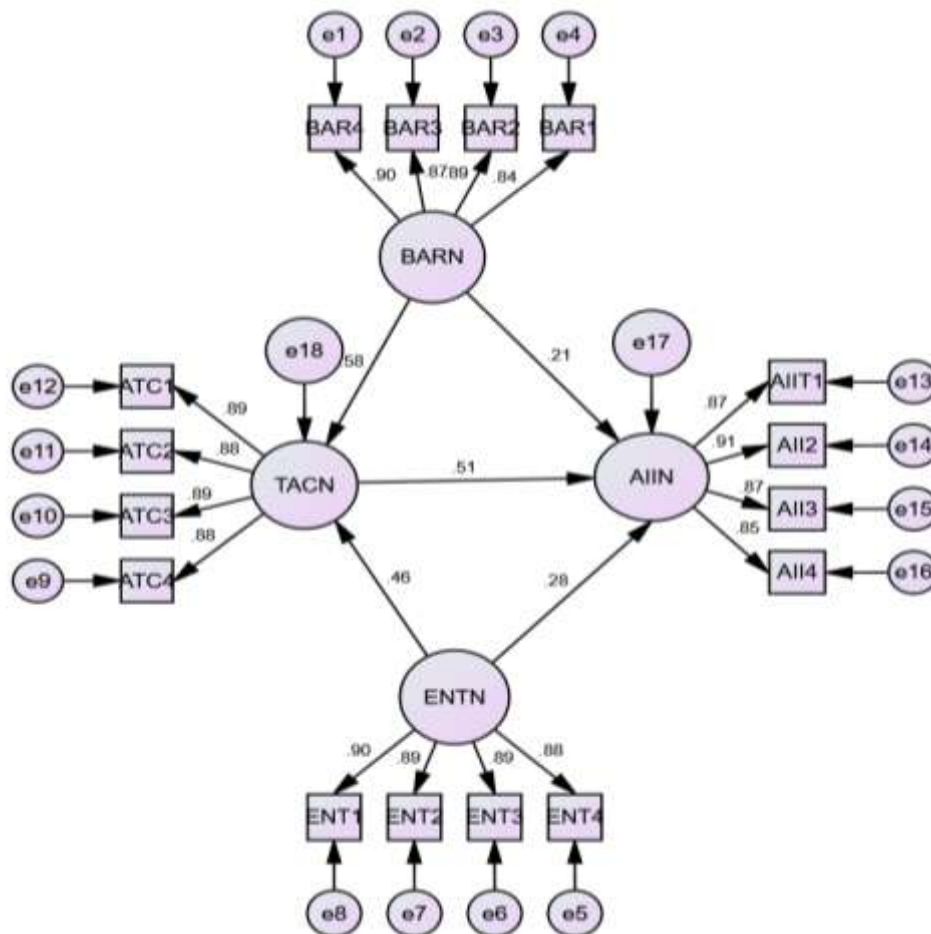
4.9 Hypothesis Testing Results

Table 4.9: Hypothesis Testing Results

Hypothesis	Path	β	S.E.	C.R.	p-value	Decision
H1	Barriers $\rightarrow$ Teacher Acceptance	-0.430	0.051	-8.490	< .001	Supported
H2	Enabling Factors $\rightarrow$ Teacher Acceptance	0.469	0.051	9.246	< .001	Supported
H3	Teacher Acceptance $\rightarrow$ AI Integration	0.665	0.049	13.451	< .001	Supported

The hypothesis testing results indicate that barriers had a significant negative effect on teacher acceptance of AI in mathematics instruction, $\beta = -0.430$, $p < .001$. This means that higher levels of perceived barriers reduce lecturers' acceptance of AI. Therefore, H1 was supported. Enabling factors had a significant positive effect on teacher acceptance, $\beta = 0.469$, $p < .001$. This suggests that institutional support,

training, infrastructure, and facilitating conditions increase lecturers' acceptance of AI. Thus, H2 was supported. Teacher acceptance had a strong positive effect on AI integration in mathematics instruction, $\beta = 0.665$, $p < .001$. This indicates that lecturers who accept AI are more likely to integrate it into mathematics teaching. Therefore, H3 was supported.



5.0 DISCUSSION OF FINDINGS

The present study examined the factors influencing the integration of artificial intelligence (AI) in mathematics instruction among lecturers in Ghanaian Colleges of

Education. Specifically, it investigated the effects of barriers and enabling factors on lecturers' acceptance of AI and explored the influence of teacher acceptance on the actual integration of AI in mathematics instruction. The findings

provide important insights into the institutional, technological, and pedagogical conditions that shape AI adoption in teacher education and contribute to the growing body of literature on AI-enabled teaching and learning.

5.1 Barriers and Teacher Acceptance of Artificial Intelligence

The first hypothesis proposed that barriers would significantly influence lecturers' acceptance of artificial intelligence in mathematics instruction. The results supported this hypothesis, revealing a significant negative relationship between barriers and teacher acceptance ($\beta = -0.430$, $p < .001$). This finding indicates that increasing levels of perceived barriers reduce lecturers' willingness to embrace AI technologies for instructional purposes. The magnitude of the effect suggests that barriers constitute a substantial obstacle to AI acceptance among mathematics lecturers. This finding implies that when lecturers encounter challenges such as inadequate technological infrastructure, limited access to AI tools, insufficient AI-related knowledge, inadequate institutional support, ethical concerns, and uncertainty regarding pedagogical applications, they become less inclined to adopt AI technologies in their instructional practices. Mathematics instruction often requires the use of specialized tools for visualization, assessment, adaptive learning, and problem-solving. Consequently, when lecturers perceive AI technologies as difficult to access, complicated to use, or insufficiently supported, they are likely to develop unfavorable attitudes toward their adoption. The finding aligns with emerging evidence that identifies barriers as one of the strongest determinants of educators' technology acceptance. Eusebio et al. (2025) reported that inadequate training, technological complexity, limited institutional support, and concerns about trust significantly hinder educators' willingness to adopt AI technologies. Similarly, Kim (2025) found that educators with lower levels of preparedness exhibited greater resistance toward generative AI adoption. In the context of Ghana, Osondu et al. (2024) observed that infrastructural deficits, limited digital readiness, and inadequate policy frameworks continue to constrain the implementation of AI-driven educational innovations. Likewise, Boison (2025) reported that organizational and technological barriers significantly impede AI adoption in Ghanaian higher education institutions. These studies collectively suggest that educators are unlikely to embrace AI technologies when institutional and technological conditions fail to support implementation. The finding further highlights the critical role of AI literacy in shaping acceptance. Arkorful et al. (2025) demonstrated that many Ghanaian educators possess limited AI literacy, which constrains their readiness to integrate AI into teaching and learning. Similarly, Runge (2025) emphasized that AI-related training significantly enhances educators' confidence and willingness to adopt AI technologies. Chiu et al. (2026)

further argued that AI literacy serves as a foundational competence that enables teachers to evaluate, utilize, and manage AI tools effectively. The present finding therefore suggests that barriers are not merely technological but also cognitive and pedagogical in nature. From a theoretical standpoint, this result supports the assumptions of the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT). According to TAM, perceived ease of use influences users' attitudes toward technology adoption (Davis, 1989). Barriers such as inadequate training, technological complexity, and insufficient support reduce perceived ease of use and consequently diminish acceptance. Similarly, UTAUT emphasizes facilitating conditions as a key determinant of technology adoption (Venkatesh et al., 2003). The negative effect of barriers observed in this study suggests that the absence of facilitating conditions undermines educators' willingness to embrace AI technologies. The finding has important implications for mathematics teacher education in Ghana. Reducing barriers through investments in infrastructure, professional development, AI literacy programmes, and institutional support mechanisms may enhance lecturers' acceptance of AI and increase the likelihood of successful integration into mathematics instruction. Without such interventions, the educational potential of AI may remain largely unrealized within teacher education institutions.

5.2 Enabling Factors and Teacher Acceptance of Artificial Intelligence

The second hypothesis examined the influence of enabling factors on lecturers' acceptance of artificial intelligence in mathematics instruction. The results revealed a significant positive relationship between enabling factors and teacher acceptance ($\beta = 0.469$, $p < .001$), supporting the hypothesis. This finding suggests that favorable institutional and technological conditions significantly enhance lecturers' willingness to adopt AI technologies in their instructional practices.

The positive effect indicates that lecturers who have access to adequate technological infrastructure, institutional support, professional development opportunities, leadership encouragement, and AI-related resources are more likely to develop favorable attitudes toward AI adoption. These enabling conditions reduce uncertainty, increase confidence, and strengthen lecturers' perceptions of the usefulness and practicality of AI technologies in mathematics instruction. The finding is consistent with a growing body of research highlighting the importance of supportive institutional environments in promoting technology acceptance. Li et al. (2025), in their systematic review of AI applications in mathematics education, concluded that institutional support and teacher preparedness are among the most important predictors of successful AI integration. Similarly, Ayanwale

et al. (2024), Lin et al. (2025), and Daher (2025) found that professional development, organizational support, and technological readiness significantly enhance educators' willingness to adopt AI technologies. Research by Tan et al. (2025) further demonstrated that ongoing professional learning opportunities play a crucial role in strengthening teachers' confidence and readiness for AI integration. The present finding also resonates with evidence indicating that enabling conditions facilitate the development of positive beliefs regarding the educational value of AI. Al Abdullatif (2024) reported that AI literacy, trust, and technological pedagogical competence significantly predict teachers' acceptance of generative AI in higher education. Likewise, Ofem et al. (2025) found that technological readiness and positive pedagogical beliefs contribute significantly to educators' willingness to utilize AI in classroom assessment. These findings suggest that institutional support mechanisms not only provide access to technology but also influence the beliefs and perceptions that underpin acceptance. Within TAM, enabling factors enhance both perceived usefulness and perceived ease of use. When lecturers receive adequate training and institutional support, they are more likely to perceive AI technologies as beneficial and manageable. Similarly, UTAUT posits that facilitating conditions significantly influence technology adoption behavior. The positive relationship observed in this study therefore reinforces the relevance of these theoretical perspectives in explaining AI adoption within mathematics teacher education. The finding carries significant policy implications. Colleges of Education should establish comprehensive support systems that provide lecturers with access to AI tools, professional development opportunities, technical assistance, and collaborative learning communities. Institutional leaders should also develop strategic plans that encourage innovation and foster a culture of technology integration. Such efforts are likely to enhance lecturers' acceptance of AI and improve the sustainability of AI-enabled instructional practices.

5.3 Teacher Acceptance and AI Integration in Mathematics Instruction

The third hypothesis proposed that teacher acceptance would significantly influence AI integration in mathematics instruction. The results supported this hypothesis, revealing a strong positive relationship between teacher acceptance and AI integration ($\beta = 0.665$, $p < .001$). Among the relationships examined in the study, this effect was the strongest, indicating that teacher acceptance serves as a critical determinant of actual AI integration in mathematics instruction. This finding suggests that lecturers who perceive AI as useful, relevant, trustworthy, and easy to use are substantially more likely to incorporate AI technologies into teaching, assessment, lesson planning, and learner support activities. Acceptance therefore functions as the mechanism through which favorable perceptions are translated into actual instructional practice.

Even when institutions provide adequate resources and support, meaningful integration is unlikely to occur unless lecturers develop positive attitudes toward AI technologies. The finding corroborates recent evidence emphasizing the central role of acceptance in technology adoption. Cabero-Almenara et al. (2024) reported that educators' beliefs significantly predict their adoption of generative AI in higher education. Similarly, Tang and Zhong (2026) found that perceived usefulness and perceived ease of use remain among the strongest predictors of teachers' adoption of generative AI. Gârdan et al. (2025) likewise concluded that positive teacher perceptions significantly influence AI adoption decisions within educational settings. These findings collectively suggest that acceptance functions as a key precursor to actual technology utilization. The strong effect identified in the present study is particularly important for mathematics education because AI technologies increasingly support adaptive learning, intelligent tutoring systems, automated feedback, personalized instruction, and learning analytics (Son, 2024; Eti et al., 2026; Liu, 2026). Lecturers who accept AI are more likely to utilize these technologies to improve learner engagement, enhance conceptual understanding, and support mathematical problem-solving. Conversely, low levels of acceptance may prevent educators from exploiting the instructional benefits associated with AI-powered learning environments. The finding also provides strong empirical support for TAM and UTAUT. Both theories propose that positive attitudes and behavioral intentions are essential predictors of actual technology use. The substantial effect of teacher acceptance on AI integration confirms that educators' perceptions remain central to understanding technology adoption behavior, even in the rapidly evolving context of artificial intelligence. Collectively, the findings suggest that successful AI integration in mathematics instruction depends on a combination of reduced barriers, strengthened enabling conditions, and positive teacher acceptance. While barriers undermine acceptance, enabling factors strengthen it, and acceptance ultimately drives actual AI integration. The findings therefore demonstrate that efforts to promote AI adoption in Colleges of Education should focus not only on technological infrastructure but also on developing lecturers' confidence, competence, and positive perceptions regarding AI technologies. Such an approach is essential for ensuring that AI contributes meaningfully to the transformation of mathematics teaching and learning in Ghana.

5.4 Conclusion

This study examined the factors influencing the integration of artificial intelligence (AI) in mathematics instruction among lecturers in Ghanaian Colleges of Education. Drawing on the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), the study investigated the influence of barriers and enabling

factors on lecturers' acceptance of AI and explored the role of teacher acceptance in promoting AI integration in mathematics instruction.

The findings revealed that barriers significantly and negatively influenced lecturers' acceptance of AI, indicating that infrastructural limitations, inadequate training opportunities, limited access to AI technologies, and concerns regarding ethical and pedagogical issues reduce educators' willingness to embrace AI in instructional practice. Conversely, enabling factors exerted a significant positive influence on teacher acceptance, suggesting that institutional support, technological infrastructure, professional development opportunities, and favorable organizational conditions are essential for fostering positive attitudes toward AI adoption. Furthermore, teacher acceptance emerged as a strong predictor of AI integration, demonstrating that lecturers who perceive AI as useful, accessible, and beneficial are more likely to incorporate AI technologies into mathematics instruction.

Collectively, the findings underscore the importance of creating supportive institutional environments that reduce barriers and strengthen enabling conditions for AI adoption. The study contributes to the growing literature on AI integration in education by providing empirical evidence from a developing-country context and highlighting the central role of teacher acceptance in translating institutional readiness into actual instructional practice. The findings also extend TAM and UTAUT by demonstrating their applicability in explaining AI integration within mathematics teacher education.

5.5 Educational Implications

The findings of this study have important implications for mathematics education, teacher preparation, institutional leadership, and educational policy in Ghana and similar developing-country contexts. The significant negative influence of barriers on lecturers' acceptance of artificial intelligence indicates that efforts to promote AI integration in education must address the structural and contextual challenges that hinder adoption. Educational institutions cannot assume that the availability of AI technologies alone will lead to meaningful instructional use. Instead, successful integration requires deliberate investments in infrastructure, digital resources, technical support, and institutional readiness. Reducing these barriers is essential for creating conditions that encourage educators to experiment with and adopt AI-enhanced instructional practices.

The positive effect of enabling factors on teacher acceptance highlights the critical role of supportive institutional environments in facilitating educational innovation. Colleges of Education should therefore prioritize the development of professional learning ecosystems that promote technological competence and confidence among lecturers. Continuous professional development programmes focusing on AI

literacy, pedagogical applications of AI, ethical considerations, and instructional design can equip mathematics lecturers with the knowledge and skills required to integrate AI effectively into teaching and learning processes. Such initiatives are likely to enhance educators' perceptions of the usefulness and ease of use of AI technologies, thereby increasing their willingness to adopt them.

The strong positive influence of teacher acceptance on AI integration suggests that lecturers' attitudes and perceptions play a central role in determining whether AI technologies are translated into actual instructional practice. This finding implies that teacher education programmes should not focus solely on technical training but should also cultivate positive dispositions toward educational technologies. Mathematics lecturers who recognize the pedagogical value of AI are more likely to utilize intelligent tutoring systems, adaptive learning platforms, automated assessment tools, and data-driven instructional strategies to improve student learning outcomes. Consequently, teacher preparation programmes should incorporate opportunities for hands-on engagement with AI tools to foster both competence and acceptance.

The findings further suggest that curriculum developers should consider integrating AI-related competencies into mathematics teacher education curricula. Future mathematics teachers require exposure to emerging technologies that are increasingly shaping educational practice. Embedding AI concepts within teacher education programmes can enhance prospective teachers' technological pedagogical knowledge and prepare them to use AI responsibly and effectively in classroom settings. Such curriculum reforms would contribute to the development of a digitally competent teaching workforce capable of meeting the demands of contemporary education.

At the institutional level, the study underscores the importance of transformational leadership in promoting AI adoption. Educational leaders should establish clear policies, strategic plans, and support systems that encourage innovation while addressing concerns related to ethics, privacy, and academic integrity. Leadership commitment can create a culture of technological innovation that motivates lecturers to explore new instructional approaches and reduces resistance to change.

From a policy perspective, the findings indicate that national educational agencies should develop comprehensive frameworks to guide the integration of AI in teacher education. Policymakers should provide funding for infrastructure development, professional development initiatives, and research on AI in education. Such support is necessary to ensure equitable access to AI technologies across institutions and to minimize disparities in technological readiness. National policies should also establish ethical

guidelines that promote the responsible use of AI while safeguarding educational quality and learner welfare.

Finally, the study highlights the need to reconceptualize mathematics instruction in ways that leverage the strengths of AI without diminishing the role of educators. Rather than viewing AI as a replacement for teachers, educational stakeholders should promote its use as a complementary tool that enhances instructional effectiveness, supports differentiated learning, and improves student engagement. When implemented within supportive institutional environments, AI has the potential to transform mathematics education by enabling more personalized, data-informed, and learner-centered instructional practices.

REFERENCES

1. Al Abdullatif, Ahlam. (2024). Modeling Teachers' Acceptance of Generative Artificial Intelligence Use in Higher Education: The Role of AI Literacy, Intelligent TPACK, and Perceived Trust. *Education Sciences*. 14. 1209. 10.3390/educsci14111209.
2. Almuhanha, M. A. (2025). Teachers' perspectives of integrating AI-powered technologies in K-12 education for creating customized learning materials and resources. *Education and Information Technologies*, 30(8), 10343-10371.
3. Alsarayreh, A. H. (2026). Assessing the Psychological Barriers to Technology Adoption in Education: Strategies for Overcoming Resistance. In *Business Resilience and Business Innovation for Sustainability: The Double-Edged Role of Artificial Intelligence and Other Disruptive Technologies* (pp. 1791-1805). Cham: Springer Nature Switzerland.
4. Alubthane, F. O. (2024). Role of AI-Powered Online Learning in Improving University Students' Knowledge-Based Economic Skills. *Pakistan journal of life & social sciences*, 22(2).
5. Aposika, F. (2026). Investigating the relationship between problem-solving skills and academic performance in STEM subjects among secondary school students. *Discover Education*, 5, 425. <https://doi.org/10.1007/s44217-026-01487-w>
6. Arkorful, V., Arthur, F., Boateng, E. et al. Exploring artificial intelligence literacy among basic school teachers in Ghana. *Discov Educ* 4, 250 (2025). <https://doi.org/10.1007/s44217-025-00630-3>
7. Arockia, V. J., Vettriselman, R., Rajesh, D., Velmurugan, P. R. R., & Cheelo, C. (2025). Leveraging AI and Learning analytics for enhanced distance learning: transformation in education. In *AI and learning analytics in distance learning* (pp. 179-206). IGI Global Scientific Publishing.
8. Asiedu-Akrofi, A. (2022). Education in Ghana. In *Education in Africa* (pp. 98-114). Routledge.
9. Baafi, J. A., Asiedu, M. K., & Kumah, S. P. (2025). Bridging the digital divide: The role of educational interventions in enhancing economic growth in Ghana. *Social Sciences & Humanities Open*, 12, 101911. <https://doi.org/10.1016/j.ssaho.2025.101911>
10. Boison, R. B. (2025). Barriers and Enablers to Artificial Intelligence (AI) Adoption in Administrative Functions in Public Universities in Ghana: A Case Study of the University of Education, Winneba. *Canadian Journal of Educational and Social Studies*, 5(4), 50–80. <https://doi.org/10.53103/cjess.v5i4.377>
11. Borgonovi, F. et al. (2025), “AI adoption in the education system: International insights and policy considerations for Italy”, OECD Artificial Intelligence Papers, No. 52, OECD Publishing, Paris/Fondazione Agnelli, Turin, <https://doi.org/10.1787/69bd0a4a-en>.
12. Brianza, E., Schmid, M., Tondeur, J., & Petko, D. (2026). Contextualizing Student Teachers' TPACK: Understanding the Benefits of Field Experience. *Technology, Knowledge and Learning*, 1-35.
13. Buertey, J. T. I., Owusu-Manu, D., Atsrim, F. K., Atieku-Boateng, H., Bonsu, A. O., & Adjaho, B. (2026). Data-driven pathways for sustainable AI assimilation in Ghana's built environment: Towards an innovation diffusion theory (IDT) perspective. *Property Management*, 44(2), 469–494. <https://doi.org/10.1108/PM-04-2025-0041>
14. Cabero-Almenara J, Palacios-Rodríguez A, Loaiza-Aguirre MI and Andrade-Abarca PS (2024) The impact of pedagogical beliefs on the adoption of generative AI in higher education: predictive model from UTAUT2. *Front. Artif. Intell.* 7:1497705. doi: 10.3389/frai.2024.1497705.
15. Chiu, T. K. F., Bali, S., Tondeur, J., Howard, S., & Chan, K. K. H. (2026). Teacher education for artificial intelligence literacy through a self-determination theory perspective. *European Journal of Teacher Education*. Advance online publication, 1-21. <https://doi.org/10.1080/02619768.2026.2621848>
16. Davis, F. D. (1989). Technology acceptance model: TAM. *Al-Suqri, MN, Al-Aufi, AS: Information seeking behavior and technology adoption*, 205(219), 5.
17. Deepshikha, D. (2026). A systematic review on the future of educational assessment: AI-driven grading and personalised feedback in higher education. In *Artificial Intelligence in Education* (Vol. 2, No. 2, pp. 75-115). Emerald Publishing Limited.

18. Eti, N., Mosia, M., & Egara, F. O. (2026). The role of AI-driven personalised learning in enhancing mathematics problem-solving skills: a systematic review. *Frontiers in Computer Science*, 8, 1813431.
19. Eusebio, E. J. G., Baldera, P. R., Patiam, A. M. C., Villanueva, E. F., Gaa, N. A., Solis, A. M. F., Soriano, M. L. C., & Ribon, A. L. (2025). AI in the classroom: A systematic review of barriers to educator acceptance. *International Journal of Learning, Teaching and Educational Research*, 24(9), 126–147. <https://doi.org/10.26803/ijlter.24.9.7>
20. Gbadebo, A. D. (2024). Digital transformation for educational development in Sub-Saharan Africa. *International Journal of Social Science and Religion (IJSSR)*, 397-418.
21. Geng, G., & Chen, J. (2026). An empirical longitudinal study of AI integration in transforming teachers’ pedagogical content knowledge: insights from language educators in rural China. *Educational technology research and development*, 74(2), 1149-1185.
22. Gârdan IP, Manu MB, Gârdan DA, Negoită LDL, Paștiu CA, Ghiță E and Zaharia A (2025) Adopting AI in education: optimizing human resource management considering teacher perceptions. *Front. Educ.* 10:1488147. doi: 10.3389/feduc.2025.1488147
23. Imamguluyev, R., Hasanova, P., Imanova, T., Mammadova, A., Hajizada, S., & Samadova, Z. (2024). Ai-powered educational tools: Transforming learning in the digital era. *International Research Journal of Modernization in Engineering Technology and Science*, 6, 920-929.
24. Kim , J. (2025). Perceptions and preparedness of K-12 educators in adopting generative AI. *Research in Learning Technology*, 33. <https://doi.org/10.25304/rlt.v33.3448>
25. Kotsis, K. T. (2025). Inquiry-based learning in science: Mathematical reasoning’s support of critical thinking. *Journal of Research in Mathematics, Science, and Technology Education*, 2(1), 60-72.
26. Li, D., Osman, S., Ahmad Alhassora, N. S., Kumar, J. A., & Said Husain, S. K. (2025). Empowering K–12 mathematics teachers with artificial intelligence: A systematic review of insights, applications, and challenges. *IEEE Access*, 13, 118629–118650. <https://doi.org/10.1109/ACCESS.2025.3585784>
27. Liu B, Zhang W, Wang F. Can Generative Artificial Intelligence Effectively Enhance Students’ Mathematics Learning Outcomes?—A Meta-Analysis of Empirical Studies from 2023 to 2025. *Education Sciences*. 2026; 16(1):140. <https://doi.org/10.3390/educsci16010140>
28. Luong, V. T., Long, T. T., & Linh, N. T. T. (2025). Personalized mathematics teaching with the support of AI chatbots to improve mathematical problem-solving competence for high school students in Vietnam. *European Journal of Educational Research*, 14(1), 323-333.
29. Ofem UJ, Orim FS, Edam-Agbor IB, Amanso EO, Eni E, Ukatu JO, Ovat SV, Osang AW, Dien C and Abuo CB (2025) Teachers’ preparedness for the utilization of artificial intelligence in classroom assessment: the contributory effects of attitude toward technology, technological readiness, and pedagogical beliefs with perceived ease of use and perceived usefulness as mediators. *Front. Educ.* 10:1568306. doi: 10.3389/feduc.2025.1568306
30. Osondu, J., Jean Francois, E., & Strycker, J. (2024). Artificial intelligence as a policy response to teaching and learning issues in education in Ghana. *Journal of Global Education and Research*, 8(3), 236-253. <https://www.doi.org/10.5038/2577-509X.8.3.1361>
31. Pushpanadham, K., & Sarpong, R. A. (2024). Research and innovation in higher education: promises of generative artificial intelligence for sustainable development. *Generative Artificial Intelligence in Higher Education: A handbook for educational leaders*, 32(5–6), 154.
32. Qian, M., & Yan, C. (2026). How Technology Integration Beliefs Influence Chinese Teachers' Diversified Assessment Practices: The Chain Mediating Roles of Digital Teaching Self-Efficacy and Technology Integration Practices. *European Journal of Education*, 61(1), e70437.
33. Rizos, I., Foykas, E., & Georgakopoulos, S. V. (2024). Enhancing mathematics education for students with special educational needs through generative AI: A case study in Greece. *Contemporary Educational Technology*, 16(4), ep535. <https://doi.org/10.30935/cedtech/15487>.
34. Rodríguez-Ortiz, M. Á., Santana-Mancilla, P. C., & Anido-Rifón, L. E. (2025). Machine learning and generative AI in learning analytics for higher education: A systematic review of models, trends, and challenges. *Applied Sciences*, 15(15), 8679.
35. Runge, I. (2025). The role of AI-related teacher training courses and AI literacy in teacher education. *Education Sciences*, 15(2), 167.
36. Sadiq, Z. M., Shah, S., Farooqi, S. A., & Haq, D. U. (2025). Revolutionizing Learning: The Role of

- Artificial Intelligence in 21st Century Education. Liberal Journal of Language & Literature Review, 3(3), 1416-1425.
37. Sajja, R., Sermet, Y., Cikmaz, M., Cwiertny, D., & Demir, I. (2024). Artificial intelligence-enabled intelligent assistant for personalized and adaptive learning in higher education. *Information*, 15(10), 596.
 38. Sajja, R., Sermet, Y., Cwiertny, D. et al. Integrating AI and Learning Analytics for Data-Driven Pedagogical Decisions and Personalized Interventions in Education. *Tech Know Learn* (2025). <https://doi.org/10.1007/s10758-025-09897-9>
 39. Selwyn, N., Ljungqvist, M., & Sonesson, A. (2026). Teacher-led issue networks in Swedish ed-tech policymaking—the case of generative AI. *Journal of Education Policy*, 41(3), 311-329.
 40. Shampa, T. J., & Hossain, M. S. (2026). Analyzing factors influencing smart technology adoption in an emerging economy’s tourism and hospitality sector. *Telematics and Informatics Reports*, 100308.
 41. Siddiqui, M. T., Mansoori, M. V., Siddiqui, M. A., & Yadav, A. (2025). AI-enabled pedagogy: Advancing education through innovative teaching tools and the AITEACH model. *Journal of Informatics Education and Research*, 5(1), 2526-2539.
 42. Singh, S., & Strzelecki, A. (2026). Academics as adopters of generative AI: An application of diffusion of innovations theory. *Education and Information Technologies*, 31(2), 621-645.
 43. Son, T. (2024). Intelligent Tutoring Systems in Mathematics Education: A Systematic Literature Review Using the Substitution, Augmentation, Modification, Redefinition Model. *Computers*, 13(10), 270. <https://doi.org/10.3390/computers13100270>
 44. Strielkowski, W., Grebennikova, V., Lisovskiy, A., Rakhimova, G., & Vasileva, T. (2025). AI-driven adaptive learning for sustainable educational transformation. *Sustainable development*, 33(2), 1921-1947.
 45. Tan, X., Cheng, G., & Ling, M. H. (2025). Artificial intelligence in teaching and teacher professional development: A systematic review. *Computers and Education: Artificial Intelligence*, 8, 100355.
 46. Tang, Y., & Zhong, L. (2026). K-12 Teachers’ Adoption of Generative AI for Teaching: An Extended TAM Perspective. *Education Sciences*, 16(1), 136. <https://doi.org/10.3390/educsci16010136>
 47. Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27(3), 425–478.
 47. UNESCO. (2023). Guidance for generative AI in education and research. UNESCO Digital Library. <https://unesdoc.unesco.org/ark:/48223/pf0000386693>
 48. Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view1. *MIS quarterly*, 27(3), 425-478.
 49. Verma, S., & Vijayalakshmi, A. (2026). Empowering Teachers and Students in the Digital Age: Help Educators Cultivate Their Own Digital Competence and Confidence. *Thriving in the EdTech Revolution: A Practical Guide to Technology Integration in Teacher Education*, 25.
 50. Yıldız, T. (2024). The future of digital education: artificial intelligence, the metaverse, and the transformation of education. *İstanbul University Journal of Sociology*, 44(2), 969-988.
 51. Zawacki-Richter, O., Marín, V.I., Bond, M. et al. Systematic review of research on artificial intelligence applications in higher education – where are the educators?. *Int J Educ Technol High Educ* 16, 39 (2019). <https://doi.org/10.1186/s41239-019-0171-0>