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Examining the Moderating Effect of Instructional Risk on the Relationship Between Relative Advantage and AI Classroom Use Among Mathematics Lecturers in Ghana

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Abstract

Artificial intelligence (AI) is increasingly reshaping instructional planning, assessment, feedback, and learner support in higher education. In mathematics education, AI tools offer possibilities for adaptive problem solving, automated feedback, mathematical visualization, lesson preparation, and differentiated instruction. However, lecturers' classroom use of AI may depend not only on perceived benefits but also on concerns about instructional risk, including academic dishonesty, inaccurate AI-generated solutions, overreliance, reduced learner reasoning, ethical uncertainty, and weakened pedagogical control. This study examined the moderating effect of instructional risk on the relationship between relative advantage and AI classroom use among mathematics lecturers in Ghanaian Colleges of Education. Anchored in Diffusion of Innovation Theory, the Technology Acceptance Model, and the Technology–Organization–Environment framework, the study employed a quantitative cross-sectional survey design. Data were collected from 230 mathematics lecturers and analysed using Structural Equation Modeling in AMOS. The measurement model showed acceptable reliability, convergent validity, and discriminant validity. The structural model demonstrated good fit: $\chi^2/df = 1.91$, CFI = .956, TLI = .947, IFI = .957, GFI = .921, AGFI = .895, RMSEA = .063, and SRMR = .046. Results revealed that relative advantage positively predicted AI classroom use, $\beta = .48$, $p < .001$, while instructional risk negatively predicted AI classroom use, $\beta = -.29$, $p < .001$. The interaction effect was also significant, $\beta = -.18$, $p < .01$, indicating that instructional risk weakens the positive influence of relative advantage on AI classroom use. The study contributes to AI adoption literature by demonstrating that perceived usefulness alone may be insufficient when lecturers perceive AI as pedagogically risky. Practical implications are discussed for AI policy, lecturer professional development, ethical guidelines, and mathematics teacher education in Ghana.

Keywords: Artificial Intelligence, Mathematics Education, Relative Advantage, Instructional Risk, Classroom Use, SEM, Ghana

1. Introduction

Artificial intelligence (AI) is increasingly transforming higher education worldwide by reshaping teaching, learning, assessment, and academic support practices. The emergence of generative AI technologies has expanded opportunities for personalized learning, intelligent tutoring, adaptive assessment, automated feedback, and instructional content generation (UNESCO, 2023; Imamguluyev *et al*., 2024; Yıldız, 2024; Sajja *et al*., 2024) [48, 23, 51, 37]. As educational institutions seek innovative ways to enhance learning outcomes and improve instructional efficiency, AI is becoming an integral component of digital transformation initiatives across universities and teacher education institutions (Gbadebo, 2024; Borgonovi *et al*., 2025) [20, 11]. Consequently, understanding the factors that influence educators' adoption and classroom use of AI has become a growing priority among educational researchers and policymakers.

The integration of AI is particularly relevant in mathematics education because of its potential to support problem-solving, conceptual understanding, personalized instruction, and real-time feedback. Recent studies indicate that AI-powered educational tools can improve students' mathematical reasoning, provide adaptive learning experiences, and facilitate differentiated instruction (Li *et al*., 2025; Son, 2024; Luong *et al*., 2025; Eti *et al*., 2026) [26, 43, 28, 18]. Similarly, generative AI technologies can assist lecturers in developing instructional materials, generating mathematical examples, creating assessments, and providing individualized support to learners (Rizos *et al*., 2024; Liu *et al*., 2026) [33, 27]. These capabilities suggest that AI has considerable potential to enhance mathematics instruction and improve learning outcomes in higher education settings.

In teacher education institutions, mathematics lecturers play a crucial role in preparing future teachers for technology-enhanced learning environments. As Ghana continues to pursue educational digitalization and technology integration reforms, Colleges of Education are expected to equip pre-service teachers with the competencies needed to utilize emerging technologies effectively (Asiedu-Akrofi, 2022; Osondu *et al*., 2024) [8, 30]. Consequently, mathematics lecturers' adoption of AI technologies has implications not only for their own instructional practices but also for the preparedness of future mathematics teachers. However, successful AI integration depends largely on lecturers' perceptions of the benefits and challenges associated with these technologies.

One of the most widely recognized determinants of technology adoption is relative advantage. According to Diffusion of Innovation Theory, relative advantage refers to the extent to which an innovation is perceived as offering superior benefits compared to existing practices (Rogers, 2003). Within educational contexts, relative advantage may be reflected in lecturers' perceptions that AI improves instructional effectiveness, enhances productivity, facilitates personalized learning, supports timely feedback, and reduces administrative workload (Cabero-Almenara *et al*., 2024; Al Abdullatif, 2024; Tan *et al*., 2025) [14, 1, 45]. Research on AI adoption among educators has consistently shown that technologies perceived as useful and beneficial are more likely to be adopted and integrated into teaching activities (Kim, 2025; Tang & Zhong, 2026; Singh & Strzelecki, 2026) [24, 46, 42]. Similarly, the Technology Acceptance Model posits that perceived usefulness significantly influences users' intentions and actual technology use (Davis, 1989) [16].

Despite these potential benefits, AI adoption in education remains accompanied by substantial concerns. Educators increasingly express apprehension regarding the reliability, ethical implications, privacy concerns, and pedagogical consequences of AI use in teaching and learning (UNESCO, 2023; Eusebio *et al*., 2025; Almuhanna, 2025) [48, 19, 2]. In mathematics education, these concerns may be particularly significant because inaccurate AI-generated solutions, flawed reasoning processes, and excessive reliance on automated systems can negatively affect students' conceptual understanding and critical thinking skills (Li *et al*., 2025; Liu *et al*., 2026) [26, 27]. Furthermore, concerns regarding academic dishonesty, diminished teacher authority, and overdependence on technology continue to shape educators' attitudes toward AI integration (Ofem *et al*., 2025; Gârdan *et al*., 2025) [29, 22].

These concerns are often conceptualized as instructional risk, which refers to educators' perceptions of the potential negative consequences associated with using AI for instructional purposes. Instructional risk may include fears relating to inaccurate content generation, ethical misuse, data privacy breaches, reduced learner autonomy, and the erosion of pedagogical control (UNESCO, 2023; Eusebio *et al*., 2025) [48, 19]. Consequently, lecturers may hesitate to incorporate AI into their teaching practices even when they recognize its potential benefits. Recent studies suggest that risk perceptions significantly influence technology adoption decisions and may either facilitate or hinder the translation of perceived benefits into actual use (Alsarayreh, 2026; Shampa & Hossain, 2026) [3, 40].

The Technology–Organization–Environment framework provides a useful perspective for understanding this phenomenon by emphasizing that technology adoption is influenced not only by technological benefits but also by contextual and environmental factors. Within this framework, instructional risk may function as a moderating variable that influences the strength of the relationship between relative advantage and AI classroom use. When instructional risk is perceived to be low, lecturers who recognize the benefits of AI may be more willing to integrate it into their instructional practices. Conversely, high levels of perceived instructional risk may weaken the positive influence of relative advantage on classroom use (Al Abdullatif, 2024; Cabero-Almenara *et al*., 2024; Tang & Zhong, 2026) [1, 14, 46].

In Ghana, the adoption of AI within educational institutions is still emerging. Although increasing attention has been given to AI literacy, digital transformation, and technology integration, evidence suggests that educators continue to face challenges relating to infrastructure, professional development, institutional support, and technological readiness (Arkorful *et al*., 2025; Boison, 2025; Baafi *et al*., 2025) [6, 10, 9]. While existing studies have examined AI awareness, readiness, and adoption among educators, limited empirical evidence exists regarding AI classroom use among mathematics lecturers in Colleges of Education. Furthermore, few studies have investigated how instructional risk influences the relationship between perceived relative advantage and AI utilization in educational settings.

This gap is particularly important because understanding the interaction between perceived benefits and perceived risks may provide a more comprehensive explanation of AI adoption behavior among mathematics lecturers. Therefore, this study examines the moderating effect of instructional risk on the relationship between relative advantage and AI classroom use among mathematics lecturers in Ghanaian Colleges of Education. The findings are expected to contribute to the growing literature on AI adoption in education while providing evidence to inform policy, professional development, and responsible AI integration in teacher education institutions.

1.1 Research Objectives

1. To examine the influence of relative advantage on AI classroom use among mathematics lecturers in Ghanaian Colleges of Education.
2. To determine the influence of instructional risk on AI classroom use among mathematics lecturers in Ghanaian Colleges of Education.
3. To investigate the moderating effect of instructional risk on the relationship between relative advantage and AI classroom use among mathematics lecturers in Ghanaian Colleges of Education.

1.2 Research Hypotheses

H1: Relative advantage has a positive and significant influence on AI classroom use among mathematics lecturers in Ghanaian Colleges of Education.

H2: Instructional risk has a negative and significant influence on AI classroom use among mathematics lecturers in Ghanaian Colleges of Education.

H3: Instructional risk significantly moderates the relationship between relative advantage and AI classroom use among mathematics lecturers in Ghanaian Colleges of Education.

2. Literature Review

2.1 Artificial Intelligence in Mathematics Education

Artificial intelligence (AI) has emerged as one of the most transformative technologies influencing contemporary educational practice. The increasing sophistication of AI-powered systems, particularly generative AI, intelligent tutoring systems, adaptive learning platforms, and learning analytics tools, has created new opportunities for enhancing teaching and learning processes across educational levels (UNESCO, 2023; Sajja *et al*., 2024; Yıldız, 2024) [48, 37, 51]. In higher education, AI is increasingly being utilized to support personalized learning, automated feedback, content generation, assessment design, and data-driven pedagogical decision-making (Rodríguez-Ortiz *et al*., 2025; Sajja *et al*., 2025) [34, 38]. These developments have attracted considerable attention from educators and researchers seeking innovative approaches to improve instructional quality and learner outcomes. Within mathematics education, AI has demonstrated considerable potential for supporting both teachers and learners. Mathematics learning often requires individualized support, timely feedback, conceptual scaffolding, and opportunities for repeated practice. AI-powered educational technologies provide mechanisms through which these needs can be addressed more efficiently than traditional instructional approaches. For example, intelligent tutoring systems can diagnose learners' misconceptions, provide adaptive feedback, and personalize learning experiences according to individual performance levels (Son, 2024) [43]. Similarly, AI-driven personalized learning environments have been found to improve students' mathematical problem-solving abilities and conceptual understanding by tailoring instructional support to learners' needs (Eti *et al*., 2026; Luong *et al*., 2025) [18, 28]. Recent systematic reviews further indicate that AI technologies can enhance mathematics instruction by supporting mathematical reasoning, facilitating visualization of abstract concepts, generating multiple solution strategies, and improving learner engagement (Li *et al*., 2025; Liu *et al*., 2026) [26, 27]. AI-enabled platforms can also assist lecturers in creating instructional materials, generating assessment items, designing differentiated learning activities, and providing immediate formative feedback. Rizos *et al*. (2024) [33] demonstrated that generative AI can support mathematics learning among students with special educational needs through adaptive instructional approaches, while Son (2024) [43] found that intelligent tutoring systems positively influence mathematics achievement when integrated with sound pedagogical practices. Despite these advantages, scholars caution against uncritical adoption of AI in mathematics education. Mathematics learning extends beyond obtaining correct answers and involves reasoning, justification, proof construction, communication, and conceptual understanding. AI-generated responses may occasionally contain computational errors, flawed reasoning, or misleading explanations, which can negatively influence learners' conceptual development if not properly monitored (Li *et al*., 2025; Liu *et al*., 2026) [26, 27]. Furthermore, excessive dependence on AI-generated solutions may reduce students' opportunities to engage in productive struggle, critical thinking, and independent problem-solving. Consequently, successful AI integration in mathematics education requires strong pedagogical oversight, AI literacy, and critical evaluation of AI outputs by educators.

2.2 Relative Advantage and Technology Adoption

Relative advantage is one of the most influential determinants of innovation adoption and constitutes a central construct within Rogers' (2003) Diffusion of Innovation Theory. It refers to the degree to which an innovation is perceived as superior to the practice, process, or technology it replaces. The greater the perceived benefits associated with an innovation, the higher the likelihood of its adoption by potential users. In educational settings, relative advantage has consistently been identified as a significant predictor of teachers' willingness to adopt new technologies and integrate them into instructional practice. The emergence of AI technologies has renewed scholarly interest in understanding how educators evaluate the advantages associated with technological innovations. Recent studies indicate that teachers are more likely to adopt AI technologies when they perceive them as capable of improving instructional effectiveness, reducing workload, enhancing student engagement, and facilitating personalized learning experiences (Cabero-Almenara *et al*., 2024; Kim, 2025; Tan *et al*., 2025) [14, 24, 45]. Similarly, Al Abdullatif (2024) [1] found that educators' perceptions of AI usefulness significantly influence their acceptance of generative AI technologies in higher education. These findings align with the Technology Acceptance Model, which emphasizes perceived usefulness as a primary determinant of technology adoption (Davis, 1989) [16]. In mathematics education, relative advantage may manifest through AI's ability to automate routine instructional tasks, provide adaptive support, generate multiple mathematical representations, and facilitate immediate feedback. AI-powered tools can support lecturers in developing instructional resources, generating worked examples, creating assessment items, and identifying learners' misconceptions more efficiently than traditional methods (Li *et al*., 2025; Luong *et al*., 2025) [26, 28]. Consequently, lecturers who perceive AI as offering significant pedagogical and professional benefits are more likely to integrate it into classroom activities. However, perceptions of relative advantage are not solely determined by technological capabilities. Previous studies suggest that educators' pedagogical beliefs, AI literacy, digital competence, and institutional context significantly influence how the benefits of AI are perceived (Al Abdullatif, 2024; Runge, 2025; Chiu *et al*., 2026) [1, 35, 15]. Therefore, while relative advantage remains an important predictor of adoption, its influence may vary across educational contexts and individual users.

2.3 Instructional Risk in Educational Technology Integration

Although AI technologies offer substantial instructional benefits, their adoption is often accompanied by concerns regarding potential risks and unintended consequences. Instructional risk refers to educators' perceptions of the uncertainties, challenges, and negative outcomes associated with using technology for teaching and learning purposes. In the context of AI-supported education, instructional risks may include inaccurate information generation, algorithmic bias, ethical concerns, privacy violations, academic dishonesty, and overdependence on automated systems (UNESCO, 2023; Eusebio *et al*., 2025) [48, 19]. The rapid expansion of generative AI technologies has intensified concerns regarding educational integrity and instructional quality. Scholars argue that AI-generated content may occasionally provide incorrect answers, fabricated information, or misleading explanations that could compromise learning outcomes if not carefully evaluated (Li *et al*., 2025; Almuhanna, 2025) [26, 2]. In mathematics education, such risks are particularly significant because learners often rely on the accuracy and logical consistency of instructional explanations. Errors in AI-generated mathematical reasoning may undermine conceptual understanding and promote misconceptions among learners (Liu *et al*., 2026) [27]. Beyond accuracy concerns, educators have expressed apprehension regarding student overreliance on AI tools. Excessive dependence on AI-generated solutions may discourage critical thinking, reduce independent problem-solving efforts, and weaken students' analytical reasoning skills (Ofem *et al*., 2025) [29]. Similarly, issues relating to plagiarism, assessment validity, and ethical misuse of AI technologies have emerged as major concerns within higher education (UNESCO, 2023; Eusebio *et al*., 2025) [48, 19]. These concerns may significantly influence lecturers' decisions regarding whether AI should be incorporated into classroom activities. Previous research suggests that risk perceptions frequently serve as barriers to technology adoption. Even when educators recognize the benefits associated with technological innovations, concerns about potential negative consequences may discourage actual use (Alsarayreh, 2026; Shampa & Hossain, 2026) [3, 40]. Therefore, instructional risk is increasingly recognized as an important factor influencing AI adoption in educational settings.

2.4 AI Classroom Use

AI classroom use refers to the actual application of AI technologies within teaching and learning activities. Unlike awareness, attitudes, or behavioral intentions, AI classroom use focuses on the extent to which educators actively integrate AI tools into instructional practice. Examples include lesson preparation, assessment development, personalized feedback provision, content generation, classroom demonstrations, learning analytics, and adaptive instructional support (Tan *et al*., 2025; Rodríguez-Ortiz *et al*., 2025) [45, 34]. The successful integration of AI into classroom practice depends on both technological and human factors. Research indicates that educators who possess higher levels of AI literacy, technological readiness, and pedagogical competence are more likely to incorporate AI into their teaching activities (Arkorful *et al*., 2025; Ofem *et al*., 2025) [6, 29]. Similarly, institutional support, professional development opportunities, and access to technological infrastructure contribute significantly to AI classroom use (Boison, 2025; Baafi *et al*., 2025) [10, 9]. Within teacher education institutions, AI classroom use assumes additional significance because lecturers serve as role models for future teachers. Mathematics lecturers who effectively integrate AI into their instructional practices may influence pre-service teachers' attitudes, competencies, and future classroom behaviors regarding educational technology adoption. Consequently, understanding the factors that influence AI classroom use among mathematics lecturers is important for promoting responsible and effective AI integration within teacher education.

2.5 Conceptual Framework

The conceptual framework proposes that relative advantage directly influences AI classroom use. It also proposes that instructional risk directly influences AI classroom use and moderates the relationship between relative advantage and AI classroom use. The model assumes that lecturers who perceive AI as beneficial are more likely to use it in mathematics instruction. However, this positive relationship is expected to weaken when lecturers perceive high instructional risk. Conceptually, the framework is represented in a diagram below.

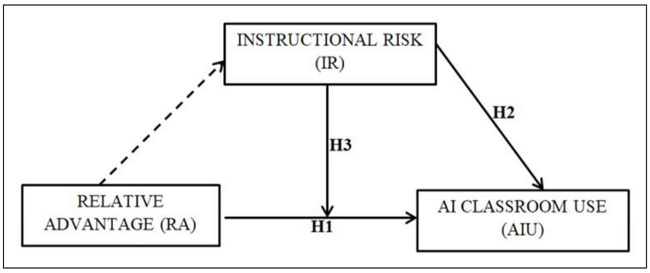


Fig 1: Diagrammatic representation of the conceptual framework

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 three latent constructs: Relative Advantage (RA), Instructional Risk (IR), and AI Classroom Use (AIU). The constructs were operationalized as reflective measures using multiple items adapted from previous studies on artificial intelligence adoption, educational technology integration, innovation diffusion, and technology.

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 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
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)

Table 4.2: Descriptive Statistics

Construct	Mean	SD	Skewness	Kurtosis
Relative Advantage	3.82	0.71	−0.42	0.31
Instructional Risk	3.26	0.76	−0.18	−0.27
AI Classroom Use	3.39	0.69	−0.25	0.14

Source: Field Survey (2026)

Table 4.2 presents the descriptive statistics for the study variables. Relative Advantage recorded the highest mean score (M = 3.82, SD = 0.71), indicating that mathematics lecturers generally perceived AI as beneficial for teaching and learning. AI Classroom Use had a mean score of 3.39 (SD = 0.69), suggesting a moderate level of AI integration in instructional activities. Instructional Risk recorded a mean score of 3.26 (SD = 0.76), indicating moderate concerns regarding the potential risks associated with AI use in mathematics instruction. The skewness values ranged from −0.42 to −0.18, while kurtosis values ranged from −0.27 to 0.31. Since all values fell within the recommended thresholds of ±2, the data were considered normally distributed and suitable for subsequent parametric analyses.

Table 4.3: Reliability Analysis

Construct	Items	Cronbach's Alpha	Composite Reliability
Relative Advantage	6	.891	.918
Instructional Risk	6	.874	.904
AI Classroom Use	6	.862	.897

Source: Field Survey (2026)

Table 4.3 presents the reliability results for the study constructs. The findings indicate that all constructs demonstrated satisfactory internal consistency reliability. Cronbach's alpha values ranged from .862 to .891, exceeding the recommended threshold of .70. Similarly, composite reliability (CR) values ranged from .897 to .918, surpassing the minimum acceptable value of .70. Among the constructs, Relative Advantage recorded the highest reliability values (α = .891, CR = .918), followed by Instructional Risk (α = .874, CR = .904) and AI Classroom Use (α = .862, CR = .897). These results suggest that the measurement items consistently captured their respective constructs and were suitable for subsequent validity assessment and structural model analysis.

Table 4.4: Convergent Validity

Construct	Loading Range	AVE
Relative Advantage	.71–.86	.652
Instructional Risk	.68–.84	.611
AI Classroom Use	.69–.83	.594

Source: Field Survey (2026

Table 4.4 presents the results of the convergent validity assessment. The standardized factor loadings ranged from .68 to .86, exceeding the recommended threshold of .50. In addition, the Average Variance Extracted (AVE) values ranged from .594 to .652, surpassing the minimum acceptable value of .50. These results indicate that the measurement items adequately converged to represent their respective constructs. Specifically, Relative Advantage recorded the highest AVE value (.652), followed by Instructional Risk (.611) and AI Classroom Use (.594). Overall, the findings confirm satisfactory convergent validity for all constructs and support their suitability for further structural model analysis.

Table 4.5: Discriminant Validity: Fornell–Larcker Criterion

Construct	RA	IR	AIU
Relative Advantage	.807		
Instructional Risk	−.312	.782	
AI Classroom Use	.563	−.418	.771

Source: Field Survey (2026)

Table 4.5 presents the results of the Fornell–Larcker criterion used to assess discriminant validity. The square root of the Average Variance Extracted (AVE) for each construct is shown on the diagonal and exceeds the corresponding inter-construct correlations. Specifically, the square roots of the AVE for Relative Advantage (.807), Instructional Risk (.782), and AI Classroom Use (.771) were greater than their correlations with other constructs. These results indicate that each construct shares more variance with its respective indicators than with other constructs in the model, thereby confirming satisfactory discriminant validity. Therefore, the constructs were empirically distinct and suitable for subsequent structural model analysis.

Table 4.6: Structural Model Fit Indices

Fit Index	Value	Recommended Threshold	Interpretation
χ^2/df	1.91	< 3.00	Good
CFI	.956	≥ .90	Good
TLI	.947	≥ .90	Good
IFI	.957	≥ .90	Good
GFI	.921	≥ .90	Acceptable
AGFI	.895	≥ .85	Acceptable
RMSEA	.063	< .08	Good
SRMR	.046	< .08	Good

Source: Field Survey (2026)

The structural model was evaluated using several goodness-of-fit indices. As shown in Table 4.6, the model demonstrated an acceptable to good fit with the observed data. The chi-square to degrees of freedom ratio (χ^2/df = 1.91) was below the recommended threshold of 3.00, indicating a good model fit. Similarly, the Comparative Fit Index (CFI = .956), Tucker–Lewis Index (TLI = .947), and Incremental Fit Index (IFI = .957) exceeded the recommended cutoff value of .90, suggesting a satisfactory fit of the model. Furthermore, the Goodness-of-Fit Index (GFI = .921) and Adjusted Goodness-of-Fit Index (AGFI = .895) met the acceptable thresholds of .90 and .85, respectively. The Root Mean Square Error of Approximation (RMSEA = .063) and Standardized Root Mean Square Residual (SRMR = .046) were both below the recommended maximum value of .08, indicating good model fit. Overall, these results confirm that the proposed structural model adequately represented the observed data and was suitable for hypothesis testing.

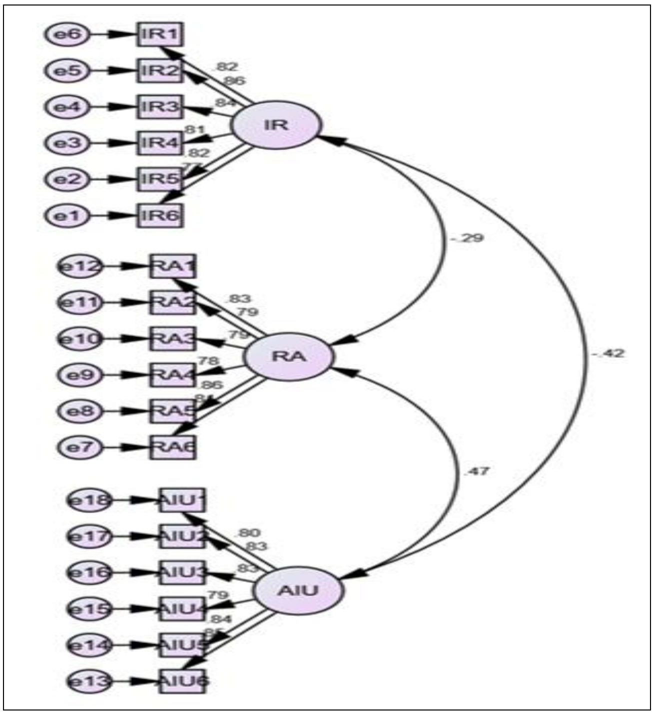
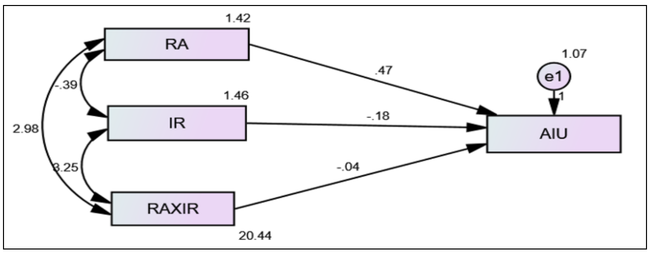


Table 4.7: Hypothesis Testing Results

Hypothesis	Path	β	SE	CR	p-value	Decision
H1	RA → AIU	.48	.067	7.16	.001	Supported
H2	IR → AIU	−.29	.061	−4.75	.001	Supported
H3	RA × IR → AIU	−.18	.058	−3.10	.002	Supported

Source: Field Survey (2026)

Table 4.7 presents the results of the structural model and hypothesis testing. The findings revealed that Relative Advantage had a positive and significant effect on AI Classroom **Use** ($\beta = .48$, $CR = 7.16$, $p < .001$), supporting H1. This suggests that mathematics lecturers who perceive AI as beneficial are more likely to integrate it into their instructional activities. The results further showed that Instructional Risk had a negative and significant effect on AI Classroom **Use** ($\beta = -.29$, $CR = -4.75$, $p < .001$), supporting H2. This indicates that concerns regarding the risks associated with AI integration reduce lecturers' likelihood of using AI in the classroom. Finally, the interaction effect between Relative Advantage and Instructional Risk was negative and statistically significant ($\beta = -.18$, $CR = -3.10$, $p = .002$), supporting H3. This finding suggests that instructional risk significantly moderates the relationship between Relative Advantage and AI Classroom Use. Specifically, the positive influence of Relative Advantage on AI Classroom Use becomes weaker when lecturers perceive higher levels of instructional risk. The results indicate that while perceived benefits encourage AI adoption, perceived instructional risks can reduce both direct AI use and the strength of the positive effect of Relative Advantage on AI Classroom Use.



5. Discussion of Findings

5.1 Relative Advantage and AI Classroom Use

The findings of this study revealed that relative advantage had a positive and significant influence on AI classroom use among mathematics lecturers in Ghanaian Colleges of Education. This result supports Hypothesis 1 and suggests that lecturers are more likely to integrate AI technologies into their instructional practices when they perceive them as offering meaningful advantages over traditional teaching approaches. The finding aligns with Rogers' (2003) Diffusion of Innovation Theory, which posits that innovations perceived as beneficial, efficient, and superior to existing practices are more readily adopted by potential users. The positive effect of relative advantage on AI classroom use suggests that mathematics lecturers recognize the instructional value of AI technologies in supporting teaching and learning processes. AI-powered tools can assist lecturers in generating instructional materials, designing assessments, providing timely feedback, and creating multiple representations of mathematical concepts. Given the abstract nature of many mathematical topics, AI technologies offer opportunities to improve conceptual explanations, personalize learning experiences, and enhance student engagement through adaptive support systems (Li *et al*., 2025; Son, 2024; Luong *et al*., 2025) [26, 43, 28]. These capabilities may explain why lecturers who perceive AI as useful are more inclined to integrate it into their classroom activities. The finding is consistent with previous studies that identified perceived usefulness and relative advantage as important predictors of AI adoption among educators. Al Abdullatif (2024) [1] reported that teachers' perceptions of the usefulness of generative AI significantly influenced their willingness to adopt AI technologies in higher education. Similarly, Cabero-Almenara *et al*. (2024) [14] found that educators were more likely to adopt generative AI when they perceived it as enhancing instructional effectiveness and professional performance. Kim (2025) [24] also reported that educators who recognized the pedagogical benefits of AI demonstrated stronger intentions to integrate AI into their teaching practices. Furthermore, Tan *et al*. (2025) [45], in their systematic review of AI in teaching and teacher professional development, concluded that perceived instructional benefits consistently emerged as one of the strongest determinants of AI adoption among educators. The findings also support the assumptions of the Technology Acceptance Model, which argues that users are more likely to adopt technologies they perceive as useful for accomplishing work-related tasks (Davis, 1989 [16]; Venkatesh *et al*., 2003). In the context of mathematics instruction, lecturers may perceive AI as a valuable instructional resource that enhances efficiency while simultaneously improving teaching effectiveness. Consequently, the results suggest that increasing lecturers' awareness of the pedagogical value of AI may promote greater classroom integration. This finding is particularly important within Ghanaian Colleges of Education, where mathematics lecturers are expected to model innovative teaching practices for future teachers.

5.2 Instructional Risk and AI Classroom Use

The study further revealed that instructional risk had a negative and significant influence on AI classroom use, thereby supporting Hypothesis 2. This finding indicates that mathematics lecturers who perceive higher levels of risk associated with AI technologies are less likely to integrate such technologies into their instructional practices. The result highlights the importance of considering not only the benefits of AI but also the concerns and uncertainties that may discourage adoption. One possible explanation for this finding is that mathematics lecturers operate within a discipline where accuracy, logical consistency, and conceptual understanding are critical. Unlike some educational applications where minor inaccuracies may have limited consequences, errors in mathematical explanations or solutions can directly affect learners' understanding of fundamental concepts. Consequently, lecturers may be reluctant to rely on AI systems if they perceive a risk that the technologies could generate inaccurate solutions, misleading explanations, or inappropriate instructional content (Li *et al*., 2025; Liu *et al*., 2026) [26, 27]. The finding is consistent with UNESCO's (2023) [48] guidance on generative AI in education, which identifies issues relating to accuracy, bias, transparency, privacy, and academic integrity as major concerns for educators. Similarly, Eusebio *et al*. (2025) [19], in their systematic review of barriers to educator acceptance of AI, reported that concerns about reliability, ethical implications, and misuse frequently discourage educators from adopting AI technologies. Almuhanna (2025) [2] also found that teachers expressed reservations about AI-generated learning materials due to concerns regarding quality assurance and pedagogical appropriateness. Another important concern relates to the potential impact of AI on students' learning behaviors. Mathematics lecturers may fear that students will become overly dependent on AI-generated solutions rather than engaging in independent reasoning and problem-solving activities. Such concerns are supported by Ofem *et al*. (2025) [29], who found that educators' concerns regarding learner dependency and reduced critical thinking significantly influenced their perceptions of AI technologies. Similarly, Gârdan *et al*. (2025) [22] reported that teachers often balance perceived technological benefits against concerns regarding educational quality and learner development when making adoption decisions. The finding suggests that successful AI integration requires more than simply providing access to AI tools. Educational institutions must address lecturers' concerns regarding accuracy, ethics, privacy, and academic integrity. Professional development programs should therefore focus not only on the technical use of AI but also on strategies for evaluating AI-generated outputs, mitigating risks, and promoting responsible classroom use.

5.3 Moderating Effect of Instructional Risk

The most significant contribution of this study lies in the finding that instructional risk significantly moderated the relationship between relative advantage and AI classroom use. Specifically, the negative interaction effect indicates that instructional risk weakens the positive influence of relative advantage on AI classroom use. Thus, although lecturers may recognize the benefits associated with AI technologies, their willingness to utilize these technologies may diminish when they perceive high levels of instructional risk. This finding provides important insights into the complexity of AI adoption within educational settings. Previous studies have largely emphasized the positive effects of perceived usefulness, relative advantage, and technological readiness on technology adoption (Al Abdullatif, 2024; Cabero-Almenara *et al*., 2024; Kim, 2025) [1, 14, 24]. However, the current study demonstrates that perceptions of benefit alone may not be sufficient to drive actual classroom use. Instead, lecturers appear to evaluate AI technologies by simultaneously considering both potential advantages and potential risks. The finding is consistent with emerging research suggesting that trust, uncertainty, and risk perceptions play a critical role in AI adoption decisions. Tang and Zhong (2026) [46] found that teachers' adoption of generative AI was influenced not only by perceived usefulness but also by concerns regarding reliability and responsible use. Likewise, Singh and Strzelecki (2026) [42] argued that educators often evaluate AI innovations through a balance of expected benefits and perceived risks before deciding whether to adopt them. These findings suggest that risk perceptions can constrain the positive effects of perceived technological advantages. From a theoretical perspective, this result extends Rogers' (2003) Diffusion of Innovation Theory by demonstrating that the influence of relative advantage is not unconditional. Although relative advantage remains a significant predictor of adoption, its effectiveness depends partly on the extent to which users perceive associated risks. The finding also extends the Technology Acceptance Model by showing that perceived usefulness may be insufficient to guarantee adoption when risk perceptions are high. Furthermore, the result supports the Technology–Organization–Environment framework, which emphasizes that technology adoption decisions are influenced by contextual and environmental factors beyond the technological characteristics themselves. The practical implications of this finding are substantial. Colleges of Education seeking to promote AI integration should not focus exclusively on communicating the benefits of AI technologies. While demonstrating the instructional value of AI remains important, equal attention should be given to addressing lecturers' concerns regarding risk. Institutional policies, ethical guidelines, AI literacy programs, professional development workshops, and quality assurance mechanisms may help reduce uncertainty and increase lecturers' confidence in AI technologies. As instructional risks are reduced, the positive influence of relative advantage on AI classroom use is likely to become stronger.The findings suggest that effective AI adoption among mathematics lecturers requires a balanced approach that simultaneously promotes the benefits of AI and addresses the risks associated with its use. Such an approach is likely to facilitate more responsible, sustainable, and pedagogically effective AI integration within Ghanaian Colleges of Education.

5.4 Practical Implications

The findings of this study offer important implications for policymakers, educational leaders, teacher educators, and practitioners seeking to promote responsible AI integration in mathematics education. At the policy level, the Ministry of Education should develop comprehensive national guidelines to regulate the use of AI in teaching and learning. Such guidelines should address issues relating to ethical AI use, academic integrity, data privacy, responsible assessment practices, and professional standards for educators. Clear policy direction will help educational institutions adopt AI technologies while minimizing potential risks. For the Ghana Tertiary Education Commission (GTEC), the findings highlight the need to incorporate AI literacy and responsible AI use into quality assurance frameworks for teacher education institutions. As AI technologies become increasingly embedded in educational practice, teacher preparation programs must ensure that future educators possess the competencies required to integrate AI effectively and ethically. For Colleges of Education, the results suggest the importance of developing institutional AI policies that clearly define acceptable uses of AI, assessment procedures, ethical responsibilities, and mechanisms for monitoring AI-supported teaching practices. Institutions should also provide lecturers with access to approved AI tools and create supportive environments that encourage responsible experimentation and innovation. For mathematics lecturers, the findings underscore the importance of adopting a critical and reflective approach to AI integration. Lecturers should verify AI-generated mathematical solutions, evaluate the accuracy of AI outputs, and design instructional activities that promote reasoning, justification, and conceptual understanding rather than mere answer generation. AI should complement, rather than replace, sound pedagogical practices. Finally, for developers and implementers of AI policies, the study demonstrates that successful adoption strategies must address both perceived benefits and perceived risks. Efforts that focus exclusively on the advantages of AI may be insufficient if educators continue to harbor concerns regarding instructional quality, academic integrity, and student learning outcomes. Therefore, initiatives aimed at promoting AI adoption should simultaneously emphasize innovation and risk mitigation.

5.5 Conclusion

This study examined the moderating effect of instructional risk on the relationship between relative advantage and AI classroom use among mathematics lecturers in Ghanaian Colleges of Education. The findings revealed that relative advantage positively influenced AI classroom use, indicating that lecturers are more likely to adopt AI technologies when they perceive them as beneficial for enhancing instructional effectiveness and improving teaching practices. The study also found that instructional risk negatively influenced AI classroom use, suggesting that concerns regarding the potential negative consequences of AI integration reduce lecturers' willingness to utilize AI in their classrooms. Most importantly, the study established that instructional risk significantly moderates the relationship between relative advantage and AI classroom use. The negative moderation effect indicates that the positive influence of perceived benefits becomes weaker when lecturers perceive higher levels of instructional risk. This finding highlights the importance of addressing both the opportunities and challenges associated with AI integration in education. The study concludes that successful AI adoption in mathematics instruction depends not only on lecturers' perceptions of the benefits of AI technologies but also on the extent to which concerns regarding instructional risks are effectively addressed. Consequently, educational institutions seeking to promote AI integration should adopt balanced strategies that simultaneously enhance awareness of AI benefits and mitigate concerns relating to instructional quality, ethical use, and academic integrity.

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