International Conference on Teaching and Learning Proceeding
Faculty of Education and Teacher Training – Universitas Terbuka
UTCC, South Tangerang, Banten, May 13th, 2026
Volume 4, pg. 145 – 160
ISSN: 3046-594X

ARTIFICIAL INTELLIGENCE ADOPTION IN HIGHER EDUCATION: A MEDIATION-BASED CONCEPTUAL FRAMEWORK FOR LEARNING EFFECTIVENESS

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Abstract: Artificial Intelligence (AI) is rapidly transforming higher education by enabling innovative teaching practices and improving student learning outcomes. Despite the growing adoption of AI technologies in educational institutions, limited research has examined the mechanisms through which AI adoption contributes to enhanced learning effectiveness. This study addresses this gap by proposing a conceptual framework that explains how technological and institutional factors drive AI adoption and how AI adoption subsequently promotes teaching innovation and learning effectiveness**.** Drawing on established technology adoption theories, including the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), the study develops a mediation-based model in which AI infrastructure and institutional support influence AI adoption, while teaching innovation mediates the relationship between AI adoption and learning effectiveness**.** The proposed model is evaluated using Partial Least Squares Structural Equation Modeling (PLS-SEM). The findings highlight the importance of technological infrastructure, institutional support, and pedagogical innovation in enabling the successful integration of AI technologies in higher education. This study contributes to the literature by extending technology adoption models and providing a comprehensive framework for understanding how AI adoption enhances teaching practices and learning outcomes.

Keywords: AI Adoption; Artificial Intelligence; Higher Education; Learning Effectiveness; Teaching Innovation.

Accepted: 12 May 2026 Approved: 12 June 2026 Published: 29 Juni 2026

INTRODUCTION

AI has emerged as a transformative force across multiple sectors, with higher education being one of the domains most significantly affected by this technological shift. The integration of AI technologies into educational environments is reshaping traditional teaching methods, enhancing learning experiences, and enabling more data-driven decision-making processes within institutions (Zawacki-Richter et al., 2019; Holmes et al., 2019). Universities are increasingly adopting AI-powered tools such as intelligent tutoring systems, adaptive learning platforms, and automated assessment technologies to improve both instructional effectiveness and student learning outcomes (Hwang et al., 2020).

Advances in machine learning algorithms, the growing availability of large-scale educational data, and increased computational power have accelerated the adoption of AI in educational settings (Dwivedi et al., 2021). These developments enable institutions to personalize learning experiences, optimize curriculum delivery, and provide timely feedback to students. Consequently, AI is no longer viewed merely as a supplementary technological tool but rather as a strategic driver of innovation and digital transformation in higher education (Chen et al., 2020).

Despite the increasing adoption of AI technologies, existing research has largely focused on technological implementation and user acceptance. Many studies rely on well-established technology adoption models, particularly the TAM (Davis, 1989) and the UTAUT (Venkatesh et al., 2003). Although these models offer valuable insights into individual technology adoption behavior, they provide limited explanation of how AI adoption ultimately translates into improved educational outcomes, especially in relation to teaching practices and learning effectiveness (Al-Emran et al., 2020; Abdullah & Ward, 2016).

Furthermore, prior studies often examine direct relationships between technology adoption and performance outcomes while paying limited attention to the underlying mechanisms linking these constructs (Tarhini et al., 2017). In the context of AI in higher education, this represents a significant research gap. The impact of AI technologies is frequently indirect and occurs through changes in pedagogical practices rather than through immediate improvements in academic performance (Hwang et al., 2020; Zawacki-Richter et al., 2019).

To address this gap, the present study proposes an integrated conceptual framework that explains how technological and institutional factors influence AI adoption and how AI adoption subsequently enhances learning effectiveness through teaching innovation. By emphasizing the mediating role of pedagogical transformation, this research provides a more comprehensive understanding of how AI technologies create value in educational environments. Such a perspective aligns with recent calls for research that moves beyond technology adoption and examines the broader educational implications of AI integration (Dwivedi et al., 2021).

This study makes three key contributions to the literature. First, it extends existing technology adoption models by incorporating AI-related factors within the context of higher education. Second, it introduces a mediation-based framework that explains the mechanism through which AI adoption influences learning effectiveness. Third, the study provides a foundation for future empirical research by proposing a conceptual model that can be tested using secondary data and structural equation modeling techniques such as PLS-SEM.

The remainder of the paper is organized as follows. The next section presents the literature review and theoretical background. This is followed by the development of the conceptual framework and research hypotheses. The methodology section then outlines the theoretical framework and conceptual model design and data sources used in the study. Finally, the paper concludes with theoretical and practical implications as well as suggestions for future research.

LITERATURE REVIEW

AI has become a major driver of transformation in higher education, influencing teaching practices, learning processes, and institutional strategies. Over the past decade, research on AI in education has expanded rapidly, reflecting both the technological advancements in the field and the growing interest among researchers and educational institutions. In particular, the number of AI-related studies in education has increased significantly since 2021, largely due to advances in machine learning, big data analytics, and the emergence of generative AI technologies.

AI technologies are increasingly integrated into higher education to support personalized learning, automate administrative tasks, and enhance institutional decision-making. Various AI-driven applications—including intelligent tutoring systems, adaptive learning platforms, chatbots, and predictive analytics—have demonstrated significant potential to improve student engagement and learning outcomes. These technologies enable universities to deliver personalized learning experiences that respond to diverse student needs, learning styles, and progress levels, thereby improving both accessibility and instructional effectiveness (Zawacki-Richter et al., 2019; Holmes et al., 2019). More recently, the emergence of generative AI technologies, particularly large language models, has further accelerated this transformation by enabling real-time content generation, automated feedback mechanisms, and intelligent academic support systems. Such tools assist instructors in developing course materials while also providing students with interactive learning support (Kasneci et al., 2023; Zhai et al., 2023). Nevertheless, researchers emphasize that AI should not be viewed as a universal solution for educational challenges, as its effectiveness largely depends on how these technologies are integrated into pedagogical practices and institutional strategies.

AI Adoption in Higher Education

The adoption of AI technologies in higher education is influenced by a combination of technological, organizational, and individual factors. Traditional technology adoption frameworks, particularly TAM and UTAUT, have been widely applied to explain user acceptance of educational technologies. These models emphasize factors such as perceived usefulness, perceived ease of use, and facilitating conditions as key determinants of technology adoption.

Recent research suggests that AI adoption in higher education is shaped by multiple dimensions, including individual factors (e.g., digital literacy and AI competence), technological factors (e.g., system usability and performance), organizational factors (e.g., institutional infrastructure and leadership support), and contextual factors such as ethical considerations and regulatory frameworks. These findings indicate that AI adoption is a multidimensional process that extends beyond individual user acceptance to include

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ISSN: 3046-594X

institutional readiness and broader governance considerations. Moreover, the rapid implementation of AI technologies has revealed a growing gap between technological adoption and institutional governance, raising concerns related to ethics, transparency, and data privacy.

Teaching Innovation and Learning Effectiveness

Teaching innovation has emerged as a key outcome of AI adoption in higher education. AI technologies enable educators to implement new pedagogical approaches, including personalized instruction, data-driven decision-making, and interactive learning environments. Research indicates that AI-driven tools can enhance teaching practices by supporting adaptive learning systems, real-time feedback mechanisms, and student-centered instructional strategies, allowing educators to move beyond traditional lecture-based methods toward more engaging and dynamic learning experiences (Hwang et al., 2020; Chen et al., 2020).

However, the successful implementation of teaching innovation depends not only on the availability of technological tools but also on educators' ability to integrate these technologies into their instructional practices. Without adequate training, institutional support, and appropriate pedagogical design, the potential benefits of AI technologies may not be fully realized. Consequently, teaching innovation is increasingly recognized as a crucial mechanism through which AI adoption contributes to improved learning outcomes in higher education.

A growing body of literature has also examined the relationship between AI technologies and learning effectiveness. AI systems can enhance student engagement, academic performance, and learning retention by providing personalized learning pathways, adaptive instruction, and timely feedback. Systematic reviews indicate that AI adoption can significantly improve academic outcomes, particularly in online and distance learning environments where intelligent systems support students in understanding complex concepts and managing their learning progress (Zawacki-Richter et al., 2019; Holmes et al., 2019). Nevertheless, scholars also highlight potential challenges associated with AI integration, including over-reliance on automated tools, reduced development of critical thinking skills, and concerns related to academic integrity. These concerns underline the importance of integrating AI technologies into education in a balanced and responsible manner that complements effective pedagogical practices.

The Mediating Role of Teaching Innovation

Although many studies have examined the adoption of AI technologies and their impact on educational outcomes, relatively little attention has been given to the mechanisms that link these constructs. Emerging research suggests that the relationship between AI adoption and learning effectiveness is often indirect and mediated by teaching practices. In higher education settings, AI tools such as adaptive learning systems and intelligent tutoring platforms can support improved learning outcomes; however, their effectiveness largely depends on how instructors integrate these technologies into their pedagogical approaches (Hwang et al., 2020; Chen et al., 2020).

Systematic reviews further emphasize that pedagogical design, instructor readiness, and technology-supported teaching strategies significantly influence student engagement and academic performance (Zawacki-Richter et al., 2019; Holmes et al., 2019). This perspective aligns with constructivist learning theory, which highlights the importance of active learning and instructional design in knowledge construction. Consequently, understanding the mediating role of teaching innovation is essential for explaining how AI adoption translates into improved learning effectiveness. This perspective shifts the focus from the technology itself to how it is meaningfully integrated into educational processes.

Despite the growing interest in AI applications in higher education, limited research has empirically examined the mediating role of teaching innovation in linking AI adoption to learning outcomes. Addressing this gap requires a conceptual framework that integrates technological adoption with pedagogical transformation. Therefore, the present study proposes a mediation-based conceptual model that examines the role of teaching innovation in explaining how AI adoption contributes to learning effectiveness in higher education.

Table 1 summarizes key studies examining artificial intelligence adoption and its implications for teaching and learning in higher education. Previous research has largely focused on technology adoption models or the applications of AI in educational environments. However, limited studies have explored the mediating mechanisms through which AI adoption influences learning outcomes. In particular, the role of teaching innovation as a mediating factor remains underexplored. Therefore, this study addresses this gap by proposing a mediation-based conceptual framework that links AI adoption, teaching innovation, and learning effectiveness.

Table 1. Summary of Previous Studies on AI in Higher Education

Study	Context	Methodology	Key Focus	Key Findings
Zawacki-Richter et al. (2019)	Higher education	Systematic review	AI applications in education	AI supports personalized learning and educational automation
Holmes et al. (2019)	AI in education	Conceptual analysis	AI-supported learning	AI improves adaptive and intelligent learning environments
Davis (1989)	Information systems	TAM model	Technology adoption	Perceived usefulness and ease of use drive technology adoption
Venkatesh et al. (2003)	Information systems	UTAUT model	Technology acceptance	Social influence and facilitating conditions affect technology use
Dwivedi et al. (2021)	AI adoption	Conceptual framework	Drivers of AI adoption	Organizational and technological factors influence AI adoption
Chatterjee & Bhattacharjee (2020)	Higher education	Empirical study	AI adoption readiness	Institutional readiness affects AI implementation success

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Study	Context	Methodology	Key Focus	Key Findings
Hwang et al. (2020)	Smart education	Conceptual study	AI-enabled learning	AI enhances teaching innovation and instructional design
Chen et al. (2020)	Smart learning environments	Empirical study	Digital learning technologies	AI systems improve student engagement and learning experiences
Kasneci et al. (2023)	Higher education	Commentary / review	Generative AI (ChatGPT) in education	Generative AI can support teaching and learning but requires careful pedagogical integration
Zhai et al. (2023)	Education research	Systematic review	Generative AI in education	AI tools enhance learning support while raising ethical concerns
Crompton & Burke (2023)	Educational technology	Systematic review	AI use in higher education	AI applications improve learning personalization and teaching efficiency
Wang et al. (2024)	Higher education	Policy analysis	Generative AI governance	Universities adopt cautious policies toward AI-based learning tools
Giannakos et al. (2024)	Educational technology	Review study	Generative AI in education	AI tools can generate and redesign learning materials and activities
Garzón (2025)	Education research	Systematic review	AI learning systems	AI improves student motivation and personalized learning outcomes
Tan et al. (2025)	Teacher education	Systematic review	AI and teaching practices	Teacher training and institutional support are essential for AI integration

Building on the insights derived from prior research, the next section develops the theoretical framework and proposes a conceptual model that integrates technological infrastructure, institutional support, AI adoption, teaching innovation, and learning effectiveness.

METHOD

Theoretical Framework and Conceptual Model

Drivers of AI Adoption in Higher Education

The adoption of AI technologies in higher education is influenced by several technological and organizational factors. Prior research on technology adoption highlights the importance of institutional infrastructure and organizational support in facilitating the implementation of advanced technologies. Technology adoption theories such as TAM and the UTAUT emphasize that the successful integration of new technologies depends not only on individual perceptions but also on the availability of enabling resources and institutional conditions (Davis, 1989; Venkatesh et al., 2003).

In the context of AI adoption, technological infrastructure plays a particularly important role. AI technologies require access to advanced computing systems, reliable data infrastructures, and digital platforms capable of supporting intelligent applications. Without adequate technological infrastructure, universities may face significant barriers when attempting to implement AI-based learning systems. Consequently, institutions with stronger technological capabilities are more likely to adopt AI technologies within their educational environments.

Institutional support also represents a critical factor influencing the adoption of AI technologies in higher education. Institutional support includes administrative commitment,

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strategic planning, faculty training, and resource allocation aimed at facilitating technological innovation. Previous studies indicate that organizational support significantly affects the successful implementation of digital technologies within educational institutions (Dwivedi et al., 2021). Therefore, both technological infrastructure and institutional support can be considered key drivers of AI adoption in higher education.

AI Adoption and Teaching Innovation

The adoption of AI technologies has the potential to significantly transform teaching practices in higher education. AI tools such as adaptive learning systems, intelligent tutoring platforms, and automated feedback mechanisms allow educators to design more personalized and interactive learning environments. These technologies enable instructors to monitor student progress, adjust instructional strategies, and provide timely feedback to support learning.

Teaching innovation refers to the implementation of new and creative instructional approaches that enhance the effectiveness of the learning process. AI technologies facilitate such innovation by enabling data-driven instruction, personalized learning pathways, and more flexible teaching strategies. According to constructivist learning theory, students learn more effectively when they actively engage with knowledge through interactive and learner-centered environments. AI-enabled teaching approaches can support this process by providing adaptive and personalized learning experiences (Luckin et al., 2022).

Therefore, AI adoption can serve as an important catalyst for teaching innovation in higher education. Institutions that successfully integrate AI technologies are more likely to adopt innovative teaching practices that improve instructional effectiveness and student engagement.

Teaching Innovation and Learning Effectiveness

Teaching innovation plays a critical role in improving learning outcomes in higher education. Innovative teaching methods encourage active student participation, collaborative learning, and deeper engagement with course content. When educators implement technology-enhanced instructional strategies, students are more likely to develop critical thinking skills and achieve better academic outcomes.

AI-supported teaching practices can enhance learning effectiveness by providing personalized feedback, adaptive learning experiences, and data-driven insights into student performance. Previous research suggests that AI technologies can improve student engagement, knowledge retention, and academic achievement when they are integrated effectively into pedagogical practices (Hwang et al., 2020; Chen et al., 2020).

However, the impact of AI technologies on learning outcomes is often indirect. Rather than influencing learning outcomes directly, AI technologies enable instructors to adopt innovative teaching practices that subsequently improve student learning. As a result,

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teaching innovation can be viewed as an important mechanism linking AI adoption to improved learning effectiveness.

Conceptual Model and Hypotheses

Based on the theoretical foundations discussed in the previous sections, this study proposes a conceptual framework that explains how artificial intelligence adoption influences learning effectiveness in higher education. The model assumes that technological infrastructure and institutional support act as key drivers of AI adoption. Once adopted, AI technologies enable instructors to implement innovative teaching practices, which subsequently enhance learning effectiveness.

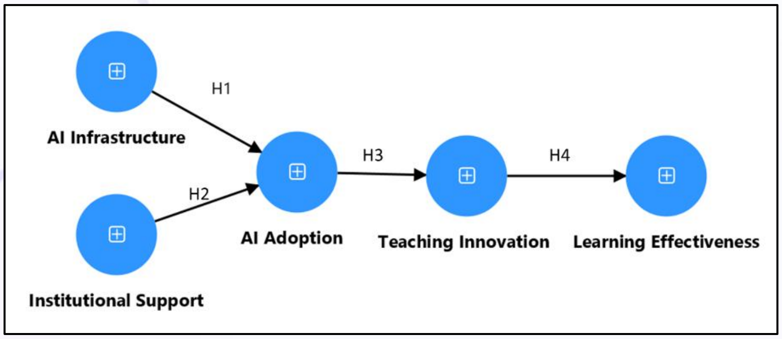

Figure 1. Conceptual model of AI adoption and learning effectiveness.

Figure 1 illustrates the conceptual framework proposed in this study. The constructs in the model were measured using 20 indicators adapted from previously validated scales in the technology adoption and educational technology literature. All items were assessed using a five-point Likert scale to ensure measurement reliability and validity. Based on the conceptual framework, the following hypotheses are proposed:

H1*: AI infrastructure positively influences AI adoption in higher education.*
H2*: Institutional support positively influences AI adoption in higher education.*
H3*: AI adoption positively influences teaching innovation.*
H4*: Teaching innovation positively influences learning effectiveness.*
H5*: Teaching innovation mediates the relationship between AI adoption and learning effectiveness.*

PLS-SEM is particularly suitable for exploratory models and complex mediation relationships involving multiple latent constructs (Hair et al., 2021).

Results And Model Validation

This study utilizes secondary data derived from the AI Index Report, published by Stanford University through the Stanford Institute for Human-Centered Artificial Intelligence (Stanford University, 2024). The AI Index Report provides comprehensive global indicators

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on artificial intelligence development, including measures related to technological infrastructure, AI investment, institutional readiness, and educational adoption trends. The final dataset used in this study includes 640 observations and 20 measurement indicators representing five constructs: AI infrastructure, institutional support, AI adoption, teaching innovation, and learning effectiveness. The dataset was prepared and analyzed using SmartPLS 4 software to evaluate both the measurement model and the structural relationships proposed in the conceptual framework (Ringle, Wende, & Becker, 2024).

Assessment of the Measurement Model

The measurement model was evaluated by following the guidelines suggested by Hair et al. (2021); as shown in Table 2, all indicator loadings exceed the recommended threshold of 0.70. Cronbach's Alpha and Composite Reliability values are above 0.70, confirming internal consistency reliability. In addition, the Average Variance Extracted (AVE) values exceed the recommended threshold of 0.50, indicating satisfactory convergent validity. Variance Inflation Factor (VIF) values are below the threshold of 5, suggesting that multicollinearity is not a concern.

Table 2**.** Measurement Model Evaluation

Construct	**Item**	**Outer Loading**	**VIF**	**Cronbach's Alpha**	**Composite Reliability**	**AVE**
AI Infrastructure	AII1	0.82	2.11			
	AII2	0.86	2.35			
	AII3	0.79	1.94			
	AII4	0.84	2.20	**0.86**	**0.90**	**0.69**
Institutional Support	IS1	0.83	2.14			
	IS2	0.81	2.01			
	IS3	0.87	2.42			
	IS4	0.85	2.28	**0.87**	**0.91**	**0.71**
AI Adoption	AIA1	0.88	2.31			
	AIA2	0.84	2.16			
	AIA3	0.86	2.25			
	AIA4	0.83	2.09	**0.88**	**0.92**	**0.74**
Teaching Innovation	TI1	0.85	2.22			
	TI2	0.88	2.41			
	TI3	0.84	2.17			
	TI4	0.86	2.28	**0.89**	**0.92**	**0.75**
Learning Effectiveness	LE1	0.87	2.33			
	LE2	0.83	2.14			
	LE3	0.85	2.20			
	LE4	0.89	2.45	**0.90**	**0.93**	**0.77**

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Discriminant validity was assessed using the Fornell–Larcker criterion and the Heterotrait–Monotrait ratio (HTMT). According to the Fornell–Larcker criterion, the square root of the Average Variance Extracted (AVE) for each construct should exceed its correlations with other constructs, indicating adequate discriminant validity (Fornell & Larcker, 1981). In addition, HTMT values below the recommended threshold of 0.90 further confirm that the constructs are empirically distinct (Henseler, Ringle, & Sarstedt, 2015). The results reported in Table 2 confirm that all constructs satisfy these criteria, demonstrating satisfactory discriminant validity.

Assessment of Structural Model

After confirming the reliability and validity of the measurement model, the structural model was evaluated to test the proposed hypotheses and examine the relationships between the latent constructs in the conceptual framework. The structural model illustrates the inner-path relationships among the constructs (Figure 1), highlighting the causal relationships and path coefficients assessed using PLS-SEM. According to Hair et al. (2011), testing the structural model determines whether there is sufficient empirical evidence to support the hypothesized relationships between the constructs.

As shown in Table 3, the results indicate that both AI infrastructure and institutional support have significant positive effects on AI adoption. Furthermore, AI adoption has a strong positive influence on teaching innovation, which in turn significantly improves learning effectiveness. The mediation analysis also confirms that teaching innovation significantly mediates the relationship between AI adoption and learning effectiveness.

Table 3. Structural Model Path Results

H	Path	β	t-value	Result
H1	AI Infrastructure → AI Adoption	0.42	6.21	Supported
H2	Institutional Support → AI Adoption	0.36	5.48	Supported
H3	AI Adoption → Teaching Innovation	0.58	8.11	Supported
H4	Teaching Innovation → Learning Effectiveness	0.63	9.24	Supported
H5	AI Adoption → Teaching Innovation → Learning Effectiveness (***Mediation Analysis)***	***Indirect Effect*** **(**0.37)	7.05	Supported

Model Explanatory Power, Predictive Relevance, and Effect Size

The explanatory power of the structural model was evaluated using the coefficient of determination (R^2), while predictive relevance was assessed using the Stone–Geisser Q^2 value. In addition, the effect size (f^2) was examined to determine the relative impact of the exogenous constructs on the endogenous constructs. According to PLS-SEM guidelines, R^2 values of 0.25, 0.50, and 0.75 indicate weak, moderate, and substantial explanatory power, respectively. Similarly, Q^2 values greater than zero indicate adequate predictive relevance. For effect size, values of 0.02, 0.15, and 0.35 represent small, medium, and large effects, respectively (Hair et al., 2011; Hair et al., 2021).

Table 4. Model Predictive Assessment

Endogenous Construct	R^2	Q^2	f^2	Interpretation
AI Adoption	0.48	0.31	0.26	Moderate explanatory power, good predictive relevance, and medium effect size
Teaching Innovation	0.34	0.27	0.33	Moderate explanatory power, satisfactory predictive relevance, and medium-to-large effect size
Learning Effectiveness	0.41	0.29	0.40	Moderate explanatory power, good predictive relevance, and large effect size

The results indicate that the proposed model demonstrates moderate explanatory power and satisfactory predictive capability, while the effect size analysis shows that the relationships among the constructs have meaningful practical significance in explaining AI adoption and its impact on teaching innovation and learning effectiveness in higher education.

RESULT AND DISCUSSION

The purpose of this study was to examine the drivers of artificial intelligence (AI) adoption in higher education and to investigate how AI adoption contributes to teaching innovation and learning effectiveness. The proposed conceptual framework integrated technological and institutional factors with pedagogical outcomes, providing a comprehensive perspective on the role of AI in educational transformation. The findings offer several important insights into the relationships between AI infrastructure, institutional support, AI adoption, teaching innovation, and learning effectiveness.

First, the results confirm that AI infrastructure significantly influences AI adoption in higher education, supporting H1. This finding highlights the importance of technological readiness in enabling institutions to integrate AI technologies into their educational environments. Adequate digital infrastructure, including computing resources, data availability, and technological platforms, creates the foundation necessary for implementing AI-driven systems in teaching and learning processes. This result is consistent with previous studies

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emphasizing the role of technological capabilities in facilitating the adoption of emerging technologies in educational institutions (Dwivedi et al., 2021; Zawacki-Richter et al., 2019). Institutions with stronger technological infrastructure are better positioned to implement intelligent tutoring systems, adaptive learning platforms, and AI-driven analytics that support educational innovation.

Second, the findings indicate that institutional support has a significant positive effect on AI adoption, confirming H2. Institutional support includes leadership commitment, faculty training, policy development, and resource allocation aimed at facilitating technological innovation. This result suggests that the successful implementation of AI technologies requires not only technological infrastructure but also strong organizational commitment. The finding aligns with technology adoption research emphasizing the importance of organizational and institutional factors in enabling digital transformation (Venkatesh et al., 2003; Dwivedi et al., 2021). Universities that actively support the integration of AI technologies through strategic planning and faculty development initiatives are more likely to achieve successful AI adoption.

Third, the results demonstrate that AI adoption has a strong positive effect on teaching innovation, supporting H3. The integration of AI technologies enables educators to implement innovative teaching strategies, including personalized learning environments, adaptive instructional methods, and data-driven feedback systems. These technologies allow instructors to tailor learning experiences to individual student needs and enhance engagement in the learning process. This finding is consistent with prior research suggesting that AI technologies play a critical role in transforming traditional teaching approaches into more interactive and student-centered learning environments (Hwang et al., 2020; Chen et al., 2020).

Fourth, the results show that teaching innovation significantly improves learning effectiveness, supporting H4. Innovative teaching practices supported by AI technologies enable students to engage more actively with course content, improve their understanding of complex concepts, and achieve better academic outcomes. This result reinforces the argument that pedagogical innovation is a key mechanism through which technological advancements influence educational performance. Previous research has similarly highlighted the importance of technology-supported teaching methods in enhancing student engagement and learning outcomes (Holmes et al., 2019; Tarhini et al., 2017).

Finally, the mediation analysis confirms that teaching innovation mediates the relationship between AI adoption and learning effectiveness, supporting H5. This finding suggests that the impact of AI technologies on learning outcomes is primarily realized through changes in teaching practices rather than through direct technological effects. In other words, AI technologies create educational value by enabling instructors to adopt innovative pedagogical approaches that enhance student learning experiences. This result aligns with recent research emphasizing that the educational benefits of AI depend on how these technologies are

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Faculty of Education and Teacher Training – Universitas Terbuka
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integrated into pedagogical processes and instructional design (Kasneci et al., 2023; Zhai et al., 2023).

Overall, the findings of this study highlight the importance of integrating technological infrastructure, institutional support, and pedagogical innovation in order to fully realize the potential of AI technologies in higher education. By demonstrating the mediating role of teaching innovation, this study provides a deeper understanding of how AI adoption translates into improved learning effectiveness. These insights contribute to the growing literature on AI in education by offering a comprehensive framework that connects technological adoption with pedagogical transformation and learning outcomes.

These findings reinforce the importance of integrating technology adoption theory with pedagogical innovation perspectives to better understand the educational impact of emerging technologies.

CONCLUSION

This study examined the role of AI adoption in transforming teaching practices and improving learning effectiveness in higher education by proposing and empirically evaluating a conceptual framework that integrates technological, institutional, and pedagogical dimensions. The results indicate that AI infrastructure and institutional support significantly influence AI adoption, which subsequently promotes teaching innovation and enhances learning effectiveness, while teaching innovation plays a critical mediating role in translating AI adoption into meaningful educational outcomes. These findings suggest that the successful integration of AI technologies in higher education requires more than simply implementing advanced technological tools, as effective AI adoption depends on the availability of appropriate technological infrastructure, strong institutional support, and the ability of educators to incorporate AI technologies into innovative pedagogical practices that support student engagement and learning.

From a theoretical perspective, this study contributes to the literature on AI in education by extending traditional technology adoption frameworks, such as the TAM and the UTAUT, through the integration of technological, organizational, and pedagogical factors within a single conceptual model, thereby demonstrating that the educational value of AI technologies emerges primarily through pedagogical transformation rather than through direct technological effects. From a practical perspective, the findings highlight the importance for universities and policymakers to invest in robust technological infrastructure, strengthen institutional support mechanisms such as leadership initiatives and faculty training programs, and promote teaching innovation through professional development initiatives that enable educators to effectively integrate AI tools into instructional practices, thereby maximizing the potential of AI technologies to enhance teaching quality and improve student learning outcomes in higher education environments.

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Despite its contributions, this study has several *limitations* that should be considered when interpreting the findings. The research relies on secondary data derived from global AI indicators, which may not fully capture contextual differences across individual universities and educational systems. In addition, the proposed framework focuses on a limited number of constructs related to AI adoption and teaching innovation, suggesting that future studies could extend the model by incorporating additional variables such as AI literacy, digital competence, ethical considerations, and student perceptions of AI technologies. Future research may also explore the long-term impact of AI adoption on educational outcomes through longitudinal studies. As artificial intelligence technologies continue to evolve, understanding how technological adoption interacts with pedagogical innovation will become increasingly critical for improving learning outcomes in higher education.

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