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#### **Research Article**



# Al and higher education: Understanding faculty roles in teaching, research, and administration

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#### **ABSTRACT**

Received: 16 Apr 2025 Accepted: 8 Oct 2025 The rapid advancement of artificial intelligence (AI) is transforming higher education, impacting pedagogical practices, administrative processes, and faculty engagement with technology. While Al holds promise to enhance learning and streamlining operations, its adoption remains complex and debated. This study examines faculty perceptions of AI integration, focusing on factors such as teaching experience, institutional context, and disciplinary specialization. Using a quantitative survey, the research explores AI engagement across institutions and disciplines, analyzing how demographic factors influence adoption. Findings suggest that junior faculty and those in technology-driven environments demonstrate higher AI confidence and adoption, whereas senior faculty engage in Al leadership yet express skepticism about its pedagogical applications. Disciplinary differences reveal that faculty in content-based fields view AI as a teaching tool, while those in applied disciplines utilize it more strategically for administrative and leadership functions. The study also addresses ethical and institutional challenges, including concerns over data privacy, algorithmic bias, and institutional readiness. By identifying these barriers, the research highlights strategies for fostering Al literacy, professional development, and ethical implementation in higher education. This study contributes to the discourse on Al in academia by presenting an educator-centered perspective, bridging the gap between technological advancement and pedagogical practice. The findings provide academic leaders and policymakers with insights on creating Al-inclusive environments that align with faculty needs, uphold ethical standards, and enhance student learning outcomes.

**Keywords:** artificial intelligence, faculty perceptions, pedagogical practices, Al adoption, ethical challenges, institutional readiness

# **INTRODUCTION**

The rapid advancement of artificial intelligence (AI) is transforming various sectors, and higher education is no exception. Al has the potential to enhance teaching methodologies, streamline administrative processes, and personalize student learning experiences. However, its adoption in academia remains a topic of debate, as faculty members grapple with the benefits and challenges associated with these technologies. Understanding educators' perspectives on AI is essential for ensuring its effective and ethical integration into higher education. Each paragraph should be neither too long nor too short. Unnecessary abbreviations should be eliminated, and necessary ones should be explained in clear terms at first mention. Metric equivalents for all non-metric units should be provided.

#### **Contextual Background**

Al has increasingly become an integral part of higher education, transforming both pedagogical practices and administrative operations. Al-powered applications such as intelligent tutoring systems, automated grading, adaptive learning platforms, and chatbot assistants have been widely adopted to enhance learning experiences and improve institutional efficiency (Chen et al., 2020; Onesi et al., 2024). Moreover, large language models (LLMs) like ChatGPT and Microsoft Copilot are reshaping the way students and educators interact with information, offering new possibilities for personalized education and research assistance (Jo & Bang, 2023).

While AI integration in education holds substantial promise, it also presents several challenges, particularly concerning faculty perceptions, readiness, and adoption. Effective AI implementation requires digital literacy, a willingness to embrace technological change, and institutional support for professional development (Papakonstantinidis et al., 2024; Suryanarayana et al., 2024). Despite AI's potential benefits, faculty members' attitudes toward these technologies vary widely based on factors such as teaching experience, discipline, and institutional culture (Alnasib, 2023; Karkoulian et al., 2025).

Faculty perceptions play a critical role in shaping AI adoption within academic institutions. Resistance to change, ethical concerns about data privacy and algorithmic biases, and apprehension regarding AI's impact on traditional teaching methods all contribute to varying levels of acceptance and engagement among educators (Nguyen et al., 2023). Additionally, demographic variables such as age, teaching experience, and field of specialization significantly influence how faculty members interact with AI technologies (Wu et al., 2024). These concerns underscore the importance of understanding faculty perspectives on AI, as their attitudes ultimately shape the trajectory of AI integration in higher education.

#### **Research Questions**

This study seeks to investigate faculty perceptions of Al adoption in academia by addressing the following research questions:

- 1. What are the primary factors influencing faculty members' attitudes toward Al adoption in higher education?
- 2. How do demographic variables such as teaching experience, discipline, and online/onsite teaching impact faculty members' perceptions of AI?
- 3. What are the key ethical and institutional barriers to AI integration in teaching and research?
- 4. To what extent do faculty members perceive AI as enhancing or diminishing pedagogical effectiveness and academic integrity?
- 5. What strategies can institutions implement to support faculty in adopting and integrating Al technologies effectively?

By addressing these questions, the study aims to provide a comprehensive understanding of the factors that drive or hinder Al adoption among faculty members and to offer insights into effective strategies for fostering Al literacy and engagement in higher education.

This research adds to the growing discourse on AI in higher education by offering an educator-focused perspective on AI adoption. Unlike many existing studies that emphasize the technological capabilities of AI or its impact on students, this study centers on faculty experiences, examining their concerns, expectations, and actual engagement with AI tools and providing a nuanced understanding of the challenges and opportunities associated with AI integration (Papakonstantinidis et al., 2024; Saleh at al., 2025).

Through a quantitative survey approach, this study investigates how faculty across diverse institutions and disciplines perceive AI in teaching and research. By considering variables such as teaching experience, discipline, and institutional culture, it provides a comprehensive view of faculty engagement with AI. Additionally, the study identifies key ethical and institutional barriers to AI adoption, including concerns about data privacy, algorithmic bias, financial constraints, and the lack of adequate training (Sethy et al., 2023; Williamson & Eynon, 2020). Understanding these barriers is essential for developing effective AI policies that align with educational goals.

Beyond identifying challenges, this research also offers practical recommendations for institutions seeking to support faculty in AI adoption. By exploring strategies such as faculty training programs, AI literacy initiatives, and ethical AI policies, the study provides actionable insights that can help build faculty confidence and foster meaningful AI integration (Lin, 2022; Zawacki-Richter et al., 2019). Furthermore, it examines how AI adoption varies across different teaching modalities, including on-campus, online, and hybrid environments, revealing how institutional settings shape faculty engagement with AI technologies. This comparative analysis is particularly relevant as universities continue to adapt to digital and blended learning environments (Jin et al., 2023).

By focusing on faculty perspectives, this study bridges the gap between technological innovation and pedagogical practice. The findings will be valuable to academic leaders, policymakers, and educators seeking to implement AI in ways that support faculty needs, maintain ethical standards, and enhance student learning experiences.

# LITERATURE REVIEW

Al is increasingly shaping higher education by enhancing educational experiences and administrative operations. Applications such as chatbots, machine translators, adaptive education systems, and intelligent tutoring systems are revolutionizing how students learn and interact with educational content (Chen et al., 2020; Onesi et. al., 2024). These tools can personalize learning, improve student outcomes, and support self-regulated learning (SRL) by promoting knowledge application (Chen et al., 2020; Jo & Bang, 2023; Onesi et al., 2024). Additionally, LLMs like ChatGPT and Microsoft Copilot can transform how educators and students engage with information (Chen, 2024).

Al is also streamlining administrative tasks, improving operational efficiency, and transforming assessment methods (Chao et al., 2021; Lukianets & Lukianets, 2023; Xia, 2024). However, the successful integration of these technologies requires digital literacy and familiarity with Al's capabilities (Suryanarayana et al., 2024). With the increasing use of Al technologies in the classroom, it is important to know what educators think of these technologies (Papakonstantinidis et al., 2024). This literature review aims to current trends, factors, ethical considerations, barriers, and strategies to enhance Al adoption.

### **Current Trends in AI Usage & Factors Influencing AI Adoption**

Three major potentials of AI are its ability to improve learning, support digital transformation, and help analyze educational data (Ali et al., 2024; Luckin & Cukurova, 2019; Okunlaya et al., 2022). AI significantly impacts personalized learning by collecting and analyzing data, allowing educators to tailor content to individual student needs (Akavova et al., 2023). With the use of virtual assistants providing instant feedback and guiding students through course materials (Adeleye et al., 2024), educators can automate routine tasks (Seo et al., 2021). This approach enhances personalized interactions and material comprehension by customizing the learning experience (Aparicio-Gómez & Aparicio-Gómez, 2024). Furthermore, AI supports SRL by promoting proactive learning behaviors and helping students manage their learning processes effectively (Ng et al., 2024).

Al and the Internet of things are two technologies with the greatest potential to cause the biggest transformation in education (Quy et al., 2023). But both technologies require faculty members' openness and readiness to adopt them. Research on Al adoption in higher education often focuses on faculty attitudes and readiness to incorporate these technologies (Papakonstantinidis et al., 2024). Alnasib (2023) found an average level of readiness for Al integration at King Faisal University, highlighting the importance of perceived benefits, attitudes towards Al, and behavioral intentions. Demographic variables such as gender, age, and teaching experience significantly affect willingness to adopt Al, indicating the need for tailored support strategies (Alnasib, 2023).

Al applications have enriched learning and teaching activities for decades (Lee et al., 2022). Technologies like Al-enabled automatic scoring, chatbots, and intelligent tutoring systems help analyze educational data and tailor teaching styles to individual learners (Fu et al., 2020). For example, in STEM education, Al analytics develops students' thinking skills and competencies (How & Hung, 2019). Al is increasingly integrated into K-

12 education worldwide through software like Perplexity.ai, responding to its growing prevalence in daily life (Miao et al., 2022).

Al systems learn and adapt pedagogical policies through reinforcement learning, enhancing teaching strategies (Iglesias et al., 2008). Al-powered assessment tools improve accuracy, provide constructive feedback, and enable tailored teaching methods (Owan et al., 2023; Pitychoutis & Al Rawahi, 2024). In addition, Al-based personalized e-learning systems enhance educational experiences by identifying learners' levels and delivering appropriate content (Murtaza et al., 2022); thus, promoting Al literacy in K-12 schools is crucial (Sadler et al., 2024). Al pedagogy, such as analogy-based methods, demystifies Al, enhances comprehension, and fosters critical thinking skills (Dai et al., 2023). Continuous Al development influences learning styles and supports educational reform (Lin, 2022), since improving Al literacy in K-12 classrooms remains essential (Zhang et al., 2024).

Cultural, institutional, and contextual factors also significantly influence AI adoption in education. Elements such as social influence, trust, innovation, resistance to change, and experience impact AI integration (Alshatti Schmidt et al., 2025; Wang et al., 2025; Wu et al., 2024). An ethical and contextual approach to AI design and use is crucial for addressing ethical and privacy concerns (Nguyen et al., 2023). Factors like AI expertise among instructors, the availability of AI-related resources, and the field of study also affect perceptions of AI adoption (Asirit & Hua, 2023; Othman et al., 2025).

Regional and institutional differences in Al adoption are evident. For example, a study in India explored factors facilitating Al adoption in management institutes, highlighting organizational factors' significance (Priya et al., 2023). In South Africa, Al technology in higher education has enhanced student achievements and promoted collaborative learning environments (Opesemowo & Adekomaya, 2024). In Vietnam, Al innovations improve pedagogical engagement in Christian education, reflecting cultural openness to Al technologies (Tran & Nguyen, 2021). Acceptance of Al in education (AlEd) is further shaped by cultural aspects and institutional characteristics (Veseli et al., 2025). Top-ranked universities may show variations in acceptance of generative Al based on the ratio of international students, academic reputation, and faculty-student ratio (loku et al., 2024). Al technologies like chatbots and AlEd for personalized learning pathways enhance educational practices by considering individual learning contexts and achievements (Tapalova & Zhiyenbayeva, 2022).

## **Ethical Considerations and Barriers to AI Integration**

The adoption of AIEd raises significant ethical considerations, regarding issues of fairness, data privacy, and transparency (Sethy et al., 2023; Williamson & Eynon, 2020). Fenu et al. (2022) call a need for equity in how AI is used in education, as algorithms can easily reinforce biases or create inequality. AI models depend on historical information–and can reflect societal inequalities of race, gender, class or other. When prior biases influence learning AI systems, they can have racial impacts. For example, by giving students unequal access to educational opportunities, grading students differently, or making biased predictions about student performance (Baker & Hawn, 2022). Moreover, the opaque nature of AI algorithms' performance can also prevent educators and students from discovering and resolving biases. Creating inclusive, regularly biasaudited, and diverse-stakeholder-informed AI systems is the key to fairness (Ferrara, 2023). Training users in algorithmic decision making and fostering transparency around AI deployment can further counteract concerns about fairness, resulting in fair results for all students.

Data privacy is another ethical consideration that impacts AI adoption in the classroom. AI-enabled academic surveillance has been criticized, for both privacy and control (Swartz & McElroy, 2023). Privacy violations occur when surveillance tools used by AI systems gather sensitive student data without user consent (Karan & Angadi, 2023). AIEd and learning analytics in particular, involve capturing and analyzing digital traces of students such as their strengths, weaknesses, and learning styles (Pardo et al., 2017). Therefore, the massive collection and processing creates privacy and security risks (Eden et al., 2024). For example, AI predictive systems can track students' performances and may thus violate privacy (Akgün & Greenhow, 2021), while data collection without consent exacerbates ethical problems (Karan & Angadi, 2023). This privacy issue is further compounded by the costs of implementing AI tools which further squeeze already stretched budgets (Zainuddin, 2024).

To mitigate these challenges, it is crucial to discuss accountability and transparency. Ensuring accountability in AI systems requires fostering an understanding of their ethical implications and establishing trust in AI-powered feedback mechanisms (Bogina et al., 2021; Pitychoutis, 2024; Tahir et al., 2025). Ethical use of AIEd necessitates balancing its potential to enhance educational practices with the need to safeguard data privacy and mitigate surveillance risks (Lin et al., 2022). Accountability should be the cornerstone of ethical use of AI. When it comes to applying AI ethically in the classroom, there is a delicate balance between using its transformational capabilities to better facilitate teaching and learning and ensuring the rights and privacy of all participants (Tang & Su, 2024). This involves building robust data governance practices, minimizing surveillance opportunities, and aligning AI tools with transparent learning principles like equity, inclusion, and the respect for human agency. Addressing these areas, as well as the common barriers to AI adoption, will enable institutions to provide a more reliable and ethical AI landscape that will be helpful to everyone within the academic community.

Common barriers to AI integration in academic institutions include financial constraints and a lack of technical expertise. Financial issues significantly impact the implementation and maintenance of AI labs (Hergan et al., 2022). This burden extends to maintaining and updating AI technologies (Barsha & Munshi, 2023). The lack of AI talent affects other barriers to AI adoption (Kar et al., 2021). Institutions may struggle with training employees to work with AI systems, and resistance to change can impede successful implementation (Lanang Triana et al., 2024). Resistance among faculty can stem from various factors, including a lack of AI adoption strategy and leadership commitment (Kar et al., 2021). The absence of formal guidelines for AI use can lead to confusion among students and instructors, further exacerbating resistance (Song, 2024). Addressing governance issues through laws and policies to regulate AI implementation is crucial to overcoming resistance (Petersson et al., 2022).

Despite concerns about the inappropriate use of AI and a lack of critical engagement, positive faculty reception suggests promising opportunities for instructional enhancement and adaptive learning (Delgado et al., 2024; Zekaj, 2023). Critical engagement with AI-generated content is essential to maintain a balance between technological efficiency and human agency, particularly in the training of higher-order skills (Sharma et al., 2022). By addressing privacy, explainability, and accountability concerns, educators can leverage AI tools effectively to improve educational outcomes while safeguarding ethical standards.

# **Strategies to Enhance Al Adoption**

The successful adoption of AI technologies also depends heavily on educators' attitudes and readiness. Faculty perceptions towards AI significantly impact their willingness to integrate AI tools into teaching, reflecting its potential to revolutionize educational practices (Alnasib, 2023; Shazly, 2021). While some educators express concerns about AI's broader implications (Hopcan et al., 2023; Zhang & Iliško, 2025), others acknowledge its potential to enhance teaching and learning processes (Albaqami & Alzahrani, 2022). Tools like ChatGPT and intelligent tutoring systems exemplify AI's ability to foster adaptive and learner-centered approaches, demonstrating its transformative potential in education (Zekaj, 2023).

Al shows significant potential in improving learning outcomes through customization and adaptive learning environments. Research indicates that Al applications enhance academic support services, provide personalized learning experiences, and lead to positive outcomes for students (Hutson et al., 2022; Wang et al., 2023; Zawacki-Richter et al., 2019). Using Al technologies like intelligent tutoring systems, adaptive systems, and personalized content generators, institutions can tailor learning experiences to individual needs, resulting in more successful outcomes (Wang et al., 2023; Zawacki-Richter et al., 2019). Studies have found that AlEd supports SRL in online environments by enhancing students' self-regulation processes (Jin et al., 2023). Al integration fosters sustainable learning outcomes by evaluating skills, knowledge, ethics, learning objectives, and outcomes (Chemlal & Azzouazi, 2023). Al improves learner-instructor interactions in online learning by personalizing experiences, automating routine tasks, and facilitating adaptive assessments (Seo et al., 2021). Al-driven adaptive content recommenders increase learning efficiency, helping learners achieve objectives more quickly and at a lower cost (Raj & Renumol, 2022).

Strategic AI incorporation can enhance access, retention rates, reduce educational costs, and decrease time to completion (Alet, 2023; Hutson et al., 2022). Faculty perceptions are crucial in adopting and effectively implementing AI technologies in higher education (Papakonstantinidis et al., 2024). Studies like Memon et al.

(2023) and Alenezi (2023) highlight the importance of promoting Al use by raising awareness, demonstrating Al's benefits, and providing technical support to faculty. Ahmad et al. (2023) also discuss the impact of demographic variables on faculty perceptions, emphasizing the relevance of individual characteristics in engaging with Al and other technologies.

Effective strategies to enhance faculty acceptance of Al include involving faculty in Al tool development through participatory design processes (Blease et al., 2019). This involvement ensures faculty members have a say in designing Al systems, increasing their likelihood of embracing the technology. Providing professional development opportunities focusing on Al literacy and data science applications helps faculty feel more prepared integrating Al into their practices (Wood et al., 2021). Transparency is crucial for fostering faculty acceptance of Al. Studies show that Al transparency is vital in building user trust (Yu et al., 2023). Ensuring transparency at multiple levels–algorithmic, interaction, and social–can increase faculty trust and adoption (Haresamudram et al., 2023). Incorporating guidelines and policies promoting transparency in Al decision-making processes can further enhance trust (Patidar et al., 2024). Addressing ethical concerns and ensuring Al systems are developed ethically can positively influence acceptance. Emphasizing ethical considerations in Al development helps faculty perceive Al as aligning with their professional values and responsibilities.

Faculty members' perceptions of AI in higher education are shaped by a complex interplay of readiness, ethical considerations, potential impacts on teaching methodologies, and challenges and opportunities presented by AI integration. Understanding these perceptions is crucial for successfully integrating AI into academic environments. As higher education evolves with technological advancements, recognizing and addressing faculty attitudes towards AI will be essential for navigating this transformative era. The next section is an overview of how the paper approached the topic to add some scholarly depth to the issue of higher education faculty perception of AI within the classroom.

### **METHODOLOGY**

#### Introduction

The purpose of this study is to explore faculty perceptions of AI in academia by utilizing the technological pedagogical and content knowledge (TPACK) framework. With the increasing integration of AIEd settings, it is crucial to understand how faculty members across different disciplines, experience levels, and teaching environments engage with AI tools. This chapter outlines the research design, participant demographics, data collection methods, instrumentation, data analysis procedures, ethical considerations, and reliability and validity measures adopted in the study.

# **Research Design**

This study employed a quantitative survey research design to examine faculty perceptions toward AI in academia using the TPACK framework (Mishra & Koehler, 2006). The study aimed to identify variations in AI adoption based on faculty teaching experience, location (on-campus vs. off-campus), and field of specialization.

# **Participants**

This study involved a total of 417 faculty members representing diverse demographics in terms of gender, age, years of teaching experience, and academic disciplines. The participants were selected from various institutions across North America, Europe, the Arab Gulf countries, and Oceania, ensuring a broad and inclusive representation.

#### Gender and age distribution

As **Table 1** shows of the 417 participants, 225 identified as male (53.96%), 161 as female (38.61%), and 31 (7.43%) preferred not to disclose their gender. The age distribution of the participants ranged from 18 to over 55 years. Specifically, 7.19% were aged 18–24, 9.83% were 25–34, whereas the majority 36.45% were 35–44, 29.50% were 45–54, and 17.03% were 55 and above. This distribution reflects a balanced representation of early-career, mid-career, and senior faculty members, providing comprehensive insights into faculty perceptions of Al across different career stages.

Table 1. Gender and age distribution of population

Criteria	Characteristics	Number	Percentage (%)
	Male	225	53.96
Gender	Female	161	38.61
	Prefer not to say	31	7.43
	18-24	30	7.19
	25-34	41	9.83
Age	35-44	152	36.45
	45–54	123	29.50
	+55	71	17.03
Number		417	

Table 2. Years of experience distribution

Criteria	Characteristics	Number	Years of experience percentage
	18 24	26	≤ 5
	18–24	4	6–10
		9	≤ 5
	25-34	13	6–10
		19	11–15
		31	6–10
Age	35-44	62	11–15
		59	16–20
_	45-54	29	11–15
		53	16–20
		41	21 ≤
		23	16–20
	+55	48	21 ≤
	≤ 5	35	8.39%
	6–10	48	11.51%
Years of experience	11–15	110	26.38%
	16–20	135	32.37%
	21 ≤	89	21.34%
Number		417	100%

# Years of teaching experience

Participants exhibited a wide range of teaching experiences (**Table 2**). Faculty with 5 years or less of experience constituted 8.39% of the sample, while those with 6–10 years accounted for 11.51%. A significant portion of the participants, 26.38%, had 11–15 years of teaching experience. Those with 16–20 years represented the largest group at 32.37%, and faculty with over 21 years of teaching experience made up 21.34% of the sample. This diversity in teaching experience allowed for an in-depth analysis of how tenure in academia influences perceptions of Al.

This comprehensive demographic profile underscores the study's robust participant base, enabling a nuanced exploration of faculty perceptions regarding Al integration in higher education. The diversity in gender, age, experience, and disciplinary background ensures that the findings are reflective of varied academic contexts and experiences.

The participants came from a broad spectrum of academic disciplines, categorized into two main groups (**Table 3**): Content and academic disciplines (CAD) and applied and professional disciplines (APD). The CAD category included humanities (115 participants), social sciences (63), natural sciences (73), and formal sciences (32), totaling 283 participants. The APD category comprised applied sciences (41), environmental studies (15), media studies (35), library studies (21), and medicine & health sciences (22), with a total of 134 participants. This disciplinary diversity facilitated an examination of AI perceptions across both theoretical and applied educational contexts.

#### **Data Collection Procedure**

Data were collected using a Microsoft Forms survey, which was distributed through institutional mailing lists and faculty professional networks on social media platforms. The survey contained a consent form,

Table 3. Type of educational discipline

Disciplines	Characteristics	Number	Number per criteria
	Humanities	115	
CAD	Social science	63	202
CAD	Natural science	73	283
	Formal science	32	
	Applied science	41	
	Environmental	15	
APD	Media studies	35	134
	Library	21	
	Medicine & health	22	
Number		417	417

ensuring voluntary participation and ethical compliance. Faculty members were required to provide consent before proceeding to the questionnaire. The data collection period lasted from April until September 2024, during which faculty members across multiple institutions had the opportunity to participate.

#### Instrumentation

The survey instrument was adapted from the TPACK framework, which assesses faculty perceptions and confidence in integrating AI into their teaching. The questionnaire was structured into four major sections:

- 1. Demographic information-Collecting details on faculty experience, location, and specialization.
- 2. Al perceptions and adoption–Measuring faculty attitudes toward Al, ease of use, and Al's impact on teaching.
- 3. Al leadership and institutional roles–Evaluating faculty engagement in Al decision-making and policy implementation.
- 4. Al-integrated teaching Sstrategies–Assessing how faculty integrate Al into their pedagogical practices. Each item was measured using a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree).

# **Data Analysis**

The survey data collected were analyzed using descriptive statistics, ANOVA, and logistic regression. The analysis was conducted to examine group differences and predictive relationships:

- 1. Descriptive statistics summarize the demographic characteristics of the sample.
- 2. ANOVA tested significant differences in Al adoption across faculty experience levels, locations, and specialization fields.
- 3. Logistic regression was used to determine the probability of Al adoption based on faculty characteristics.
- 4. All statistical analyses were performed using SPSS version 29. The significance level was set at p < .05 for all statistical tests.

#### **Ethical Considerations**

The study adhered to institutional ethical guidelines. Participants were provided with clear information about the purpose of the study, the voluntary nature of participation, and confidentiality measures. No personally identifiable information was collected, and all responses remained anonymous and confidential.

### **Reliability and Validity**

To ensure the reliability of the instrument, internal consistency was assessed using Cronbach's alpha ( $\alpha$  > 0.70). The survey instrument was also reviewed by AI and education experts to ensure content validity and alignment with the TPACK model.

#### **Conclusion**

This chapter provided a comprehensive overview of the research methodology, outlining the study's design, participant demographics, data collection approach, and analytical procedures. The use of a

Table 4. ANOVA results: Faculty experience and Al adoption

Source	df	SS	MS	F	p-value
Between groups	3	68.45	22.82	17.96	< .001
Within groups	412	520.21	1.26		
Total	415	588.66			

Table 5. Regression: Faculty experience and AI perceptions

Variable	Coefficient (β)	SE	p-value	Exp (B) 95% confidence interval
Intercept	5.921	0.654	< .001	[3.01, 11.52]
1	-0.512	0.134	< .001	[0.42, 0.74]
4	-0.783	0.162	< .001	[0.29, 0.52]
5	-0.642	0.143	< .001	[0.31, 0.62]
6	0.924	0.198	< .001	[1.52, 3.42]
19	-0.733	0.157	< .001	[0.32, 0.54]
21	0.721	0.175	< .001	[1.47, 2.98]
24	1.189	0.221	< .001	[2.08, 4.53]
28	-1.127	0.190	< .001	[0.23, 0.41]
31	-0.312	0.169	0.065	[0.52, 1.04]

quantitative survey research design enabled a systematic examination of faculty perceptions of AI across different contexts. Ethical considerations and validity measures ensured the robustness of the findings. The subsequent chapter presents the results of the data analysis, offering insights into faculty engagement with AI technologies in higher education.

#### **RESULTS**

# **Faculty Experience and AI Perceptions**

This section examines how faculty teaching experience influences their perceptions of AI in teaching, leadership, and instructional adaptation. The analysis includes ANOVA results and logistic regression models to assess experience-related differences in AI adoption (Table 4).

### Al confidence and teaching experience

Faculty members with more teaching experience were significantly less likely to perceive AI as enhancing teaching approaches or student learning (**Table 5**). ANOVA results indicate a significant effect of experience on AI confidence scores, F (3, 412) = 17.96, p < .001, with post-hoc Tukey tests revealing that faculty with less than 10 years of experience reported significantly higher AI confidence scores (mean [M] = 3.82, standard deviation [SD] = 0.91) compared to those with 20+ years of experience (M = 2.94, SD = 1.08).

Regression analysis further confirmed these findings, with a negative association between years of experience and finding AI easy to use (variable 1,  $\beta$  = -0.512, standard error [SE] = 0.134, p < .001, Exp [B] = 0.599). Similarly, experienced faculty were less likely to believe AI enhances teaching (variable 4,  $\beta$  = -0.783, SE = 0.162, p < .001, Exp [B] = 0.457) or student learning (variable 5,  $\beta$  = -0.642, SE = 0.143, p < .001, Exp [B] = 0.526).

### Al leadership and institutional roles

Despite lower engagement with AI for direct instruction, experienced faculty members were significantly more likely to take on AI leadership roles, as shown by the ANOVA results in **Table 5** (F [3, 412] = 14.21, p < .001). Faculty with 20+ years of experience had significantly higher leadership role scores (M = 4.23, SD = 0.79) compared to early-career faculty (M = 3.48, SD = 1.01).

Regression analysis confirmed this trend, showing that senior faculty members were more likely to assume Al leadership roles (variable 6,  $\beta$  = 0.924, SE = 0.198, p < .001, Exp [B] = 2.520). However, broader Al leadership responsibilities were more common among junior faculty (variable 28,  $\beta$  = -1.127, SE = 0.190, p < .001, Exp [B] = 0.324), indicating that early-career faculty are more engaged in Al-driven pedagogical innovation, whereas senior faculty focus on institutional policy.

Table 6. Regression: Faculty location and Al integration

Variable	Coefficient (β)	SE	Wald statistics	p-value	Exp (B) 95% confidence interval
Intercept	6.335	0.665	90.63	< .001	[3.21, 12.48]
1	-0.634	0.147	18.56	< .001	[0.39, 0.69]
4	-0.916	0.208	19.38	< .001	[0.29, 0.58]
5	-0.737	0.176	17.54	< .001	[0.31, 0.68]
6	0.837	0.211	15.75	< .001	[1.27, 3.42]
19	-0.885	0.136	41.76	< .001	[0.32, 0.54]
21	-0.616	0.198	9.69	0.002	[0.37, 0.79]
24	1.310	0.246	28.18	< .001	[2.28, 6.02]
28	-1.320	0.170	60.34	< .001	[0.19, 0.37]
31	-0.195	0.188	1.08	0.299	[0.57, 1.19]

# Al-integrated teaching and content development

Experienced faculty members were significantly less likely to integrate AI into content and instructional design (variable 19,  $\beta$  = -0.733, SE = 0.157, p < .001, Exp [B] = 0.481). However, ANOVA results (**Table 5**) revealed a significant effect of experience on AI pedagogical adaptation, F (3, 412) = 11.76, p < .001. Faculty with 15–20 years of experience reported the highest adaptation scores (M = 3.87, SD = 0.81), suggesting that mid-career faculty may be the most adaptable to AI integration.

Regression analysis supported this, with faculty experience positively associated with Al adaptation to teaching activities (variable 24,  $\beta$  = 1.189, SE = 0.221, p < .001, Exp [B] = 3.283).

## **Evaluative and analytical AI skills**

Faculty with more experience demonstrated significantly greater confidence in critically evaluating AI integration (variable 21,  $\beta$  = 0.721, SE = 0.175, p < .001, Exp [B] = 2.057). This was further confirmed by ANOVA results (F [3, 412] = 9.84, p < .001), showing that senior faculty had significantly higher AI evaluation scores (M = 4.05, SD = 0.76) compared to early-career faculty (M = 3.12, SD = 0.99).

Conversely, faculty with longer teaching experience were significantly less likely to feel confident in using AI to enhance student learning (variable 31,  $\beta$  = -0.312, SE = 0.169, p = 0.065, Exp [B] = 0.732), though this result did not reach statistical significance.

#### Summary of findings: Experience and AI perceptions

Faculty experience significantly influences AI perceptions. More experienced faculty members are less likely to engage with AI for teaching and lesson planning (variables 1, 4, 5, 19, and 31) but more likely to assume leadership roles (6) and critically evaluate AI applications (21). Junior faculty members are more actively engaged in AI-driven pedagogical innovation, whereas senior faculty tend to shape institutional AI policy rather than adopt AI-driven teaching methods.

### **Faculty Location (On-Site vs. Online)**

# Faculty location and AI perceptions

This section examines the relationship between faculty location (on-campus vs. off-campus) and perceptions of AI use in teaching, leadership roles, and instructional adaptation. The analysis is based on logistic regression models, which assess the likelihood of faculty engagement with AI tools across different settings (Table 6).

## Al confidence and faculty location

Faculty members who reported higher confidence in using AI for teaching and learning were significantly more likely to be working off-campus. The regression analysis revealed a negative association between working on-campus and finding AI easy to use (variable 1,  $\beta$  = -0.634, SE = 0.147, p < .001, Exp [B] = 0.530), perceiving AI as enhancing teaching approaches (variable 4,  $\beta$  = -0.916, SE = 0.208, p < .001, Exp [B] = 0.400), and believing AI improves student learning (variable 5,  $\beta$  = -0.737, SE = 0.176, p < .001, Exp [B] = 0.478). This suggests that faculty confident in AI use may prefer flexible work environments where AI tools are integrated into their teaching practices more seamlessly.

## AI leadership and institutional roles

A contrasting trend was observed in faculty members assuming leadership roles in AI integration. Oncampus faculty were significantly more likely to take on AI leadership responsibilities (variable 6,  $\beta$  = 0.837, SE = 0.211, p < .001, Exp [B] = 2.310). This suggests that institutional decision-making structures support AI adoption among physically present faculty who influence university-wide policies and implementation strategies.

However, a different type of leadership–broader Al integration responsibilities–was negatively associated with on-campus work (variable 28,  $\beta$  = –1.320, SE = 0.170, p < .001, Exp [B] = 0.267). This implies that while oncampus faculty may spearhead Al initiatives within their institutions, larger-scale Al integration efforts often occur in off-campus or administrative settings.

# Al-integrated teaching and content development

Faculty confident in combining AI with content and pedagogical approaches (variable 19,  $\beta$  = -0.885, SE = 0.136, p < .001, Exp [B] = 0.413) were significantly less likely to be working on-campus. This aligns with the finding that off-campus faculty are more likely to integrate AI into instructional design. Conversely, faculty confident in adapting AI to diverse teaching activities (variable 24,  $\beta$  = 1.310, SE = 0.246, p < .001, Exp [B] = 3.708) were more likely to work on-campus, suggesting that structured teaching environments facilitate hands-on AI adoption.

# **Evaluative and analytical AI skills**

A further distinction emerged in faculty members' ability to critically evaluate AI use in education. Faculty who were confident in assessing AI effectiveness (variable 21,  $\beta$  = -0.616, SE = 0.198, p = 0.002, Exp [B] = 0.540) were significantly less likely to work on-campus, indicating that evaluative skills are more prevalent among off-campus faculty. Meanwhile, faculty confident in using AI to enhance student learning (variable 31,  $\beta$  = -0.195, SE = 0.188, p = 0.299, Exp [B] = 0.822) were also less likely to be found on-campus, though this association was not statistically significant.

# Summary of findings: Location (on/off-campus)

Faculty location significantly influences engagement with generative Al. Faculty confident in Al use (variables 1, 4, 5, 19, and 31) are more likely to work off-campus, likely due to greater flexibility in adopting Al tools. Conversely, on-campus faculty are more inclined to assume leadership roles (6, 24), reflecting a focus on policy and structured implementation. However, the lower adoption rates for Al-enhanced teaching among on-campus faculty may stem from traditional teaching styles or institutional constraints. These findings highlight the need for Al adoption strategies that balance technological confidence among off-campus faculty with the leadership strengths of on-campus educators.

#### **Faculty Specialization and AI Perceptions**

Faculty specialization is categorized into two broad groups: CAD and APD. CAD includes fields such as humanities, social sciences, natural sciences, and formal sciences, which traditionally emphasize theoretical knowledge and conceptual understanding. APD, on the other hand, comprises applied sciences, media studies, environmental studies, library science, and medicine & health, where the focus is on practical applications, professional training, and industry-relevant skills. The distinction between these two categories helps in understanding how different disciplinary orientations influence faculty engagement with Al technologies in teaching and institutional leadership.

This section analyses the impact of faculty field of specialization on their perceptions of AI in teaching, leadership, and instructional adaptation (Table 7). The findings are derived from logistic regression models assessing the relationship between academic disciplines and adoption of AI.

### AI confidence and faculty specialization

Faculty in CAD disciplines (humanities, social sciences, natural sciences, and formal sciences) were significantly more likely to find AI easy to use (variable 1,  $\beta$  = 0.785, SE = 0.142, p < .001, Exp [B] = 2.192) and

**Table 7.** Regression: Faculty specialization and AI perceptions

Variable	Coefficient (β)	SE	p-value	Exp (B) 95% confidence interval
1	0.785	0.142	< .001	[1.75, 2.74]
5	-0.691	0.153	< .001	[0.41, 0.61]
6	1.034	0.187	< .001	[2.02, 3.91]
19	0.952	0.159	< .001	[1.97, 3.41]
24	0.912	0.181	< .001	[1.68, 3.71]
28	-0.811	0.173	< .001	[0.32, 0.58]
31	-0.524	0.165	0.003	[0.47, 0.79]

integrate it into their teaching practices (variable 19,  $\beta$  = 0.952, SE = 0.159, p < .001, Exp [B] = 2.591). These findings suggest that CAD faculty are more open to AI adoption, potentially due to a pedagogical focus that encourages technological experimentation.

Conversely, APD faculty (applied sciences, media studies, environmental studies, library science, medicine & health) were significantly less likely to perceive AI as enhancing student learning (variable 5,  $\beta$  = -0.691, SE = 0.153, p < .001, Exp [B] = 0.501). This suggests a possible disconnect between AI tools and discipline-specific pedagogical needs.

# Al leadership and strategic roles

Faculty in APD disciplines were significantly more likely to assume AI leadership roles (variable 6,  $\beta$  = 1.034, SE = 0.187, p < .001, Exp [B] = 2.813). This indicates that AI leadership initiatives may be more prominent in applied and technical disciplines where AI is perceived as an administrative or strategic tool rather than a direct instructional asset.

In contrast, broader AI leadership responsibilities were more common among CAD faculty (variable 28,  $\beta$  = -0.811, SE = 0.173, p < .001, Exp [B] = 0.444), suggesting that while CAD faculty are more likely to use AI in their teaching, they are less involved in administrative AI policy-making.

# Al integration and pedagogical adaptation

Faculty in CAD disciplines reported significantly higher confidence in adapting AI tools to diverse teaching activities (variable 24,  $\beta$  = 0.912, SE = 0.181, p < .001, Exp [B] = 2.489), reinforcing the idea that AI is perceived as an instructional aid rather than a managerial tool in these disciplines.

Conversely, APD faculty were significantly more likely to be skeptical of Al's role in improving content delivery (variable 31,  $\beta$  = -0.524, SE = 0.165, p = 0.003, Exp [B] = 0.592), suggesting possible concerns about Al's applicability to specialized or highly technical subjects.

# Summary of findings: Specialization and AI perceptions

Faculty specialization significantly shapes attitudes toward AI adoption. CAD faculty are more likely to perceive AI as a beneficial teaching tool (variables 1, 19, and 24), while APD faculty demonstrate greater skepticism about AI's ability to enhance student learning and content delivery (variable 5 and variable 31).

Additionally, APD faculty are more involved in Al leadership roles (variable 6), while CAD faculty are more engaged in direct Al integration into teaching but less involved in strategic Al planning (variable 28). These findings highlight the importance of tailoring Al training and policy initiatives to discipline-specific needs, ensuring that Al integration is both pedagogically relevant and strategically effective.

## **DISCUSSION**

# **AI Confidence and Teaching Experience**

This study's results identify the relationship between faculty teaching experience and their perceptions and implementation of AI in higher education. The data shows a distinct separation between junior and senior faculty regarding their confidence with how their institutions should approach AI integration into educational practices. Analysis shows faculty who have less than 10 years of teaching experience possess a stronger belief in AI's capacity to improve educational outcomes as reflected by superior AI confidence scores (variable 1,

 $\beta$  = -0.512, SE = 0.134, p < .001). According to the study's findings, professors with longer teaching careers display greater skepticism towards new technologies because they have established teaching routines or lack knowledge about AI resources. The current research supports previous studies (Chao et al., 2021; Lukianets & Lukianets, 2023; Xia, 2024), which show that educators from younger generations tend to integrate new technology tools into their teaching methods more confidently than their older colleagues.

#### **AI Leadership and Institutional Roles**

Although senior faculty members engage less with Al for instructional purposes, the same people occupy leadership roles related to Al at a higher rate (variable 6,  $\beta$  = 0.924, SE = 0.198, p < .001). Experienced faculty members might not lead classroom Al integration, but they are essential for developing institutional Al policies and strategies. Junior faculty members lead Al-driven teaching innovations (variable 28,  $\beta$  = –1.127, SE = 0.190, p < .001), which demonstrates a bottom-up adoption model where teaching front-runners introduce novel practices.

Teaching activity data show that faculty members with 15–20 years of experience demonstrate the most extensive adaptation to AI integration, which is measured as variable 24 with  $\beta$  = 1.189 and SE = 0.221 leading to statistical significance p < .001. The data implies that faculty members in their mid-career stage combine sufficient experience with an openness to new methods to effectively integrate AI into educational design. Institutions can take advantage of this faculty adaptability to launch AI pilot programs because these members can act as influential change facilitators within their academic departments.

Faculty with more experience show higher confidence when critically examining AI applications (variable 21,  $\beta$  = 0.721, SE = 0.175, p < .001) which helps them evaluate AI's effectiveness and ethical issues in educational settings. The low level of confidence among experienced faculty to use AI for student learning improvement (variable 31) indicates an area that needs professional development attention. Senior educators would likely adopt AI tools more broadly if training programs demonstrated their practical teaching applications.

This research highlights that faculty experience must be factored into AI integration planning. Academic institutions need to acknowledge how faculty members at various career stages contribute differently to AI implementation. Junior faculty members push AI innovation through experimental work but senior faculty ensure the strategic guidance of AI projects to match educational goals. When institutions advance collaboration between faculty groups they establish a unified and successful method for integrating AI into education.

### Al and Faculty Location (On-Site vs. Online)

Research findings reveal how faculty location affects perceptions and implementation of AI technology in educational settings based on whether faculty members work on-campus or off-campus. This research reveals specific engagement and leadership patterns related to AI that differ between faculty who teach onsite and online, which must be considered when developing AI integration strategies at educational institutions. Faculty members working off-campus report higher confidence levels in using AI for teaching and learning according to the analysis. The negative relationship between working on-campus and faculty perceptions of AI ease of use (variable 1,  $\beta$  = -0.634, SE = 0.147, p < .001) extends to faculty views on AI's enhancement of teaching approaches (variable 4,  $\beta$  = -0.916, SE = 0.208, p < .001) and AI's improvement of student learning (variable 5,  $\beta$  = -0.737, SE = 0.176, p < .001). Our findings show that faculty members who work off-campus could gain advantages from work environments that allow them to easily integrate AI tools into their teaching methods.

The data reveals that faculty working on-campus assume AI leadership responsibilities at higher rates compared to their off-campus counterparts (variable 6,  $\beta$  = 0.837, SE = 0.211, p < .001). Current institutional decision-making processes show preference towards faculty members who maintain physical presence at the university because they have the ability to shape both policies and implementation strategies at the institutional level. Extensive AI projects tend to happen outside campus facilities or within administrative offices as shown by the negative relationship between broader AI integration duties and on-campus work positions (variable 28,  $\beta$  = -1.320, SE = 0.170, p < .001).

Faculty who feel confident merging AI with educational content and methods tend to work off-campus as shown by variable 19 which demonstrates a negative association ( $\beta$  = -0.885, SE = 0.136, p < .001). The data confirms that faculty who teach at online institutions have a greater tendency to include AI applications in their teaching design, which is a result of their technology savviness. Faculty members who are capable of adapting AI to different teaching tasks tend to work on-campus (variable 24,  $\beta$  = 1.310, SE = 0.246, p < .001), implying that structured teaching environments help promote hands-on AI integration.

Faculty members display different levels of ability when it comes to critically assessing AI applications in educational settings. Faculty members who feel secure in evaluating AI effectiveness tend to teach off-campus (variable 21,  $\beta$  = -0.616, SE = 0.198, p = 0.002) which reveals that faculty with strong evaluative skills predominantly work solely online. Faculty members working on-campus show lower confidence levels in using AI to enhance student learning (variable 31,  $\beta$  = -0.195, SE = 0.188, p = 0.299) but the difference lacks statistical significance.

Where faculty members work greatly affects their involvement with generative AI systems. Faculty members who demonstrate confidence in AI usage (variables 1, 4, 5, 19, and 31) tend to work off-campus because they can adopt AI tools more flexibly. Faculty members based on campus tend to take on leadership roles (variable 6 and variable 24) because of their focus on structured policies and implementation. Oncampus faculty show lower rates of AI-enhanced teaching implementation which likely results from their traditional teaching methods and institutional limitations. The results show a requirement for AI adoption approaches that merge off-campus faculty's technological expertise with the administrative capabilities of oncampus educators.

Consequently, the study reveals important data about the effects of faculty specialization on the perception and implementation of AI technologies in educational institutions. Through faculty grouping into CAD and APD the study reveals unique trends in AI interaction and leadership roles which directly impact discipline-specific AI implementation approaches.

# **Al Confidence and Faculty Specialization**

Faculty from the CAD disciplines which include humanities, social sciences, natural sciences, and formal sciences show higher likelihood to easily use AI (variable 1,  $\beta$  = 0.785, SE = 0.142, p < .001) and implement AI tools in their teaching methods (variable 19,  $\beta$  = 0.952, SE = 0.159, p < .001). The research indicates that faculty teaching CAD subjects show greater willingness to embrace AI technology as they benefit from pedagogical approaches that promote technological experimentation and innovation. APD faculty members from applied sciences, media studies, environmental studies, library science, and medicine & health disciplines perceive AI as less effective for student learning enhancement (variable 5,  $\beta$  = -0.691, SE = 0.153, p < .001) which demonstrates a potential gap between AI applications and the teaching requirements of these fields.

Faculty members from APD disciplines demonstrate a higher tendency to take up AI leadership positions (variable 6,  $\beta$  = 1.034, SE = 0.187, p < .001) which shows that AI leadership efforts are more dominant in applied and technical fields where AI serves as an administrative or strategic instrument. AI administrative leadership roles are more commonly held by CAD faculty members (variable 28,  $\beta$  = -0.811, SE = 0.173, p < .001) yet these faculty members tend to use AI more in teaching rather than participating in AI policy-making roles. Different academic disciplines engage with AI differently where CAD faculty use AI for teaching purposes while APD faculty apply AI for strategic purposes.

# **Al Integration and Pedagogical Adaptation**

The confidence level of CAD faculty to utilize AI tools across various teaching methods is significantly higher (variable 24,  $\beta$  = 0.912, SE = 0.181, p < .001), which confirms that AI functions predominantly as an instructional resource rather than a managerial device in these academic areas. APD instructors show greater skepticism toward AI's potential to improve content delivery (variable 31,  $\beta$  = -0.524, SE = 0.165, p = 0.003) because they doubt AI's effectiveness for specialized or technical subject matters. The skepticism of APD faculty likely arises because their disciplines require precise applications which current AI tools cannot fully meet.

Faculty specialization plays a major role in determining how faculty members perceive AI adoption. The CAD faculty group tends to view AI as helpful for teaching purposes based on variables 1, 19, and 24 but APD

faculty show more doubt about Al's potential to improve learning outcomes and course content delivery according to variable 5 and variable 31. APD faculty members have greater participation in Al leadership roles according to variable 6 but CAD faculty members show higher engagement in direct Al application for teaching even though they participate less in strategic Al planning as per variable 28. The results show that Al training programs and policy development need customization to meet the unique requirements of different disciplines to achieve both educational relevance and strategic success in Al use. Institutions need to account for differences between academic disciplines when designing Al adoption plans to fully leverage Al benefits in various fields of study.

### **Summary of Discussion**

Our research offers an extensive evaluation of the factors faculty experience and academic focus have on Al acceptance and implementation in educational institutions. Faculty members who have fewer years of teaching experience and who work remotely show higher levels of confidence in Al utilization because of their greater openness to technological advancements and flexible work arrangements. Senior faculty members and those teaching on campus tend to take leadership positions where they concentrate on institutional Al strategies and policy development. Junior faculty members and those working remotely lead teaching innovations through Al while senior faculty members stationed on campus develop institutional Al strategies. Faculty specialization determines Al adoption patterns where CAD faculty show greater openness to teaching Al applications but APD faculty demonstrate stronger leadership involvement although they remain doubtful about Al's teaching advantages.

The analysis of faculty roles and perceptions demonstrates how discipline-focused AI education and policies become essential. Institutions can use these findings to create partnerships among faculty of different expertise levels which will lead to AI adoption that meets pedagogical requirements and strategic objectives. The present study improves educational AI knowledge by demonstrating that AI tool integration succeeds when it matches faculty requirements and institutional objectives in multiple academic settings.

#### CONCLUSION

The present research supports existing literature on the essential role of educators' viewpoints for successful AI implementation (Papakonstantinidis et al., 2024). The research examines faculty viewpoints on AI integration in higher education and investigates how teaching experience intersects with institutional positions and academic disciplines. Through a quantitative survey method, the research determines essential elements that influence faculty perspectives on AI which includes demographic aspects, ethical issues and organizational obstacles.

Educational technology holds more promise for junior faculty members who have less than ten years of teaching experience according to the research findings. Research literature supports that younger educators show a higher tendency to embrace new technologies according to Xia (2024) and Lukianets and Lukianets (2023). Senior faculty members who hold leadership positions play a critical role in forming institutional Al policies as shown by this study which supports Kar et al. (2021) who pointed out how leadership commitment helps to overcome Al resistance.

The present study reveals how faculty location impacts the adoption rate of AI systems. Faculty who teach at off-campus locations show greater confidence in using AI for teaching which may result from flexible environments that better support technology integration. The paper confirms theoretical perspectives which state digital literacy combined with AI knowledge remains essential (Suryanarayana et al., 2024). The study shows that faculty who work on-campus take on strategic roles, which indicates physical presence affects policy-making and confirms Nguyen et al.'s (2023) conclusions about institutional culture effects.

The research shows different levels of AI adoption depending on faculty academic specialization areas. AI adoption for teaching is more common among CAD faculty who use AI while APD faculty maintain leadership roles despite their skepticism about AI applications. The findings demonstrate partial agreement with AInasib (2023) which indicates demographic factors such as field of study affect AI adoption but also reveal new information about distinct disciplinary applications and leadership dynamics.

Finally, the study presents valuable insights but admits to having several limitations. Self-reported data can create bias and the cross-sectional study design restricts the ability to make causal interpretations. Limiting the research to faculty perspectives risks missing important student and administrative viewpoints which previous studies have shown to be essential for comprehensive AI integration (Onesi et al., 2024). Future research ought to utilize longitudinal studies to track faculty perceptions' evolution alongside AI's effects on student learning results. AI research will achieve full comprehension of AI's role through the inclusion of diverse educational contexts and stakeholder viewpoints which will validate and enhance existing scholarly frameworks.

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**Declaration of interest:** The authors declared no competing interest.

**Data availability:** The data supporting the findings of this study involve human participants and contain potentially identifiable information. As such, they are not publicly available. Researchers who wish to access the data may contact the corresponding author and submit a formal request, which will be subject to review and approval by the American University of the Middle East Research Ethics Committee. Access will be granted only under conditions that ensure the confidentiality and anonymity of participants.

#### REFERENCES

- Adeleye, O. O., Eden, C. A., & Adeniyi, I. S. (2024). Innovative teaching methodologies in the era of artificial intelligence: A review of inclusive educational practices. *World Journal of Advanced Engineering Technology and Sciences*, *11*(2), 69–79. https://doi.org/10.30574/wjaets.2024.11.2.0091
- Ahmad, W., Azam, T., Arshad, M., Ahmed, B., & Zaman, H. M. F. (2023). Faculty members' perception of learning organization: A case of higher education institutions. *Sage Open, 13*(1). https://doi.org/10.1177/21582440 231154409
- Akavova, A., Temirkhanova, Z., & Lorsanova, Z. (2023). Adaptive learning and artificial intelligence in the educational space. *E3S Web of Conferences*, *451*, Article 06011. https://doi.org/10.1051/e3sconf/2023451
- Akgün, S., & Greenhow, C. (2021). Artificial intelligence in education: Addressing ethical challenges in K-12 settings. *Al and Ethics, 2,* 431–440. https://doi.org/10.1007/s43681-021-00096-7
- Albaqami, S. E., & Alzahrani, D. (2022). Transition to online EFL teaching in Saudi Arabian universities during the COVID-19 outbreak. *Arab World English Journal*, (Second Special Issue on COVID-19 Challenges), 216–232. https://doi.org/10.24093/awej/covid2.14
- Alenezi, F. Y. (2023). Artificial intelligence versus Arab universities: An enquiry into the Saudi context. Humanities and Management Sciences–Scientific Journal of King Faisal University, 24(1). https://doi.org/10.37575/h/edu/220038
- Alet, J. (2023). Effective integration of artificial intelligence: Key axes for business strategy. *Journal of Business Strategy*, 45(2), 107–114. https://doi.org/10.1108/jbs-01-2023-0005
- Ali, M. Y., Naeem, S. B., Bhatti, R., & Richardson, J. (2024). Artificial intelligence application in university libraries of Pakistan: SWOT analysis and implications. *Global Knowledge, Memory, and Communication, 73*(1/2), 219–234. https://doi.org/10.1108/gkmc-12-2021-0203
- Alnasib, B. N. M. (2023). Factors affecting faculty members' readiness to integrate artificial intelligence into their teaching practices: A study from the Saudi higher education context. *International Journal of Learning, Teaching, and Educational Research*, 22(8), 465–491. https://doi.org/10.26803/ijlter.22.8.24

- Alshatti Schmidt, D., Alboloushi, B., Thomas, A., & Magalhães, R. (2025). Integrating artificial intelligence in higher education: Perceptions, challenges, and strategies for academic innovation. *Computers and Education Open*, *9*, Article 100274. https://doi.org/10.1016/j.caeo.2025.100274
- Aparicio-Gómez, O., Aparicio-Gómez, W. (2024). Consideraciones éticas para el uso académico de sistemas de inteligencia artificial [Ethical considerations for the academic use of artificial intelligence systems]. *Revista Internacional de Filosofía Teórica Y Práctica, 4*(1), 175–198. https://doi.org/10.51660/riftp.v4i1.95
- Asirit, L. B. L., & Hua, J. H. (2023). Converging perspectives: Assessing Al readiness and utilization in Philippine higher education. *Polaris Global Journal of Scholarly Research and Trends, 2*(3), 1–50. https://doi.org/10.58429/pgjsrt.v2n3a152
- Baker, R. S., & Hawn, A. (2022). Algorithmic bias in education. *International Journal of Artificial Intelligence in Education*, *32*(4), 1052–1092. https://doi.org/10.1007/s40593-021-00285-9
- Barsha, S., & Munshi, S. A. (2023). Implementing artificial intelligence in library services: A review of current prospects and challenges of developing countries. *Library Hi Tech News, 41*(1), 7–10. https://doi.org/10.1108/lhtn-07-2023-0126
- Blease, C., Kaptchuk, T. J., Bernstein, M. H., Mandl, K. D., Halamka, J. D., & DesRoches, C. M. (2019). Artificial intelligence and the future of primary care: Exploratory qualitative study of UK general practitioners' views. *Journal of Medical Internet Research*, *21*(3), Article e12802. https://doi.org/10.2196/12802
- Bogina, V., Hartman, A., Kuflik, T., & Shulner-Tal, A. (2021). Educating software and AI stakeholders about algorithmic fairness, accountability, transparency, and ethics. *International Journal of Artificial Intelligence in Education*, *32*, 808–833. https://doi.org/10.1007/s40593-021-00248-0
- Chao, P., Hsu, T., Liu, T., & Cheng, Y. (2021). Knowledge of and competence in artificial intelligence: Perspectives of Vietnamese digital-native students. *IEEE Access*, *9*, 75751–75760. https://doi.org/10.1109/access.2021.3081749
- Chemlal, Y., & Azzouazi, M. (2023). Fostering sustainable development through artificial intelligence in education (ESD): A comprehensive evaluation framework and key criteria analysis. *Research Square*. https://doi.org/10.21203/rs.3.rs-3372485/v1
- Chen, L., Chen, P., & Lin, Z. (2020). Artificial intelligence in education: A review. *IEEE Access, 8*, 75264–75278. https://doi.org/10.1109/access.2020.2988510
- Chen, W.-Y. (2024). Intelligent tutor: Leveraging ChatGPT and Microsoft Copilot Studio to deliver a generative AI student support and feedback system within teams. *arXiv*. https://doi.org/10.48550/arXiv.2405.13024
- Dai, Y., Lin, Z., Liu, A., Dai, D., & Wang, W. (2023). Effect of an analogy-based approach of artificial intelligence pedagogy in upper primary schools. *Journal of Educational Computing Research*, *61*(8), 159–186. https://doi.org/10.1177/07356331231201342
- Delgado, N., Carrasco, L. C., Maza, M. S., & Etxabe-Urbieta, J. M. (2024). Application of artificial intelligence (Al) in education: Benefits and limitations of Al as perceived by primary, secondary, and higher education teacher. *Revista Electronica Interuniversitaria de Formacion del Profesorado, 27*(1), 207–224. https://doi.org/10.6018/reifop.577211
- Eden, C. A., Chisom, O. N., Adeniyi, I. S. (2024). Integrating Al in education: Opportunities, challenges, and ethical considerations. *Magna Scientia Advanced Research and Reviews, 10*(2), 6–13. https://doi.org/10.30574/msarr.2024.10.2.0039
- Fenu, G., Galici, R., Marras, M. (2022). Experts' view on challenges and needs for fairness in artificial intelligence for education. In M. M. Rodrigo, N. Matsuda, A. I. Cristea, & V. Dimitrova (Eds.), *Artificial intelligence in education. AIED 2022. Lecture notes in computer science, vol 13355* (pp. 243–255). Springer. https://doi.org/10.1007/978-3-031-11644-5 20
- Ferrara, E. (2024). Fairness and bias in artificial intelligence: A brief survey of sources, impacts, and mitigation strategies. *Sci*, *6*(1), 3. https://doi.org/10.3390/sci6010003
- Fu, S., Gu, H., & Yang, B. (2020). The affordances of Al-enabled automatic scoring applications on learners' continuous learning intention: An empirical study in China. *British Journal of Educational Technology, 51*(5), 1674–1692. https://doi.org/10.1111/bjet.12995
- Haresamudram, K., Larsson, S., & Heintz, F. (2023). Three levels of Al transparency. *Computer, 56*(2), 93–100. https://doi.org/10.1109/mc.2022.3213181

- Hergan, K., Zinterhof, P., Abed, S., Schörghofer, N., Knapitsch, C., Sommer, O., Meissnitzer, M., & Schlattau, A. (2022). Challenges implementing and running an Al-lab: Experience and literature review. *Biomedical Journal of Scientific & Technical Research*, 45(4). https://doi.org/10.26717/bjstr.2022.45.007222
- Hopcan, S., Türkmen, G., & Polat, E. (2023). Exploring the artificial intelligence anxiety and machine learning attitudes of teacher candidates. *Education and Information Technologies, 29*, 7281–7301. http://doi.org/10.1007/s10639-023-12086-9
- How, M., & Hung, W. L. D. (2019). Educing Al-thinking in science, technology, engineering, arts, and mathematics (STEAM) education. *Education Sciences*, *9*(3). https://doi.org/10.3390/educsci9030184
- Hutson, J., Jeevanjee, T., Graaf, V. V., Lively, J., Weber, J., Weir, G., Arnone, K., Carnes, G., Vosevich, K., Plate, D., Leary, M., & Edele, S. (2022). Artificial intelligence and the disruption of higher education: Strategies for integrations across disciplines. *Creative Education*, *13*(12), 3953–3980. https://doi.org/10.4236/ce.2022. 1312253
- Iglesias, A., Martínez, P., Aler, R., & Fernández, F. (2008). Learning teaching strategies in an adaptive and intelligent educational system through reinforcement learning. *Applied Intelligence*, *31*, 89–106. https://doi.org/10.1007/s10489-008-0115-1
- loku, T., Kondo, S., & Watanabe, Y. (2024). Acceptance of generative Al in higher education: A latent profile analysis of policy guidelines. *Research Square*. https://doi.org/10.21203/rs.3.rs-4515787/v1
- Jin, S., Im, K., Yoo, M., Roll, I., & Seo, K. (2023). Supporting students' self-regulated learning in online learning using artificial intelligence applications. *International Journal of Educational Technology in Higher Education*, 20(1). https://doi.org/10.1186/s41239-023-00406-5
- Jo, H., & Bang, Y. (2023). Analyzing ChatGPT adoption drivers with the TOEK framework. *Scientific Reports, 13*, Article 22606. https://doi.org/10.1038/s41598-023-49710-0
- Kar, S., Kar, A. K., & Gupta, M. P. (2021). Modeling drivers and barriers of artificial intelligence adoption: Insights from a strategic management perspective. *Intelligent Systems in Accounting, Finance & Management, 28*(4), 217–238. https://doi.org/10.1002/isaf.1503
- Karan, B., & Angadi, G. R. (2023). Potential risks of artificial intelligence integration into school education: A systematic review. *Bulletin of Science, Technology & Society, 43*(3–4), 67–85. https://doi.org/10.1177/02704676231224705
- Karkoulian, S., Sayegh, N. & Sayegh, N. (2025). ChatGPT unveiled: Understanding perceptions of academic integrity in higher education A qualitative approach. *Journal of Academic Ethics*, *23*, 1171–1188. https://doi.org/10.1007/s10805-024-09543-6
- Lanang Triana, I. K. D., Agustina, P. D. C., Febrian, R., Wiadnya, I. D. G. P., & Paramarta, V. (2024). Role of artificial intelligence in developing hospital information management systems. *JMMR Jurnal Medicoeticolegal Dan Manajemen Rumah Sakit, 13*(1), 130–141. https://doi.org/10.18196/jmmr.v13i1.127
- Lee, D., Kim, H., & Sung, S. (2022). Development research on an AI English learning support system to facilitate learner-generated-context-based learning. *Educational Technology Research and Development, 71*, 629–666. https://doi.org/10.1007/s11423-022-10172-2
- Lin, H. (2022). Influences of artificial intelligence in education on teaching effectiveness: The mediating effect of teachers' perceptions of educational technology. *International Journal of Emerging Technologies in Learning*, *17*(24), 144–156. https://doi.org/10.3991/ijet.v17i24.36037
- Lin, J., Sha, L., Li, Y., Gašević, D., & Chen, G. (2022). Establishing trustworthy artificial intelligence in automated feedback. *EdArXiv*. https://doi.org/10.35542/osf.io/5efxn
- Luckin, R., & Cukurova, M. (2019). Designing educational technologies in the age of Al: A learning sciences-driven approach. *British Journal of Educational Technology, 50*(6), 2824–2838. https://doi.org/10.1111/bjet. 12861
- Lukianets, H., & Lukianets, T. (2023). Promises and perils of AI use on the tertiary educational level. *Grail of Science*, *25*, 306–311. https://doi.org/10.36074/grail-of-science.17.03.2023.053
- Memon, S. S., Murad, S., Shah, S. A. R., Iqbal, Z., Saeed, R., & Abid, J. (2023). Perception about artificial intelligence in medical education. *Pakistan Journal of Medical and Health Sciences, 17*(3), 419–420. https://doi.org/10.53350/pjmhs2023173419
- Miao, Y., Jong, M. S., & Dai, Y. (2022). Pedagogical design of K-12 artificial intelligence education: A systematic review. *Sustainability*, *14*(23), Article 15620. https://doi.org/10.3390/su142315620

- Mishra, P., & Koehler, M. J. (2006). Technological pedagogical content knowledge: A new framework for teacher knowledge. *Teachers College Record*, *108*(6), 1017–1054. https://doi.org/10.1111/j.1467-9620.2006. 00684.x
- Murtaza, M., Ahmed, Y., Shamsi, J. A., Sherwani, F., & Usman, M. (2022). Al-based personalized e-learning systems: Issues, challenges, and solutions. *IEEE Access, 10*, 81323–81342. https://doi.org/10.1109/access. 2022.3193938
- Ng, D. T. K., Tan, C. W., & Leung, J. K. L. (2024). Empowering student self-regulated learning and science education through CHATGPT: A pioneering pilot study. *British Journal of Educational Technology*, *55*(4), 1328–1353. https://doi.org/10.1111/bjet.13454
- Nguyen, A., Ngo, H. N., Hong, Y., Dang, B., & Nguyen, B. (2023). Ethical principles for artificial intelligence in education. *Education and Information Technologies, 28*, 4221–4241. https://doi.org/10.1007/s10639-022-11316-w
- Okunlaya, R. O., Syed Abdullah, N., & Alias, R. A. (2022). Artificial intelligence (AI) library services innovative conceptual framework for the digital transformation of university education. *Library Hi Tech, 40*(6), 1869–1892. https://doi.org/10.1108/LHT-07-2021-0242
- Onesi-Ozigagun, O., Ololade, Y. J., Eyo-Udo, N. L., & Ogundipe, D. O. (2024). Revolutionizing education through Al: A comprehensive review of enhancing learning experiences. *International Journal of Applied Research in Social Sciences*, *4*(6), 589–607. https://doi.org/10.51594/ijarss.v6i4.1011
- Opesemowo, O. A. G., & Adekomaya, V. (2024). Harnessing artificial intelligence for advancing sustainable development goals in South Africa's higher education system: A qualitative study. *International Journal of Learning, Teaching, and Educational Research*, *23*(3), 67–86. https://doi.org/10.26803/ijlter.23.3.4
- Othman, M. A., Ja'afar, A. S., Manap, R. A., Misran, M. H., Said, M. A. M., Suhaimi, S., Hassan, N. I., & Nugraha, Y. T. (2025). Comparative analysis of Al training uptake in Malaysian and Indonesian universities. *International Journal of Research and Innovation in Social Science*, 9(1), 4657–4665. https://doi.org/10.47772/ijriss.2025.9010359
- Owan, V. J., Abang, K. B., Idika, D. O., Etta, E. O., & Bassey, B. A. (2023). Exploring the potential of artificial intelligence tools in educational measurement and assessment. *Eurasia Journal of Mathematics, Science and Technology Education*, *19*(8), Article em2307. https://doi.org/10.29333/ejmste/13428
- Papakonstantinidis, S., Kwiatek, P., & Spathopoulou, F. (2024). Embrace or resist? Drivers of artificial intelligence writing software adoption in academic and non-academic contexts. *Contemporary Educational Technology, 16*(2), Article ep495. https://doi.org/10.30935/cedtech/14250
- Pardo, A., Jovanović, J., Dawson, S., Gašević, D., & Mirriahi, N. (2017). Using learning Analytics to scale the provision of personalised feedback. *British Journal of Educational Technology, 50*(1), 128–138. https://doi.org/10.1111/bjet.12592
- Patidar, N., Mishra, S., Jain, R., Prajapati, D., Solanki, A., Suthar, R., Patel, K., & Patel, H. (2024). Transparency in Al decision making: A survey of explainable Al methods and applications. *Advances in Robotic Technology*, 2(1). https://doi.org/10.23880/art-16000110
- Petersson, L., Larsson, I., Nygren, J. M., Nilsen, P., Neher, M., Reed, J. E., Tyskbo, D., & Svedberg, P. (2022). Challenges to implementing artificial intelligence in healthcare: A qualitative interview study with healthcare leaders in Sweden. *BMC Health Services Research*, 22, Article 850. https://doi.org/10.1186/s12913-022-08215-8
- Pitychoutis, K. M. (2024). Harnessing AI chatbots for EFL essay writing: A paradigm shift in language pedagogy. *Arab World English Journal*, (Special Issue on ChatGPT), 197–209. https://doi.org/10.24093/awej/ChatGPT. 13
- Pitychoutis, K. M., & Al Rawahi, A. (2024). Smart teaching: The synergy of multiple intelligences and artificial intelligence in English as a foreign language instruction. *Forum for Linguistic Studies*, *6*(6), 249–260. https://doi.org/10.30564/fls.v6i6.7297
- Priya, S., Jain, V., Priya, M. S., Dixit, S. K., & Joshi, G. (2023). Modelling the factors in the adoption of artificial intelligence in Indian management institutes. *Foresight, 25*(1), 20–40. https://doi.org/10.1108/fs-09-2021-0181
- Quy, V. K., Thanh, B. T., Chehri, A., Linh, D. M., & Tuan, D. A. (2023). Al and digital transformation in higher education: Vision and approach of a specific university in Vietnam. *Sustainability*, *15*(14), Article 11093. https://doi.org/10.3390/su151411093

- Raj, N. S., & Renumol, V. G. (2022). A systematic literature review on adaptive content recommenders in personalized learning environments from 2015 to 2020. *Journal of Computers in Education*, *9*(1), 113–148. https://doi.org/10.1007/s40692-021-00199-4
- Sadler, T. D., Mensah, F. M., & Tam, J. (2024). Artificial intelligence and the Journal of Research in Science Teaching. *Journal of Research in Science Teaching*, *61*(4), 739–743. https://doi.org/10.1002/tea.21933
- Saleh, Z. T., Rababa, M., Elshatarat, R. A., Alharbi, M., Alhumaidi, B. N., Al-Za'areer, M. S., Jarrad, R. A., Al Niarat, T. F., Almagharbeh, W. T., Al-Sayaghi, K. M., & Fadila, D. E. S. (2025). Exploring faculty perceptions and concerns regarding artificial intelligence Chatbots in nursing education: potential benefits and limitations. *BMC Nursing*, *24*, Article 440. https://doi.org/10.1186/s12912-025-03082-0
- Seo, K., Tang, J., Roll, I., Fels, S., & Yoon, D. (2021). The impact of artificial intelligence on learner-instructor interaction in online learning. *International Journal of Educational Technology in Higher Education, 18*(54). https://doi.org/10.1186/s41239-021-00292-9
- Sethy, A., Shaik, N., Yadavalli, P. K., & Anandaraj, S. P. (2023). Al: Issues, concerns, and ethical considerations. In V. H. C. de Albuquerque, P. Raj, & S. Prakash Yavad (Eds.), *Toward artificial general intelligence: Deep learning, neural networks, generative Al* (pp. 189–211). De Gruyter. https://doi.org/10.1515/9783111323749-009
- Sharma, A. K., Pareta, A., Meena, J., & Sharma, R. (2022). A long-term impact of artificial intelligence and robotics on higher education. In *Proceedings of the IEEE 2022 International Conference on Advances in Computing, Communication, and Applied Informatics* (pp. 1–4). http://doi.org/10.1109/ACCAI53970.2022. 9752633
- Shazly, R. (2021). Effects of artificial intelligence on English speaking anxiety and speaking performance: A case study. *Expert Systems*, *38*(3), Article e12667. https://doi.org/10.1111/exsy.12667
- Song, N. (2024). Higher education crisis: Academic misconduct with generative Al. *Journal of Contingencies and Crisis Management, 32*, Article e12532. https://doi.org/10.1111/1468-5973.12532
- Suryanarayana, K. S., Prasad Kandi, V. S., Pavani, G., Rao, A. S., Rout, S., & Krishna, T. S. R. (2024). Artificial intelligence enhanced digital learning for the sustainability of education management system. *The Journal of High Technology Management Research*, *2*(35), Article 100495. https://doi.org/10.1016/j.hitech. 2024.100495
- Swartz, M., & McElroy, K. (2023). The "Academicon": Al and surveillance in higher education. *Surveillance & Society*, 21(3), 276–281. https://doi.org/10.24908/ss.v21i3.16105
- Tahir, M., Noor, A., & Raza, H. (2025). Explore the role of artificial intelligence to support teachers at higher education institutions in South Punjab. *The Critical Review of Social Sciences Studies*, *3*(3), 2421–2433. https://doi.org/10.59075/c098vs88
- Tang, L., & Su, Y.S. (2024). Ethical implications and principles of using artificial intelligence models in the classroom: A systematic literature review. *International Journal of Interactive Multimedia and Artificial Intelligence*, *5*(8), 25–36. https://doi.org/10.9781/ijimai.2024.02.010
- Tapalova, O., & Zhiyenbayeva, N. (2022). Artificial intelligence in education: AIEd for personalised learning pathways. *The Electronic Journal of E-Learning*, *20*(5), 639–653. https://doi.org/10.34190/ejel.20.5.2597
- Tran, K., & Nguyen, T. (2021). Preliminary research on the social attitudes toward Al's involvement in Christian education in Vietnam: Promoting Al technology for religious education. *Religions*, *12*(3). https://doi.org/10.3390/rel12030208
- Veseli, A., Hasanaj, P., & Bajraktari, A. (2025). Perceptions of organizational change readiness for sustainable digital transformation: Insights from learning management system projects in higher education institutions. *Sustainability*, *17*(2), Article 619. https://doi.org/10.3390/su17020619
- Wang, T., Lund, B. D., Marengo, A., Pagano, A., Mannuru, N. R., Teel, Z. A., & Pange, J. (2023). Exploring the potential impact of artificial intelligence (AI) on international students in higher education: Generative AI, chatbots, analytics, and international student success. *Applied Sciences, 13*(11), Article 6716. https://doi.org/10.3390/app13116716
- Wang, X., Zhao, S., Xu, X., Zhang, H., & Lei, V. (2025). Al adoption in Chinese universities: Insights, challenges, and opportunities from academic leaders. *Acta Psychologica*, *258*, Article 105160, https://doi.org/10.1016/j.actpsy.2025.105160
- Williamson, B., & Eynon, R. (2020). Historical threads, missing links, and future directions in Al in education. *Learning Media and Technology, 45*(3), 223–235. https://doi.org/10.1080/17439884.2020.1798995

- Wood, E. A., Ange, B. L., & Miller, D. D. (2021). Are we ready to integrate artificial intelligence literacy into medical school curriculum: Students and faculty survey. *Journal of Medical Education and Curricular Development*, 8. https://doi.org/10.1177/23821205211024078
- Wu, C., Hung, C., Shen, C., & Yu, J. (2024). Enhancing the willingness of adopting AI in education using back-propagation neural networks. *Sensors and Materials, 36*(3), Article 905. https://doi.org/10.18494/sam4485
- Xia, Q. (2024). A scoping review on how generative artificial intelligence transforms assessment in higher education. *International Journal of Educational Technology in Higher Education, 21*(1). https://doi.org/10.1186/s41239-024-00468-z
- Yu, L., Li, Y., & Fan, F. (2023). Employees' appraisals and trust of artificial intelligences' transparency and opacity. *Behavioral Sciences*, *13*(4). https://doi.org/10.3390/bs13040344
- Zainuddin, N. (2024). Does artificial intelligence cause more harm than good in schools? *International Journal of Language Education and Applied Linguistics*, *14*(1), 1–3. https://doi.org/10.15282/ijleal.v14i1.10432
- Zawacki-Richter, O., Marín, V., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education–Where are the educators? *International Journal of Educational Technology in Higher Education*, *16*(1). https://doi.org/10.1186/s41239-019-0171-0
- Zekaj, R. (2023). Al language models as educational allies: Enhancing instructional support in higher education. *International Journal of Learning, Teaching, and Educational Research, 22*(8), 120–134. https://doi.org/10.26803/IJLTER.22.8.7
- Zhang, H., Lee, I., & Moore, K. (2024). An effectiveness study of teacher-led Al literacy curriculum in K-12 classrooms. *Proceedings of the AAAI Conference on Artificial Intelligence, 38*(21), 23318–23325. https://doi.org/10.1609/aaai.v38i21.30380
- Zhang, W., & Iliško, D. (2025). Al-driven innovation in educational management: A multi-case study of Chinese higher education institutions. *Edelweiss Applied Science and Technology*, 9(4), 2109–2128. https://doi.org/10.55214/25768484.v9i4.6498

