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Bridging the AI Usage-Application Gap: Empowering Higher Education Lecturer Performance Through Dynamic Digital Capabilities

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ABSTRACT

Although knowledge acquisition is widely assumed to translate directly into knowledge application, prior research has rarely examined why this transfer often fails in AI-supported academic settings, leaving a theoretical gap regarding the mechanisms that connect the two processes. This study aims to analyze the influence of artificial intelligence (AI) usage on lecturer performance, considering the roles of knowledge acquisition, knowledge application, and the moderating effect of AI literacy. A quantitative approach was employed using Structural Equation Modeling (SEM) based on Partial Least Squares (PLS). The respondents consisted of 351 lecturers from private universities in Malang City, selected using the Slovin formula. The results show that AI usage has a significant positive effect on knowledge acquisition, knowledge application, and lecturer performance. Furthermore, AI literacy significantly moderates the relationship between AI usage and both knowledge-related variables, indicating that AI literacy plays a critical role in optimizing the use of AI in academic settings. However, knowledge acquisition does not have a direct effect on knowledge application, suggesting a gap between gaining and applying knowledge; this unexpected result implies that the acquisition-application transfer is not automatic and instead depends on enabling conditions such as practical training, institutional support, and lecturers' confidence in translating AI-derived knowledge into practice. On the other hand, both knowledge acquisition and knowledge application significantly influence lecturer performance. These findings highlight the importance of enhancing AI literacy and adopting integrative strategies to support digital transformation in higher education.

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1. INTRODUCTION

Within the framework of national development, the role of university lecturers as professional educators is a key factor in realizing the nation's grand vision outlined in the Asta Cita agenda, as well as in supporting the achievement of the Sustainable Development Goals (SDGs). Lecturers play a strategic role in producing high-quality human resources, fostering innovation, and building a knowledge-based society. Optimal lecturer performance directly contributes to the realization of Asta Cita 5, which aims to improve the quality of life for Indonesians, and Asta Cita 6, which emphasizes enhancing national productivity and competitiveness. In a global context, lecturers also serve as central actors in achieving SDG 4, which promotes inclusive and quality education for all (Tirtana et al., 2024). Therefore, improving and optimizing lecturer performance is crucial, not only for the advancement of higher education institutions, but also for the comprehensive and sustainable development of the nation.

However, numerous studies have shown that the performance of lecturers in Indonesia continues to face various challenges that hinder their optimal contribution to national and global development (Gunawan, 2020). Various reports indicate that many lecturers still fall short of performance standards in areas such as scientific publication, community service, innovation, and professional development (Graham, 2015). Low levels of digital literacy, limited access to and management of knowledge, and the underutilization of technologies such as Artificial Intelligence (AI) are among the key factors exacerbating this issue. Suboptimal lecturer performance not only affects the quality of higher education, but also poses a significant obstacle to achieving national development goals and the global SDGs, which heavily depend on the quality of human resources (Qurtubi, 2023). Therefore, innovative approaches are needed to sustainably optimize lecturer performance (Handayani et al., 2025).

Malang City, recognized as one of Indonesia's leading educational hubs, is home to numerous private universities (PTS) that play a strategic role in producing high-quality graduates (Ramaditya et al., 2023). However, various studies reveal that lecturer performance in PTS across Malang still faces significant challenges (Sulistiarini, 2024). Common issues include a high administrative workload, limited access to continuous professional development, lack of support for research and scientific publication, and uneven levels of digital literacy (Mardiana, 2024). Moreover, the adoption of advanced technologies such as Artificial Intelligence (AI) in teaching and research remains relatively low (Karim et al., 2025). As a result, many lecturers are still unable to deliver innovative and research-based learning (Wahyuni et al., 2021). This low level of academic productivity directly affects institutional accreditation, the quality of graduates, and contributions to scientific development, as well as national agendas such as the Asta Cita and the Sustainable Development Goals (SDGs) (Brahimi et al., 2016).

With the advancement of technology, artificial intelligence (AI) offers significant opportunities to address lecturer performance challenges, particularly within private universities (PTS) (Zawacki-Richter et al., 2019). AI can be utilized to streamline academic administrative processes, provide real-time learning analytics, and recommend more effective and personalized teaching strategies (Bauer et al., 2025). In the research context, AI supports lecturers in automated literature reviews, large-scale data processing, and plagiarism detection (Li et al., 2021). On the other hand, AI also facilitates the development of multimedia-based learning content and adaptive learning systems, enhancing the overall student learning experience (Oshima et al., 2020). With adequate AI literacy and effective utilization, lecturers can not only improve their productivity and academic performance quality but also reinforce their strategic role in supporting institutional achievement of the Asta Cita and Sustainable Development Goals (SDGs), particularly in relation to quality education (SDG 4) and innovation (SDG 9) (Routray & Khandelwal, 2024).

From the perspective of the Knowledge-Based View (KBV) and Dynamic Capability Theory, organizations including higher education institutions, heavily rely on the adaptive capabilities of individuals for knowledge acquisition and knowledge application (Grant, 1996). However, most existing research on the use of artificial intelligence in universities remains focused on administrative functions or student-centered teaching, and has yet to comprehensively examine how AI can enhance the dynamic capabilities of lecturers as key drivers of educational quality (Bhutoria, 2022). Previous studies also tend to overlook the mediating role of knowledge acquisition and application processes in the relationship between AI literacy and utilization with lecturer performance improvement (Ifenthaler & Yau, 2020) (Jia & Tu, 2024). In fact, strengthening these two aspects is fundamental to fostering adaptive, innovative, and productive lecturers in teaching, research, and community service (Teece, 2018). More importantly, existing studies have largely treated knowledge acquisition and knowledge application as a single, undifferentiated process, implicitly assuming that once knowledge is acquired through AI it will automatically be applied in professional practice. This assumption has rarely been tested empirically in the context of AI-supported higher education, leaving the literature unable to explain why the transfer from acquisition to application frequently breaks down. Dynamic Capability Theory suggests that sensing and seizing opportunities (analogous to acquisition) and reconfiguring resources into practice (analogous to application) are distinct organizational capabilities that do not automatically follow one another; disentangling these two processes, rather than assuming a direct causal link, constitutes the primary novelty of this study. Therefore, this study aims to fill the gap in the literature by exploring how AI literacy and utilization, mediated by knowledge acquisition and application processes, can be optimized to enhance lecturer performance, particularly in the context of private higher education institutions.

Amid the accelerating pace of digital transformation, the use of AI by lecturers does not always directly lead to enhanced knowledge capabilities (Dwivedi et al., 2021). Although AI usage provides broad access to information and automates various processes, the individual’s ability to understand and manage the technology referred as AI literacy, serves as a key determinant of its effective utilization. AI literacy encompasses an understanding of how AI works, its ethical boundaries, and the ability to apply AI-based tools within teaching and research contexts (Long & Magerko, 2020). In this regard, AI literacy has the potential to act as a moderating variable that either strengthens or weakens the relationship between AI usage and knowledge acquisition as well as knowledge application (Zhang et al., 2020). In other words, lecturers with high AI literacy are more likely to leverage AI strategically to acquire and apply new knowledge, compared to those with lower literacy levels (J. Shi et al., 2025). This pattern is consistent with Diffusion of Innovation theory, which posits that an innovation's rate of adoption depends on individual users' knowledge, persuasion, and ability to integrate the innovation into existing routines; lecturers with limited AI literacy may instead experience technostress, a state of discomfort arising from the effort required to adapt to new technology, which can suppress the translation of acquired knowledge into actual practice. Therefore, understanding the moderating role of AI literacy is crucial for designing targeted policy interventions and training programs aimed at improving lecturer performance through technology-based strategies.

Lecturer performance plays a strategic role in supporting the Asta Cita agenda and the Sustainable Development Goals (SDGs), particularly in ensuring the quality of education and the competitiveness of human resources. However, many private universities (PTS), including those in Malang City, continue to face challenges related to suboptimal lecturer performance. In the digital era, the adoption of AI presents a significant opportunity to enhance academic performance, yet its effectiveness is largely influenced by AI literacy as well as knowledge acquisition and application capabilities. Unfortunately, research on the moderating role of AI literacy in the relationship between AI usage, knowledge acquisition, and application remains limited. This study aims to address this gap and provide both conceptual and practical contributions to optimizing lecturer performance through technology utilization.

2. METHODS

This study employs a quantitative approach, as it aligns with the research objective of analyzing the relationships among the study variables. The respondents consist of lecturers from private universities (PTS) in the Malang City area, with a total of 351 participants determined using Slovin's formula. Data collection was carried out in 2025, and all discussions of AI adoption, institutional conditions, and lecturer performance in this article refer to that period. [Author: please confirm the exact data-collection month(s) so this statement matches your ethics/consent documentation.] The research methodology is illustrated in Figure 1.

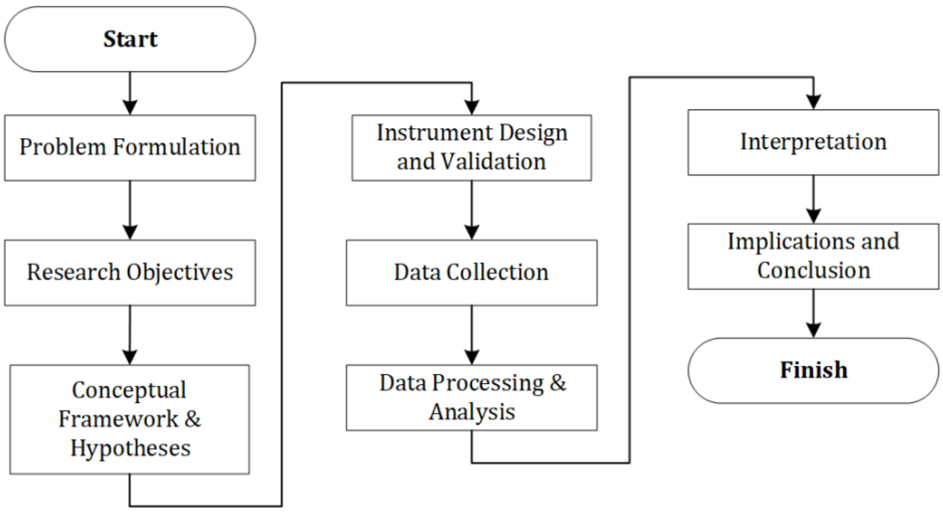

Figure 1. Research Methodology

The formulation of the research problem was derived from a phenomenological review and supported by previous studies. The research objectives were then defined to address the identified problems. Following this, a conceptual model and research hypotheses were developed. The conceptual model and research hypotheses are presented in Figure 2.

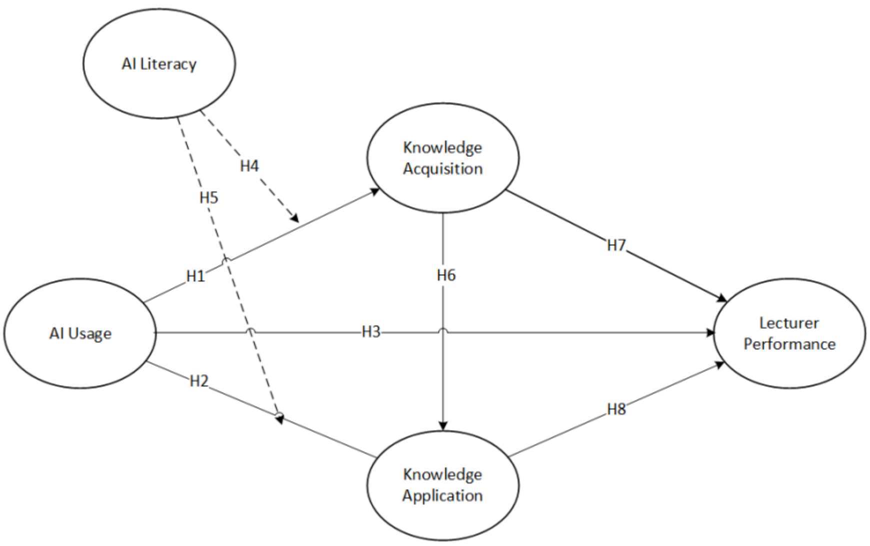

Figure 2. Conceptual Framework

AI Usage (X1) is defined as the extent to which lecturers utilize AI in teaching, research, and academic administration. In this study, "AI" refers to the range of tools lecturers reported using, encompassing generative AI conversational assistants (e.g., ChatGPT), AI-based data analysis tools for processing research data, and AI-driven Learning Management System (LMS) features such as automated grading and content recommendation. The indicators used in this study are adapted from (Kabanda, 2025), namely: frequency of AI use, searching for academic information, and automation of administrative tasks. Knowledge Acquisition (X2) refers to the degree of knowledge improvement among lecturers after using AI (Thomas et al., 2020). This variable includes three indicators adapted from previous studies: understanding of new concepts, analytical ability, and academic insight. Knowledge Application (X3) is defined as the extent to which acquired knowledge is applied in real practice, such as in teaching, research, or decision-making (Gold et al., 2001). The indicators for this variable include integration of new knowledge into teaching, new applications in research methods, and knowledge-based collaboration. Lecturer Performance (Y1) reflects the overall performance of lecturers, measured through the Tri Dharma of Higher Education: education and teaching, research and development, and community service (Tirtana et al., 2024). The moderating variable, AI Literacy, refers to the level of understanding and skills lecturers possess in using AI. It includes three indicators: AI knowledge, skills in using AI, and attitudes toward AI (Long & Magerko, 2020).

3. FINDINGS AND DISCUSSION

The results obtained from the research have to be supported by sufficient data. The research results and the discovery must be the answers, or the research hypothesis stated previously in the introduction part.

The data collection for this study was conducted online using a Google Form questionnaire, which was distributed via email and chat groups consisting of lecturers from private universities in Malang City who met the predefined qualifications. A total of 45 statement items were measured using a 5-point Likert scale. The characteristics of the respondents in this study are presented in Table 1.

Table 1. Respondent Characteristics

Characteristics	Categories	n	%
Gender	Male	198	56.4
	Female	153	43.6
Age	<30 years	24	6.8
	30-39 years	148	42.2
	40-49 years	113	32.2
	≥50 years	66	18.8
Academic Rank	Assistant Professor	75	21.4
	Associate Professor	172	49
	Senior Associate Professor	92	26.2
	Professor	12	3.4
Education	Master	267	76.1
	Doctor	84	23.9
Field of Study	Science and Technology	107	30.5
	Social Sciences & Humanities	76	21.6
	Economic and Business	83	23.6

	Education	61	17.4
	Arts and Design	24	6.8
Teaching Experience	<5 years	49	14
	5-10 years	134	38.2
	≥10 years	168	47.9

To test the research hypotheses, this study employed Structural Equation Modeling using Partial Least Squares (SEM-PLS). In SEM-PLS, the outer model is used to assess the validity and reliability of the indicators, while the inner model is used to analyze causal relationships (Ketchen, 2013). The path analysis of this study is illustrated in Figure 3.

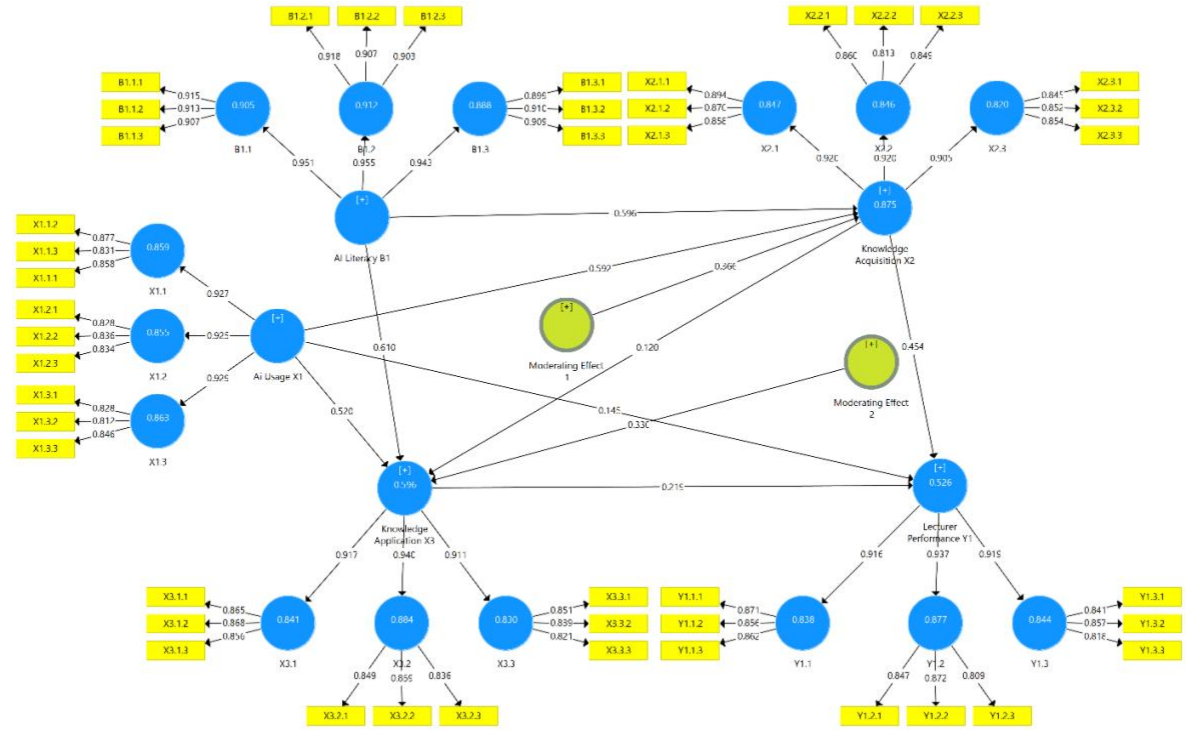

Figure 3. Path Analysis

3.1 Outer Model Evaluation

In the Partial Least Squares (PLS) approach, validity testing was conducted through two types of analyses: convergent validity and discriminant validity. Meanwhile, the reliability of the instrument was assessed using Cronbach's Alpha and Composite Reliability values. Convergent validity in the measurement model using reflective indicators was evaluated based on the correlation between the component scores and construct scores, which was calculated using PLS through the Average Variance Extracted (AVE) value. In early-stage research, indicators are considered to meet validity requirements if they have loading factor values between 0.50 and 0.60. A loading factor above 0.70 is categorized as high, indicating a strong correlation with the measured construct. Based on the analysis results, all indicators in this study showed loading factor values above 0.50; thus, no indicators were eliminated and all were deemed valid. The detailed values of AVE, Cronbach's Alpha, and Composite Reliability in this study are presented in Table 2.

Table 2. AVE, Cronbach Alpha, Composite Reliability

Variabel	AVE	Cronbach Alpha	Composite Reliability	Annotation
AI Usage	0.605	0.918	0.932	Valid & Reliable
Knowledge Acquisition	0.612	0.921	0.934	Valid & Reliable
Knowledge Application	0.614	0.921	0.935	Valid & Reliable
Lecturer Performance	0.614	0.921	0.922	Valid & Reliable
AI Literacy	0.745	0.957	0.963	Valid & Reliable

3.2 Inner Model Evaluation

The R-Square value is used to evaluate the extent to which independent variables influence dependent variables. Meanwhile, the Q-Square test, in the context of predictive relevance, assesses how well the model can generate accurate observed values, including the estimation of relevant parameters. In this study, the R-Square values obtained were 0.875 for the Knowledge Acquisition (KAQ) variable, 0.596 for Knowledge Application (KAP), and 0.526 for Lecturer Performance (LP). The Q-Square test result was 0.891, exceeding the threshold of 0.35. This indicates that the developed model has a very strong predictive relevance for the dependent constructs analyzed.

3.3 Hypothesis Testing

Hypothesis testing is a critical stage in research, aiming to determine whether the proposed hypotheses can be accepted or rejected. The decision is based on statistical calculations, particularly the p-value and t-statistic (t-value). In this study, a hypothesis is considered statistically significant and accepted if the p-value is less than 0.05 and the t-value exceeds 1.96, based on a 5% significance level. The results of the hypothesis testing are presented in Table 3.

Table 3. Hypothesis Testing Results

Hypothesis	Relationship	Path Coefficient	p-value	t-statistics	Result
H1	X1 → X2	0.592	0.000	18.738	Accepted
H2	X1 → X3	0.529	0.000	3.084	Accepted
H3	X1 → Y1	0.145	0.019	2.346	Accepted
H4	X1*B1 → X2	0.366	0.000	13.705	Accepted
H5	X1*B1 → X3	0.330	0.004	2.893	Accepted
H6	X2 → X3	-0.120	0.657	0.444	Rejected
H7	X2 → Y1	0.454	0.000	4.751	Accepted
H8	X3 → Y1	0.219	0.028	2.211	Accepted

Based on the results of hypothesis testing, out of six direct relationship hypotheses, five were found to have a positive and significant relationship. Therefore, hypotheses H1, H2, H3, H5, H7, and H8 are accepted, as they meet the significance criteria, specifically a p-value < 0.05 and a t-statistic > 1.96. Meanwhile, hypothesis H6 is deemed not significant, with a p-value of 0.657, which exceeds the

0.05 threshold. Regarding the moderation effect testing, hypotheses H4 and H5 yielded positive and significant results, and thus are also accepted. These findings indicate that the moderating variable in this study plays a role in strengthening the relationship between the independent and dependent variables under investigation.

The results of this study indicate that AI usage has a positive and significant effect on knowledge acquisition among lecturers. This is evidenced by a p-value < 0.05 and a t-statistic > 1.96, suggesting that the more intensively lecturers utilize AI technology in academic activities, such as research, teaching, and professional development the greater the knowledge they acquire. These findings are consistent with the Technology Acceptance Model (TAM), which posits that the adoption of technology perceived positively can enhance individual performance and capability. Previous studies (Munaye et al., 2025) (Z. R. Shi et al., 2020) also support this finding, demonstrating that the use of AI can accelerate access to scientific information, foster interdisciplinary collaboration, and improve lecturers' ability to understand and develop content based on data and emerging technologies. Beyond the technical dimension, this pattern also reflects a psychological and cultural shift among lecturers: those who are more open to exploring AI tools tend to be more confident and proactive in searching for academic literature and information independently (an indicator of the Acquisition construct), whereas lecturers embedded in a more risk-averse academic culture may hesitate to rely on AI for scholarly information-seeking, regardless of the tool's availability. The practical implication of this finding is the importance for higher education institutions particularly private universities (PTS) in Malang City to provide broader access to AI technologies and to organize relevant training programs for lecturers. The availability of supportive systems such as digital repositories, AI-driven learning platforms, and incentives for lecturers who integrate AI into academic activities will serve as key strategies in promoting digital transformation and sustainably enhancing lecturer quality. Accordingly, institutions can play an active role in accelerating technology adoption within higher education environments.

The results of the study show that AI usage has a positive and significant effect on knowledge application among lecturers, as indicated by a p-value of less than 0.05 and a t-statistic greater than 1.96. This suggests that the higher the intensity of AI use by lecturers, the greater their ability to apply acquired knowledge. In this study, knowledge application encompasses three key indicators: the integration of new knowledge into teaching processes, the adoption of new approaches in research methods, and knowledge-based collaboration among lecturers. These findings affirm that AI is not merely a technical tool but has emerged as a catalyst for transformation in academic development. Through AI, lecturers can more easily access the latest literature, analyze data efficiently, and develop more innovative approaches to both research and teaching. Moreover, AI facilitates interdisciplinary collaboration via digital platforms that support dynamic knowledge exchange. The implication is that higher education institutions particularly private universities in Malang City need to support lecturers in strategically enhancing their AI capabilities, not only from a technical standpoint but also in terms of practical application across the three pillars of higher education (teaching, research, and community service), thereby maximizing the potential of AI to improve overall academic quality.

The analysis results indicate that AI usage has a positive and significant impact on lecturer performance. This suggests that the more frequently and optimally lecturers utilize AI technology in their academic activities, the higher their performance achievements. In this context, lecturer performance is assessed not only through teaching effectiveness but also includes research productivity, community service effectiveness, and involvement in academic collaboration. AI has been shown to assist lecturers in accelerating lesson planning, providing more relevant and up-to-date materials, and supporting data analysis for research purposes (Gârdan et al., 2025). Moreover, AI encourages lecturers to become more adaptive to digital technologies, which is a key indicator in the ongoing transformation of higher education. The implication of this finding is the urgent need for institutions particularly private universities in Malang City to provide training and supporting infrastructure for AI utilization, thereby enhancing lecturers’ performance in a sustainable manner as they face challenges and opportunities in the digital era (Phua et al., 2025).

The findings reveal that AI literacy positively and significantly moderates the relationship between AI usage and knowledge acquisition among lecturers. This means that the higher a lecturer’s level of AI literacy, the stronger the effect of AI usage on the acquisition of knowledge. In this context, lecturers who not only use AI but also understand its principles, functions, and limitations are more likely to absorb new knowledge effectively. AI literacy enables lecturers to select, interpret, and utilize AI tools appropriately, thereby enhancing the efficiency of information exploration and learning processes. The implication of this finding underscores the importance for institutions not only to provide access to AI technologies but also to offer AI-based digital literacy training, ensuring that the adoption of AI directly contributes to the advancement of lecturers' academic capacities (Zawacki-Richter et al., 2019).

The findings of this study indicate that AI literacy positively and significantly moderates the relationship between AI usage and knowledge application among lecturers. This implies that the impact of AI usage on lecturers' ability to integrate new knowledge into teaching, adopt new approaches in research, and engage in knowledge-based collaboration becomes stronger when lecturers possess a high level of AI literacy. Lecturers who understand how AI works along with its potential and limitations are able to utilize the technology more strategically, not only to acquire information but also to apply it productively within academic contexts. The implication of this finding is the critical importance of enhancing AI literacy as part of faculty competency development, ensuring that AI usage moves beyond knowledge exploration to drive meaningful innovation in teaching practices, research activities, and scholarly collaboration (Tlili et al., 2023).

The results of the study indicate that knowledge acquisition does not have a significant effect on knowledge application among lecturers. This suggests that although lecturers may acquire new knowledge through the use of AI, it does not automatically lead to its application in teaching, research, or academic collaboration. These findings point to a gap between the process of acquiring knowledge and its implementation in academic contexts. This gap may be attributed to various factors, such as a lack of practical training, limited institutional support, or internal barriers such as hesitation to adopt new approaches. This result contrasts with previous studies (Gold et al., 2001) (Ahn, 2024), which argue that knowledge acquisition promotes knowledge application, particularly when its context aligns with professional tasks. Conversely, the finding aligns with (Jeilani & Abubakar, 2025), which found that acquired knowledge is not necessarily applied without sufficient confidence in the technology and institutional support. Therefore, higher education institutions must not only provide access to AI technologies and learning resources but also cultivate an ecosystem that actively supports the translation of knowledge into real academic practices.

The results of the study indicate that knowledge acquisition has a positive and significant effect on lecturer performance. This means that the greater a lecturer’s ability to acquire new knowledge particularly through the use of technologies such as AI, the better their performance in fulfilling the tri dharma of higher education: teaching, research, and community service. The knowledge acquired contributes to improved teaching effectiveness, enhanced research development, and higher-quality community engagement. These findings are consistent with previous research (Hong et al., 2019), which states that knowledge acquisition positively impacts individual performance, and are further supported by (Sharma et al., 2021), which shows that lecturers who actively update their knowledge tend to perform more adaptively and innovatively. Therefore, it is essential for higher education institutions to facilitate access to knowledge resources and technological training to support ongoing improvements in lecturer performance.

The results of this study indicate that knowledge application has a positive and significant effect on lecturer performance. This means that the greater a lecturer's ability to apply acquired knowledge, the better their performance in the areas of teaching, research, and community service. The application of new knowledge is reflected in the integration of innovation into teaching methods, the adoption of more relevant research approaches, and more productive academic collaboration. These findings align with the study by (Adim et al., 2025), which highlights knowledge application as a key factor in enhancing work effectiveness and innovation. Furthermore, this research supports the view of (Nonaka & Takeuchi, 1995), which emphasizes the importance of converting and utilizing knowledge to create individual competitive advantage. Therefore, strengthening lecturers' capacity to apply knowledge serves as a strategic priority in improving the overall quality of higher education institutions.

3.4 Implications for the Advancement of Knowledge

Theoretically, this study revises and extends the knowledge management model proposed by (Gold et al., 2001), which positions knowledge acquisition and knowledge application as sequential capabilities within a single knowledge process architecture. The non-significant path from Knowledge Acquisition to Knowledge Application (H6) found in this study indicates that, when a smart technology such as AI is introduced as a key intervention, acquisition and application no longer function as an automatic sequence but instead become two capabilities that must each be deliberately cultivated and supported by separate enabling conditions, such as AI literacy, institutional training, and lecturers' confidence in translating AI-derived knowledge into professional practice. This finding likewise nuances Nonaka and Takeuchi's (1995) knowledge-conversion model (SECI), which assumes that externalized and combined knowledge will be internalized and applied through continuous organizational interaction. In an AI-mediated context, this study suggests that the internalization stage is not automatic: without adequate AI literacy and institutional support, knowledge that has been acquired through AI risks remaining externalized without ever completing the conversion cycle into applied practice. Consequently, this study contributes to the knowledge management literature by positioning AI literacy as a critical boundary condition that determines whether AI-acquired knowledge progresses into the application stage of the knowledge value chain, an intervention that was not explicitly modeled in either the (Gold et al., 2001) or (Nonaka & Takeuchi, 1995) frameworks.

4. CONCLUSION

Based on the results of the study, it can be concluded that AI usage has a positive and significant impact on enhancing knowledge acquisition, knowledge application, and lecturer performance. This indicates that lecturers who actively utilize AI technologies tend to acquire new knowledge, effectively apply it in teaching and research practices, and demonstrate overall improved performance. Moreover, AI literacy has been shown to strengthen the relationship between AI usage and both knowledge acquisition and application, highlighting the critical role of AI literacy in optimizing the effective use of such technologies.

However, the study also found that knowledge acquisition does not have a direct impact on knowledge application, suggesting that the accumulation of knowledge does not necessarily lead to its application without the presence of additional enabling factors. Nonetheless, both knowledge acquisition and knowledge application were found to positively contribute to lecturer performance. These findings underscore the importance of developing strategies to enhance faculty capacity through AI utilization, accompanied by improvements in AI literacy, in order to support better teaching quality and academic productivity within higher education institutions.

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Conflicts of Interest: The author declares that there are no conflicts of interest associated with the conduct, analysis, or reporting of this research. The study was carried out independently and objectively, without any personal, institutional, or financial relationships that could have influenced the interpretation or presentation of the research findings.

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