



Beyond AI Competence: Building Strategic Teaching Capability Through AI Pedagogical Orchestration Capability

Hapzi Hapzi*

Universitas Bhayangkara Jakarta Raya, Jakarta,
INDONESIA

Muhammad Asif Khan

Universitas Bhayangkara Jakarta Raya, Jakarta,
INDONESIA

Muhammad Richo Rianto

Universitas Bhayangkara Jakarta Raya, Jakarta,
INDONESIA

Andri Yandi

Universitas Batanghari, Jambi,
INDONESIA

M. Rizky Mahaputra

Universitas Winaya Mukti,
INDONESIA

M. Ridho Mahaputra

Bina Nusantara University, Jakarta,
INDONESIA

Article Info

Article history:

Received: April 19, 2026

Revised: June 17, 2026

Accepted: August 19, 2026

Keywords:

Artificial Intelligence;

AI Competence;

AI Pedagogical Creativity;

AI Pedagogical Orchestration;

Teaching Effectiveness.

Abstract

The rapid adoption of generative artificial intelligence (GenAI) in higher education has shifted attention from whether lecturers use AI to how effectively they integrate it into teaching. However, existing research has largely emphasized AI literacy, competence, and technology adoption, providing limited explanation of the higher-order capabilities required to strategically coordinate AI with pedagogy. This study examines how Human-AI Co-Teaching Competence, AI Pedagogical Creativity, and AI Pedagogical Experimentation contribute to Lecturer Teaching Effectiveness through AI Pedagogical Orchestration Capability (AI-POC). A quantitative cross-sectional survey was conducted among lecturers from public and private universities in Indonesia, and the proposed model was examined using Partial Least Squares Structural Equation Modeling (PLS-SEM). The findings show that all three AI-related capabilities positively contribute to AI-POC, which in turn is positively associated with perceived teaching effectiveness. AI-POC also mediates these relationships, highlighting its central role in translating lecturers' AI-related capabilities into coherent pedagogical practice. The findings suggest that effective AI-enabled teaching depends not merely on technical competence, but on lecturers' capacity to strategically align AI with instructional objectives, classroom interactions, assessment, and professional judgment. This study extends dynamic capabilities and sociotechnical systems perspectives by conceptualizing AI-POC as a higher-order capability for AI-enabled teaching and offers implications for AI-oriented professional development in higher education.

To cite this article: Hapzi, H., Khan, M. A., Rianto, M. R., Yandi, A., Mahaputra, M. R., & Mahaputra, M. R. (2026). Beyond AI Competence: Building Strategic Teaching Capability Through AI Pedagogical Orchestration Capability. *Online Learning in Educational Research*, 6(3), 21-37. <https://doi.org/10.58524/oler.v6i3.1483>

INTRODUCTION

The rise of generative AI technology has substantially disrupted higher education, changing the way lecturers design, deliver, and evaluate their instruction. After the emergence of ChatGPT and subsequent large language models, universities adopted GenAI at a surprisingly fast pace, using it for building curricula, checking learners' progress, giving feedback, and even trying to provide personalised learning experiences (Mariappan & Krishnan, 2022; Mishra & Srivastava, 2024). This kind of uptake has driven a substantial reconfiguration of lecturers' roles, shifting them from transmitting knowledge to facilitating learning in the era of AI-assisted education (Kasneji et al., 2023). Even so, while these emerging tools promise considerable gains in educational quality and learner engagement, their real educational value may depend less on their technical sophistication

* Corresponding Author

Hapzi Hapzi, Universitas Bhayangkara Jakarta Raya, INDONESIA ✉ hapzi.ali@gmail.com

than on how educators actually weave them into the teaching process (Aljemely, 2024; Arif et al., 2026; Jenjić et al., 2025; Salim et al., 2026; Suman, 2025). Therefore, the successful integration of AI technology relies both on educators' technical competence and on their ability to blend these tools with pedagogical methods and the day-to-day interactions that happen in classrooms (Choudhury et al., 2026; Guntara et al., 2021; Syukur et al., 2024). Although AI technology is being rapidly integrated into higher education, current research mainly considers issues related to technology acceptance, AI literacy, digital competence, and behavioural intentions of users, largely drawing on the broader AI-in-education literature rather than studies specific to lecturers (Jannah et al., 2026; Rodzi et al., 2023; Xhumari et al., 2025; Xia, 2019).

Habibi et al. (2023) and Strzelecki (2023) provide evidence that facilitating conditions and behavioral intentions support ChatGPT adoption in higher education, but this research does not directly address AI's role in effective teaching. Recent evidence by Khan et al. (2026) similarly suggests that AI-related capabilities improve performance only when paired with complementary organisational capabilities, indicating that AI adoption alone does not guarantee better educational outcomes. Even with a fairly high level of competence in using AI technologies, lecturers often stumble over issues like understanding when AI should be used, for the purpose of strengthening learning, when professional judgment is actually the better option, and how the material produced through AI could be woven into a workable learning process (Aljemely, 2024; Jenjić et al., 2025; Mulianah et al., 2025; Phuong et al., 2026; Shetty & Hegde, 2024). Consequently, the current challenge for higher education institutions is not simply to secure AI adoption, but to build lecturers' capability to integrate AI into teaching and learning in a genuinely effective way.

This problem is especially topical for Indonesia: the country's higher education sector is undergoing digital transformation through the *Merdeka Belajar-Kampus Merdeka* (MBKM) policy, which explicitly encourages flexible, technology-enabled, and industry-relevant learning models (Yusriadi et al., 2024), while simultaneously needing to respond to the rapid growth of generative AI. MBKM has already pushed lecturers across a large and institutionally diverse higher-education system to redesign curricula and pedagogy, creating a natural context in which to examine whether lecturers' AI-related capabilities, rather than mere access to AI tools, translate into orchestrated, effective teaching.

This pattern of findings points to a specific gap in theory. What is already known is that several frameworks, including the TPACK model (Mishra & Koehler, 2006), AI literacy frameworks, and technology acceptance models, explain how educators acquire AI-related knowledge and decide to adopt new technologies. What these frameworks do not explain is how lecturers who have already adopted AI go on to use it strategically: none of them specifies how AI is coordinated with pedagogy, classroom interaction, and instructional decisions in a way that increases teaching effectiveness. This is the unresolved problem the present study addresses. Liu and Zhong (2025) note that generative AI unsettles the traditional approach to technology integration by challenging educators to reconsider how technological and pedagogical knowledge is developed and used in AI-enabled learning environments but stop short of specifying the underlying capability that would let lecturers do this deliberately.

The major theoretical basis for this study is Dynamic Capabilities Theory (DCT) (Teece et al., 1997; Teece, 2007), which explains how actors respond to dynamic environments by managing and reconfiguring resources. Although originally developed to explain performance at the organisational level, this study applies DCT at the level of the individual lecturer, consistent with more recent applications of the theory to individual and team-level capabilities. At the lecturer level, sensing corresponds to recognising when and where generative AI can meaningfully support a specific instructional goal; seizing corresponds to trying, adapting, and refining AI-based teaching methods; and reconfiguring corresponds to integrating AI outputs with pedagogical judgement and collaborative routines to realign teaching practice with changing instructional needs. Sociotechnical Systems Theory (Bostrom & Heinen, 1977; Trist & Bamforth, 1951) provides an auxiliary perspective by emphasising the alignment between human capabilities and technological systems, supporting the view that effective AI-enabled teaching depends on how lecturers collaborate with AI in planning, conducting, and evaluating instruction.

AI Pedagogical Orchestration Capability is proposed as a new, higher-order capability construct that captures this reconfiguring process specifically for AI-enabled teaching; it is not an existing scale

relabelled, but an extension of the broader concept of pedagogical and classroom orchestration (Dillenbourg, 2013; Prieto et al., 2018) into the domain of human–AI teaching. It is distinguished from the three antecedent capabilities as follows: AI Pedagogical Creativity concerns generating original instructional ideas for using AI; AI Pedagogical Experimentation concerns the iterative trying-out and refinement of those ideas in practice; Human–AI Co-Teaching Competence concerns how a lecturer divides labour and judgement between themselves and AI; and AI Pedagogical Orchestration Capability concerns the higher-order, real-time coordination of all three within a coherent instructional sequence, rather than any one of these constituent behaviours on its own.

Generative AI offers opportunities to improve teaching through individualized feedback, learning materials, and interactive instructional activities (Bai, 2024). AI Pedagogical Creativity refers to lecturers' capacity to generate original AI-supported instructional ideas and adapt learning activities to different educational contexts (Henriksen et al., 2021; Kasneci et al., 2023). The value of experimentation depends on lecturers' ability to integrate their experimental experience into systematic instructional practice that links AI with learning goals, instructional activities, and assessments. Consequently, lecturers who demonstrate high levels of AI Pedagogical Experimentation are expected to develop high levels of AI Pedagogical Orchestration Capability.

AI Pedagogical Orchestration Capability is expected to enhance Lecturer Teaching Effectiveness because it enables lecturers to coordinate AI with instructional objectives, learning activities, assessment, and classroom interaction. Based on the theoretical arguments above, this study proposes that Human–AI Co-Teaching Competence, AI Pedagogical Creativity, and AI Pedagogical Experimentation contribute to the development of AI Pedagogical Orchestration Capability, while AI Pedagogical Orchestration Capability contributes to Lecturer Teaching Effectiveness. The study also examines the direct relationships between selected antecedent capabilities and Lecturer Teaching Effectiveness. Accordingly, the following hypotheses are proposed:

H1: Human–AI Co-Teaching Competence positively influences AI Pedagogical Orchestration Capability.

H2: AI Pedagogical Creativity positively influences AI Pedagogical Orchestration Capability.

H3: AI Pedagogical Experimentation positively influences AI Pedagogical Orchestration Capability.

H4: AI Pedagogical Orchestration Capability positively influences Lecturer Teaching Effectiveness.

H5: Human–AI Co-Teaching Competence positively influences Lecturer Teaching Effectiveness.

H6: AI Pedagogical Experimentation positively influences Lecturer Teaching Effectiveness.

Figure 1 summarises the hypothesised relationships (H1–H6) tested in this study, consistent with the constructs and directional paths described.

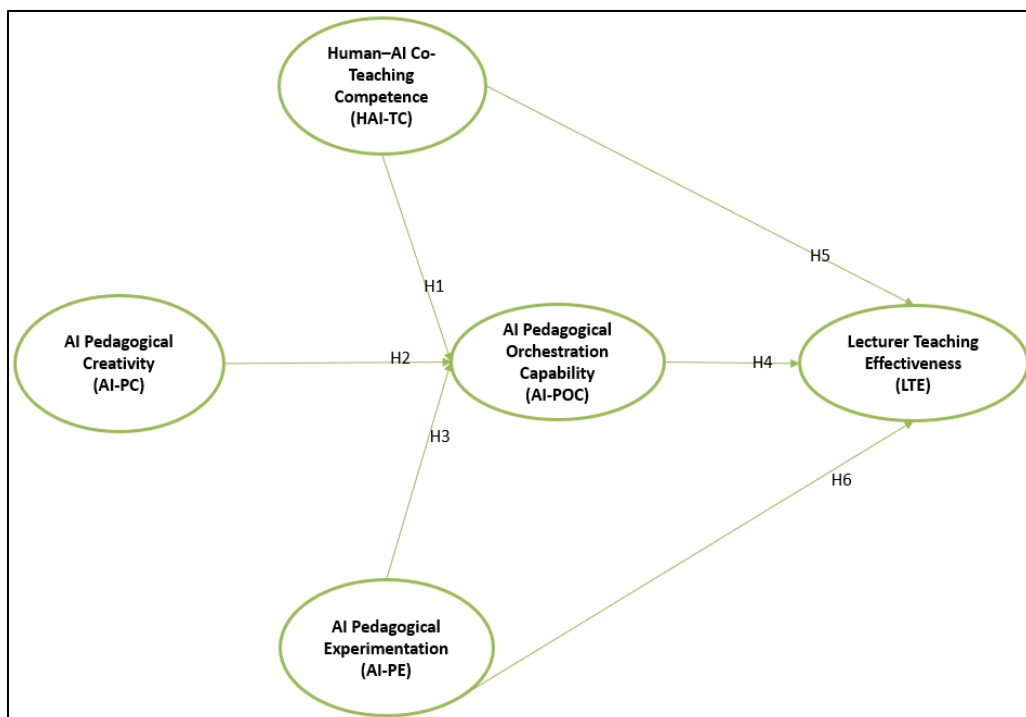


Figure 1. Conceptual Framework

METHOD

A quantitative, cross-sectional survey research design was used in this study to investigate relationships between AI Pedagogical Creativity (AI-PC), AI Pedagogical Experimentation (AI-PE), Human–AI Co-Teaching Competence (HAI-TC), AI Pedagogical Orchestration Capability (AI-POC), and Lecturer Teaching Effectiveness (LTE). Academic staff of Indonesian universities, both private and public institutions, who had experience in employing artificial intelligence to facilitate learning and teaching were purposively recruited as the sample for this study; because purposive sampling was used, the achieved sample represents AI-experienced lecturers rather than a statistically representative cross-section of the full population of Indonesian lecturers. Recruitment drew on multiple public and private institutions of varying types (research-intensive universities, teaching-focused universities, and polytechnics) across different regions of Indonesia, using university and academic-association email lists. Eligibility required that respondents hold an active teaching position and have personal experience using AI in connection with their teaching or related academic duties; this criterion was stated in the invitation and reconfirmed through a screening item at the start of the questionnaire. The purposive sampling technique was applied to make sure that participants had sufficient knowledge and experience in the employment of AI to assist teaching and learning.

To gather data, a structured online questionnaire was distributed to participants via email lists of universities and academic associations over a multi-week recruitment period. In total, 470 questionnaires were sent out, and 312 questionnaires were received, corresponding to a response rate of 66.4%. Every returned questionnaire was screened for completeness and response quality before being admitted to the analysis sample: questionnaires with more than 10% missing responses, or with an identical (straight-lined) response repeated across all items of an entire construct, were treated as indicative of inadequate engagement and excluded. This screening identified ten such questionnaires, leaving 302 valid questionnaires for analysis. This achieved sample size exceeds standard PLS-SEM adequacy benchmarks: applying Kock and Hadaya's (2018) inverse square root method with a minimum anticipated path coefficient of 0.10 (below every path coefficient obtained in this study), a 5% significance level, and 80% statistical power indicates a minimum recommended sample of approximately 155 respondents, well below the 302 lecturers retained here.

The structure of the questionnaire was divided into two parts. The first one included demographic variables such as academic qualifications, academic positions, teaching subjects, experience in using AI technology, and frequency of usage. The second part consisted of reflective indicators of the study constructs developed based on previously validated scales and tailored to fit the context of AI-based teaching in higher education. All indicators were assessed using a seven-point Likert scale, where 1 indicates strongly disagree and 7 strongly agree. A seven-point response format was chosen for a number of reasons. Firstly, it reflects greater variation in perceptions of respondents; it is a more sensitive measure and helps to increase the reliability of latent construct assessment without putting additional cognitive effort on the respondents (Finstad, 2010).

Table 1. Measurement Constructs, Indicators, and Sources

Construct	Indicators	Source
Human–AI Co-Teaching Competence (HAI-TC)	AI-assisted teaching collaboration (HAI-TC1); Integration of AI with pedagogical expertise (HAI-TC2); Balance between AI support and professional judgment (HAI-TC3)	Ji et al. (2023); Celik et al. (2022)
AI Pedagogical Creativity (AI-PC)	Creative teaching activities (AI-PC1); Innovative learning experiences (AI-PC2); Original instructional materials (AI-PC3)	Kasneci et al. (2023); Chiu (2023)
AI Pedagogical Experimentation (AI-PE)	Experimentation with AI tools (AI-PE1); Testing AI-supported instructional approaches (AI-PE2); Exploration of AI integration (AI-PE3)	Zawacki-Richter et al. (2019); Chiu (2023)
AI Pedagogical Orchestration Capability	Coordination of AI with teaching strategies (AI-POC1); AI-integrated lesson planning (AI-POC2); Adaptation of AI-generated content (AI-POC3); Strategic integration	Prieto et al. (2018);

Construct	Indicators	Source
(AI-POC)	of AI and pedagogy (AI-POC4); Management of AI-student-instruction interaction (AI-POC5)	Dillenbourg (2013)
Lecturer Teaching Effectiveness (LTE)	Student learning outcomes (LTE1); Student engagement (LTE2); Achievement of learning objectives (LTE3); Overall teaching effectiveness (LTE4)	Marsh (1982); Abrami et al. (2007)

Each construct's items were adapted from the previously validated scales identified in the measurement table above (e.g., Human-AI Co-Teaching Competence from Ji et al. (2023) and Celik et al. (2022); Lecturer Teaching Effectiveness from Marsh (1982) and Abrami et al. (2007), retaining each source scale's underlying dimensionality while rewording items to refer specifically to AI-assisted teaching rather than to the more general instructional contexts in which the original scales were developed. AI Pedagogical Experimentation and AI Pedagogical Orchestration Capability do not correspond to a single pre-existing scale; their items were newly developed from the construct definitions set out in the Theoretical Foundation section, informed by the classroom- and pedagogical-orchestration literature (Dillenbourg, 2013; Prieto et al., 2018). All adapted and newly developed items were reviewed by a small panel of subject-matter experts in educational technology for content validity and clarity and revised accordingly. Because the source scales are published in English and the questionnaire was administered to Indonesian-speaking lecturers, items were translated into *Bahasa Indonesia* and back-translated into English by an independent bilingual reviewer to confirm semantic equivalence. The revised instrument was then piloted with a small group of lecturers who did not participate in the main study, to confirm that items were clear and interpreted as intended before full-scale data collection began. To reduce the potential for common method bias, predictor, mediator, and outcome items were presented in a single continuous, randomised (rather than construct-grouped) order, and respondents were assured of anonymity and confidentiality (see the Ethics Statement) to reduce evaluation apprehension. Finally, because Lecturer Teaching Effectiveness was measured through lecturers' own ratings of their teaching outcomes rather than through independent student-level or administrative performance data, it is more precisely interpreted as perceived teaching effectiveness; this interpretation is maintained throughout the manuscript and claims about objectively measured student learning outcomes are avoided accordingly.

The suggested research model was tested employing Partial Least Squares Structural Equation Modelling (PLS-SEM) in the software package SmartPLS 4. The choice of PLS-SEM for the data analysis was made due to the fact that the current research aims at evaluating the existence of several relationships among latent variables with a focus on prediction and theory development (Hair et al., 2019). Because questionnaires with missing or straight-lined responses were excluded during the data-screening step described above rather than imputed, the measurement and structural models were estimated using complete cases only, with no further missing-data treatment required at the estimation stage. In line with recommended practice, the data analysis was done in two stages. First, the measurement model was estimated in terms of the evaluation of indicators' reliability and internal consistency (Cronbach's alpha, rho_A, and composite reliability), convergence validity with the average variance extracted (AVE) index, discriminant validity using the Fornell-Larcker criterion and heterotrait-monotrait ratio (HTMT), and multicollinearity by means of variance inflation factors (VIFs). Having checked the quality of the measurement model, the structural model was estimated in terms of the coefficient of determination (R^2), effect size (f^2), predictive relevance (Q^2_{predict}), and indices of global model fitness (standardized root mean square residual (SRMR) and normed fit index (NFI)). The significance of the hypothesized relationships was examined via the bootstrapping procedure with 5,000 resamples, using a two-tailed test at the 5% significance level, following standard PLS-SEM recommendations (Hair et al., 2019); statistical significance was defined in terms of path coefficients, t-values, p-values, and 95% bootstrapped confidence intervals.

RESULTS AND DISCUSSION

The demographic characteristics of the respondents are presented in Table 2. The profile includes respondents' academic qualifications, academic positions, and patterns of AI-related teaching experience, providing an overview of the characteristics of the sample included in the analysis.

Table 2. Respondent Profile

Characteristic	Distribution, n (%)
Academic Qualification	Master's 62 (20.5)
	Doctoral 240 (79.5)
Academic Position	Lecturer 117 (38.7)
	Senior Lecturer 70 (23.2)
	Associate Professor 68 (22.5)
	Professor 47 (15.6)
Teaching Discipline	Business & Management 47 (15.6)
	Engineering 32 (10.6)
	IT/Computer Science 32 (10.6)
	Education 27 (8.9)
	Social Sciences 51 (16.9)
	Health Sciences 42 (13.9)
	Natural Sciences 38 (12.6)
	Arts & Humanities 33 (10.9)
AI Experience	<6 months 29 (9.6)
	6–12 months 75 (24.8)
	1–2 years 80 (26.5)
	2–3 years 76 (25.2)
	>3 years 42 (13.9)
AI Use Frequency	Never 33 (10.9)
	Rarely 72 (23.8)
	Sometimes 72 (23.8)
	Often 80 (26.5)
	Very Often 45 (14.9)

Note: *N* = 302 valid responses. Respondents holding a professorship are classified under the Doctoral category for Academic Qualification, since professorship is an academic rank rather than a degree and, in the Indonesian academic system, presupposes the holding of a doctorate.

Table 2 provides information on the demographic variables of the participants. The final sample was made up of 302 academic staff of higher education institutions, both private and state-owned, in Indonesia. Academic qualification is reported separately from academic position (rank), since a professorship is an academic rank rather than a degree and, in the Indonesian system, presupposes the holding of a doctorate; accordingly, respondents who hold a professorship are counted under the Doctoral qualification category. This 'Never' category most plausibly reflects lecturers who satisfied the eligibility criterion through AI-related exposure outside their own classroom (for example, institutional training or departmental piloting) without yet having personally applied AI within a teaching episode at the time of the survey; this variation in the intensity and recency of AI use is addressed further under Limitations. Overall, the sample provides an appropriate basis for testing the proposed research model.

Measurement Model Assessment

The reliability, convergent validity, and collinearity of the measurement model were assessed to establish the adequacy of the constructs before evaluating the structural relationships. The results of these assessments are presented in Table 3.

Table 3. Reliability, Convergent Validity, and Collinearity Assessment

Construct	Cronbach's α	rho_A	Composite Reliability	AVE	Maximum VIF
AI-PC	0.884	0.889	0.928	0.811	2.920
AI-PE	0.898	0.898	0.936	0.831	2.990
AI-POC	0.923	0.925	0.942	0.765	3.078
HAI-TC	0.896	0.899	0.935	0.828	3.128
LTE	0.869	0.869	0.910	0.718	2.221

Discriminant validity

Discriminant validity was subsequently assessed using the Fornell–Larcker criterion to determine whether each construct was empirically distinct from the other constructs in the model. The results of the Fornell–Larcker assessment are presented in Table 4.

Table 4. Discriminant Validity Assessment using the Fornell–Larcker Criterion

Construct	AI-PC	AI-PE	AI-POC	HAI-TC	LTE
AI-PC	0.901				
AI-PE	0.438	0.912			
AI-POC	0.392	0.779	0.874		
HAI-TC	0.196	0.633	0.675	0.910	
LTE	0.388	0.739	0.779	0.724	0.847

As an additional assessment of discriminant validity, the heterotrait–monotrait ratio (HTMT) was examined to provide a more sensitive evaluation of the distinctiveness among the study constructs. The HTMT results are reported in Table 5.

Table 5. Heterotrait–Monotrait Ratio (HTMT)

Construct	AI-PC	AI-PE	AI-POC	HAI-TC
AI-PC				
AI-PE	0.493			
AI-POC	0.432	0.855		
HAI-TC	0.219	0.705	0.740	
LTE	0.442	0.836	0.867	0.820

The measurement model was tested by assessing the reliability of indicators, internal consistency reliability, convergent validity, discriminant validity, and collinearity. As illustrated in Table 3, all constructs displayed adequate internal consistency. The Cronbach's alpha values ranged from 0.869 to 0.923, while the rho_A values ranged from 0.869 to 0.925, surpassing the recommended threshold of 0.70. The same applies to composite reliability values, which ranged from 0.910 to 0.942, implying internal consistency of the measurement items. Moreover, the convergent validity of the measurement model was confirmed by the average variance extracted (AVE), which ranged from 0.718 to 0.831 for all constructs, surpassing the recommended minimum value of 0.50. Additionally, the maximum variance inflation factor (VIF) values ranged from 2.221 to 3.128, comfortably below the conservative threshold of 5.0 and consistent with the absence of a multicollinearity problem among the indicators. As a further check, common method bias was assessed using the full-collinearity test recommended by Kock (2015): the resulting variance inflation factors for all constructs, including the criterion construct, fell within approximately 1.8 to 3.1, below the conservative threshold of 3.3, suggesting that common method bias is unlikely to materially affect the results. Discriminant validity was checked using the Fornell–Larcker criterion and the heterotrait–monotrait ratio (HTMT). As indicated in Table 4, the square root of the AVE for each construct surpassed the inter-construct correlations, meeting the Fornell–Larcker criterion and showing that each construct shared more variance with its own indicators than with other latent variables.

As a further, more sensitive test, the HTMT criterion was examined. According to Table 5, all HTMT values ranged from 0.219 to 0.867, remaining below the recommended threshold of 0.90. The highest value (0.867, between AI-POC and AI-PE) approaches this threshold more closely than the others, which is plausible given the conceptual proximity of these two constructs; both concern

lecturers' active, hands-on engagement with AI in their teaching, but it remains distinctly below 1.0 and below the applied 0.90 cut-off, supporting discriminant validity; bootstrapped confidence intervals for HTMT were not computed in the original analysis, which is noted as a limitation and a direction for replication (see Limitations). Taken together, these results indicate that the measurement model has satisfactory reliability, convergent validity, discriminant validity, and acceptable collinearity. Having confirmed the adequacy of the measurement model, the analysis continued with the evaluation of the structural model by testing the model's explanatory power, predictive relevance, effect sizes, global model fit, and the significance of the hypothesised relationships.

Structural Model Assessment

Following confirmation of the reliability of the measurement model, the structural model was examined for its explanatory power, effect sizes, predictive relevance, and model fit. The results are provided in Tables 6–9. As can be seen from Table 6, the model possesses high explanatory power regarding both endogenous constructs. The predictors accounted for 66.8% of the variance in AI Pedagogical Orchestration Capability (AI-POC) ($R^2 = 0.668$; Adjusted $R^2 = 0.665$) and 70.2% of the variance in Lecturer Teaching Effectiveness (LTE) ($R^2 = 0.702$; Adjusted $R^2 = 0.699$). Thus, the model explained a large portion of the variation in the dependent constructs, suggesting that the proposed framework provided a statistically strong account of lecturer teaching effectiveness in this sample. In addition, the magnitude of contribution of each predictor was determined in terms of f^2 effect size, as provided in Table 7. Among the structural relationships, AI Pedagogical Experimentation (AI-PE) had a large effect on AI Pedagogical Orchestration Capability (AI-POC) ($f^2 = 0.433$), the largest of any antecedent's contribution to orchestration capability. Moderate effect sizes were identified for the relationships between Human–AI Co-Teaching Competence (HAI-TC) and AI-POC ($f^2 = 0.178$), HAI-TC and LTE ($f^2 = 0.173$), and AI-POC and LTE ($f^2 = 0.156$). By comparison, the effects of AI Pedagogical Creativity (AI-PC) on AI-POC ($f^2 = 0.021$) and AI-PE on LTE ($f^2 = 0.079$) were small, thus contributing to the model to a lesser extent. The predictive capability of the model was tested using Q^2 predict, the results of which are provided in Table 8. Both endogenous constructs yielded positive Q^2 predict values, equal to 0.660 and 0.656 for AI-POC and LTE, respectively, indicating that the model's out-of-sample predictions outperform a naive mean-based benchmark and thus demonstrating satisfactory predictive relevance (Shmueli et al., 2019). The RMSE and MAE values reported in Table 8 are presented descriptively rather than against a formal linear-model PLSpredict benchmark; a full indicator-level PLS-versus-LM comparison, as recommended by Shmueli et al. (2019), was not performed in the original analysis and is noted as a direction for more conservative predictive validation in future replications of this model.

The fit of the model was assessed with the help of SRMR, NFI, d_ULS, and d_G indices. As follows from Table 9, the estimated model had an SRMR value of 0.041, which is lower than the recommended value of 0.08 and signifies a good model-data fit. Similarly, the NFI value of 0.903 exceeds the recommended value of 0.90, indicating an acceptable model fit. The d_ULS and d_G values for the estimated model (0.289 and 0.233, respectively) are close to those of the saturated model (0.254 and 0.229); because these discrepancy measures are conventionally evaluated against bootstrapped HI99 reference values rather than fixed cut-offs, and such reference values were not computed in the original analysis, they are reported here as descriptive fit information alongside SRMR and NFI rather than as confirmatory evidence in their own right (Hair et al., 2019). All in all, the findings support a reasonable model fit, satisfactory predictive capability, strong explanatory power, and meaningful effect sizes for the structural model. Having established the reliability of the structural model, the next section discusses the results of hypothesis testing based on the bootstrapping analysis.

Table 6. Coefficient of Determination (R^2) and Predictive Accuracy

Construct	R-square	R-square adjusted
AI-POC	0.668	0.665
LTE	0.702	0.699

Table 7. Effect Size Assessment (f^2)

Construct	f-square
AI-PC -> AI-POC	0.021
AI-PE -> AI-POC	0.433
AI-PE -> LTE	0.079
AI-POC -> LTE	0.156
HAI-TC -> AI-POC	0.178
HAI-TC -> LTE	0.173

Table 8. Predictive Relevance Assessment (Q^2_{predict})

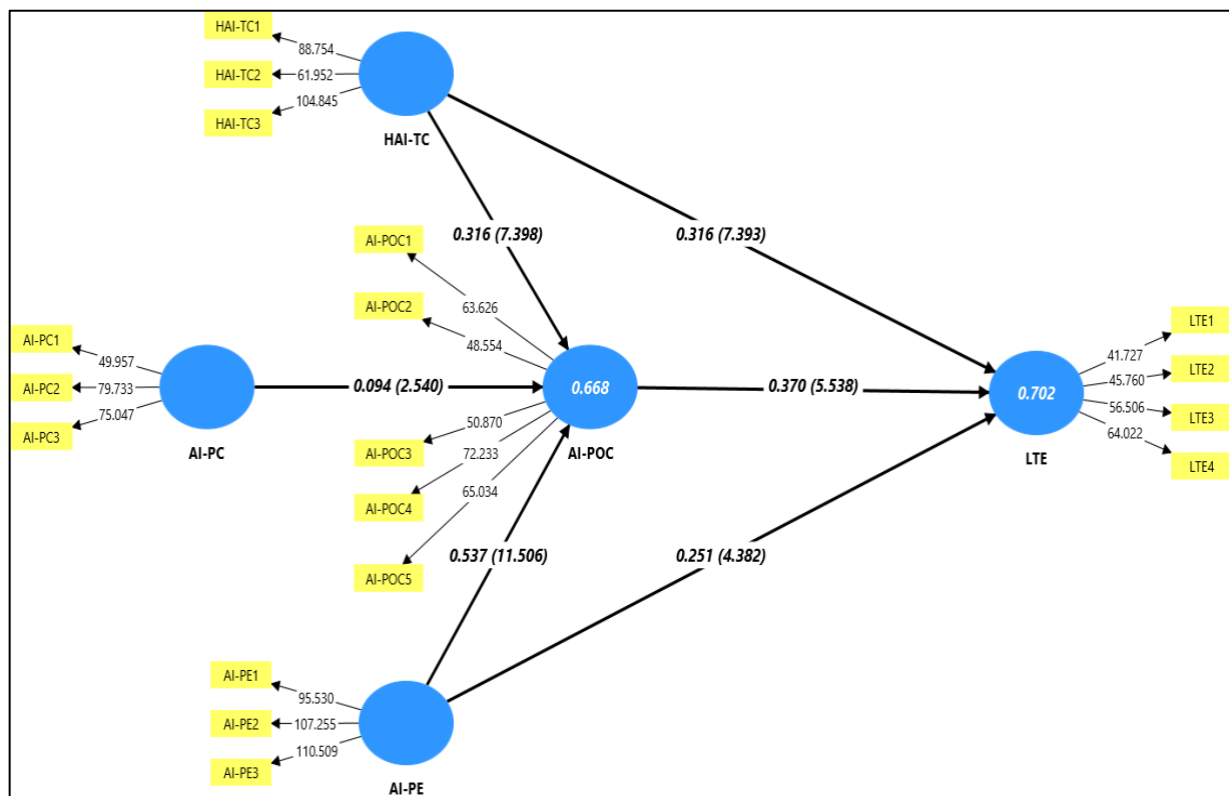
Construct	Q^2_{predict}	RMSE	MAE
AI-POC	0.660	0.587	0.464
LTE	0.656	0.591	0.478

Table 9. Global Model Fit Assessment

Measure(s)	Saturated model	Estimated model
SRMR	0.039	0.041
d_ULS	0.254	0.289
d_G	0.229	0.233
Chi-square	412.988	418.080
NFI	0.904	0.903

Coefficient and Path Analysis: Direct Effect

Following the assessment of the measurement model, the structural model was evaluated to examine the hypothesised relationships among the study constructs. Figure 2 presents the estimated structural model and the directional paths among AI Pedagogical Creativity, AI Pedagogical Experimentation, Human-AI Co-Teaching Competence, AI Pedagogical Orchestration Capability, and Lecturer Teaching Effectiveness.

**Figure 2.** Structural Model Analysis

The direct effects among the study constructs were then examined to evaluate the proposed hypotheses. Table 10 presents the estimated path coefficients, standard errors, t-statistics, and p-values used to determine the significance and direction of the hypothesised relationships.

Table 10. Direct Effects and Hypothesis Testing

Construct	Original sample (O)	Sample mean (M)	Standard deviation	T statistics (O/STDEV)	P values	Hypothesis	95% CI
AI-PC -> AI-POC	0.094	0.094	0.037	2.540	0.011	H2 – Supported	[0.021, 0.167]
AI-PE -> AI-POC	0.537	0.539	0.047	11.506	< 0.001	H3 – Supported	[0.445, 0.629]
AI-PE -> LTE	0.251	0.249	0.057	4.382	< 0.001	H6 – Supported	[0.139, 0.363]
AI-POC -> LTE	0.370	0.374	0.067	5.538	< 0.001	H4 – Supported	[0.239, 0.501]
HAI-TC -> AI-POC	0.316	0.316	0.043	7.398	< 0.001	H1 – Supported	[0.232, 0.400]
HAI-TC -> LTE	0.316	0.314	0.043	7.393	< 0.001	H5 – Supported	[0.232, 0.400]

Table 11. Specific Indirect Effect

Construct	Original sample (O)	Sample mean (M)	Standard deviation	T statistics (O/STDEV)	P values	95% CI
AI-PC -> AI-POC -> LTE	0.035	0.036	0.017	2.031	0.042	[0.002, 0.068]
AI-PE -> AI-POC -> LTE	0.199	0.201	0.039	5.140	< 0.001	[0.123, 0.275]
HAI-TC -> AI-POC -> LTE	0.117	0.119	0.028	4.214	< 0.001	[0.062, 0.172]

Analysis, interpretation and Discussion

The findings indicate that AI Pedagogical Creativity (AI-PC) positively affects AI Pedagogical Orchestration Capability (AI-POC) ($\beta = 0.094$, $t = 2.540$, $p = 0.011$). Although the relationship is statistically significant, the small coefficient suggests that pedagogical creativity alone makes only a modest contribution to orchestration capability. This finding is broadly consistent with TPACK (Mishra & Koehler, 2006), which similarly holds that technological skill must be combined with pedagogical knowledge to optimise instruction; here, TPACK is used as a point of comparison rather than as one of the study's primary theoretical foundations, which remain Dynamic Capabilities Theory and Sociotechnical Systems Theory (see Theoretical Foundation). At the same time, the modest coefficient suggests that orchestrating AI-assisted instruction is not achieved through technical and pedagogical skill alone: confidence, organisational support, and active collaboration with AI systems also appear to matter, echoed respectively by the stronger coefficients observed for AI-PE and HAI-TC below. This finding is consistent with prior research suggesting that pedagogical capability is a necessary, but on its own insufficient, condition for effective AI orchestration.

Another finding is that, of all the antecedents examined, AI Pedagogical Experimentation (AI-PE) has the strongest association with AI Pedagogical Orchestration Capability ($\beta = 0.537$, $t = 11.506$, $p < 0.001$). This suggests that lecturers who more actively try out, adapt, and refine AI-based teaching methods develop a correspondingly stronger capability to orchestrate AI in their instruction. This finding is broadly consistent with previous research by Zawacki-Richter et al. (2019) and Celik et al.

(2022) linking positive, active engagement with AI to greater readiness among educators to integrate intelligent technologies into teaching. However, while those studies focused mainly on adoption intentions, the present findings suggest that hands-on experimentation is associated not only with adoption but also with the subsequent capability to orchestrate AI within teaching practice.

As with AI Pedagogical Orchestration Capability, Lecturer Teaching Effectiveness is positively associated with AI Pedagogical Experimentation ($\beta = 0.251$, $t = 4.382$, $p < 0.001$). This finding suggests that lecturers who experiment more actively with AI are also better able to create engaging learning environments and use AI to improve the quality of instruction. It is broadly consistent with the systematic review by Bond et al. (2024), which reports that the integration of AI into teaching is associated with educational benefits. The present study extends this literature by showing that experimentation is associated with Lecturer Teaching Effectiveness both directly and indirectly, through AI Pedagogical Orchestration Capability.

In addition, the findings show that Human–AI Co-Teaching Competence (HAI-TC) is positively associated with AI Pedagogical Orchestration Capability ($\beta = 0.316$, $t = 7.398$, $p < 0.001$) and Lecturer Teaching Effectiveness ($\beta = 0.316$, $t = 7.393$, $p < 0.001$). These findings are consistent with the view that AI orchestration is most successful when educators and AI systems work together rather than separately. This finding is supported by Ji et al. (2023), who report that conversational AI is associated with better educational outcomes when teachers actively supervise the integration of AI-generated material into classroom activities. Similarly, Labadze et al. (2023) found that AI chatbots are more effective for teaching under conditions of consistent human supervision. Unlike previous studies that focused only on AI tools in isolation, the current study's findings suggest that human–AI cooperation is associated not only with greater instructional effectiveness but also with a stronger capability among educators to orchestrate AI-assisted instruction.

One further notable finding is that AI Pedagogical Orchestration Capability has a significant positive association with Lecturer Teaching Effectiveness ($\beta = 0.370$, $t = 5.538$, $p < 0.001$). This suggests that lecturers' capability to coordinate different components of AI-assisted instruction plays an important role in how AI relates to learning outcomes. While previous research by Bond et al. (2024) and Castillo-Martínez et al. (2024) highlighted the growing significance of AI in transforming higher education, both also noted a lack of empirical evidence on the mechanisms linking AI to teaching effectiveness. The present study addresses part of this gap by identifying AI Pedagogical Orchestration Capability as one such mechanism connecting AI-related competencies to learning outcomes. The mediation analysis supports this interpretation, subject to the caveat below. AI Pedagogical Orchestration Capability significantly mediates the relationship between AI Pedagogical Creativity and Lecturer Teaching Effectiveness ($\beta = 0.035$, $t = 2.031$, $p = 0.042$), albeit with a small effect, suggesting that part of pedagogical creativity's contribution to teaching effectiveness operates through lecturers' ability to orchestrate AI-supported instruction. AI Pedagogical Orchestration Capability also significantly mediates the effect of AI Pedagogical Experimentation on Lecturer Teaching Effectiveness ($\beta = 0.199$, $t = 5.140$, $p < 0.001$), suggesting that orchestration capability is one route through which active experimentation translates into effective teaching. Similarly, the indirect effect of Human–AI Co-Teaching Competence on Lecturer Teaching Effectiveness through AI Pedagogical Orchestration Capability is positive and significant ($\beta = 0.117$, $t = 4.214$, $p < 0.001$). Because the design is cross-sectional, these indirect effects provide statistical evidence consistent with mediation rather than evidence of the temporal causal sequence that the term “mediation” technically implies; the mediation relationships tested here were framed on an exploratory basis (see Literature Review), and 95% confidence intervals for these indirect effects are reported in Table 11.

Based on the results presented above, the antecedent most strongly associated with AI Pedagogical Orchestration Capability is AI Pedagogical Experimentation, followed by Human–AI Co-Teaching Competence, with AI Pedagogical Creativity showing the weakest, though still significant, association. More broadly, the results of this study support the role of AI Pedagogical Orchestration Capability as a mechanism through which educators' capabilities, experimentation, and collaborative practices with AI are associated with higher lecturer teaching effectiveness. In addition to the structural model evaluation, an Importance-Performance Map Analysis (IPMA) was conducted to identify which factors have the greatest total effect on Lecturer Teaching Effectiveness (LTE) relative to their current performance levels. Importance was measured as each construct's total effect on LTE,

while performance scores reflected the rescaled (0–100) level of each construct as reported by respondents.

As shown in Figure 3, AI Pedagogical Experimentation (AI-PE) has both the greatest importance (0.452) and the highest performance score (65.6), making it the most influential factor for Lecturer Teaching Effectiveness among those examined. This result is consistent with the structural model analysis, where AI-PE showed the strongest direct effect on AI Pedagogical Orchestration Capability as well as a significant direct effect on LTE. Consequently, sustaining and further encouraging lecturers' active experimentation with AI is expected to have the greatest impact on teaching effectiveness. Human–AI Co-Teaching Competence (HAI-TC) ranks second in importance (0.432) but records the lowest performance score of the four constructs (54.8). Thus, although collaboration between educators and AI has a substantial impact on learning effectiveness, HAI-TC is the area with the most room for improvement. Institutions could accordingly benefit from targeted training and guidelines to help educators collaborate more effectively with AI technologies.

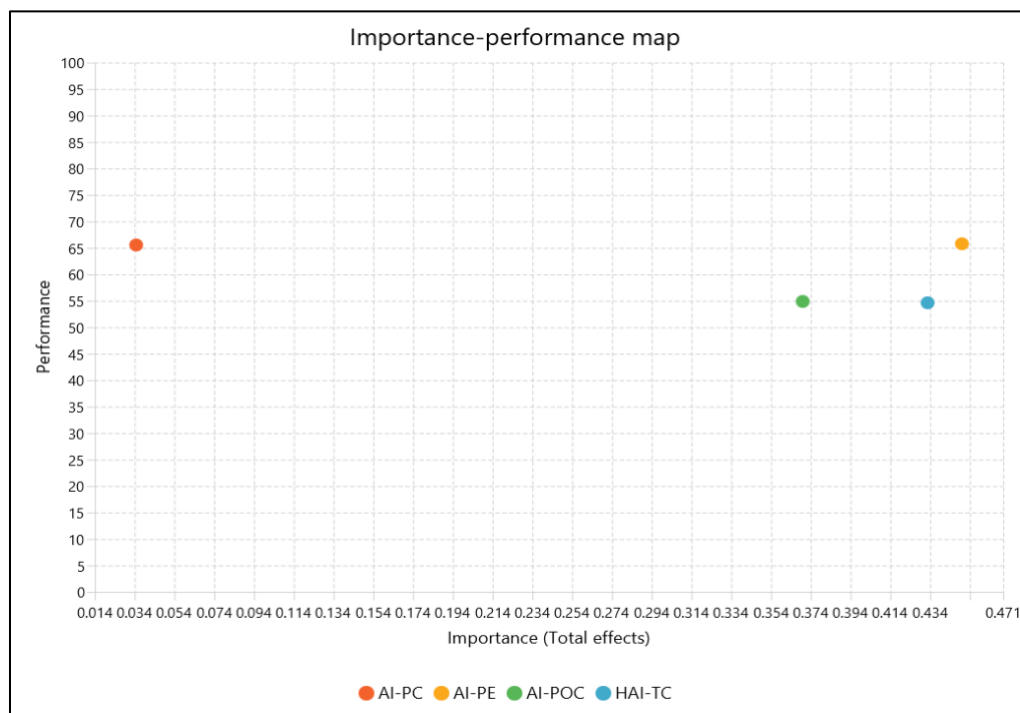


Figure 3. Importance–Performance Map Analysis Construct Projections

AI Pedagogical Orchestration Capability (AI-POC) ranks third in importance (0.369), behind AI-PE and HAI-TC, with a performance score of 55.2, higher than HAI-TC's 54.8, though still modest in absolute terms. As such, strengthening educators' competencies in coordinating AI tools with pedagogical methods remains a further area worth exploring to enhance teaching quality, alongside the higher-priority improvements to HAI-TC noted above. AI Pedagogical Creativity (AI-PC) ranks lowest in importance (0.034), while showing a relatively high-performance score (65.4); this suggests that respondents already regard themselves as reasonably competent in basic AI-related pedagogical skills. This pattern implies that additional investment in basic AI creativity skills is likely to yield less improvement in teaching effectiveness than efforts focused on AI Pedagogical Experimentation and Human–AI Co-Teaching Competence.

Theoretical and Practical Contribution

This study carries several theoretical implications. First, it contributes to Dynamic Capabilities Theory (Teece et al., 1997; Teece, 2007) in a specific way: rather than simply relabelling the theory's organisational-level sensing–seizing–reconfiguring logic, it extends that logic to the level of the individual lecturer (see Theoretical Foundation) and proposes AI Pedagogical Orchestration Capability as the empirical expression of lecturer-level reconfiguring for AI-enabled teaching the mechanism through which lecturers convert emerging AI-related capabilities (creativity,

experimentation, and co-teaching competence) into coordinated instructional practice. This is a modest but specific extension rather than a claim to have transformed the theory itself. While Dynamic Capabilities Theory is extensively used in organisational and strategic-management research, its application at the individual-lecturer level for AI-enabled teaching remains rare. The results of this study are consistent with the proposition that AI-related skills create educational value not solely through technology adoption, but through lecturers' capability to manage AI within their teaching practice.

Second, this study contributes to the body of research associated with Sociotechnical Systems Theory (Bostrom & Heinen, 1977; Trist & Bamforth, 1951). It provides evidence consistent with the view that the effectiveness of AI-enabled teaching activities depends on the alignment of technological engagement and human pedagogical knowledge. In particular, AI Pedagogical Creativity, AI Pedagogical Experimentation, and Human–AI Co-Teaching Competence each contribute to AI Pedagogical Orchestration Capability, consistent with the sociotechnical perspective that successful educational outcomes follow from the alignment of human and technological elements; because the structural model tests additive paths rather than statistical interaction terms, this is evidence of joint contribution rather than of a formally tested synergistic (interactive) effect. Lastly, this study contributes to AI-in-education research through a shift in emphasis: while previous literature has often treated AI literacy, technical skill, and adoption intentions as the critical levers of educational innovation, this study highlights AI Pedagogical Orchestration Capability as a further driver of how AI-related skills translate into teaching practice. The study thus represents an attempt to bring Dynamic Capabilities Theory and Sociotechnical Systems Theory together within an integrated framework for AI-enabled teaching.

In addition to these theoretical insights, this study carries practical implications for universities seeking to embed generative AI in their teaching practices. Rather than treating AI literacy as sufficient on its own, universities should build on foundational AI literacy and skills training by also deliberately developing lecturers' AI Pedagogical Orchestration Capability, so that technical familiarity with AI is translated into strategically integrated instructional design, assessment, and classroom interaction.

LIMITATIONS

This study has several limitations that should be considered when interpreting the results, each pointing to a corresponding direction for future research. First, the cross-sectional design means the data were collected at a single point in time; consequently, the reported associations, including the mediation results, provide statistical evidence consistent with the proposed relationships rather than proof of a temporal causal process, and longitudinal or experimental designs would be valuable for establishing directionality and change over time. Second, all constructs, including Lecturer Teaching Effectiveness, were measured through lecturers' self-report; because predictor, mediator, and outcome measures were collected from the same respondents in the same questionnaire, common method bias is a relevant concern. Relatedly, Lecturer Teaching Effectiveness was measured through lecturers' perceptions rather than independent student or administrative data. Third, participants were recruited through purposive sampling, which was necessary to ensure that respondents had relevant AI-related teaching experience but which, together with the achieved response rate, means the sample may not be representative of all Indonesian lecturers. The sample may also be subject to self-selection and nonresponse bias. Probability-based sampling in future work would help address this. Fourth, the study was conducted among lecturers in the Indonesian higher education context, and findings may not generalise to other national, institutional, or cultural settings without further testing. Fifth, respondents were drawn from a range of teaching disciplines and varied considerably in the length and intensity of their AI use (Table 2), and the present model did not test whether these factors moderate the hypothesised relationships; discipline-specific or experience-based differences remain an open question for future research. Sixth, two of the constructs (AI Pedagogical Experimentation and AI Pedagogical Orchestration Capability) were measured with newly developed items rather than an established prior scale; although these items were grounded in the construct definitions and literature described in the Method section, further psychometric validation of these scales in independent samples would strengthen confidence in the measurement model. Finally, as

noted in the Results, bootstrapped confidence intervals for HTMT and a formal PLS-versus-benchmark PLSpredict comparison were not computed in the original analysis; incorporating these more conservative diagnostics would further strengthen future replications of this model.

CONCLUSION

As the application of generative AI continues to grow, higher education institutions are likely to see major changes in how teaching is designed and delivered, requiring lecturers to re-examine their instructional approaches. The present study suggests that the educational potential of AI depends substantially on lecturers' ability to implement the technology in their teaching, rather than being determined by the capabilities of the AI tools themselves. Consistent with the final validated model tested in this study, AI Pedagogical Creativity, AI Pedagogical Experimentation, and Human–AI Co-Teaching Competence are each positively associated with AI Pedagogical Orchestration Capability, which is, in turn, positively associated with Lecturer Teaching Effectiveness. Because the design is cross-sectional and based on self-reported measures, these findings should be read as statistically significant associations rather than as demonstrated improvements caused by the predictors. Taken together, the results are consistent with the view that the effective application of AI in teaching depends substantially on lecturers' ability to unite technological and pedagogical capability and knowledge. Within the framework of Dynamic Capabilities Theory and Sociotechnical Systems Theory, this paper offers a view of how AI-related capabilities may translate into teaching practice for this sample of Indonesian lecturers. As generative AI continues to develop, it will likely remain important not only to promote its use in higher education but also to identify the capabilities lecturers need to orchestrate it effectively; the perspective presented here is offered as one basis for that continuing research agenda.

AUTHOR CONTRIBUTIONS

HH was responsible for the conceptualization, supervision, methodology, validation, project administration, data interpretation, and writing- review and editing, and served as the corresponding author. MAK handled the investigation, data curation, formal analysis, and preparation of the original draft. MRR was involved in reviewing and editing the manuscript. AY contributed to the methodology and data analysis. MRizM was responsible for formal analysis, resources, and reviewing and editing the manuscript. MRidM handled the visualization, proofreading, and final review of the manuscript. All authors approved the final manuscript.

ACKNOWLEDGMENTS

The authors would like to express their gratitude to all lecturers who participated in this study and generously contributed their time and insights to the research. The authors also acknowledge the support and constructive contributions of colleagues and academic peers who provided valuable feedback during the development of this manuscript. Their contributions have been instrumental in supporting the completion of this study.

REFERENCES

- Abrami, P. C., d'Apollonia, S., & Rosenfield, S. (2007). The dimensionality of student ratings of instruction: What we know and what we do not. In R. P. Perry & J. C. Smart (Eds.), *The Scholarship of Teaching and Learning in Higher Education: An Evidence-Based Perspective* (pp. 385–456). Springer. https://doi.org/10.1007/1-4020-5742-3_10
- Aljemely, Y. (2024). Challenges and best practices in training teachers to utilize artificial intelligence: A systematic review. *Frontiers in Education*, 9. <https://doi.org/10.3389/feduc.2024.1470853>
- Arif, M., Aziz, M. K. N. A., Hassan, H., Fikri, Y., Zekkari, M., & Rismawati, B. V. (2026). Artificial intelligence in Islamic Religious Education: A PRISMA-based review and the SEI-CHAT framework. *Online Learning in Educational Research*, 6(1), 65–85. <https://doi.org/10.58524/oler.v6i1.993>

- Bai, J. (2024). The application, challenges, and reflection of generative Artificial Intelligence in the field of education. *Education Reform and Development*, 6(10), 273–281. <https://doi.org/10.26689/erd.v6i10.8522>
- Bond, M., Khosravi, H., De Laat, M., Bergdahl, N., Negrea, V., Oxley, E., Pham, P., Chong, S. W., Siemens, G., et al. (2024). A meta systematic review of artificial intelligence in higher education: A call for increased ethics, collaboration, and rigour. *International Journal of Educational Technology in Higher Education*, 21, 4. <https://doi.org/10.1186/s41239-023-00436-z>
- Bostrom, R. P., & Heinen, J. S. (1977). MIS problems and failures: A socio- technical perspective. *MIS Quarterly*, 1(3), 17–32. <https://doi.org/10.2307/248710>
- Castillo-Martínez, I. M., Flores-Bueno, D., Gómez-Puente, S. M., & Vite-León, V. O. (2024). AI in higher education: A systematic literature review. *Frontiers in Education*, 9, 1391485. <https://doi.org/10.3389/educ.2024.1391485>
- Celik, I., Dindar, M., Muukkonen, H., & Järvelä, S. (2022). The promises and challenges of Artificial Intelligence for teachers: A systematic review of research. *TechTrends*, 66(4), 616–630. <https://doi.org/10.1007/s11528-022-00715-y>
- Chiu, T. K. F. (2023). The impact of Generative AI (GenAI) on practices, policies and research direction in education: A case of ChatGPT and Midjourney. *Interactive Learning Environments*, 32(10), 6187–6203. <https://doi.org/10.1080/10494820.2023.2253861>
- Choudhury, S., Biswas, S., Deb, J. P., Chattopadhyay, A., Devi, A., & Boruah, A. S. (2026). Role of ICT self-efficacy and TPACK in linking AI literacy to digital transformation. *Online Learning in Educational Research*, 6(1), 185–197. <https://doi.org/10.58524/oler.v6i1.1105>
- Dillenbourg, P. (2013). Design for classroom orchestration. *Computers & Education*, 69, 485–492. <https://doi.org/10.1016/j.compedu.2013.04.013>
- Finstad, K. (2010). The usability metric for user experience. *Interacting with Computers*, 22(5), 323–327. <https://doi.org/10.1016/j.intcom.2010.04.004>
- Guntara, Y., Hafid, T., & Sari, I. F. (2021). Does TPACK mastery affect teamwork skills? A causal-comparative study of pre-service physics teachers. *Jurnal Ilmiah Pendidikan Fisika Al-Biruni*, 10(1), 37–46. <https://doi.org/10.24042/jipfalbiruni.v10i1.8327>
- Habibi, A., Muhaimin, M., Danibao, B. K., Wibowo, Y. G., Wahyuni, S., & Octavia, A. (2023). ChatGPT in higher education learning: Acceptance and use. *Computers and Education: Artificial Intelligence*, 5, 100190. <https://doi.org/10.1016/j.caeai.2023.100190>
- Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, 31(1), 2–24. <https://doi.org/10.1108/EBR-11-2018-0203>
- Henriksen, D., Creely, E., Henderson, M., & Mishra, P. (2021). Creativity and technology in teaching and learning: A literature review of the uneasy space of implementation. *Educational Technology Research and Development*, 69(4), 2091–2108. <https://doi.org/10.1007/s11423-020-09912-z>
- Jannah, D. M., Huda, S., Yasin, M., Sanatang, Fakhri, M. M., Wahid, S. N., Kaswar, A. B., Soeharto, & Amukune, S. (2026). AI literacy, technical skills, and ethical awareness in predicting students' learning performance. *Online Learning in Educational Research*, 6(1). <https://doi.org/10.58524/oler.v6i1.565>
- Jenjić, S., Kević-Zrnić, S., & Stanković-Janković, T. (2025). Challenges and teachers' interests in the implementation of artificial intelligence in education. 107–120. <https://doi.org/10.46793/zbVO25UEI.107J>
- Ji, H., Han, I., & Ko, Y. (2023). A systematic review of conversational AI in language education: Focusing on the collaboration with human teachers. *Journal of Research on Technology in Education*, 55(1), 48–63. <https://doi.org/10.1080/15391523.2022.2142873>
- Kasneci, E., Sessler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., Gasser, U., Groh, G., Günemann, S., Hüllermeier, E., Krusche, S., Kutyniok, G., Michaeli, T., Nerdel, C., Pfeffer, J., Poquet, O., Sailer, M., Schmidt, A., Seidel, T., ... Kasneci, G. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. *Learning and Individual Differences*, 103, 102274. <https://doi.org/10.1016/j.lindif.2023.102274>
- Khan, M. A., Syamil, A., & Navanti, D. (2026). AI-enabled human resource practices and organizational agility: The mediating role of employee voice and the moderating effect of AI-readiness culture

- in ASEAN countries. *Diponegoro International Journal of Business*, 9(1), 77–94. <https://doi.org/10.14710/dijb.9.1.2026.77-94>
- Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. *International Journal of e-Collaboration*, 11(4), 1–10. <https://doi.org/10.4018/ijec.2015100101>
- Kock, N., & Hadaya, P. (2018). Minimum sample size estimation in PLS-SEM: The inverse square root and gamma-exponential methods. *Information Systems Journal*, 28(1), 227–261. <https://doi.org/10.1111/isj.12131>
- Labadze, L., Grigolia, M., & Machaidze, L. (2023). Role of AI chatbots in education: Systematic literature review. *International Journal of Educational Technology in Higher Education*, 20(1), 56. <https://doi.org/10.1186/s41239-023-00426-1>
- Liu, X., & Zhong, B. (2025). Integrating generative Artificial Intelligence into student learning: A systematic review from a TPACK perspective. *Educational Research Review*, 49, 100741. <https://doi.org/10.1016/j.edurev.2025.100741>
- Mariappan, J., & Krishnan, C. (2022). *Integration of AI in Learning* (pp. 263–275). Igi Global. <https://doi.org/10.4018/978-1-6684-4083-4.ch014>
- Marsh, H. W. (1982). SEEQ: A reliable, valid, and useful instrument for collecting students' evaluations of university teaching. *British Journal of Educational Psychology*, 52(1), 77–95. <https://doi.org/10.1111/j.2044-8279.1982.tb02505.x>
- Mishra, K., & Srivastava, A. K. (2024). An analysis of integration of Artificial Intelligence in higher studies. *Revista Review Index Journal of Multidisciplinary*, 4(1), 44–54. <https://doi.org/10.31305/rrijm2024.v04.n01.006>
- Mishra, P., & Koehler, M. J. (2006). Technological pedagogical content knowledge: A framework for teacher knowledge. *Teachers College Record: The Voice of Scholarship in Education*, 108(6), 1017–1054. <https://doi.org/10.1111/j.1467-9620.2006.00684.x>
- Mulianah, B., Usman, F., Rokhman, M., Fatikh, M. A., Andriana, I., Nabila, M. A., & Nur Kholis, M. M. (2025). The Role and Threats of Using ChatGPT in Higher Education: Balancing Pedagogical Potential and Ethical Risks. *Nazhruna: Jurnal Pendidikan Islam*, 8(3), 550–560. <https://doi.org/10.31538/nzh.v8i3.218>
- Phuong, H. T. B., Du, T. T., & The, N. H. (2026). Reframing feedback in EFL paragraph writing: Complementary roles of teachers and ChatGPT-3.5. *Online Learning in Educational Research*, 6(2), 1–10. <https://doi.org/10.58524/oler.v6i2.1220>
- Prieto, L. P., Sharma, K., Kidzinski, Ł., & Dillenbourg, P. (2018). Orchestration load indicators and patterns: In-the-wild studies using mobile eye-tracking. *IEEE Transactions on Learning Technologies*, 11(2), 216–229. <https://doi.org/10.1109/TLT.2017.2690687>
- Rodzi, Z. M., Rahman, A. A., Razali, I. N., Nazri, I. S. M., & Abd Gani, A. F. (2023). *Unraveling the drivers of Artificial Intelligence (AI) adoption in higher education*. 1–6. <https://doi.org/10.1109/InCULT59088.2023.10482651>
- Salim, A., Gonibala, R., Talibo, I., & Baba, M. A. (2026). Divine Concepts, Tawhid, and Algorithmic Thinking: A Comparative Analysis of Christian and Islamic Perspectives on Educational Theology in the Era of Artificial Intelligence. *Nazhruna: Jurnal Pendidikan Islam*, 9(1), 1–17. <https://doi.org/10.31538/nzh.v9i1.196>
- Shetty K, U., & Hegde S, V. (2024). Teachers perception on role of Artificial Intelligence in higher education- an empirical study. *ShodhKosh: Journal of Visual and Performing Arts*, 5(7). <https://doi.org/10.29121/shodhkosh.v5.i7.2024.4998>
- Shmueli, G., Sarstedt, M., Hair, J. F., Cheah, J.-H., Ting, H., Vaithilingam, S., & Ringle, C. M. (2019). Predictive model assessment in PLS-SEM: Guidelines for using PLSpredict. *European Journal of Marketing*, 53(11), 2322–2347. <https://doi.org/10.1108/EJM-02-2019-0189>
- Strzelecki, A. (2023). Students' acceptance of ChatGPT in higher education: An extended unified theory of acceptance and use of technology. *Innovative Higher Education*, 49(2), 223–245. <https://doi.org/10.1007/s10755-023-09686-1>
- Suman, S. (2025). The inclusion of Artificial Intelligence in Teaching learning process is blessing or curse. *Journal of Information Systems Engineering and Management*, 10(26s), 593–612. <https://doi.org/10.52783/jisem.v10i26s.4265>

- Syukur, F., Maghfurin, A., Marhamah, U., & Jehwae, P. (2024). Integration of Artificial Intelligence in Islamic higher education: Comparative responses between Indonesia and Thailand. *Nazhruna: Jurnal Pendidikan Islam*, 7(3), 531–553. <https://doi.org/10.31538/nzh.v7i3.13>
- Teece, D. J. (2007). Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance. *Strategic Management Journal*, 28(13), 1319–1350. <https://doi.org/10.1002/smj.640>
- Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal*, 18(7), 509–533. [https://doi.org/10.1002/\(SICI\)1097-0266\(199708\)18:7<509::AID-SMJ882>3.0.CO;2-Z](https://doi.org/10.1002/(SICI)1097-0266(199708)18:7<509::AID-SMJ882>3.0.CO;2-Z)
- Trist, E. L., & Bamforth, K. W. (1951). Some social and psychological consequences of the longwall method of coal-getting. *Human Relations*, 4(1), 3–38. <https://doi.org/10.1177/001872675100400101>
- Xhumari, E., Maxhelaku, S. V., Perri, R., Baka, A., Kosta, A., & Lili, I. (2025). Integration of the Artificial Intelligence in higher education: A Case Study from the University of Tirana (Quality Education SDG). *Journal of Lifestyle and SDGs Review*, 5(6), e03915. <https://doi.org/10.47172/2965-730X.SDGsReview.v5.n06.pe03915>
- Xia, P. (2019). *Application scenario of Artificial Intelligence technology in higher education* (pp. 221–226). Springer. https://doi.org/10.1007/978-3-030-25128-4_29
- Yusriadi, Y., Farida, U., & Misnawati, M. (2024). "Merdeka Belajar Kampus Merdeka" policies in Indonesia higher education institutions: New public policy reform. *Al-Tanzim: Jurnal Manajemen Pendidikan Islam*, 8(1), 344–360. <https://doi.org/10.33650/al-tanzim.v8i1.7173>
- Zawacki-Richter, O., Marín, V. I., 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, 39. <https://doi.org/10.1186/s41239-019-0171-0>