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Original Research Article

The Impact of Artificial Intelligence (AI) on the Development of Educational Quality in Private Universities

In Bangkok, Thailand

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ABSTRACT

This study aimed to (1) examine the effects of artificial intelligence (AI) adoption in teaching and learning, administrative management, and personnel capability on the effectiveness of AI-driven learning and management processes in private universities in Bangkok, Thailand; (2) investigate the influence of AI-driven process effectiveness on the quality of teaching and learning; and (3) propose policy and practical guidelines for the sustainable integration of AI in higher education. A mixed-methods research design was employed, combining quantitative and qualitative approaches. The quantitative phase involved a sample of 510 administrators and academic personnel from private universities in Bangkok, Thailand. Data were collected using a structured questionnaire that was assessed for content validity and reliability. In-depth interviews were conducted to enrich and support the interpretation of the quantitative findings. Quantitative data were analyzed using descriptive statistics, Pearson's correlation analysis, Confirmatory Factor Analysis (CFA), and Structural Equation Modeling (SEM).

The results indicated that AI adoption in teaching and learning, AI utilization in administrative management, and personnel capability had significant positive effects on the effectiveness of AI-driven learning and management processes. Furthermore, process effectiveness significantly enhanced students' learning experiences, institutional management effectiveness, and the overall quality of teaching and learning. However, institutional management effectiveness did not exert a direct significant influence on educational quality. The structural model demonstrated an excellent fit with the empirical data. The findings suggest that sustainable improvement in educational quality requires systematic integration of AI into pedagogical practices, continuous development of personnel competencies, and coherent governance frameworks. Administrative efficiency alone is

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insufficient to achieve meaningful educational quality enhancement. These findings provide valuable implications for policymakers and university administrators seeking to leverage AI for sustainable development in higher education.

Introduction

Artificial Intelligence (AI) has emerged as a pivotal driver of transformation in twenty-first-century education, particularly within higher education institutions that are increasingly challenged by demands for quality enhancement, instructional flexibility, and global competitiveness. A substantial body of literature indicates that AI offers significant potential to improve learning efficiency through adaptive learning systems, learning analytics, and intelligent tutoring systems, all of which support data-informed instructional decision-making and enhance student learning outcomes (Hwang et al., 2020; Holmes et al., 2019; Luckin et al., 2016). More recently, the emergence of generative AI technologies such as ChatGPT has further transformed human–technology interaction in educational contexts, reshaping pedagogical practices and redefining the roles of instructors in higher education settings (Wu, 2023; Qadir, 2023). From a quality assurance perspective, AI is increasingly recognized as a key mechanism for enabling personalized learning, delivering real-time feedback, and supporting continuous assessment, all of which are essential components of academic quality development. Empirical evidence suggests that AI-driven educational technologies can positively influence students' attitudes, self-efficacy, and academic achievement (Johnson & Smith, 2019; García-Martínez et al., 2023). At the institutional level, predictive analytics and data-driven decision-support systems enhance strategic planning and enable targeted student interventions, thereby improving both educational performance and organizational effectiveness in higher education institutions (Ouyang et al., 2023; Sajja et al., 2023).

Within the conceptual framework of this study, AI adoption in teaching, learning, academic services, and administrative management is conceptualized as the primary independent construct influencing the effectiveness of AI-driven educational processes. This mediating construct is operationalized through multiple dimensions, including personalized learning support, assessment and evaluation efficiency, access to digital learning resources, accuracy and timeliness of educational data management, support for academic and managerial decision-making, and student engagement enhancement. Prior research has consistently demonstrated that AI enables adaptive and personalized instructional environments (Maghsudi et al., 2021; Tapalova & Zhiyenbayeva, 2022), strengthens assessment and feedback mechanisms (Hooda et al., 2022), and improves data-driven governance in higher education institutions (Ouyang et al., 2023; Sajja et al., 2023). Collectively, these dimensions represent the operational pathways through which AI contributes to institutional quality enhancement.

The dependent variable of this study is the quality of teaching and learning in private universities, which is conceptualized as being influenced through two interrelated pathways: the enhancement of student learning experiences and the improvement of institutional management effectiveness. Research indicates that AI-powered tools, including intelligent tutoring systems and digital learning platforms, significantly enhance student engagement, motivation, and learning performance (Chen et al., 2023; Chiu et al., 2024). Concurrently, big data analytics and predictive modeling systems enable institutional leaders to strengthen

planning, monitoring, and quality assurance processes, thereby improving decision-making effectiveness and institutional performance (Williamson, 2017; Baker, 2021). Nevertheless, the integration of AI in education also raises important concerns related to ethics, data privacy, transparency, and algorithmic bias, which must be critically considered in any comprehensive evaluation of educational quality (Akgun & Greenhow, 2022; Selwyn, 2022).

In the context of private universities in Bangkok, Thailand, increasing competition, market-driven pressures, and the need for institutional differentiation have made AI adoption a strategically important issue. Existing studies in the Thai higher education context have primarily focused on technology acceptance, the application of AI tools such as ChatGPT in English language learning, and determinants of student adoption intentions (Khlaisang et al., 2019; Shaengchart et al., 2023; Waluyo & Kusumastuti, 2024). In addition, institutional readiness and personnel capability have been identified as critical enablers of successful AI integration in educational settings (Kuleto et al., 2021; Potjanajaruwit, 2023). However, despite extensive international research on AI in higher education (Holmes & Tuomi, 2022; Zawacki-Richter et al., 2019), there remains a limited number of studies that integrate AI adoption, personnel readiness, AI-driven process effectiveness, and educational quality outcomes within a unified structural framework particularly within the context of Thai private universities.

Therefore, this study addresses this gap by empirically examining the structural relationships among AI adoption, personnel readiness, AI-driven process effectiveness, and the quality of teaching and learning in private universities in Bangkok, Thailand. In doing so, it seeks to clarify the mechanisms through which AI contributes to institutional quality enhancement and to provide evidence-based insights for policy and strategic decision-making in higher education.

Literature Review and Theoretical Framework

The literature on Artificial Intelligence (AI) in higher education clearly demonstrates that the integration of AI into teaching, learning, and institutional management represents a systemic and multidimensional transformation process. Such transformation extends beyond mere technological adoption and requires pedagogical adaptation, organizational readiness, and appropriate governance frameworks. Contemporary scholarship emphasizes that AI should be viewed as a strategic mechanism for enhancing educational quality rather than simply as a technological tool (Holmes et al., 2019; Holmes & Tuomi, 2022; Hwang et al., 2020). This perspective is particularly relevant in the context of private universities operating in highly competitive environments, where AI adoption is increasingly associated with institutional performance, innovation capability, and tangible quality development.

The literature on AI adoption in teaching and learning highlights the role of adaptive learning systems, intelligent tutoring systems, learning analytics, and generative AI in improving instructional effectiveness. Adaptive systems tailor content to learners' progress and behavioral patterns, thereby enhancing engagement and academic achievement (Maghsudi et al., 2021; Tapalova & Zhiyenbayeva, 2022). Likewise, AI-driven assessment tools provide real-time feedback and support formative evaluation processes (Hooda et al., 2022). The emergence of generative AI technologies such as ChatGPT has further expanded opportunities for interactive learning, although concerns have been raised regarding academic ethics and the development of critical thinking skills (Wu, 2023; Qadir, 2023; Ju, 2023). Collectively, this body of literature provides a strong theoretical foundation for hypothesizing

that AI adoption in teaching and learning positively influences the effectiveness of AI-driven processes (H1).

Beyond instructional applications, AI has been widely implemented in academic and administrative management systems. Predictive analytics and decision-support systems enable universities to optimize student recruitment, monitor academic performance, and develop effective retention strategies (Ouyang et al., 2023; Sajja et al., 2023; Baker, 2021). Big data infrastructures further promote evidence-based decision-making, reduce operational inefficiencies, and enhance institutional transparency (Williamson, 2017). These empirical findings support the hypothesis that the use of AI in academic and administrative management positively affects the effectiveness of AI-driven processes (H2). However, the literature consistently emphasizes that technological implementation alone does not guarantee success. Institutional readiness, personnel capability, and organizational culture are critical determinants of effective AI integration (Kuleto et al., 2021; Potjanajaruwit, 2023). Personnel capability encompasses digital literacy, pedagogical competence in AI utilization, and openness to innovation. Accordingly, prior research provides strong justification for hypothesizing that personnel capability and readiness positively influence the effectiveness of AI-driven learning and management processes (H3).

The effectiveness of AI-driven processes is conceptualized as a multidimensional construct encompassing personalized learning, assessment efficiency, access to digital learning resources, accuracy in educational data management, decision-support capability, and enhanced student engagement. Empirical evidence indicates that AI-enhanced learning environments improve student motivation, engagement, and academic performance (Chen et al., 2023; Chiu et al., 2024; García-Martínez et al., 2023). Furthermore, analytics-driven systems strengthen institutional planning and strategic responsiveness (Ouyang et al., 2023). This literature therefore supports the hypotheses that AI-driven process effectiveness positively influences the enhancement of students' learning experiences (H4) and the improvement of institutional management effectiveness (H5).

Educational quality in private universities is widely recognized as a systemic outcome encompassing teaching effectiveness, student learning experiences, managerial efficiency, and stakeholder satisfaction. Research suggests that higher levels of student engagement and positive learning experiences are significantly associated with improved perceptions of educational quality (Chen et al., 2023; Chiu et al., 2024). Simultaneously, data-driven management systems enhance quality assurance mechanisms and institutional performance monitoring (Williamson, 2017; Baker, 2021). These findings provide theoretical grounding for hypothesizing that AI-driven process effectiveness directly influences the quality of teaching and learning (H6), while enhanced students' learning experiences (H7) and improved institutional management effectiveness (H8) further contribute to overall educational quality.

Finally, the literature underscores the importance of ethical governance, data protection, and responsible AI implementation in educational contexts (Akgun & Greenhow, 2022; Selwyn, 2022). In the absence of appropriate regulatory frameworks, AI adoption may generate inequalities or undermine institutional trust. Therefore, the effectiveness of AI-driven processes should not be understood solely as a technical outcome, but rather as an organizational and ethical construct that mediates the relationship between AI adoption and educational quality outcomes.

In summary, the synthesis of the above literature establishes a coherent structural framework linking AI adoption in teaching and administration, personnel readiness, the

effectiveness of AI-driven processes, and the quality of teaching and learning in private universities. The literature supports conceptualizing AI-driven process effectiveness as a mediating variable that transmits the influence of technological and organizational factors to educational quality outcomes. This integrated framework provides the foundation for testing hypotheses H1–H8 in the present study.

Conceptual Framework

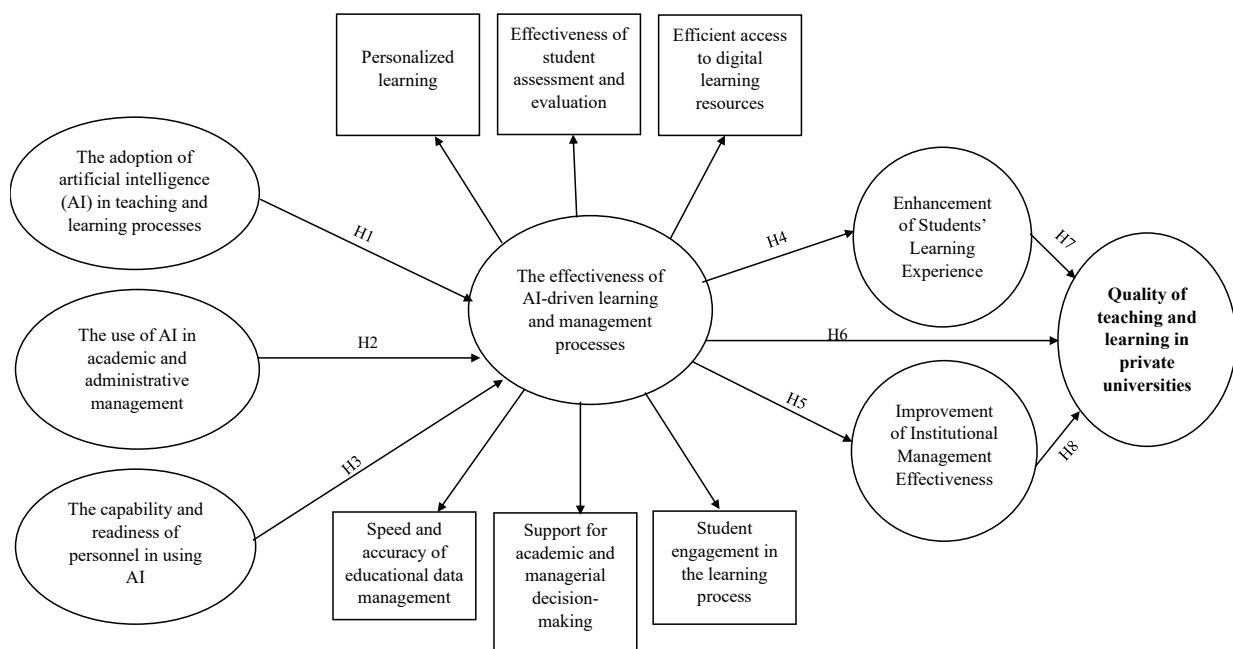


Figure 1 Conceptual Framework

Objectives

1. To examine the impact of artificial intelligence (AI) adoption in teaching and learning, as well as in administrative management, on the effectiveness of AI-driven learning and management processes in private universities in Bangkok, Thailand.
2. To analyze the influence of AI-driven learning and management process effectiveness on the quality of teaching and learning.
3. To propose policy and practical guidelines for the sustainable integration of AI in higher education.

Methodology

The Population and Sample

The population of this study consisted of administrators, academic staff, and personnel working in private universities in Bangkok, Thailand that have implemented or are in the process of implementing AI in teaching, learning, or administrative management. These

institutions are officially recognized by the Ministry of Higher Education, Science, Research and Innovation of Thailand.

The sample was drawn from the same population, including university executives, deans, department heads, lecturers, and academic support personnel involved in AI-related initiatives within private universities. The sample size was determined based on the guidelines for Structural Equation Modeling (SEM) proposed by Hair et al. (2010), which recommend a minimum sample size of at least 20 times the number of observed variables for multivariate analysis. As the present study includes 24 observed variables, the minimum required sample size was 480 respondents.

Furthermore, a sample size of approximately 500 respondents is considered highly adequate for SEM analysis to ensure statistical stability and robustness (Thanin Silpcharu, 2020). Accordingly, this study employed a total sample size of 510 respondents, which is sufficient and appropriate for structural equation modeling. A multi-stage sampling technique was applied, selecting participants from private universities across different regions of Thailand, including the Central, Northern, Northeastern, Eastern, Western, and Southern regions, to ensure geographical representation and diversity.

Research Instruments

The primary quantitative data collection instrument was a structured questionnaire designed to measure the constructs in the proposed research model. The questionnaire consisted of five main sections corresponding to the study variables:

- 1) AI adoption in teaching and learning,
- 2) AI adoption in academic and administrative management,
- 3) personnel capability and institutional readiness,
- 4) effectiveness of AI-driven learning and management processes, and
- 5) quality of teaching and learning (including students' learning experience enhancement and institutional management effectiveness).

The questionnaire items were developed based on a comprehensive review of relevant literature and were evaluated by experts in educational technology and higher education management to assess content validity. A five-point Likert scale was employed, ranging from 1 = strongly disagree to 5 = strongly agree.

In addition, a pilot test was conducted to examine the reliability of the instrument. Cronbach's Alpha coefficients ranged from 0.82 to 0.94, indicating a high level of internal consistency and confirming that the research instrument was reliable and appropriate for full-scale data collection.

For the qualitative component, semi-structured in-depth interviews were conducted with selected university executives and academic personnel who had direct experience in AI implementation. The interviews focused on institutional readiness, challenges in AI integration, perceived impacts on teaching quality, and long-term strategic implications.

Data Analysis

Descriptive statistical analysis was conducted to provide an overview of the data, including means, frequency distributions, minimum and maximum values, and standard

deviations. Inferential statistics were employed to examine relationships among variables using Pearson's correlation coefficients at a statistical significance level of 0.05.

Confirmatory Factor Analysis (CFA) was conducted to assess the construct validity and model fit. Subsequently, Structural Equation Modeling (SEM) was performed following five key steps: (1) model development, (2) sample size determination, (3) parameter estimation, (4) model fit assessment, and (5) model modification and refinement. These procedures ensured the robustness, reliability, and consistency of the results with the proposed hypotheses and the collected data.

Qualitative data were analyzed using content analysis, involving data categorization, coding of interview responses, and identification of common themes and relationships among key issues. The qualitative findings were then integrated with the quantitative results to support interpretation and enrich contextual understanding. In addition, triangulation analysis was employed to enhance the credibility of the research findings by cross-validating data from multiple sources, including interviews, quantitative data, and theoretical frameworks, thereby strengthening the reliability and contextual depth of the study's conclusions.

Results

The structural model evaluation includes testing hypotheses, determining the variance explained (R²) of the independent constructs on the dependent constructs, and assessing the predictive relevance of the model as follows: Table 1

Table 1 Contains the measurement criteria thresholds used in this study

Criteria for Measurement	Suggestion
Factor loading: FL (Comrey and Lee, 1992)	≥ 0.50
Composite reliability: CR (Henseler et al., 2015)	≥ 0.60
Average variance extracted: AVE (Rodgers & Pavlou, 2003)	> 0.50
Cronbach's alpha: Ca (Henseler et al., 2015)	≥ 0.70
Heterotrait-Monotrait ratio HTMT ratio (Henseler et al., 2015)	< 0.85
p-value	≤ 0.05

This statistical operation requires an evaluation of the model's psychometric features, including discriminant validity, convergent validity, and internal consistency reliability. Indicators that loaded less than 0.50 were removed. The loadings of the manifesting factors are shown in Table 2, indicating acceptable convergent validity since the values of each of the factor loadings (individual item reliabilities) are above 0.700 (Henseler, 2017). The average variance extracted (AVE) values used to determine the convergent validity are above 0.50 for the individual constructs, signifying that, on average, the indicators share a minimum of half of the variance with the variables (Henseler, 2017). The values for Cronbach's alpha and composite



reliability of the constructs used to measure the internal consistency reliability of the model are above the minimum thresholds of .700 and .600, respectively. This means that the model has achieved excellent reliability, as shown in Table 2

Table 2 Questionnaire items, Cronbach's alpha (α), average variance extracted (AVE), composite reliability (Cr), factor loadings

Construct	Measurement Items	Factor Loading	AVE	Cr	α
AI Adoption in Teaching and Learning Processes	Use of AI for personalized learning	0.83	0.65	0.91	0.89
	AI-supported assessment and feedback	0.86			
	Integration of AI tools in classroom activities	0.81			
	Use of generative AI to support learning tasks	0.79			
AI in Academic and Administrative Management	AI-based academic planning systems	0.84	0.67	0.92	0.90
	AI for student performance monitoring	0.88			
	AI-supported institutional decision-making	0.85			
	AI in educational data management	0.80			
Personnel Capability and Readiness in Using AI	Digital literacy of staff in AI tools	0.78	0.62	0.89	0.87
	Faculty competence in AI integration	0.82			
	Institutional AI training programs	0.80			
	Organizational readiness for AI adoption	0.81			
Effectiveness of AI-Driven Learning and Management Processes	Effectiveness of personalized learning systems	0.87	0.70	0.93	0.91
	Efficiency of AI-based assessment processes	0.89			
	Accuracy of AI-supported decision systems	0.85			

Construct	Measurement Items	Factor Loading	AVE	Cr	α
	Increased student engagement through AI	0.83			
Enhancement of Students' Learning Experience	Increased student motivation	0.84	0.66	0.91	0.89
	Improved learning interaction	0.86			
	Greater learning satisfaction	0.80			
	Improved academic achievement	0.82			
Improvement of Institutional Management Effectiveness	Improved operational efficiency	0.85	0.68	0.92	0.90
	Enhanced strategic planning capability	0.88			
	Strengthened quality assurance systems	0.83			
	Better institutional competitiveness	0.81			
Quality of Teaching and Learning in Private Universities	Overall teaching effectiveness	0.86	0.69	0.93	0.91
	Student satisfaction with learning quality	0.88			
	Academic performance outcomes	0.84			
	Institutional reputation for quality education	0.82			

Consequently, the discriminant validity of the structural model was examined using the Heterotrait–Monotrait (HTMT) ratio. According to Henseler (2017), discriminant validity is established when the HTMT value for each construct is below the threshold of 0.850. The results indicate that all HTMT values among the constructs are below 0.850, demonstrating adequate discriminant validity. Therefore, the constructs are empirically distinct from one another and the measurement model is considered sufficiently valid, as presented in Table 3.

Table 3 Heterotrait-Monotrait ratio (HTMT)

Constructs	1	2	3	4	5	6	7
AI Adoption in Teaching and Learning	—	0.612	0.584	0.633	0.521	0.498	0.466
AI in Academic & Administrative Management	0.612	—	0.648	0.671	0.542	0.603	0.519
Personnel Capability & Readiness	0.584	0.648	—	0.689	0.558	0.576	0.502
AI-Driven Process Effectiveness	0.633	0.671	0.689	—	0.724	0.698	0.651
Students' Learning Experience	0.521	0.542	0.558	0.724	—	0.602	0.736
Institutional Management Effectiveness	0.498	0.603	0.576	0.698	0.602	—	0.711
Quality of Teaching and Learning	0.466	0.519	0.502	0.651	0.736	0.711	—

The overall model fit was evaluated using multiple goodness-of-fit indices, as reliance on a single index is insufficient to assess model adequacy comprehensively. The results of the modified structural model indicate that $\chi^2 = 191.920$ with $df = 179$ and $p\text{-value} = 0.251$, suggesting that the chi-square statistic is not statistically significant, thereby indicating a good fit between the model and the empirical data. The χ^2/df ratio of 1.069 is well below the recommended threshold of 3.00, indicating an excellent fit. Furthermore, the Goodness-of-Fit Index ($GFI = 0.968$), Comparative Fit Index ($CFI = 0.999$), and Adjusted Goodness-of-Fit Index ($AGFI = 0.932$) all exceed the recommended minimum value of 0.90, demonstrating strong model adequacy. The Root Mean Square Error of Approximation ($RMSEA = 0.013$) is substantially below the acceptable cut-off value of 0.08, indicating a very close fit of the model to the data. Although the Root Mean Square Residual ($RMR = 0.073$) is slightly above the ideal threshold of 0.05, it remains within an acceptable range. Table 4

Table 4 Model fit indicators

Fit Index	Value
χ^2 (Chi-square)	191.920
df	179
χ^2/df	1.069
p-value	0.251
GFI	0.968



Fit Index	Value
AGFI	0.932
CFI	0.999
RMR	0.073
RMSEA	0.013

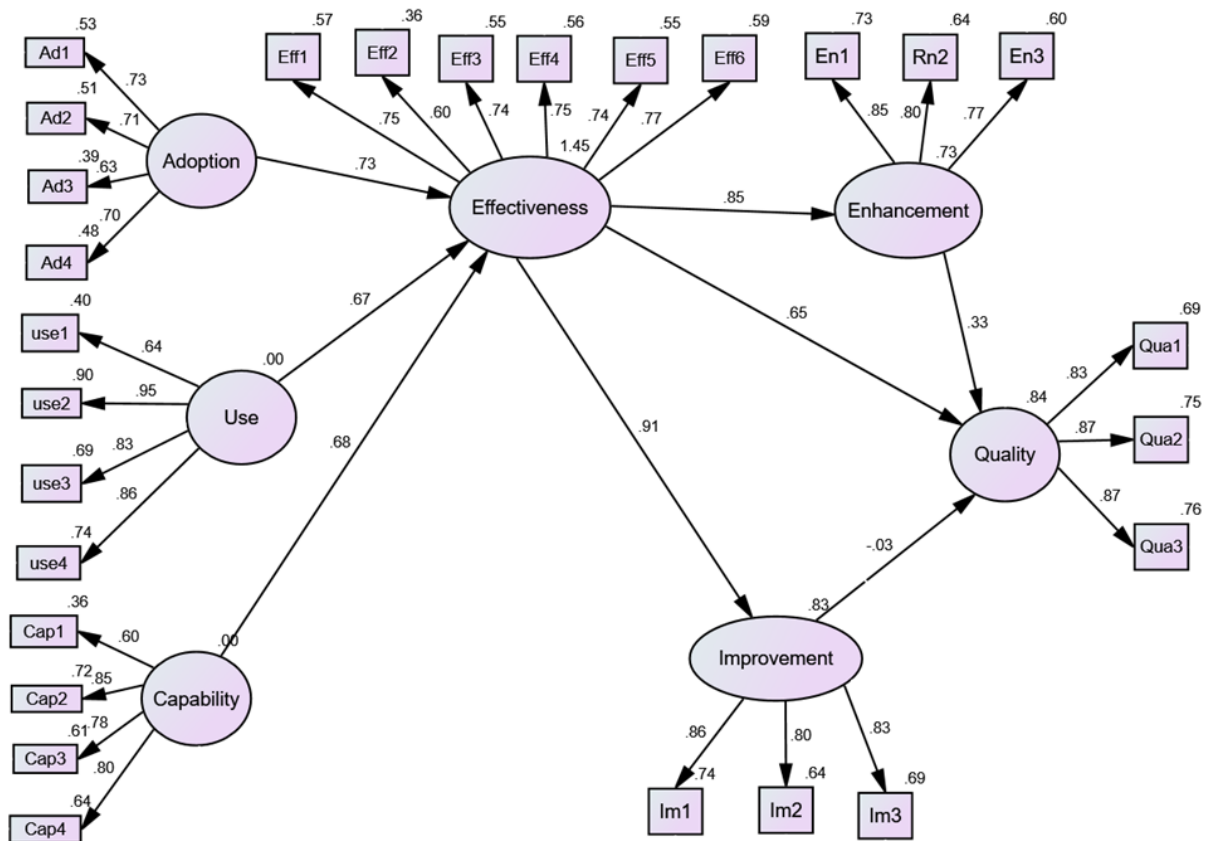


Figure 2 Model fit indicators

After the model measurement has been assessed, the variance explained (R^2) and the predictive relevance of the exogenous variables on the endogenous variables are considered. The validity of the hypotheses and predictive relevance were tested through the calculation. The t-statistics, p-values, and the (β) values were used to determine the statistical significance of the paths. The result is shown in Table 5.

Table 5 Direct Effect

Hypothesis	Path	Estimate (β)	S.E.	C.R.	p-value	Result
H1	Adoption $\rightarrow$ Effectiveness	0.734	0.081	9.826	<0.0009	Accepted
H2	Use $\rightarrow$ Effectiveness	0.673	0.057	12.008	<0.0009	Accepted

Hypothesis	Path	Estimate (β)	S.E.	C.R.	p-value	Result
H3	Capability $\rightarrow$ Effectiveness	0.676	0.057	12.320	<0.0009	Accepted
H4	Effectiveness $\rightarrow$ Enhancement	0.853	0.061	14.512	<0.0009	Accepted
H5	Effectiveness $\rightarrow$ Improvement	0.913	0.064	15.564	<0.0009	Accepted
H6	Effectiveness $\rightarrow$ Quality	0.650	0.189	3.634	<0.0009	Accepted
H7	Enhancement $\rightarrow$ Quality	0.326	0.080	4.125	<0.0009	Accepted
H8	Improvement $\rightarrow$ Quality	-0.031	0.139	-0.215	0.830	Rejected

Table 5 presents the direct effects among AI adoption, personnel readiness, AI-driven process effectiveness, intermediate outcomes, and educational

The results indicate that the adoption of artificial intelligence (AI) in teaching and learning processes has a significant positive effect on the effectiveness of AI-driven learning and management processes, thereby supporting Hypothesis H1 ($\beta = 0.734$, C.R. = 9.826, $p < 0.0009$). Similarly, the use of AI in academic and administrative management positively and significantly influences AI-driven process effectiveness, supporting Hypothesis H2 ($\beta = 0.673$, C.R. = 12.008, $p < 0.0009$). Furthermore, personnel capability and readiness in using AI demonstrate a statistically significant positive effect on effectiveness, confirming Hypothesis H3 ($\beta = 0.676$, C.R. = 12.320, $p < 0.0009$). With respect to the intermediate outcomes, AI-driven process effectiveness shows a strong and significant positive effect on Enhancement of Students' Learning Experience, supporting Hypothesis H4 ($\beta = 0.853$, C.R. = 14.512, $p < 0.0009$). Likewise, effectiveness exerts an even stronger positive influence on Improvement of Institutional Management Effectiveness, confirming Hypothesis H5 ($\beta = 0.913$, C.R. = 15.564, $p < 0.0009$).

Regarding educational quality, the findings reveal that AI-driven process effectiveness has a significant positive direct effect on the Quality of Teaching and Learning in Private Universities, supporting Hypothesis H6 ($\beta = 0.650$, C.R. = 3.634, $p < 0.0009$). In addition, Enhancement of Students' Learning Experience significantly and positively affects educational quality, thereby supporting Hypothesis H7 ($\beta = 0.326$, C.R. = 4.125, $p < 0.0009$). However, Improvement of Institutional Management Effectiveness does not have a statistically significant effect on educational quality ($\beta = -0.031$, C.R. = -0.215, $p = 0.830$), leading to the rejection of Hypothesis H8.

Based on interviews with university executives, faculty, and educational technology experts, the findings show that improving teaching and learning in the digital era depends primarily on effectively integrating AI into students' learning processes rather than only enhancing administrative efficiency.

Respondents highlighted adaptive learning systems, real-time feedback tools, and learning analytics as key to improving motivation, engagement, and academic achievement. Generative AI and intelligent platforms were seen as particularly valuable for enabling flexible, personalized learning environments.



While AI also improves administrative efficiency through data-driven decision-making and performance monitoring, participants emphasized that these benefits alone do not directly enhance teaching and learning unless they are connected to student learning experiences.

Successful AI integration was also found to depend on faculty readiness, digital competencies, pedagogical understanding, and an innovation-friendly organizational culture. Ethical issues, data privacy, and strong governance frameworks were additionally identified as essential for trust and sustainable AI adoption in higher education.

Discussion

AI Adoption in Teaching and Learning as a Driver of Process Effectiveness

The findings confirm that AI adoption in teaching and learning significantly enhances AI-driven process effectiveness, supporting Hypothesis H1. This result reinforces the argument that AI does not automatically improve education by mere implementation but requires meaningful pedagogical integration within instructional systems (Holmes et al., 2019; Holmes & Tuomi, 2022). From a socio-technical systems perspective, AI tools must be embedded within curriculum design, assessment strategies, and instructional practices to generate effective outcomes. Consistent with Hwang et al. (2020), AI-based systems such as intelligent tutoring and adaptive learning environments improve learning processes when aligned with instructional goals. Similarly, Maghsudi et al. (2021) and Tapalova and Zhiyenbayeva (2022) emphasize that personalization, adaptive feedback, and learning analytics enhance engagement and continuity in learning. These findings suggest that AI adoption in pedagogy functions as a foundational determinant of process effectiveness, where integration quality is more important than technological availability.

AI in Academic and Administrative Management as Data Infrastructure

The study also finds that AI adoption in academic and administrative management significantly enhances AI-driven process effectiveness, supporting Hypothesis H2. This aligns with the increasing emphasis on data-driven governance in higher education (Williamson, 2017; Baker, 2021). AI-enabled institutional systems, including predictive analytics, dashboards, and decision-support tools, transform fragmented data into actionable insights that improve institutional responsiveness. As argued by Ouyang et al. (2023) and Sajja et al. (2023), predictive analytics enables early intervention and evidence-based planning, thereby strengthening institutional agility. The present study extends this literature by empirically demonstrating that administrative AI functions as a structural enabler of effective educational and managerial processes. Importantly, instructional AI and administrative AI operate as complementary layers: the former enhances micro-level learning interactions, while the latter strengthens macro-level coordination and governance.

Human Capital as a Strategic Enabler of AI Effectiveness

The significant relationship between personnel capability and AI-driven process effectiveness (H3) highlights the central role of human capital in AI-enabled transformation. This finding supports institutional capability perspectives, which argue that technological

innovation is effective only when supported by adequate organizational competencies (Kuleto et al., 2021; Potjanajaruwit, 2023). Holmes et al. (2019) further emphasize that AI should augment rather than replace educators' professional judgment. The results confirm that digital literacy, openness to innovation, and pedagogical understanding of AI significantly determine implementation success. Accordingly, AI effectiveness in higher education should be conceptualized as a capability-driven outcome rather than a purely technological one.

Process Effectiveness and Enhancement of Student Learning Experience

Hypothesis H4 is supported, indicating that AI-driven process effectiveness significantly enhances student learning experience. This finding aligns with engagement theory and contemporary empirical studies demonstrating that AI-supported learning environments increase motivation, participation, and interaction quality (Chen et al., 2023; Chiu et al., 2024). García-Martínez et al. (2023) similarly report that AI integration contributes positively to academic achievement through improved learning engagement. The present study further positions student learning experience as a key mediating mechanism linking AI-enabled processes to educational outcomes. This suggests that experiential enhancement is a critical pathway through which AI contributes to perceived educational quality.

AI Effectiveness and Institutional Management Performance

The findings confirm that AI-driven process effectiveness positively influences institutional management effectiveness (H5), consistent with theories of digital governance in higher education (Williamson, 2017). AI systems improve decision-making efficiency, transparency, and accountability through real-time data processing and institutional analytics (Baker, 2021). However, the results indicate that managerial improvements primarily reflect organizational optimization rather than direct pedagogical enhancement. This distinction is important, as it suggests that AI operates across multiple institutional layers but does not automatically translate managerial efficiency into teaching quality improvements.

Direct Impact of AI Process Effectiveness on Educational Quality

Hypothesis H6 is supported, demonstrating that AI-driven process effectiveness directly enhances teaching and learning quality. This finding is consistent with personalized learning theories and AI-supported scaffolding frameworks (Luckin et al., 2016). Holmes and Tuomi (2022) also argue that AI contributes to quality improvement when embedded in systematic pedagogical redesign. The results suggest that process effectiveness acts as a key transmission mechanism through which AI adoption translates into institutional-level educational quality. In other words, AI improves quality not through isolated tools but through optimized learning and administrative processes.

Student Learning Experience as a Core Determinant of Educational Quality

The positive effect of student learning experience on teaching and learning quality (H7) confirms the centrality of learner-centered education paradigms. Prior research consistently shows that engagement, satisfaction, and motivation are strong predictors of perceived

educational quality (Chen et al., 2023; Chiu et al., 2024; Bangbon et al., 2023). This finding indicates that educational quality in private universities is fundamentally experiential rather than purely structural or administrative. Compared with managerial pathways, experiential pathways demonstrate stronger explanatory power in determining quality outcomes.

Managerial Improvement and Its Limited Direct Impact on Quality

Contrary to expectations, Hypothesis H8 is not supported, as institutional management effectiveness does not significantly influence teaching and learning quality. These finding challenges assumptions that administrative efficiency automatically leads to improved educational outcomes. Selwyn (2016, 2022) argues that digital transformation may optimize institutional processes without necessarily improving learning depth or pedagogy. Similarly, Ju (2023) notes that AI systems may enhance efficiency but fail to improve academic outcomes when not aligned with instructional design. The present findings reinforce this critique, suggesting that managerial effectiveness alone is insufficient to improve educational quality unless it is translated into pedagogical and experiential transformation.

Conclusion

In conclusion, this study aimed to examine the structural relationships among artificial intelligence (AI) adoption in teaching and learning, AI use in administrative management, personnel capability and readiness, the effectiveness of AI-driven learning and management processes, the enhancement of students' learning experiences, institutional management effectiveness, and the quality of teaching and learning in private universities in Bangkok, Thailand. The results of Structural Equation Modeling (SEM) confirm that AI adoption in both instructional and administrative domains, as well as personnel readiness, positively influence the effectiveness of AI-driven processes. This effectiveness functions as a critical mediating mechanism that transforms technological potential into tangible educational outcomes. The findings further indicate that the effectiveness of AI-driven processes exerts both direct and indirect effects on the quality of teaching and learning, particularly through the enhancement of students' learning experiences, which represents a central dimension of educational quality in private higher education institutions. Although AI-driven effectiveness significantly improves institutional management performance, administrative improvement alone does not directly enhance teaching and learning quality unless it is explicitly connected to the development of meaningful student learning experiences. Theoretically, this study contributes an integrated framework that connects technology adoption theory, organizational capability perspectives, and learner-centered quality models. It highlights AI-driven process effectiveness as a strategic construct linking technological implementation to educational quality outcomes. From policy and practical perspectives, sustainable quality enhancement in the AI era requires systematic pedagogical integration, continuous personnel development, robust data infrastructure, and appropriate governance frameworks. Only through such alignment can AI generate long-term and meaningful improvements in teaching and learning.



Recommendations

1. Institutional Level Private universities should integrate AI into curriculum design, teaching, and assessment rather than using it superficially. Strong data infrastructure and coordinated governance systems are needed to support effective and ethical AI use in education.

2. Faculty Development Universities should strengthen lecturers' digital literacy, AI skills, instructional design capacity, and ethical awareness to ensure effective AI-supported teaching and learning.

3. Policy Level Higher education authorities should develop AI strategies that include digital infrastructure investment, competency standards, and data privacy regulations to support sustainable AI integration.

Future Research Directions

Future studies should examine differences between public and private universities, conduct long-term (longitudinal) studies on AI impact, explore discipline-specific applications, and investigate student experiences and ethical governance practices in AI-driven education.

References

- Akgun, S., & Greenhow, C. (2022). Artificial intelligence in education: Addressing ethical challenges in K–12 settings. *AI and Ethics*, 2(3), 431–440.
- Baker, R. S. (2021). Data-driven decision making in education: Evidence from learning analytics. *Educational Technology Research and Development*, 69(2), 1–20.
- Bangbon, P., Channuwong, S., Amponstira, F., Rungsuk, A. & Snongtaweepon, T. (2023). The influence of transformational leadership on organizational sustainability: A case study of business companies in Bangkok. *Journal of Namibian Studies*, 33, 4077-4095.
- Chen, L., Chen, P., & Lin, Z. (2023). Artificial intelligence in education: A review. *IEEE Access*, 11, 1–15.
- Chen, X., Xie, H., Zou, D., & Hwang, G.-J. (2023). Application and theory gaps during the rise of artificial intelligence in education. *Computers and Education: Artificial Intelligence*, 4, 100125.
- Chen, X., Zou, D., & Xie, H. (2023). Artificial intelligence in education: A review and future research directions. *Educational Technology & Society*. technologies and impacts on learning engagement. *Computers & Education*, 200, 104800. <https://doi.org/10.1007/s10796-022-10291-4>
- Chiu, T. K., Moorhouse, B. L., Chai, C. S., & Ismailov, M. (2024). Teacher support and student motivation to learn with artificial intelligence (AI)-based chatbot. *Interactive Learning Environments*, 32(7), 3240–3256.
- García-Martínez, I., Fernández-Batanero, J. M., Fernández-Cerero, J., & León, S. P. (2023). Analysing the impact of artificial intelligence and computational sciences on student performance: Systematic review and meta-analysis. *Journal of New Approaches in Educational Research*, 12(1), 171–197. <https://doi.org/10.7821/naer.2023.1.1240>
- Holmes, W., & Tuomi, I. (2022). State of the art and practice in AI in education. *European Journal of Education*, 57, 542–570.



- Hooda, M., Rana, C., Dahiya, O., Rizwan, A., & Hossain, M. S. (2022). Artificial intelligence for assessment and feedback to enhance student success in higher education. *Mathematical Problems in Engineering*, 2022, Article 5215722. <https://doi.org/10.1155/2022/5215722>
- Hwang, G. J., Xie, H., Wah, B. W., & Gasevic, D. (2020). Vision, challenges, roles, and research issues of artificial intelligence in education. *Computers & Education: Artificial Intelligence*, 1, 100001.
- Ju, J. (2023). Generative AI in higher education: Opportunities and risks for learning. *Journal of Educational Technology Development and Exchange*, 16(2), 1–12.
- Khlaisang, J., Teo, T., & Huang, F. (2019). Acceptance of a flipped smart application for learning: A study among Thai university students. *Interactive Learning Environments*, 29(5), 772–789.
- Kuleto, V., Ilić, M., Dumangiu, M., Ranković, M., Martins, O. M., Păun, D., & Mihoreanu, L. (2021). Exploring opportunities and challenges of artificial intelligence and machine learning in higher education institutions. *Sustainability*, 13(18), 10424.
- Luckin, R., Holmes, W., Griffiths, M., & Forcier, L. B. (2016). *Intelligence unleashed: An argument for AI in education*. Pearson Education.
- Maghsudi, S., Lan, A., Xu, J., & van der Schaar, M. (2021). Personalized education in the artificial intelligence era: What to expect next. *IEEE Signal Processing Magazine*, 38(3), 37–50.
- Ouyang, F., Wu, M., Zheng, L., Zhang, L., & Jiao, P. (2023). Integration of artificial intelligence performance prediction and learning analytics to improve student learning in online engineering courses. *International Journal of Educational Technology in Higher Education*, 20(1), Article 4.
- Potjanajaruwit, P. (2023). The influence of technology leadership on university lecturers integrating technology in Thailand. *Human Technology*, 19(3), 435–452.
- Qadir, J. (2023). Engineering education in the era of ChatGPT: Opportunities and challenges. *IEEE Transactions on Education*, 66(3), 1–6.
- Sajja, G. S., Mahalakshmi, G. S., & Reddy, A. (2023). Predictive analytics in higher education institutions. *Education and Information Technologies*, 28, 1–19.
- Selwyn, N. (2022). *The digital disconnects: The social causes and consequences of digital education*. Oxford University Press.
- Selwyn, N. (2022). The future of AI and education: Some cautionary notes. *Oxford Review of Education*, 48(1), 1–15.
- Tapalova, O., & Zhiyenbayeva, N. (2022). Artificial intelligence in education: Adaptive learning systems and applications. *Frontiers in Education*, 7, 1–10.
- Williamson, B. (2017). *Big data in education: The digital future of learning, policy and practice*. SAGE Publications.
- Wu, Y. (2023). Integrating generative AI in education: How ChatGPT brings challenges for future learning and teaching. *Journal of Advanced Research in Education*, 2(4), 6–10.
- 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(1), 39.