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Research paper

AI Integration Readiness in Academic Management: Evidence from Thailand

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ABSTRACT

Artificial intelligence (AI) is expanding beyond teaching and learning into academic management, institutional planning, and decision-making. Successful integration, however, depends on institutional readiness, workforce capability, governance, and clearly prioritised development needs. This study examined readiness and priority needs for AI integration in academic management across Thailand's Rajamangala University of Technology (RMUT) system. Quantitative data were collected from 400 purposively recruited academic staff using a validated 64-item questionnaire covering eight domains of academic management. Analyses included descriptive statistics, the modified Priority Needs Index (PNI-modified), independent-samples t-tests, one-way ANOVA, and effect sizes. Qualitative data from 16 key informants were integrated to explain the quantitative findings. Planning and administrative management showed the highest priority need (PNI = 0.187), followed by teaching and learning management (PNI = 0.135) and resource and support management (PNI = 0.134). The most urgent operational needs were AI for work scheduling (PNI = 0.2311) and learning activity design (PNI = 0.2139). Only 17.2% of items fell within urgent categories, supporting phased rather than system-wide implementation. Age differences were statistically significant but small ($\eta^2 = .040$), whereas gender differences were non-significant and negligible ($d = 0.09$). The findings position AI adoption as an institutional development and governance challenge and provide evidence-based guidance for capability building, policy prioritisation, and responsible phased implementation in Thai and comparable Asia-Pacific higher education contexts.

Keywords: artificial intelligence, academic management, institutional readiness, digital transformation, needs assessment

Artificial intelligence (AI) has become a significant force in the transformation of higher education. While early attention focused primarily on teaching and learning applications, recent scholarship shows that AI now extends into broader institutional functions such as planning, coordination, student support, research assistance, quality assurance, and administrative decision-making (Bond et al., 2024; Sposato, 2025; Zawacki-Richter et al., 2019). In this broader sense, AI is no longer simply a classroom tool; it is increasingly becoming part of the infrastructure of academic management and institutional governance.

At the same time, the integration of AI into higher education is rarely a purely technical matter. Research on AI readiness and digital leadership suggests that successful adoption depends on multiple interrelated conditions, including technological infrastructure, data quality, top management support, collaborative culture, organizational

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capability, and strategic leadership (Ali & Khan, 2025; Jameson et al., 2022). In higher education, these issues are especially complex because universities must balance innovation, academic values, professional autonomy, and governance responsibilities while responding to rapid digital change.

These challenges are particularly salient in developing and emerging higher education contexts, where digital transformation often proceeds unevenly across institutional functions. The Rajamangala University of Technology (RMUT) system provides an important case for examining these questions. As a network of technological universities in Thailand with strong applied and professional missions, RMUT operates within a context where academic management, resource coordination, and instructional adaptation are all central to institutional effectiveness. Understanding where the most significant AI-related gaps lie within such a system can help inform policy prioritization and phased implementation.

LITERATURE GROUNDING: AI IN HIGHER EDUCATION AND INSTITUTIONAL READINESS

The literature on AI in higher education has expanded rapidly, but its center of gravity has remained uneven. Much of the earlier work emphasised student-facing applications, intelligent tutoring systems, adaptive learning, learning analytics, and instructional innovation (Ouyang et al., 2022; Popenici & Kerr, 2017; Zawacki-Richter et al., 2019). More recent reviews argue that AI in higher education should be examined in a broader way, incorporating ethical concerns, governance, cross-functional institutional use, and the organizational conditions needed to support meaningful implementation (Bond et al., 2024; Sposato, 2025).

Foundational and contemporary reviews describe AI in education as a continuum extending from intelligent tutoring, adaptive learning, and automated feedback to learning analytics, research support, and institution-level decision support (Luckin et al., 2016; Holmes et al., 2019; Chen et al., 2020; Crompton & Burke, 2023). This wider perspective is important because the institutional value of AI depends not only on the sophistication of individual tools, but also on whether universities can align those tools with educational purposes, professional judgement, and organisational processes. Critical scholarship simultaneously cautions that poorly governed adoption may intensify surveillance, inequity, academic-integrity risks, and dependence on opaque systems (Prinsloo, 2020; Selwyn, 2022; Cotton et al., 2024).

Recent evidence from Thailand also suggests that AI adoption in higher education is advancing rapidly but unevenly across contexts and user groups. At Chulalongkorn University, for example, institutional efforts to integrate generative AI into teaching and learning were already formally recognised in the 2023 academic year, yet student responses revealed a more complex pattern of cautious acceptance, perceived usefulness, and concern about appropriate use in academic and professional writing contexts. These findings indicate that AI integration in Thai higher education is not simply a matter of technological availability, but also of guidance, trust, and contextual fit (Tantivejakul et al., 2024).

Other Thai higher education studies point to similar patterns. Research on English instructors in Thai universities found that generative AI was seen as potentially transformative for both routine and higher-level academic work, but also revealed substantial gaps in professional development, curriculum design, ethics, and institutional guidance. At the student level, a large multi-university study of 911 Thai higher education students found that generative-AI adoption was still at a relatively early stage and was shaped by perceived usefulness, ease of use, and broader concerns about academic integrity and equitable access. Together, these studies suggest that the Thai context is characterised by growing interest in AI alongside continuing uncertainty about capability development, ethical use, and institution-level support (Kohnke & Ulla, 2024; Kanont et al., 2024).

The policy environment reinforces the importance of this institution-level perspective. Thailand's National AI Strategy and Action Plan (2022–2027) identifies human-capacity development, ethical and regulatory readiness, infrastructure, and public-sector adoption as mutually dependent priorities (AI Thailand, 2022). At the regional level, the ASEAN Guide on AI Governance and Ethics similarly emphasises accountability, transparency, fairness, data governance, security, and human oversight (ASEAN Secretariat, 2024). For Thai universities, AI readiness therefore involves translating national and regional ambitions into institution-specific governance, capability-building, and implementation arrangements.

This broader institutional perspective is important because university transformation depends not only on pedagogical innovation, but also on the organizational systems that sustain planning, coordination, quality improvement, and operational management. Studies of digital leadership and AI readiness increasingly emphasize that technology adoption succeeds when institutions possess coherent strategy, leadership support, collaborative culture, implementation capability, and high-quality data environments (Ali & Khan, 2025; Jameson et al., 2022). Where such conditions are weak, AI adoption may remain fragmented, experimental, or uneven across institutional domains.

Organisational-readiness theory provides a complementary explanation of why institutions with access to similar technologies may implement them differently. Weiner (2009) conceptualises readiness for change as shared

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commitment and collective confidence in the ability to implement change. AI-specific research further identifies strategic alignment, resources, knowledge, culture, data, and governance as interdependent readiness factors (Jöhnk et al., 2021). These ideas are consistent with diffusion, technology-adoption, and technology–organisation–environment perspectives, which show that perceived value, organisational capability, leadership support, and external conditions jointly shape adoption (Rogers, 2003; Tornatzky & Fleischer, 1990; Venkatesh et al., 2003). Accordingly, the present study treats readiness as a multi-level institutional condition rather than an individual attitude toward a single technology.

Responsible-AI scholarship adds a normative dimension to readiness. UNESCO guidance calls for human-centred implementation, protection of privacy and agency, institutional validation of AI systems, and sustained development of AI competencies (Miao & Holmes, 2023; Miao & Cukurova, 2024). European and international frameworks likewise stress transparency, fairness, accountability, security, and meaningful human control (European Commission, 2022; Nguyen et al., 2023). These principles are especially relevant to academic management because decisions about scheduling, budgeting, student support, quality assurance, and performance monitoring can affect rights, opportunities, and institutional trust. Data governance, AI literacy, and clear lines of accountability should therefore be understood as core readiness conditions, not optional safeguards added after deployment.

A further implication of this literature is that AI-related readiness should not be assumed to be uniform across university functions. Administrative, teaching, research, and support systems may develop at different speeds, creating uneven readiness across the institution. This makes needs assessment especially valuable as a policy-oriented tool because it allows institutions to identify the largest gaps between present conditions and desired conditions, and to sequence development efforts accordingly.

RESEARCH GAP AND STUDY PURPOSE

Despite the growing literature on AI in higher education, comparatively limited attention has been paid to AI integration in academic management and to the organisational conditions required to support it, particularly within technological university systems in developing and emerging contexts. Existing studies predominantly examine teaching, learning, student acceptance, or isolated tools; fewer studies identify cross-functional readiness gaps across planning, curriculum, quality assurance, student development, resource management, academic service, and research. Important questions therefore remain regarding where the largest current–desired gaps lie, which functions require the most urgent support, and how priority patterns should inform governance, leadership, workforce development, and phased implementation.

The RMUT context provides a particularly relevant setting for examining these issues because the data indicate a distinctive institutional readiness pattern. The respondents were highly qualified and experienced academic personnel: 97.5% held graduate degrees and 65.0% had more than 10 years of work experience. At the same time, their experience with AI was relatively recent, with 73.75% reporting first use in the previous academic year and a further 25.0% beginning in the current academic year. This pattern reflects a form of institutional readiness that may be described as a "domain expert, technology novice" condition, in which the central challenge lies not in a lack of professional maturity, but in the gap between established expertise and emerging digital capability.

Against this background, the present study examined institutional readiness and priority needs for AI integration in academic management within the RMUT system in Thailand. Specifically, it investigated current and desired conditions across key domains of academic management, identified priority needs using the modified Priority Needs Index (PNI-modified), and considered the implications of these findings for institutional leadership, capability development, and phased implementation.

METHODS

Research design

This article draws on the needs-assessment phase of a larger mixed-methods and research-and-development study on AI use in higher education management. The broader project included four objectives: identifying institutional needs, developing a promotion model, implementing the model, and evaluating its effectiveness. The present article focuses exclusively on the first objective in order to produce a stand-alone empirical contribution on institutional readiness and priority needs.

The quantitative component used a needs-assessment approach based on the modified Priority Needs Index (PNI-modified), which compares current conditions with desired conditions in order to identify development priorities. To deepen interpretation, the study also integrated qualitative findings from interviews with key informants.

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Participants and context

The target population comprised permanent academic staff across all nine institutions in the RMUT system whose duties involved one or more academic-management functions, including teaching and learning, research, academic service, quality assurance, curriculum development, student development, and management of resources and support systems. The study frame covered RMUT Bangkok, RMUT Eastern, RMUT Thanyaburi, RMUT Phra Nakhon, RMUT Rattanakosin, RMUT Lanna, RMUT Srivijaya, RMUT Suvarnabhumi, and RMUT Isan. An online questionnaire invitation was disseminated through institutional academic networks, and participation was voluntary. The final analytic sample comprised 400 complete responses. Purposive eligibility criteria required respondents to (a) hold at least a bachelor's degree, (b) perform academic or academic-management duties, and (c) have direct professional experience using AI tools. Because recruitment was purposive and institution-level quotas were not imposed, the sample should be interpreted as a cross-system expert-user sample rather than a proportionally representative sample of each RMUT institution.

The respondent profile was as follows: 55.0% were male and 45.0% female; 50.0% were aged 41–50, 26.25% were aged 31–40, 22.50% were over 50, and 1.25% were in another or unspecified age category; 50.0% held a master's degree and 47.5% a doctoral degree; 65.0% had more than 10 years of professional experience; 73.75% reported first using AI in the previous academic year, and 25.0% began in the current academic year. Respondents were academic staff whose roles intersected with the eight domains assessed by the instrument rather than members of a single administrative unit. This profile reflects a workforce with substantial domain expertise but relatively recent engagement with AI tools.

The qualitative component involved 16 key informants selected through purposive and snowball sampling to represent four complementary perspectives: (a) lecturers with documented experience of AI use, (b) educational technology and AI specialists, (c) senior administrators responsible for institutional implementation, and (d) experts in educational administration and institutional governance. Selection sought variation in operational, managerial, technical, and policy experience. Interviews continued until the major categories required to interpret the quantitative priority patterns were adequately represented.

Instrument and variables

The quantitative instrument assessed current and desired conditions of AI integration using paired five-point Likert ratings for each item (current condition: "What is"; desired condition: "What should be"). Item development began with a review of academic-management functions, AI-in-higher-education literature, and the operational responsibilities of RMUT academic staff. An initial pool of 80 items was constructed across eight domains, with 10 draft items per domain: (1) planning and administrative management, (2) teaching and learning management, (3) resource and support management, (4) curriculum development, (5) educational quality assurance, (6) student development, (7) academic service, and (8) research and development. Examples include AI-supported work scheduling, educational trend forecasting, budget planning, risk analysis, learning-activity design, classroom and laboratory management, research retrieval, and research-data analysis.

Content validity was established through a panel of five experts in educational administration and educational technology. The experts evaluated the relevance, clarity, and domain alignment of each draft item using the Index of Item–Objective Congruence (IOC). Sixty-four items with IOC values of at least 0.80 were retained for the final instrument; lower-scoring or overlapping items were revised or removed. A pilot study with 30 respondents who were not included in the main sample was used to check item clarity and rating instructions. Internal consistency was high: Cronbach's alpha was 0.93 for the full instrument and ranged from 0.87 to 0.95 across domain subscales. Analyses reported in this article used the 400 complete questionnaires; no item-level values were imputed.

The qualitative interview protocol was developed in parallel with the questionnaire and addressed three areas: enabling conditions for AI integration, barriers to implementation, and recommendations for institutional action. Interviews were conducted individually, audio-recorded with consent, and transcribed verbatim in Thai. A structured content-analysis process was then used: transcripts were read repeatedly; meaning units were assigned initial codes; related codes were grouped into categories; and categories were consolidated into themes that could explain, extend, or qualify the quantitative findings. Coding and interpretation were completed in Thai before selected quotations were translated into English and checked against the original transcripts to preserve meaning.

Data analysis

Quantitative analysis used descriptive statistics and the modified Priority Needs Index, calculated as PNI-modified = (Desired Mean − Current Mean) / Current Mean. The index expresses the relative gap between desired and current conditions; higher values therefore indicate larger development needs. For policy-oriented interpretation, item values were classified using the study's predefined categories: very high or critical (> 0.20), high (0.15–0.20), moderate (0.10–< 0.15), and low (< 0.10). These thresholds were used to support sequencing,

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while rankings were interpreted as relative implementation priorities rather than as proof of causal importance or absolute institutional unpreparedness.

Inferential analyses included an independent-samples t-test for gender and one-way ANOVA for age and work-experience groups, with $\alpha = .05$. The analysis considered independence of observations, approximate group-level normality, and variance comparability before interpretation. Scheffé's procedure was used for age-group post-hoc comparisons. Effect sizes were reported as Cohen's d for the t-test and eta squared (η^2) for ANOVA; values were interpreted cautiously alongside p-values (Cohen, 1988). The work-experience result at $p = .051$ was treated as non-significant because it did not meet the prespecified .05 threshold. Qualitative findings were integrated with quantitative results through a joint display that identified convergence, complementarity, and implementation implications.

Ethical considerations

This study complied with the ethical standards of Rajamangala University of Technology Thanyaburi (RMUTT) and national research guidelines, and was exempt from formal ethics review under RMUTT's Exemption Guidelines (Resolution No. 2/2021) and the NRCT Guidelines for Human Research in Behavioural Sciences, Social Sciences, and Humanities (March 18, 2021). Exemption criteria were met: data were collected solely through anonymous surveys and interviews, with no physical intervention or personally identifiable information. All participants were adults who participated voluntarily. The study adhered to the principles of the Declaration of Helsinki (2013 revision).

RESULTS

Respondent profile and institutional readiness context

Table 1 presents the demographic profile of the respondents. Overall, the sample reflects a highly qualified and experienced academic workforce. Nearly all respondents held graduate degrees, and most had substantial work experience in higher education. At the same time, AI use among respondents was relatively recent, with most participants reporting that they had only begun using AI in the previous academic year or the current academic year. This pattern suggests a form of institutional readiness in which professional expertise is already well established, but AI-related capability is still emerging. In other words, the central challenge does not appear to be a lack of academic maturity, but rather the need to translate existing professional capacity into effective AI-supported practice.

Table 1

Demographic Characteristics of Respondents (N = 400)

Variable	Category	n	%
Gender	Male	220	55.0
	Female	180	45.0
Age	31-40 years	105	26.25
	41-50 years	200	50.0
	Over 50 years	90	22.50
	Other/unspecified	5	1.25
Education	Master's degree	200	50.0
	Doctoral degree	190	47.5
	Other	10	2.5
Work experience	6-10 years	80	20.0
	More than 10 years	260	65.0
	Other/under 6 years	60	15.0
AI experience	Began in previous academic year	295	73.75
	Began in current academic year	100	25.0
	Other	5	1.25

Domain-level priority needs for AI integration

Table 2 shows the priority needs for AI integration across the eight domains of academic management. The highest institutional priority need was planning and administrative management (PNI = 0.187), followed by

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teaching and learning management (PNI = 0.135) and resource and support management (PNI = 0.134). Moderate priority needs were observed in curriculum development, educational quality assurance, and student development, while academic service and research and development showed relatively lower PNI values. Even so, research and development recorded the highest desirable-condition mean, indicating that respondents placed strong importance on this domain while also perceiving it as comparatively more developed at present.

Overall, the domain-level pattern suggests uneven institutional development. AI-related gaps were largest in administrative and instructional functions, whereas research-related functions appeared relatively more mature. This finding implies that AI integration in higher education may be progressing more rapidly in specialist academic work than in the organizational systems that support routine academic management.

Table 2

Domain-level priority needs for AI integration in academic management

Domain	Desired Mean	Current Mean	PNI-modified	Rank
Planning and administrative management	4.06	3.42	0.187	1
Teaching and learning management	4.05	3.56	0.135	2
Resource and support management	3.83	3.38	0.134	3
Curriculum development	3.94	3.53	0.115	4
Educational quality assurance	3.85	3.45	0.114	5
Student development	3.82	3.44	0.111	6
Academic service	3.95	3.58	0.102	7
Research and development	4.31	3.93	0.097	8

Note. PNI-modified = (Desired Mean − Current Mean) / Current Mean. Higher values indicate larger relative gaps and thus higher development priority. Rankings indicate comparative sequencing priorities within this dataset and should not be interpreted as causal effects.

High-priority operational needs

At the operational level, Table 3 identifies the five most urgent priorities for AI integration. The highest-ranked item was AI for work scheduling (PNI = 0.2311), followed by AI for learning activity design (PNI = 0.2139), AI for educational trend forecasting (PNI = 0.1980), AI for budget planning (PNI = 0.1868), and AI for risk analysis (PNI = 0.1835). These findings indicate that the most immediate needs are concentrated in two intersecting areas: operational coordination and instructional improvement.

The prominence of work scheduling, educational forecasting, budget planning, and risk analysis suggests that respondents saw AI as especially valuable for decision support and the coordination of institutional processes. At the same time, the high ranking of learning activity design indicates that pedagogical adaptation remains a major expectation of AI use. Taken together, these patterns suggest that AI integration should be understood as a cross-functional issue linking administration and teaching rather than as a narrowly bounded technological intervention.

Table 3

Top five operational priority needs

Rank	Item	Desired Mean	Current Mean	PNI-modified
1	AI for work scheduling	4.23	3.43	0.2311
2	AI for learning activity design	4.22	3.48	0.2139
3	AI for educational trend forecasting	4.29	3.58	0.1980
4	AI for budget planning	4.06	3.42	0.1868
5	AI for risk analysis	4.15	3.51	0.1835

Note. Items are ranked by PNI-modified value. Only the five highest-ranked operational items are shown.

Selected item-level needs by domain

To provide a more detailed view of the domain-level findings, Table 4 presents selected item-level needs across planning and administrative management, teaching and learning management, resource and support management, and research and development. Within planning and administrative management, strategic planning data analysis and human resource management showed notable gaps. Within teaching and learning management, lesson planning and teaching media creation were prominent, while resource and support management showed strong needs in laboratory management, classroom management, and safety management. In research and development, the main needs were concentrated in research retrieval, research data analysis, and research trend analysis.

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These item-level patterns further confirm that AI-related needs are distributed across both managerial and academic functions. They also suggest that universities may obtain the greatest short-term benefit by targeting use cases that directly improve workflow efficiency, instructional preparation, and resource coordination.

Table 4

Selected item-level needs by domain

Domain	Item	Desired Mean	Current Mean	PNI-modified
Planning and administrative management	Strategic planning data analysis	4.04	3.46	0.1667
	Human resource management	3.85	3.33	0.1565
Teaching and learning management	Lesson planning	4.26	3.61	0.1806
	Teaching media creation	4.49	3.91	0.1480
	Test construction	4.12	3.61	0.1442
	Online classroom management	4.15	3.66	0.1351
	Individual learner analysis	3.90	3.44	0.1332
Resource and support management	Laboratory management	3.99	3.37	0.1826
	Classroom management	3.97	3.45	0.1525
	Safety management	3.80	3.36	0.1305
	Resource utilization efficiency	3.91	3.49	0.1196
	Environmental management	3.76	3.36	0.1192
	Equipment management	3.73	3.34	0.1178
	Utility systems management	3.68	3.35	0.1008
Research and development	Research retrieval	4.59	4.07	0.1283
	Research data analysis	4.34	3.90	0.1133
	Research trend analysis	4.25	3.86	0.1024

Note. Selected items only. Full item list available from the corresponding author upon request.

Distribution of urgency and implications for sequencing

Applying the predefined urgency categories, 2 items (3.1%) were classified as very high or critical (PNI > 0.20), 9 items (14.1%) as high (0.15–0.20), 37 items (57.8%) as moderate (0.10–< 0.15), and 16 items (25.0%) as low (PNI < 0.10). Thus, 17.2% of the 64 items fell into urgent categories, whereas 82.8% were suitable for progressive development. The categories provide a transparent decision rule for sequencing; they do not imply that low-ranked domains are unimportant.

This distribution supports a phased implementation strategy rather than immediate large-scale reform. The findings suggest that institutions may benefit most from addressing a limited number of high-impact priorities first, particularly those likely to generate spillover benefits across multiple functions, such as scheduling, instructional design, planning, and risk analysis. In practical terms, this pattern provides a basis for staged institutional planning, enabling universities to address the most urgent gaps before extending AI integration to lower-priority areas.

Group differences in priority needs

Gender differences were not statistically significant (**Table 5**). Male respondents reported a mean PNI of 0.123 (SD = 0.045), compared with 0.119 (SD = 0.042) for female respondents, $t(398) = 0.835$, $p = .404$, Cohen's d = 0.09, indicating a negligible effect. Age differences were statistically significant, $F(3, 396) = 5.581$, $p = .001$, $\eta^2 = .040$, representing a small effect. Scheffé post-hoc comparisons indicated that respondents aged 41–50 years reported higher needs than those aged 31–40 years and those over 50 years. Work experience did not reach statistical significance, $F(3, 396) = 2.614$, $p = .051$, $\eta^2 = .020$. Although respondents with more than 10 years of experience had the highest reported mean, the $p = .051$ result was interpreted as non-significant rather than as evidence of a difference.

The demographic findings should therefore be interpreted in terms of magnitude as well as statistical significance. The small age effect suggests that mid-career personnel may be particularly sensitive to institutional gaps because operational responsibility, academic leadership, and implementation demands often intersect in this career stage. However, demographic characteristics explain only a limited proportion of variation, and the findings do not justify narrowly targeting AI-development initiatives by age or gender.

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Table 5

Inferential analysis by demographic variables

Variable	Test	Group results	Effect size	Interpretation
Gender	$t(398) = 0.835$, $p = .404$	Male: $M = 0.123$, $SD = 0.045$; Female: $M = 0.119$, $SD = 0.042$	$d = 0.09$ (negligible)	No statistically significant difference
Age	$F(3, 396) = 5.581$, $p = .001$	41–50: $M = 0.135$, $SD = 0.048$; 31–40: $M = 0.112$, $SD = 0.039$; >50: $M = 0.110$, $SD = 0.035$	$\eta^2 = .040$ (small)	Significant; Scheffé: 41–50 higher than 31–40 and >50
Work experience	$F(3, 396) = 2.614$, $p = .051$	>10 years: $M = 0.125$ (highest reported group mean)	$\eta^2 = .020$ (small)	Not significant at $\alpha = .05$; interpreted cautiously

Note. PNI-modified values were the dependent variable. Cohen's d was computed for the two-group comparison; η^2 was calculated from the ANOVA sums of squares. Effect sizes are reported to distinguish statistical significance from practical magnitude. The work-experience result ($p = .051$) did not meet $\alpha = .05$ and is not interpreted as statistically significant.

Qualitative enrichment of the quantitative findings

The qualitative findings clarified why the largest quantitative gaps were concentrated in planning and administrative management, teaching and learning management, and resource and support management. Analysis of the 16 interviews produced themes concerning enabling conditions, implementation barriers, cross-functional uses, and responsible human oversight. The themes were compared directly with PNI results rather than reported as a separate parallel strand (**Table 6**).

Table 6

Joint display integrating priority-needs results and qualitative evidence

Quantitative priority	Qualitative evidence	Integrated interpretation	Implementation implication
Planning and administrative management: PNI = 0.187; scheduling PNI = 0.2311	Leadership, data quality, change management, and governance were repeatedly emphasised. "If data are low quality or not ready, AI cannot operate effectively" (Interviewee 8).	The largest gap reflects organisational and data-readiness constraints, not merely lack of tools.	Establish governance ownership and data standards; begin with bounded scheduling/planning pilots.
Teaching and learning management: PNI = 0.135; learning-activity design PNI = 0.2139	Staff development was a dominant need. "Continuous staff training is needed to keep pace with technological change" (Interviewee 6).	Instructional demand depends on AI literacy, pedagogical judgement, and ongoing professional learning.	Provide role-specific AI-literacy and design training with human review of outputs.
Resource and support management: PNI = 0.134; laboratory management PNI = 0.1826	Barriers included expert shortages (14/16), budget limitations (11/16), data readiness (10/16), and security concerns (8/16).	Resource applications require technical capacity, interoperable data, and realistic financing.	Use pilot projects, shared services, security controls, and staged investment.
Only 17.2% of items were urgent	Resistance to change was reported by 12/16 informants; interviewees recommended communicating tangible benefits.	A small urgent cluster supports sequencing rather than institution-wide simultaneous deployment.	Prioritise high-impact cases, evaluate outcomes, and expand only after readiness improves.
Cross-domain need for human oversight	"AI is a tool for improving efficiency, but important decisions still require human wisdom" (Interviewee 1).	Responsible adoption requires retained human accountability across all domains.	Define approval rights, audit trails, ethical review, and appeal mechanisms before scale-up.

Note. The joint display links quantitative gaps with qualitative explanations and action implications. Quotations were translated from Thai after thematic coding and checked against the original transcripts.

First, informants consistently described staff capability, data infrastructure, leadership, change management, and governance as enabling conditions. One informant stated, "Continuous staff training is needed to keep pace with technological change" (Interviewee 6), while another explained, "If data are low quality or not ready, AI cannot operate effectively" (Interviewee 8). Leadership was understood as active commitment rather than symbolic policy: "Administrators must understand and be committed to using AI; policy alone is not enough—they must act" (Interviewee 1). These accounts help explain why administrative and instructional priorities cannot be addressed through software acquisition alone.

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Second, the interviews identified a consistent barrier pattern: lack of expert personnel was mentioned by 14 informants, resistance to change by 12, budget limitations by 11, inadequate data readiness by 10, and security concerns by 8. These constraints explain why high perceived usefulness may coexist with limited implementation capacity. The proposed responses included systematic training, communication of demonstrable benefits, pilot projects, open-source options where appropriate, data-governance improvement, and stronger security controls.
Third, informants reinforced the cross-functional nature of AI demand. Teaching and learning received the highest frequency of discussion, followed by management and administration, research and development, and quality assurance. At the same time, participants emphasised that AI should support rather than replace professional judgement: "AI is a tool for improving efficiency, but important decisions still require human wisdom" (Interviewee 1). This evidence converges with the quantitative pattern and supports a governance model in which human accountability is retained throughout planning, deployment, review, and evaluation.

DISCUSSION

The findings suggest that AI integration in higher education should be understood primarily as an issue of institutional development rather than a narrowly technical innovation problem. Across the quantitative and qualitative evidence, four interrelated themes emerged: institutional readiness, uneven development across university functions, workforce reskilling, and phased implementation. Together, these themes provide a clearer explanation of why some domains in the RMUT system appear more urgent than others and how universities might respond strategically.

Institutional readiness as the foundation of AI integration

The first and most fundamental finding concerns institutional readiness. The highest-priority needs were concentrated in planning and administrative management, followed by teaching and learning management and resource and support systems. This pattern indicates that the strongest demand lies in the organisational core of the university, particularly in functions dependent on coordination, forecasting, scheduling, and resource allocation. The qualitative findings reinforce this interpretation by identifying staff development, data infrastructure, leadership commitment, change management, and governance as necessary enabling conditions. The result aligns with Weiner's (2009) view of readiness as collective commitment and change efficacy and with AI-readiness research that identifies strategy, resources, knowledge, culture, data, and governance as interdependent factors (Jöhnk et al., 2021). Tool availability alone is therefore insufficient; institutional readiness requires coordinated people, processes, data, authority, and accountability.

Uneven development across university functions

The second major theme is uneven development across institutional domains. Research and development recorded the highest desired mean but the lowest PNI, suggesting that respondents regarded it as highly important while also perceiving it as relatively more advanced than other domains. By contrast, administration and teaching showed larger gaps, indicating that AI adoption has not progressed uniformly across university functions. This pattern is consistent with broader reviews of AI in higher education, which show that some areas—especially adaptive learning, student-facing technologies, and certain research uses—have advanced more rapidly than organizational and context-sensitive forms of implementation (Bond et al., 2024; Zawacki-Richter et al., 2019). The present findings extend this literature by showing that such unevenness is not only evident in published research, but also reflected in institutional need patterns within a Thai technological university system.

The item-level results sharpen this interpretation. The prominence of work scheduling, educational forecasting, budget planning, and risk analysis points to strong demand in administrative coordination and decision support, while the equally strong emphasis on learning activity design points to parallel demand for pedagogical adaptation. Taken together, these findings suggest that AI integration should be framed as a cross-functional institutional issue linking administration and pedagogy, rather than as an isolated innovation in one area alone.

Workforce reskilling as the key human-capital challenge

The third theme concerns workforce reskilling. One of the most striking features of the respondent profile is the combination of high professional maturity and relatively recent AI experience. The respondents were highly qualified and experienced academic personnel, yet most had only recently begun to use AI. This "domain expert, technology novice" pattern suggests that the principal challenge is not a lack of general competence, but the need to convert existing professional expertise into AI-supported practice. Universities may therefore already possess substantial human capital, but still require deliberate reskilling strategies to make AI adoption effective in real academic and administrative settings.

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This interpretation is reinforced by the qualitative findings, in which staff development was among the most frequently cited enabling conditions. It also aligns with research emphasising organisational capability, collaborative culture, data quality, and top-management support as preconditions for AI implementation (Ali & Khan, 2025; Jöhnk et al., 2021). UNESCO's AI Competency Framework for Teachers further indicates that effective capacity development should combine a human-centred mindset, ethics, AI foundations, pedagogy, and professional learning rather than focus only on tool operation (Miao & Cukurova, 2024). For RMUT institutions, reskilling should therefore be role-specific: administrators require data-informed decision and governance capabilities, lecturers require pedagogical design and assessment capabilities, and technical/support personnel require data, security, and system-integration capabilities.

The significant age effect adds an important practical dimension to the findings. Respondents aged 41–50 reported significantly higher levels of need than both the 31–40 group and those over 50, as confirmed by Scheffé's post-hoc test. This suggests that mid-career professionals may occupy a particularly important position in institutional AI transformation. Individuals in this age group are often situated at the intersection of academic work, managerial responsibility, and policy implementation, which may make them more sensitive to institutional inefficiencies and more aware of the potential value of AI for improving academic management. By contrast, the absence of significant gender differences suggests that AI-related institutional needs are broadly distributed and should therefore be addressed through system-wide strategies rather than demographic targeting.

Phased implementation as the most defensible strategic response

The fourth major theme is phased implementation. Because only 17.2% of all items fell into urgent categories, the findings do not support an immediate, large-scale institutional overhaul. Instead, they point to the value of a staged strategy in which universities begin with a limited number of high-impact priorities and then expand implementation as institutional capacity matures. In the present study, these priorities include scheduling, instructional design, educational forecasting, budget planning, and risk analysis.

From a policy perspective, phased implementation is one of the study's most important implications. Universities constrained by budget, expertise, infrastructure, and data readiness are unlikely to benefit from attempting to transform all functions simultaneously. A defensible approach is to begin with urgent, bounded use cases that offer cross-functional spillovers—such as scheduling, learning-activity design, forecasting, budget planning, and risk analysis—while establishing evaluation criteria and governance safeguards before expansion. This sequencing is consistent with digital-leadership scholarship that emphasises maturity-building and strategic coherence (Jameson et al., 2022). It also operationalises Thailand's national priorities for human-capacity development, ethical readiness, infrastructure, and responsible public-sector AI adoption (AI Thailand, 2022) and the ASEAN principles of accountability, transparency, fairness, security, and human oversight (ASEAN Secretariat, 2024).

Implications for higher education leadership

Taken together, institutional readiness, uneven development, workforce reskilling, and phased implementation indicate that AI integration should be conceptualised as institutional transformation rather than the acquisition of discrete technical tools. Responsible implementation requires data governance, role clarity, human oversight, monitoring, and mechanisms for correcting harmful or inaccurate outputs. This interpretation accords with human-centred and responsible-AI guidance that prioritises privacy, agency, fairness, transparency, and institutional validation (European Commission, 2022; Miao & Holmes, 2023; Nguyen et al., 2023). The RMUT case adds context-sensitive evidence showing how these principles intersect with practical priority gaps in a multi-institution technological university system.

Limitations

Several limitations should be acknowledged. First, purposive recruitment required respondents to have professional experience using AI. This criterion ensured informed judgements about current and desired conditions, but it may overrepresent early adopters and personnel already interested in AI. The findings should therefore not be generalised to all RMUT staff or interpreted as population prevalence estimates.

Second, although the study frame covered all nine RMUT institutions, institution-level quotas were not imposed and the article does not estimate institution-specific readiness. Differences among campuses, institutional sizes, disciplines, infrastructure, and local governance arrangements may therefore be obscured by the system-level analysis. Future work should use stratified sampling and report institutional distributions and multilevel comparisons.

Third, the cross-sectional, self-reported design captures perceptions at one point in a rapidly changing technological environment. Common-method and social-desirability biases are possible, and PNI rankings

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measure perceived relative gaps rather than verified implementation performance or causal effects. Longitudinal studies should combine survey data with institutional records, system-use data, governance audits, and observed outcomes.

Fourth, the qualitative sample (n = 16) was purposively selected to enrich interpretation and cannot represent the full diversity of the RMUT system. The translated quotations illustrate themes but do not substitute for a full bilingual qualitative report. Finally, the small "other/unspecified" demographic groups and the absence of retained formal diagnostic outputs for every inferential assumption limit fine-grained subgroup interpretation; consequently, p-values were interpreted jointly with effect sizes and the p = .051 work-experience result was treated as non-significant.

CONCLUSION

This study examined institutional readiness and priority needs for AI integration in academic management within the Rajamangala University of Technology (RMUT) system in Thailand. The findings demonstrate that AI-related needs are not distributed evenly across university functions. The largest gaps were identified in planning and administrative management, teaching and learning management, and resource and support management, whereas research and development appeared comparatively more mature. At the operational level, the most urgent priorities were work scheduling and learning activity design, indicating that both administrative coordination and pedagogical adaptation constitute key fronts of AI-related institutional transformation.

The study also identified a distinctive readiness pattern among respondents. Although participants were highly qualified and professionally experienced, most were still relatively new to AI use. This suggests that the central challenge lies not in a lack of academic capability, but in the need to translate existing professional expertise into AI-supported practice through targeted institutional reskilling. The qualitative findings reinforce this interpretation by showing that successful transformation depends not only on technological tools, but also on staff development, strategic planning, data readiness, leadership commitment, change management, and ethical governance.

Taken together, the findings support a phased implementation strategy rather than immediate system-wide reform. Universities may benefit from prioritising a small number of high-impact use cases, developing role-specific AI literacy, improving data governance, and establishing human-oversight and evaluation mechanisms before scaling. In this respect, AI integration in higher education should be approached as a matter of institutional readiness, responsible governance, leadership, and strategic sequencing rather than technology acquisition alone.

The study contributes to current discussions on digital transformation in higher education by providing context-sensitive evidence from a Thai technological university system. Future research may build on these findings by comparing readiness patterns across institutional types, examining implementation outcomes longitudinally, and linking identified needs to specific intervention models and policy designs.

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Ethical statement

This study was exempt from formal ethics review under the Exemption Guidelines of Rajamangala University of Technology Thanyaburi (RMUTT) (Resolution No. 2/2021) and the NRCT Guidelines for Human Research in Behavioural Sciences, Social Sciences, and Humanities (March 18, 2021), as data were collected solely through an anonymous online questionnaire and key-informant interviews involving voluntary adult participants in non-sensitive educational contexts, with no physical intervention. Participants were informed of the study's objectives, data handling procedures, and their right to withdraw at any time without consequence. Participation in the questionnaire was voluntary and anonymous, and informed consent was obtained from all interview participants before the interviews were audio-recorded. All data were anonymized, and participants are represented in the findings without personal or institutional identifiers. The study adhered to the principles of the Declaration of Helsinki (2013 revision).

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Competing interests

The authors declare no competing interests.

Author contributions

Svangnabha Tuanpusa, Thongdee Sritragarn, Yudthavee Kaewthongyai, and Pongpith Tuenpusa contributed to the conceptualization, methodology, data collection, formal analysis, interpretation, writing of the original draft, and review and editing of the final manuscript.

Data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

AI disclosure

AI-based tools were used solely for language editing and stylistic refinement under full author supervision. The authors verified the accuracy of all statements, references, and interpretations and take full responsibility for the final content.

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REFERENCES

AI Thailand. (2022). *Thailand national AI strategy and action plan (2022–2027).* https://ai.in.th/about-ai-thailand/

Ali, W., & Khan, A. Z. (2025). Factors influencing readiness for artificial intelligence: A systematic literature review. *Data Science and Management, 8*(2), 224–236. https://doi.org/10.1016/j.dsm.2024.09.005

ASEAN Secretariat. (2024). *ASEAN guide on AI governance and ethics.* https://asean.org/book/asean-guide-on-ai-governance-and-ethics/

Bond, M., Khosravi, H., De Laat, M., Bergdahl, N., Negrea, V., Oxley, E., Pham, P., Chong, S. W., & Siemens, G. (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*(1), Article 4. https://doi.org/10.1186/s41239-023-00436-z

Chen, L., Chen, P., & Lin, Z. (2020). Artificial intelligence in education: A review. *IEEE Access, 8*, 75264–75278. https://doi.org/10.1109/ACCESS.2020.2988510

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Lawrence Erlbaum Associates.

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Cotton, D. R. E., Cotton, P. A., & Shipway, J. R. (2024). Chatting and cheating: Ensuring academic integrity in the era of ChatGPT. *Innovations in Education and Teaching International, 61*(2), 228–239. https://doi.org/10.1080/14703297.2023.2190148

Crompton, H., & Burke, D. (2023). Artificial intelligence in higher education: The state of the field. *International Journal of Educational Technology in Higher Education, 20*(1), Article 22. https://doi.org/10.1186/s41239-023-00392-8

European Commission. (2022). *Ethical guidelines on the use of artificial intelligence (AI) and data in teaching and learning for educators*. Publications Office of the European Union. https://doi.org/10.2766/153756

Holmes, W., Bialik, M., & Fadel, C. (2019). *Artificial intelligence in education: Promises and implications for teaching and learning*. Center for Curriculum Redesign. https://curriculumredesign.org/our-work/artificial-intelligence-in-education/

Jameson, J., Rumyantseva, N., Cai, M., Markowski, M., Essex, R., & McNay, I. (2022). A systematic review and framework for digital leadership research maturity in higher education. *Computers and Education Open, 3*, Article 100115. https://doi.org/10.1016/j.caeo.2022.100115

Jöhnk, J., Weißert, M., & Wyrtki, K. (2021). Ready or not, AI comes—An interview study of organizational AI readiness factors. *Business & Information Systems Engineering, 63*(1), 5–20. https://doi.org/10.1007/s12599-020-00676-7

Kanont, K., Pingmuang, P., Simasathien, T., Wisnuwong, S., Wiwatsiripong, B., Poonpirome, K., Songkram, N., & Khlaisang, J. (2024). Generative-AI, a learning assistant? Factors influencing higher-ed students' technology acceptance. *Electronic Journal of e-Learning, 22*(6), 18–33. https://doi.org/10.34190/ejel.22.6.3196

Kohnke, L., & Ulla, M. B. (2024). Embracing generative artificial intelligence: The perspectives of English instructors in Thai higher education institutions. *Knowledge Management & E-Learning, 16*(4), 653–670. https://doi.org/10.34105/j.kmel.2024.16.030

Luckin, R., Holmes, W., Griffiths, M., & Forcier, L. B. (2016). *Intelligence unleashed: An argument for AI in education*. Pearson. https://discovery.ucl.ac.uk/id/eprint/1475756/

Miao, F., & Cukurova, M. (2024). *AI competency framework for teachers*. UNESCO. https://doi.org/10.54675/ZJTE2084

Miao, F., & Holmes, W. (2023). *Guidance for generative AI in education and research*. UNESCO. https://doi.org/10.54675/EWZM9535

Nguyen, A., Ngo, H. N., Hong, Y., Dang, B., & Nguyen, B.-P. T. (2023). Ethical principles for artificial intelligence in education. *Education and Information Technologies, 28*(4), 4221–4241. https://doi.org/10.1007/s10639-022-11316-w

Ouyang, F., Zheng, L., & Jiao, P. (2022). Artificial intelligence in online higher education: A systematic review of empirical research from 2011 to 2020. *Education and Information Technologies, 27*(6), 7893–7925. https://doi.org/10.1007/s10639-022-10925-9

Popenici, S. A. D., & Kerr, S. (2017). Exploring the impact of artificial intelligence on teaching and learning in higher education. *Research and Practice in Technology Enhanced Learning, 12*(1), Article 22. https://doi.org/10.1186/s41039-017-0062-8

Prinsloo, P. (2020). Data frontiers and frontiers of power in (higher) education: A view of/from the Global South. *Teaching in Higher Education, 25*(4), 366–383. https://doi.org/10.1080/13562517.2020.1723537

Rogers, E. M. (2003). *Diffusion of innovations* (5th ed.). Free Press.

Selwyn, N. (2022). The future of AI and education: Some cautionary notes. *European Journal of Education, 57*(4), 620–631. https://doi.org/10.1111/ejed.12532

Sposato, M. (2025). Artificial intelligence in educational leadership: A comprehensive taxonomy and future directions. *International Journal of Educational Technology in Higher Education, 22*(1), Article 20. https://doi.org/10.1186/s41239-025-00517-1

Tantivejakul, N., Chantharasombat, J., & Kongpolphrom, W. (2024). Voices of the future: Exploring students' views on the use of GenAI in academic and professional PR writing. *LEARN Journal: Language Education and Acquisition Research Network, 17*(2), 511–537. https://doi.org/10.70730/PVTD8302

Tornatzky, L. G., & Fleischer, M. (1990). *The processes of technological innovation*. Lexington Books.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425–478. https://doi.org/10.2307/30036540

Weiner, B. J. (2009). A theory of organizational readiness for change. *Implementation Science, 4*(1), Article 67. https://doi.org/10.1186/1748-5908-4-67

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), Article 39. https://doi.org/10.1186/s41239-019-0171-0

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