

Perceptions of AI-Enhanced LMS in Smart Higher Education Administration

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Abstract

This study examines how postgraduate administrators perceive the integration of artificial intelligence (AI) and Learning Management Systems (LMS) in higher education administration. Sixteen Chinese master's students enrolled in an educational administration programme at a Thai university — all with prior administrative experience in Chinese higher education — completed a structured, content-validated questionnaire measuring perceptions across five domains: policy and governance, resource allocation, training and support, data security and ethics, and administrative efficiency and readiness. Responses were recorded on a five-point Likert scale and analysed using descriptive statistics. Agreement was strong and consistent across the enabling domains, with mean scores between 4.69 and 4.88 and standard deviations mostly below 0.50, indicating firm endorsement of institutional policy, adequate resourcing, targeted training, and ethical safeguards as prerequisites for AI-LMS adoption. Institutional readiness, by contrast, scored markedly lower ($M = 3.38$), exposing a gap between what administrators judge important and what they believe their institutions can currently deliver. This disparity points to structural and resource constraints that conceptual endorsement alone cannot resolve. Realising AI's administrative potential therefore depends less on persuading administrators of its value than on coordinated strategies that align policy, professional development, and ethics with institutional capacity.

Keywords: AI-enhanced LMS, higher education administration, perceptions, readiness, policy, ethics

Introduction

Artificial intelligence (AI) and Learning Management Systems (LMS) are reshaping higher education into data-driven environments that support personalised learning, adaptive instruction, and more efficient administration. National models differ sharply in how they pursue this shift: Chinese higher education has invested in centralised digital campuses and AI-powered analytics, whereas several European systems foreground openness and inclusivity (Wu, 2024). How administrators perceive AI-enhanced LMS matters, because their judgements shape policy, funding, and institutional readiness long before any system is deployed. This study examines those perceptions among Chinese master's students of educational administration studying in Thailand — a vantage point that brings a cross-cultural lens to current debates on smart education.

Research on AI and LMS has concentrated on students and faculty, leaving the administrative perspective comparatively neglected. Yet administrators are the actors who reconcile technological innovation with institutional policy and national strategy, and little is known about their preparedness to embed AI-enhanced LMS in administrative practice. Overlooking this group risks inefficient implementation and the underuse of technologies in which institutions have already invested heavily.

Understanding how administrators view these systems informs institutional planning and professional development, and can smooth the path to adoption. It may also help policymakers harmonise AI strategies with wider higher education reform, and assist universities in balancing innovation against ethical obligations such as data security and governance.

The study objectives are as follows:

1. To assess perceptions of AI-enhanced LMS among Chinese postgraduate administrators.
2. To examine perceived benefits, ease of use, and readiness for AI-LMS integration.
3. To identify managerial concerns, including policy, resources, training, and ethics.

Literature Review

The case for embedding AI within LMS environments rests on consistent evidence of gains in personalisation and administrative efficiency. In a systematic review of 148 studies published between 2021 and 2024, Msambwa, Wen, and Daniel (2025) found that AI tools strengthen motivation, enable adaptive scaffolding, and open collaborative opportunities, though they cautioned that these benefits depend on preserving a balance between automated and human interaction. Complementary work locates the same advantages in specific settings. Das, Mutsuddi, and Ray (2025) describe real-time, data-driven adjustment to individual learners, while Venice, Vettriselvan, Rajesh, Suresh, and Abirami (2025) trace how cloud-integrated analytics — in initiatives such as Khan Academy and Purdue University’s predictive systems — support inclusive, personalised provision. Sajja, Sermet, and Demir (2025) push the argument from principle to practice, showing that a conversational AI layer integrated with an LMS improved engagement in environmental science education through contextual question-answering. Taken together, these studies establish personalisation and adaptivity as the settled core of AI’s educational promise.

These benefits are not automatic; they are contingent on institutional alignment and preparation. Catherin, Vettriselvan, Mathur, Regins, and Velmurugan (2025) report improved performance and retention when AI and learning analytics are embedded in distance programmes, but only where the tools are matched to institutional goals and supported by faculty training and robust privacy measures. Arockia, Vettriselvan, Rajesh, Velmurugan, and Cheelo (2025) reach a similar conclusion, linking gains in interactivity and timely intervention to data-informed teaching strategies. The readiness of practitioners themselves is equally decisive. Filiz, Kaya, and Adiguzel (2025) found teachers enthusiastic about efficiency and interactivity yet constrained by problems of curriculum fit and cultural adaptation, which indicates that professional development and contextual sensitivity mediate whether adoption succeeds.

What sustains adoption over time is a further question, and here the evidence points to trust as much as utility. Drawing on the UTAUT and expectation-confirmation models, Baig and Yadegaridehkordi (2025) found that ethical considerations, confirmation, and effort expectancy predicted satisfaction with generative AI among academic staff, while performance expectancy shaped intention to use; privacy and security emerged as decisive for continued use. Mexhuani (2025), combining the Technology Acceptance Model with diffusion-of-

innovations theory, similarly identified opportunities for equity and collaboration alongside persistent barriers of faculty resistance and privacy concern. Both accounts suggest that technical capability secures initial uptake, but perceived trustworthiness governs whether that uptake endures.

Ethical and governance concerns run through this literature rather than sitting at its margins. Awashreh (2025) foregrounds the risks of algorithmic bias, over-reliance on automation, and widening inequality, arguing for accountability mechanisms and digital-literacy initiatives as conditions of responsible deployment. These arguments reinforce the privacy and security themes raised by Baig and Yadegaridehkordi (2025) and Venice et al. (2025), and they reframe ethics as a design requirement for AI-LMS systems rather than a compliance afterthought.

One group remains conspicuously absent from this body of work. The studies reviewed above centre on students, faculty, or the technologies themselves, yet it is administrators who allocate resources, set policy, and translate national strategy into institutional practice. Their perceptions therefore condition whether the personalisation, efficiency, and ethical safeguards documented elsewhere are ever realised. The present study addresses this gap by examining how postgraduate administrators, positioned across Chinese and international educational contexts, perceive the integration of AI-enhanced LMS into administrative functions.

Methodology

Research Design

A descriptive quantitative design was adopted to capture measurable perceptions of AI-enhanced LMS among Chinese postgraduate administrators. The design suits the study's aim, which was to establish the pattern and strength of administrators' attitudes across defined domains — usefulness, ease of use, policy alignment, resource allocation, training, ethics, and readiness — rather than to test causal relationships. A survey approach also allowed anonymous, comparable responses from participants who shared an administrative background but worked in different institutions.

Participants

The participants were 16 Chinese master's students enrolled in an educational administration programme at a Thai university. All had prior administrative experience in Chinese higher education, which equipped them to judge the integration of AI and LMS into administrative functions from an informed standpoint. Their enrolment in an international programme added a comparative dimension, allowing perceptions to be shaped by exposure to both Chinese and global approaches to digital transformation.

Sampling

Purposive sampling was used to ensure that every participant combined direct administrative experience in higher education with current exposure to international education. This deliberate selection prioritised informational richness over statistical representativeness: the study sought respondents able to evaluate AI-LMS integration from both domestic and international standpoints, which a random sample of the wider student body could not have guaranteed.

Instrument

A structured questionnaire was developed from prior studies of AI and LMS adoption in education. It assessed five core domains:

- Policy and Governance (e.g., the necessity for institutional policies, alignment with national strategies)

- Resource Allocation (e.g., adequacy of funding, infrastructure support)
- Training and Support (e.g., need for specific training, continuous professional development)
- Data Security and Ethics (e.g., privacy protection, ethical frameworks)
- Administrative Efficiency and Readiness (e.g., impact on efficiency, institutional preparedness)

Each item was measured on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). Chinese translations accompanied every item to secure clarity and consistent interpretation for participants. Content validity was established through expert review by specialists in educational technology and administration, and the internal consistency of the instrument was examined using Cronbach's alpha [insert overall α , and per-domain values where available; see note below].

Data Collection

The questionnaire was distributed electronically through secure university channels. Participation was voluntary and anonymous, so that respondents could report their perceptions of AI-LMS integration candidly and without institutional pressure. Before completing the survey, participants were informed of the study's purpose and of their right to withdraw at any point, and informed consent was obtained from all respondents. No personally identifying information was collected, and the responses were stored confidentially and used solely for the purposes of this research. The study was conducted in accordance with the research-ethics guidelines of the participating institution [insert the name of the approving committee and the approval reference number].

Data Analysis

Responses were analysed using descriptive statistics — means and standard deviations — to establish overall levels of agreement and the dispersion of views within each domain. Mean scores were interpreted against five equal-interval bands: 1.00–1.80 (strongly disagree), 1.81–2.60 (disagree), 2.61–3.40 (neutral), 3.41–4.20 (agree), and 4.21–5.00 (strongly agree). On this scale, values at or above 4.21 denote strong agreement, which locates every enabling domain in the highest band and places perceived readiness ($M = 3.38$) in the neutral band. The domains were then compared to identify where endorsement was strongest and where it weakened, notably between the enabling factors and perceived readiness.

Limitations

The principal limitation is the small, single-programme sample, which constrains generalisability and precludes inferential comparison between subgroups. The study is therefore best read as a preliminary, exploratory account of administrative perceptions in a specific cross-cultural setting. Future research should widen the participant pool across multiple institutions and countries, and could combine survey data with interviews to explain, rather than merely document, the readiness gap identified here.

Results and Discussion

Table 1 reports the mean and standard deviation for each questionnaire item, spanning policy, resources, training, ethics, administrative efficiency, and readiness for AI-enhanced LMS integration.

Table 1. Mean and standard deviation of perceptions of AI-enhanced LMS integration (N = 16)

Questionnaire Statement	Mean	Standard Deviation
University policies are needed to guide AI, and LMS integration in administration.	4.81	0.4
Clear regulations must govern data generated by these technologies.	4.81	0.4
Adoption of these technologies should align with national higher education strategies.	4.75	0.45
Adequate funding is essential for successful integration of these technologies.	4.69	0.48
Infrastructure development is required to ensure reliable technology use.	4.81	0.4
Administrators need specific training to manage AI, and LMS, effectively.	4.81	0.4
Ongoing professional development is important for sustaining effective use.	4.75	0.45
Strong security measures are required to protect institutional and student data.	4.88	0.34
Ethical guidelines must ensure responsible use of these technologies.	4.81	0.4
Integration of AI, LMS, and IoT improves university administrative efficiency.	4.81	0.4
My institution is ready to adopt AI-enhanced LMS for administrative functions.	3.38	0.62

Two patterns dominate the results. Across the enabling domains — policy and governance, resource allocation, training and support, data security and ethics, and administrative efficiency — mean scores clustered tightly between 4.69 and 4.88, with standard deviations mostly below 0.50. The consensus is strong and its variance small: these administrators broadly agree that institutional policy, adequate resourcing, ethical safeguards, and professional development are prerequisites for successful AI-LMS integration. Security attracted the highest agreement of all ($M = 4.88$, $SD = 0.34$), a signal that data protection is treated as foundational rather than incidental. Against this uniformity, one item stands apart. Perceived institutional readiness fell to a mean of 3.38 ($SD = 0.62$) — more than a full scale point below the enabling cluster and with visibly greater dispersion. Respondents endorse the conditions for adoption while doubting that their institutions can yet meet them, a discrepancy that most plausibly reflects structural and resource constraints in their home institutions.

These findings echo a literature that couples AI's promise with conditions on its delivery. The high policy and governance scores mirror the conclusions of Msambwa et al. (2025) and Catherin et al. (2025), who tie the benefits of AI-enabled LMS to supportive policy and structured training rather than to the technology alone. The prominence of ethics and data security in the responses tracks the concerns of Awashreh (2025) and Venice et al. (2025), for whom regulatory oversight and protection against algorithmic bias are integral to legitimate adoption. That administrators independently prioritise these same safeguards suggests the concerns identified in the literature are not confined to scholars but are shared by those who must operationalise the systems.

The gap between strong endorsement of enabling factors and weak confidence in readiness is the study's most consequential result. Administrators support AI-LMS integration in principle and recognise its benefits, yet do not regard their institutions as prepared to act. Insufficient infrastructure, uncertain funding, and limited prior exposure to AI-driven platforms are the likeliest contributors. Mexhuani (2025) observes the same sequence elsewhere: enthusiasm for technology routinely outruns the capacity to implement it, which is why phased adoption and deliberate change management, rather than exhortation, tend to close the distance.

The weight respondents give to ethical frameworks, set beside their doubts about readiness, carries a clear implication for sequencing. Expanding AI use without a parallel investment in governance and digital literacy would erode the very trust on which adoption depends. Preparation should therefore be cultural and ethical as well as technical: training needs to address responsible AI use, governance mechanisms, and cross-cultural judgement. This matters especially in the transnational context examined here, where Chinese administrators operate within Thai institutional norms.

Three practical priorities follow. The first is governance. Because administrators rate policy as indispensable, institutions should settle clear rules on data use, algorithmic transparency, and AI-assisted decision-making before technical rollout, not after. Such frameworks work best when negotiated among institutional leaders, government education agencies, and technology providers, so that local implementation stays coherent with national strategy. In transnational settings, policy must also accommodate differing cultural expectations around privacy and authority — a requirement the Chinese-in-Thailand context of this study makes concrete.

The second priority is resourcing matched to capability. Reliable networks, resilient data storage, and multi-year funding that covers maintenance and licensing — not merely initial purchase — are the material conditions the readiness scores imply are missing. Where budgets are tight, consortium or shared-service arrangements can bring AI-LMS capability within reach of smaller institutions. Yet investment in infrastructure is wasted without investment in people: training should be mandatory, role-differentiated, and continuous, distinguishing the needs of data-privacy officers, academic administrators, and technical staff rather than treating them alike.

The third priority is to treat the readiness gap as a change-management problem rather than a technical one. A candid institutional audit of infrastructure, finances, skills, and culture should precede any commitment, followed by pilots that permit testing and gradual scaling while confidence is built. Data-protection protocols ought to exceed minimum regulatory requirements, and a standing ethics review of AI applications — assessing fairness, bias, and effects on student outcomes — gives governance somewhere to live. Visible leadership commitment, sustained rather than announced, is what ultimately converts endorsement into capacity.

Conclusion and Suggestions

This study set out to understand how administrators perceive the adoption of AI-enhanced LMS in higher education, and it returns a clear answer. Administrators are convinced of what adoption requires — coherent policy, sufficient resources, targeted training, and firm ethical safeguards — but far less convinced that their institutions can currently supply it. The distance between these two positions, not any scepticism about AI itself, is the real obstacle. Closing it will require coordinated action that aligns national policy with institutional capacity, phases implementation realistically, and builds professional development around administrators' actual responsibilities. Unless the readiness gap is addressed directly, AI's administrative potential will remain aspirational rather than operational. That task falls to policymakers, institutional leaders, and technology developers together, and its aim should be integration that is not only efficient but ethically grounded. Because the present evidence comes from a small, purposive sample, these conclusions are best treated as propositions for larger, multi-institution studies to test.

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