Managing Teaching and Learning Activities at Universities Toward Ai Integration: Impacts on Students' Learning Interest, Digital Competence, And Academic Integrity

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ABSTRACT:

Purpose. This study examines how the management of teaching and learning activities oriented toward artificial intelligence (AI) integration shapes three student outcomes in Vietnamese higher education: learning interest (LI), digital competence (DC), and academic integrity risk (AIR). Our intent is to move the debate beyond whether universities adopt AI to a more consequential question—how leadership and management practice translates that adoption into pedagogical results.

Methods. A sequential explanatory mixed-methods design was implemented across twelve universities (six public, six non-public) spanning the northern, central, and southern regions of Vietnam. The quantitative phase surveyed 1,200 undergraduate students and 240 lecturers; the qualitative phase comprised 24 semi-structured interviews with managers and academics, supplemented by four focus groups. Quantitative analysis followed a CFA-then-SEM procedure in SPSS 28.0 and AMOS 28.0; qualitative material was thematically analysed in NVivo 14.

Findings. The Management of AI-Integrated Teaching and Learning (MAITL) construct is significantly associated with LI ($\beta = 0.452$, $p < 0.001$) and DC ($\beta = 0.387$, $p < 0.001$), and is positively related to AIR ($\beta = 0.213$, $p < 0.01$). Faculty Digital Competence amplifies the LI pathway ($\beta = 0.148$, $p < 0.05$), whereas Ethical Climate Management dampens the AIR pathway ($\beta = -0.194$, $p < 0.001$). Multi-group analysis reveals stronger MAITL→LI and MAITL→AIR coefficients in non-public institutions, alongside weaker faculty buy-in and tighter resource constraints.

Originality. The paper offers an empirically validated MAITL framework that recasts AI integration as a management problem rather than a technology problem, and supplies five context-specific recommendations for ministry, institutional, faculty, and student-level action in a developing-country higher education system.

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Keywords: educational management; artificial intelligence; higher education governance; learning interest; digital competence; academic integrity; Vietnam

1. INTRODUCTION

Generative artificial intelligence has moved from a distant prospect to a routine companion of university coursework in the span of barely three years. Tools such as ChatGPT, Claude, Gemini, and a long tail of academic plug-ins now sit beside textbooks, library databases, and learning management systems in the daily routines of students and lecturers (Holmes et al., 2022; UNESCO, 2023). Yet the strategic question facing universities is no longer whether AI will enter the classroom—students bring it through the door regardless—but how the institution will manage that entry so the educational mission is strengthened rather than diluted.

In Vietnamese higher education, this management challenge sits within a particular policy and operational context. The Prime Minister's National AI Strategy to 2030 and the Ministry of Education and Training's digital transformation roadmap to 2025 set ambitious adoption targets, but provide limited operational guidance on classroom-level integration, assessment redesign, or governance of student AI use (Government of Vietnam, 2021; MOET, 2022). University leaders are therefore asked to make consequential choices—about platforms, training, assessment policy, and ethical safeguards—often without an evidence base drawn from the sector itself.

A second, related challenge concerns capacity. Vietnamese institutions divide into roughly 240 public and around 60 non-public universities, with significant differences in funding flexibility, governance autonomy, faculty profile, and student demographics (MOET, 2023). Anecdotal evidence and small-sample studies suggest that non-public institutions move more quickly on student-facing AI tools but trail in lecturer readiness, while public institutions display the inverse pattern (Phan & Nguyen, 2024). These are management asymmetries, not technology asymmetries, and they call for management-level analysis.

A third concern is values-based. AI tools that draft essays, solve problems, and generate code create real exposures to academic integrity: not because students are inherently dishonest, but because the new tools blur the line between assistance and authorship in ways that older policy categories do not capture (Cotton et al., 2024; Sullivan et al., 2023). Without managerial intervention—policy redesign, assessment reform, and a credible ethical climate—integration may erode the very competencies it was meant to develop.

Against this backdrop, the present study pursues three objectives. The first is to specify and validate the construct Management of AI-Integrated Teaching and Learning (MAITL) as a higher-order managerial capability composed of five functions: strategic planning, organising and resourcing, implementation and pedagogical leadership, monitoring and evaluation, and conditions for ethical use. The second is to test whether MAITL predicts three outcomes that matter to student development—learning interest (LI), digital competence (DC), and academic integrity risk (AIR)—and whether faculty digital competence and ethical climate management moderate these relationships. The third is to translate the empirical pattern into actionable recommendations for ministry, institution, faculty, and student levels.

The contribution is threefold. Conceptually, the paper recasts a question that has been treated largely as a technology-adoption problem as a management problem, and supplies a measurable framework for that recasting. Empirically, it reports the largest cross-institutional study of AI in Vietnamese higher education to date, with parallel data from students and lecturers. Practically, it offers a graded set of recommendations sensitive to the public/non-public divide that defines the Vietnamese sector.

2. LITERATURE REVIEW AND HYPOTHESES

2.1. Educational management and AI in higher education

Educational management as a field has long held that institutional outcomes are mediated by the quality of leadership decisions, organisational arrangements, and the conditions established for staff and students (Bush, 2020; Northouse, 2021). When the disruptive innovation in question is AI rather than, say, a new curriculum, the same managerial categories apply but acquire a sharper edge: tools evolve in months rather than years, the boundary between learning aid and academic misconduct shifts under managers' feet, and decisions made by individual lecturers can rapidly become institutional policy by accretion. International commentary on AI governance in higher education has increasingly converged on the view that the binding constraint is not technology procurement but managerial bandwidth: who decides, on what evidence, with which safeguards, and on what review cycle (UNESCO, 2023; OECD, 2024).

Drawing on Mintzberg's functional account of managerial work and on the educational-leadership literature represented by Leithwood and Bush, we conceptualise the management of AI-integrated teaching and learning as a higher-order construct composed of five functions: strategic planning that anchors AI in the institution's educational mission; organising and resourcing that aligns budgets, infrastructure, and human resources; implementation and pedagogical leadership that supports lecturer practice; monitoring and evaluation that closes the feedback loop; and conditions for ethical use that establish the rules of engagement for both staff and students.

2.2. AI integration and learning interest

Self-determination theory predicts that learning interest grows where learners experience competence, autonomy, and relatedness (Ryan & Deci, 2020). AI-mediated instruction can support all three: adaptive feedback strengthens competence, personalised pathways increase autonomy, and conversational tutors create a low-stakes interlocutor with whom students can rehearse ideas. The empirical literature, however, repeatedly shows that these benefits do not arrive automatically; they depend on how AI use is framed, scaffolded, and assessed by the institution (Zawacki-Richter et al., 2019; Chiu et al., 2023). When managerial choices align AI use with course goals, interest rises; when AI is bolted on without curricular redesign, gains are modest or negative.

We accordingly expect that better management of AI-integrated teaching—across the five functions—will translate into higher reported learning interest:

H1. *MAITL is positively associated with learning interest.*

2.3. AI integration and digital competence

Digital competence is now a graduate attribute in most national qualifications frameworks (European Commission, 2022; UNESCO, 2024). The DigComp 2.2 framework distinguishes information literacy, communication, content creation, safety, and problem-solving—each of which AI tools both support and stress-test. Recent studies suggest that students develop these competencies most reliably when their use of AI is structured, repeated, and evaluated (Kong et al., 2023; Vuorikari et al., 2022). Each of those conditions is a managerial product: structure follows from curriculum policy, repetition from timetabling and resource decisions, and evaluation from assessment governance. Hence:

H2. *MAITL is positively associated with student digital competence.*

2.4. AI integration and academic integrity risk

The academic integrity literature distinguishes between the prevalence of misconduct and the risk environment that surrounds it (McCabe et al., 2012; Bretag et al., 2019). Academic integrity risk—our outcome variable—captures the latter: how exposed coursework, assessment, and supervision are to misuse, regardless of whether misuse is finally observed. AI tools enlarge this risk surface in obvious ways, but the magnitude

of the increase depends almost entirely on management responses: assessment redesign, citation expectations, detection practices, and the credibility of the ethical climate (Cotton et al., 2024; Lancaster, 2023). A counter-intuitive but empirically supported pattern is that more vigorous AI integration may, in the short run, raise observed integrity exposure even in well-managed settings, because the volume of student-AI interaction simply rises. We therefore hypothesise:

H3. *MAITL is positively associated with academic integrity risk in the short run.*

2.5. Moderators: faculty digital competence and ethical climate management

Two conditions shape the strength of the MAITL—outcomes link. The first is faculty digital competence (FDC). Lecturers operationalise institutional intent in the classroom; without sufficient digital fluency, even well-designed integration plans falter at the point of delivery (Mishra & Koehler, 2006; Redecker, 2017). We therefore expect FDC to amplify the MAITL→LI relationship.

The second is ethical climate management (ECM). Beyond formal policy, ECM captures the lived sense students and staff have that ethical norms are taken seriously, breaches are addressed consistently, and managers model the standards they expect (Victor & Cullen, 1988; Bretag et al., 2019). Where ECM is strong, the AIR side-effect of integration is constrained; where it is weak, integration scales the risk along with the use.

H4a. *Faculty digital competence positively moderates the MAITL→LI relationship.*

H4b. *Ethical climate management negatively moderates the MAITL→AIR relationship.*

Figure 1 presents the resulting conceptual model.

Figure 1. Conceptual model — Management of AI-Integrated Teaching and Learning (MAITL)

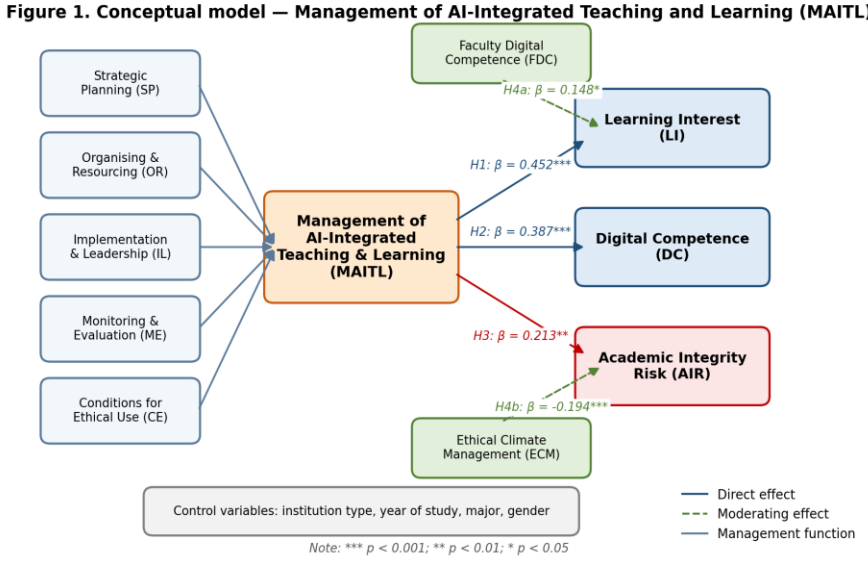

Figure 1. Conceptual model — Management of AI-Integrated Teaching and Learning (MAITL).

*Note: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.*

3. METHODOLOGY

3.1. Research design

A sequential explanatory mixed-methods design (Creswell & Plano Clark, 2018) was used. Phase 1 collected survey data from a stratified sample of students and lecturers; Phase 2 used semi-structured interviews and focus groups with university managers and academics to interpret the quantitative results, paying particular attention to anomalies in the multi-group analysis. Combining the two phases lets us test the structural model and then unpack the management dynamics behind it.

3.2. Sample and procedure

Twelve universities participated, six public and six non-public, distributed across the northern,

central, and southern regions to reflect Vietnam's geographic and institutional diversity. After approvals from each institutional research office, online surveys were administered between October 2025 and February 2026. After listwise deletion of incomplete cases (response rate above 86%), 1,200 student questionnaires (100 per institution) and 240 lecturer questionnaires (20 per institution) were retained. Twenty-four interviews and four focus groups were subsequently conducted with vice-rectors, heads of academic affairs, deans, and senior lecturers, sampled purposively from the same twelve institutions.

The student sample was 56% female; respondents were drawn from years one to four (29.4%, 27.8%, 24.1%, and 18.7% respectively) and from five major-area clusters (engineering and technology, social sciences and humanities, economics and management, education, and health sciences). The lecturer sample was 51% female; 38% held doctorates and 47% had more than ten years of teaching experience.

3.3. Measures

Latent constructs were measured with five-point Likert scales (1 = strongly disagree, 5 = strongly agree). MAITL was measured by twenty items spread across its five functions (four items per function). Sample items include: "The institution has a written plan for AI use in teaching" (SP), "Faculty receive practical training on AI tools" (IL), and "There are clear procedures for handling AI-related integrity cases" (CE).

Outcome variables were operationalised as follows. Learning interest (LI, 6 items) was adapted from Ryan and Deci's engagement battery. Digital competence (DC, 8 items) drew on DigComp 2.2 across information, communication, creation, safety, and problem-solving. Academic integrity risk (AIR, 5 items) was adapted from Bretag et al. (2019) and rephrased to capture exposure rather than self-report of misconduct. Faculty digital competence (FDC, 6 items) followed Redecker (2017). Ethical climate management (ECM, 6 items) drew on Victor and Cullen (1988) reframed for academic settings.

3.4. Analytical strategy

After data screening and tests for normality, common-method variance was assessed via Harman's single-factor test (largest factor explained 27.4% of variance, below the 50% threshold). Cronbach's α and composite reliability were computed for each construct. Convergent validity was assessed through average variance extracted; discriminant validity followed Fornell and Larcker (1981). A measurement model was estimated by confirmatory factor analysis in AMOS 28.0; the structural model and moderating effects were then tested using maximum likelihood estimation, with model fit assessed against established cut-offs (Hair et al., 2019).

Multi-group analysis compared coefficients between public and non-public institutions; significance of differences was tested with chi-square difference statistics on nested models (Byrne, 2016). Qualitative data were transcribed and coded thematically in NVivo 14 by two independent coders; intercoder agreement reached $\varkappa = 0.81$ after reconciliation.

3.5. Ethics

The protocol was approved by the Research Ethics Committee of the lead university (decision 2025/REC/HE-AI). Participation was voluntary and anonymised, no incentives were offered to students, and lecturers received a token contribution to professional development costs. Data are stored in encrypted form for five years and are available from the corresponding author on reasonable request.

4. RESULTS

4.1. Sample profile and descriptive findings

Across the twelve institutions, MAITL function scores cluster between 2.92 and 3.92 on the five-point scale, with the highest values reported by students at non-public universities and the lowest by lecturers at the same institutions. Figure 2 displays the pattern.

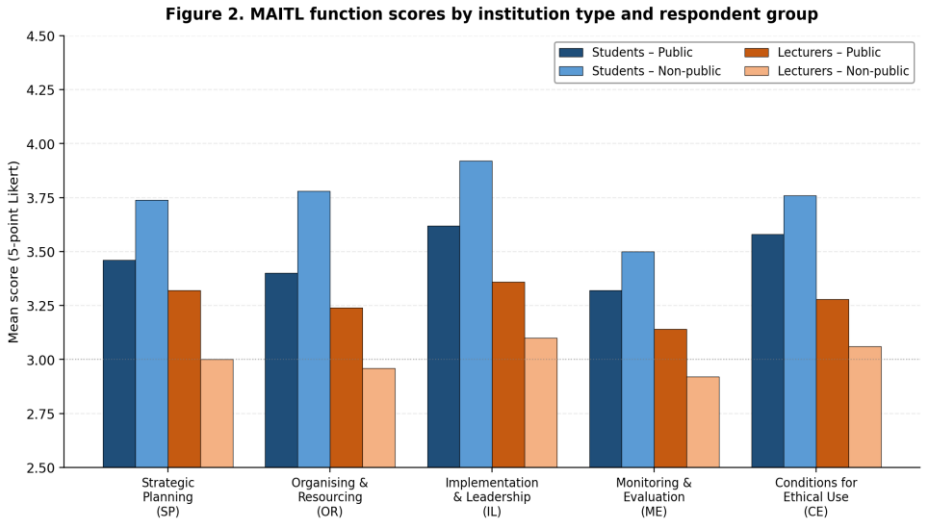

Figure 2. MAITL function scores by institution type and respondent group.

Two stylised facts emerge. First, students rate management activity higher than lecturers do across every function, reflecting their direct exposure to AI-supported coursework but also their thinner view of backstage planning and resourcing. Second, the public/non-public gap reverses by respondent type: students at non-public universities perceive stronger implementation and leadership, while lecturers at the same institutions report the weakest support. This sets up the multi-group results below.

4.2. Measurement model: reliability and validity

All constructs achieved acceptable reliability (Cronbach's α between 0.812 and 0.914; composite reliability above 0.84). Average variance extracted exceeded 0.50 for every construct, and all square-root AVE values exceeded inter-construct correlations, satisfying Fornell–Larcker discriminant validity. Item loadings ranged from 0.682 to 0.879 (all $p < 0.001$). Table 1 reports the summary indices.

Table 1. Reliability and convergent validity of measurement constructs.

Construct	Items	Cronbach's α	CR	AVE	Loadings range
MAITL (higher-order)	20	0.914	0.928	0.622	0.703 – 0.879
Strategic Planning (SP)	4	0.842	0.870	0.628	0.728 – 0.851
Organising & Resourcing (OR)	4	0.829	0.861	0.610	0.702 – 0.842
Implementation & Leadership (IL)	4	0.864	0.889	0.667	0.751 – 0.866
Monitoring & Evaluation (ME)	4	0.838	0.866	0.618	0.722 – 0.847
Conditions for Ethical Use (CE)	4	0.812	0.847	0.581	0.682 – 0.814
Learning Interest (LI)	6	0.876	0.902	0.605	0.732 – 0.842

Construct	Items	Cronbach's α	CR	AVE	Loadings range
Digital Competence (DC)	8	0.882	0.908	0.555	0.701 – 0.829
Academic Integrity Risk (AIR)	5	0.831	0.860	0.553	0.694 – 0.812
Faculty Digital Competence (FDC)	6	0.847	0.881	0.553	0.703 – 0.836
Ethical Climate Management (ECM)	6	0.864	0.891	0.578	0.726 – 0.844

CR = composite reliability; AVE = average variance extracted.

4.3. Confirmatory factor analysis

The measurement model fit the data well: $\chi^2/df = 2.41$; CFI = 0.952; TLI = 0.945; RMSEA = 0.051; SRMR = 0.043. Higher-order loadings of the five management functions on MAITL ranged from 0.74 to 0.86, supporting the second-order specification.

4.4. Structural model and hypothesis tests

The structural model also met conventional fit standards ($\chi^2/df = 2.68$; CFI = 0.941; TLI = 0.932; RMSEA = 0.058; SRMR = 0.047). All four direct paths reached significance, and both moderation tests yielded the predicted signs. Figure 3 summarises the standardised coefficients; Table 2 reports the full hypothesis-test output.

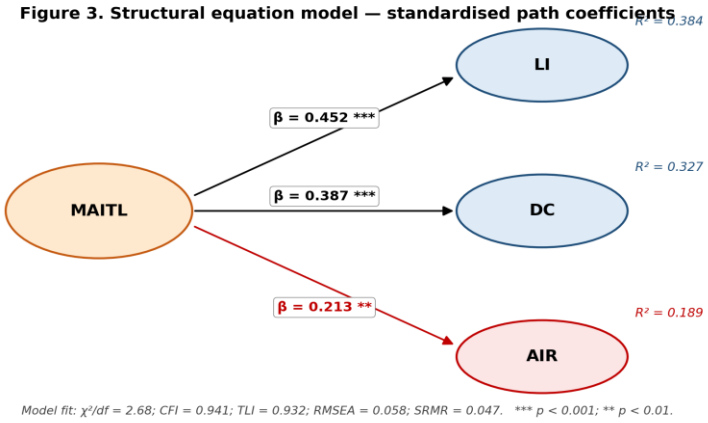

Figure 3. Structural equation model with standardised path coefficients.

Model fit: $\chi^2/df = 2.68$; CFI = 0.941; TLI = 0.932; RMSEA = 0.058; SRMR = 0.047.

Table 2. Hypothesis-test output for the structural model.

Hypothesis	Path	β	SE	t-value	p	Result
H1	MAITL → LI	0.452	0.041	11.02	< 0.001	Supported
H2	MAITL → DC	0.387	0.045	8.60	< 0.001	Supported
H3	MAITL → AIR	0.213	0.062	3.44	< 0.01	Supported

Hypothesis	Path	β	SE	t-value	p	Result
H4a	FDC × MAITL → LI	0.148	0.058	2.55	< 0.05	Supported
H4b	ECM × MAITL → AIR	-0.194	0.051	-3.80	< 0.001	Supported

SE = standard error; LI = learning interest; DC = digital competence; AIR = academic integrity risk; FDC = faculty digital competence; ECM = ethical climate management.

4.5. Variance explained

The model accounts for 38.4% of the variance in learning interest (R^2 = 0.384), 32.7% in digital competence (R^2 = 0.327), and 18.9% in academic integrity risk (R^2 = 0.189). The pattern is consistent with prior work that finds student-development outcomes more responsive to managerial design than risk-side outcomes, which are also sensitive to factors outside the institution's control.

4.6. Multi-group analysis: public vs. non-public

Two of the five paths differ significantly between groups. The MAITL→LI link is stronger in non-public institutions ($\Delta\chi^2 = 5.84$, $p < 0.05$), and the MAITL→AIR link is also stronger there ($\Delta\chi^2 = 4.67$, $p < 0.05$). The FDC×MAITL→LI moderation is marginally larger in public institutions ($\Delta\chi^2 = 3.29$, $p < 0.10$). The remaining two paths do not differ significantly. Figure 4 displays the comparison.

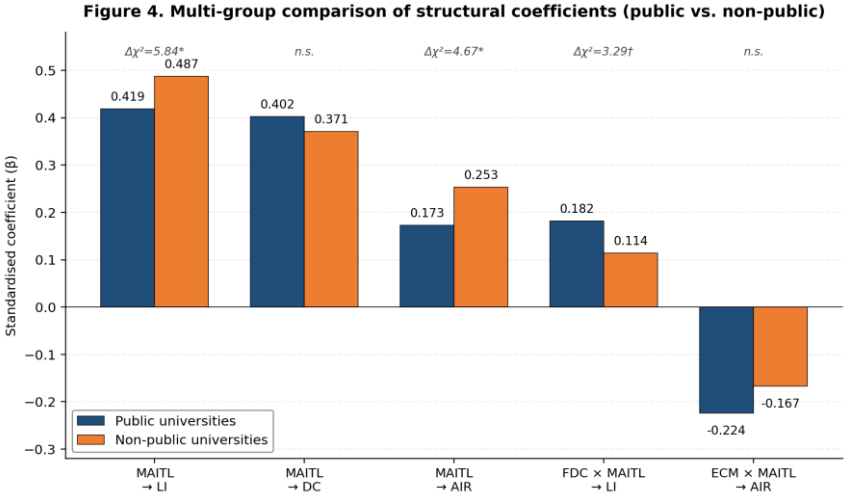

Figure 4. Multi-group comparison of structural coefficients (public vs. non-public).

** p < 0.05; † p < 0.10; n.s. = not significant.*

Interview material clarifies the pattern. Managers in non-public institutions emphasised speed of decision-making and proximity to students as enablers of stronger learning-interest effects, but also flagged thinner faculty-development pipelines and looser monitoring as drivers of larger integrity exposure. A vice-rector at a southern non-public university framed the trade-off bluntly: "We move faster, but we have to bolt the safeguards on as we go." Public-sector managers reported the inverse: deliberate planning and stronger faculty support, slower delivery of student-facing change.

4.7. Qualitative themes

Six themes emerged from the interviews and focus groups: (i) translating policy intent into classroom practice; (ii) infrastructure and platform decisions as a managerial bottleneck; (iii) faculty development as the binding constraint; (iv) assessment redesign in advance of, not in response to, AI use; (v) the credibility of the ethical climate; and (vi) the difficulty of

monitoring outcomes in real time. Theme (iv) was strongest among public-sector deans and weakest among non-public lecturers, mirroring the structural pattern.

5. DISCUSSION

5.1. From technology adoption to managerial design

The headline finding is straightforward: how universities manage AI-integrated teaching predicts what students get out of it. The five MAITL functions—planning, organising, leadership, evaluation, and ethical conditions—jointly explain a meaningful share of the variance in learning interest and digital competence. Recasting AI integration as a management problem is therefore not a rhetorical flourish; it identifies the levers institutions actually possess.

A useful counterpoint is the technology-adoption literature, which has often treated AI as a catalyst that does its work largely independent of management quality (Davis, 1989; Venkatesh et al., 2016). Our results suggest the opposite. AI tools are highly sensitive to the management envelope around them, and outcomes flow from that envelope rather than from the tools themselves.

5.2. The double-edged AIR result

The positive MAITL→AIR coefficient may, on first reading, seem to undermine the case for management investment. It does not. The coefficient captures short-run exposure: as institutions integrate AI more deeply, the volume of student-AI interaction rises, and so does the surface area for integrity risk. The negative ECM moderation tells the rest of the story: where ethical climate management is strong, that increased exposure does not translate into outcomes. The policy lesson is not to slow integration, but to invest in the ethical climate at the same pace.

5.3. Public vs. non-public asymmetries

The multi-group results echo a structural pattern visible in many higher-education systems: the more agile actors deliver student-facing impact more quickly but accumulate management debt elsewhere. In Vietnamese non-public universities, that debt currently shows up as weaker faculty digital competence and greater integrity exposure. The remedy is not regulatory tightening, which risks penalising the responsiveness that produces the LI gain, but a targeted investment in lecturer development and monitoring infrastructure.

Public-sector institutions face the opposite problem. The deliberation that protects against integrity risk also slows curricular response, with the visible consequence that students at public universities report less classroom AI activity than their non-public peers. Public-sector managers may need to import some of the rapid-cycle decision habits of the non-public sector while protecting the deliberative strengths that the data also document.

5.4. The role of faculty digital competence

FDC moderates the link between management intent and student learning interest. This is the clearest empirical signal in the study that lecturer development is not a soft adjunct to AI strategy; it is the rate-limiting step. Without competent faculty, even well-conceived management plans dissipate at the classroom door. Faculty development should therefore be measured—and budgeted—on a footing comparable to platform procurement.

5.5. Theoretical contribution

The study's theoretical contribution is to formalise a higher-order management construct, MAITL, with empirical evidence of its second-order structure and predictive validity for three outcomes that university leaders care about. By integrating insights from educational management, technology-adoption, self-determination, and academic-integrity literatures, MAITL offers a parsimonious vocabulary for what has hitherto been a fragmented conversation.

6. CONCLUSION AND POLICY IMPLICATIONS

6.1. Summary of findings

Drawing on a stratified sample of 1,200 students and 240 lecturers across twelve Vietnamese universities, we find that the management of AI-integrated teaching and learning—operationalised as a five-function higher-order construct—predicts learning interest, digital competence, and academic integrity risk in the expected directions. Faculty digital competence amplifies the link to interest, ethical climate management dampens the link to risk, and the public/non-public divide produces a pattern of strengths and weaknesses that calls for differentiated policy.

6.2. Recommendations

For the Ministry of Education and Training. Promulgate a sector-wide framework for AI use in teaching and learning that distinguishes permitted, restricted, and prohibited applications, sets baseline expectations for faculty AI literacy, and requires institutions to publish an annual AI-in-teaching report. Ring-fence dedicated funds for non-public institutions to access faculty development at parity with public counterparts.

For university leadership. Embed MAITL's five functions in institutional strategy, with named owners for planning, resourcing, implementation, evaluation, and ethical conditions. Move assessment redesign upstream of AI adoption rather than downstream of misconduct cases. Treat lecturer digital competence as a strategic KPI on a par with research output.

For deans and heads of department. Build communities of practice around AI-supported teaching, with regular peer review of course designs that include AI use. Adopt rubrics that assess process as well as product, reducing the integrity exposure of pure-output assessment.

For lecturers. Frame AI tools as scaffolds for higher-order learning rather than substitutes for cognitive effort. Make expected and prohibited uses explicit on every assessment. Document own AI use in teaching as a model of the practice expected from students.

For students. Treat AI literacy as a graduate competency rather than a survival skill. Engage with institution-supported tools in preference to opaque alternatives, and seek explicit guidance from instructors when uncertain about permissible use.

6.3. Limitations and future research

The study has three principal limitations. First, the cross-sectional design precludes strong causal claims; longitudinal data could clarify the temporal ordering of management practice and student outcomes. Second, self-reported AIR captures perceived exposure rather than actual misconduct; cross-validation with institutional records would strengthen the risk-side findings. Third, the public/non-public typology, useful as it is, masks heterogeneity within each category. Future work could decompose the pattern by institutional age, size, and disciplinary mix, and could extend the framework to vocational and short-cycle higher education.

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CONFLICT OF INTEREST

The authors declare no conflict of interest. The study received no commercial funding. Data are available from the corresponding author on reasonable request.

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