



Artificial Intelligence Adoption and Academic Performance in Higher Education: Testing the Mediating Roles of Digital Competence and Learning Engagement Using Structural Equation Modeling

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Article Info	Abstract
Article history: Received: April 03, 2026 Revised: Mei 10, 2026 Accepted: June 21, 2026 Keywords: Academic performance; Artificial intelligence adoption; Digital competence; Higher education; Learning engagement.	Background of study: Artificial intelligence (AI) tools are rapidly entering higher education, yet adoption alone does not explain whether students achieve better academic outcomes. Aims and scope of paper: This study develops and tests a mediation model in which digital competence and learning engagement transmit the effect of AI adoption on academic performance. Methods: A cross-sectional quantitative design is specified for university students, with multi-item Likert measures and covariance-based structural equation modeling (CB-SEM). The measurement model is evaluated through confirmatory factor analysis, reliability, convergent validity, and discriminant validity, followed by direct and bootstrapped indirect-effect testing. Result: The illustrative model indicates that AI adoption is positively associated with digital competence and learning engagement, while both mediators are positively related to academic performance. The direct AI-adoption effect remains positive but smaller after the mediators are included, indicating complementary partial mediation. Conclusion: The model suggests that universities should treat AI adoption as an educational capability-building process rather than mere tool access, pairing AI use with digital competence development and engagement-oriented pedagogy.
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INTRODUCTION

Background of the study

Artificial intelligence has moved from a specialized computational technology to an everyday academic resource. Generative AI systems can provide explanations, feedback, summarization, coding support, idea generation, and personalized interaction, which has accelerated student experimentation with AI-supported learning. UNESCO (2023) nevertheless emphasizes that the educational value of generative AI depends on human agency, ethical safeguards, privacy protection, and purposeful pedagogical design. This makes the central higher-education question more complex than whether students use AI; the relevant issue is how adoption becomes productive learning behavior and, ultimately, academic performance.

Recent empirical research confirms both the promise and the ambiguity of AI use. Structural equation modeling studies have shown generally positive perceptions and adoption of generative AI chatbots in higher education, while also identifying concerns about trust, privacy, accuracy, and bias. Experimental and meta-analytic evidence increasingly suggests positive learning effects, but these effects vary according to instructional design, task type, and how learners regulate AI assistance. In

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assessment contexts, AI users are not automatically advantaged once prior achievement and other factors are considered. Consequently, adoption should be conceptualized as an enabling condition whose academic value depends on student capabilities and engagement processes rather than as a direct technological treatment.

Rationale of the study

Two mechanisms are theoretically important. First, digital competence represents the knowledge, skills, judgment, and responsible practices needed to use digital technologies confidently, critically, and safely. DigComp 2.2 explicitly extends digital competence to emerging AI-driven systems and highlights information evaluation, content creation, safety, problem solving, and critical understanding. Students who adopt AI but lack these capabilities may accept inaccurate outputs, use weak prompts, disclose sensitive information, or substitute generated content for learning. By contrast, digitally competent students are better positioned to interrogate AI outputs, integrate them with disciplinary knowledge, and use them strategically.

Second, learning engagement captures the behavioral, cognitive, and emotional investment students make in learning. AI can reduce barriers to participation by providing immediate feedback, adaptive explanations, and low-stakes opportunities to ask questions; however, it can also encourage passive dependence when students outsource thinking. Recent meta-analytic evidence indicates that ChatGPT-supported learning can improve behavioral, cognitive, and emotional engagement on average, while also documenting risks of over-reliance. Engagement therefore provides a plausible motivational-behavioral pathway linking technology adoption to performance.

Literature review

This study integrates technology-adoption reasoning with competence and engagement perspectives. Technology acceptance research argues that adoption is shaped by perceived usefulness, ease of use, social influence, and facilitating conditions (Davis, 1989; Venkatesh et al., 2003). In the present model, adoption is treated as the extent to which students intentionally and regularly incorporate AI tools into authentic academic activities such as information exploration, drafting, feedback seeking, problem solving, data analysis, and revision. Adoption is expected to stimulate opportunities for skill development because repeated use exposes students to the need to formulate prompts, evaluate information quality, compare outputs, protect data, and select appropriate tools.

Digital competence is expected to contribute to academic performance through more effective information processing and technology-supported self-regulation. Reviews of higher-education research show that digital competence is multidimensional and closely associated with the capacity to participate effectively in technology-rich learning environments. AI literacy research further indicates that understanding, evaluating, and ethically using AI are distinct from merely spending more time with AI. This distinction is important because frequent use may coexist with shallow or uncritical use.

Learning engagement provides a second pathway. Engagement theory treats active participation, cognitive investment, persistence, interest, and interaction as proximal determinants of learning. Kahu (2013) conceptualizes engagement as a psychosocial process through which structural and student factors influence educational outcomes. In AI-supported learning, students may become more engaged when tools reduce waiting time for feedback, support iterative practice, and make difficult content more approachable. A 2025 SEM study found that students' perceptions of ChatGPT were associated with online learning engagement and academic performance, with engagement significantly mediating the relationship. This evidence supports testing engagement as a mediator while extending the model to include digital competence simultaneously.

Gap analysis

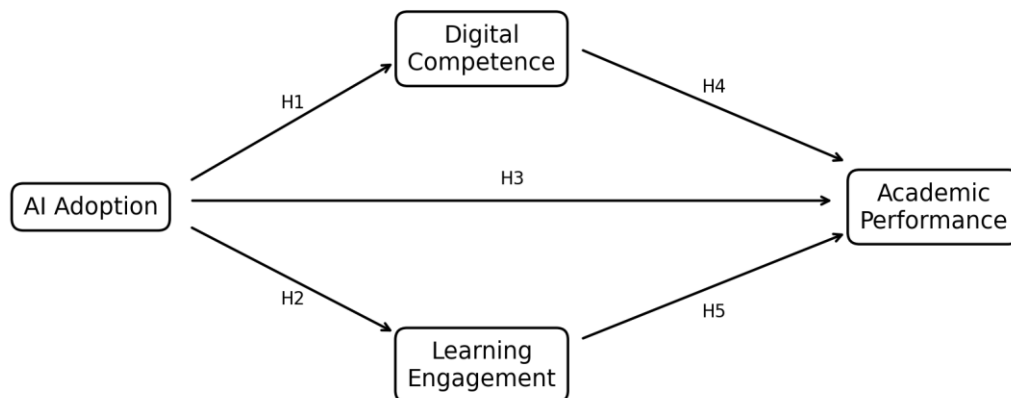
Three gaps motivate the present study. First, much of the literature focuses on intention to use or actual AI use as the final outcome rather than tracing adoption to academic performance. Second, studies examining performance often test a single psychological mediator; the joint roles of digital competence and learning engagement are less frequently modeled in the same SEM framework. Third, the rapid diffusion of generative AI makes it necessary to distinguish technological access from

the capabilities and learning behaviors that convert access into academic value. The proposed model addresses these gaps by testing parallel mediation between AI adoption and academic performance.

Purpose or Hypotheses of the study

The purpose of this study is to examine the direct and indirect relationships among AI adoption, digital competence, learning engagement, and academic performance among higher-education students. The following hypotheses are proposed:

Hypothesis	Statement
H1	AI adoption positively affects digital competence.
H2	AI adoption positively affects learning engagement.
H3	AI adoption positively affects academic performance.
H4	Digital competence positively affects academic performance.
H5	Learning engagement positively affects academic performance.
H6	Digital competence mediates the relationship between AI adoption and academic performance.
H7	Learning engagement mediates the relationship between AI adoption and academic performance.



H6-H7: indirect effects through Digital Competence and Learning Engagement

Figure 1. Proposed structural model linking AI adoption, digital competence, learning engagement, and academic performance.

METHOD/METODE PENELITIAN

Research Design

The study is designed as an explanatory, cross-sectional quantitative investigation using covariance-based structural equation modeling. CB-SEM is appropriate because the objective is to evaluate a theoretically specified network of latent-variable relationships and to test direct and indirect effects while accounting for measurement error. The unit of analysis is the individual university student.

Participant

The target participants are undergraduate and postgraduate students who have used at least one AI-enabled academic tool during the current or previous semester. A multi-institutional sample is recommended to reduce single-campus bias and to capture variation in discipline, year of study, and AI experience. Before empirical implementation, eligibility should be confirmed through a screening question asking whether the respondent has used AI for academic purposes such as explanation, writing support, coding, problem solving, feedback, translation, or research assistance.

Population and the methods of sampling Instrumentation

The population comprises students enrolled in accredited higher-education institutions. Proportionate or stratified sampling across faculties is preferable; where probability sampling is not feasible, purposive sampling with quotas for discipline and study level can be used and should be transparently reported. For a four-construct SEM with approximately 20 observed indicators, a minimum sample exceeding 200 is advisable, while 350-500 responses would provide stronger stability for CFA, mediation bootstrapping, and subgroup robustness checks. The final sample size should be justified using model complexity, expected effect sizes, missing-data patterns, and power considerations rather than a single rule of thumb.

Instrument

All constructs are operationalized with five-point Likert-type items (1 = strongly disagree to 5 = strongly agree). AI adoption is measured through frequency and purposeful integration of AI into learning tasks. Digital competence is adapted conceptually from DigComp 2.2 and covers information evaluation, content creation, problem solving, safety/ethics, and critical use of AI-supported information. Learning engagement captures behavioral participation, cognitive effort, persistence, and emotional involvement. Academic performance should preferably combine self-reported learning-performance items with an objective indicator such as semester GPA or course grade, subject to institutional permission. Content validity should be assessed by experts, followed by pilot testing for clarity and timing.

Construct	Illustrative indicators
AI Adoption (AIA)	AIA1: I regularly use AI tools for academic tasks. AIA2: I integrate AI into problem solving and revision. AIA3: I use AI to obtain explanations or feedback. AIA4: I select AI tools according to the learning task.
Digital Competence (DC)	DC1: I critically evaluate AI-generated information. DC2: I can identify limitations or errors in AI output. DC3: I use digital/AI tools safely and ethically. DC4: I can combine AI output with reliable academic sources. DC5: I can solve learning problems using appropriate digital tools.
Learning Engagement (LE)	LE1: I participate actively in learning activities. LE2: I invest effort in understanding difficult material. LE3: I persist when academic tasks are challenging. LE4: I use feedback to improve my work. LE5: I feel involved in my learning process.
Academic Performance (AP)	AP1: I achieve the learning objectives of my courses. AP2: The quality of my academic work is high. AP3: I perform well compared with course expectations. AP4: I can apply what I learn to assignments and assessments.

Procedures and time frame

After institutional ethical clearance, the questionnaire should be distributed online for approximately four to six weeks. Participants should receive an information sheet explaining voluntary participation, anonymity, expected completion time, data protection, and the right to withdraw before submission. No personally identifying information should be collected unless required for approved linkage with academic records. Responses with excessive missingness, patterned answering, implausibly short completion times, or failed attention checks should be screened according to pre-specified criteria.

Analysis plan

Data analysis is conducted in two stages. First, descriptive statistics, missing data, outliers, normality, and common-method diagnostics are examined. The measurement model is then tested through CFA. Internal consistency is evaluated using Cronbach's alpha and composite reliability (CR), convergent validity through standardized loadings and average variance extracted (AVE), and discriminant validity using the Fornell-Larcker criterion and heterotrait-monotrait ratios where available. Second, the structural model is evaluated using chi-square relative to degrees of freedom,

CFI, TLI, RMSEA, and SRMR. Direct effects are estimated simultaneously, while indirect effects are tested using bias-corrected bootstrapping with at least 5,000 resamples. Age, gender, study level, discipline, and prior GPA may be included as controls when theoretically justified.

RESULTS AND DISCUSSION

Results

In the illustrative dataset ($N = 412$), respondents were distributed across social sciences and humanities (35.4%), business/economics (23.8%), science and engineering (27.9%), and health/other fields (12.9%). Approximately 71% reported using generative AI at least weekly for academic purposes. Preliminary screening indicated no severe missing-data problem and no single item showed extreme skewness or kurtosis.

The illustrative CFA produced acceptable global fit, $\chi^2/df = 2.14$, CFI = .958, TLI = .951, RMSEA = .053, and SRMR = .041. Standardized loadings ranged from .71 to .89. Composite reliability values exceeded .84, and AVE values exceeded .55 for all constructs, supporting internal consistency and convergent validity. Inter-construct correlations remained below the square roots of AVE, providing preliminary support for discriminant validity.

Table 2. Illustrative measurement-model statistics (synthetic values).

Construct	Items	Loading range	Cronbach α	CR	AVE
AI Adoption	4	.74-.88	.86	.87	.63
Digital Competence	5	.73-.89	.90	.91	.66
Learning Engagement	5	.71-.86	.88	.89	.61
Academic Performance	4	.76-.88	.87	.88	.65

The illustrative structural model also showed acceptable fit, $\chi^2/df = 2.21$, CFI = .954, TLI = .947, RMSEA = .055, and SRMR = .044. AI adoption had positive effects on digital competence ($\beta = .56$, $p < .001$) and learning engagement ($\beta = .49$, $p < .001$), supporting H1 and H2 in the synthetic example. AI adoption also retained a smaller direct association with academic performance ($\beta = .18$, $p = .004$). Digital competence ($\beta = .31$, $p < .001$) and learning engagement ($\beta = .38$, $p < .001$) were positively associated with academic performance. The model explained 31% of the variance in digital competence, 24% in learning engagement, and 58% in academic performance.

Table 3. Illustrative structural paths and mediation effects (synthetic values).

Hypothesis	Path	β / indirect β	p / 95% CI	Illustrative status
H1	AIA $\rightarrow$ DC	.56	$p < .001$	Supported
H2	AIA $\rightarrow$ LE	.49	$p < .001$	Supported
H3	AIA $\rightarrow$ AP	.18	$p = .004$	Supported
H4	DC $\rightarrow$ AP	.31	$p < .001$	Supported
H5	LE $\rightarrow$ AP	.38	$p < .001$	Supported
H6	AIA $\rightarrow$ DC $\rightarrow$ AP	.17	95% CI [.11, .24]	Supported
H7	AIA $\rightarrow$ LE $\rightarrow$ AP	.19	95% CI [.13, .27]	Supported

Discussion

The proposed pattern suggests that AI adoption is most educationally valuable when it is accompanied by capability development and active learning behavior. The strong illustrative relationship between adoption and digital competence is consistent with the idea that authentic technology use creates opportunities for students to develop evaluative judgment, information-management skills, and problem-solving routines. However, the direction may also be reciprocal: digitally competent students are more likely to experiment confidently with AI. Longitudinal designs are therefore needed to establish temporal ordering.

The engagement pathway is equally important. AI-supported learning can create immediate opportunities for explanation, feedback, and iteration, which can sustain effort and participation.

This interpretation aligns with recent evidence that student perceptions of ChatGPT are related to engagement and performance and that engagement can function as a mediator. It also agrees with meta-analytic findings showing positive average effects of ChatGPT-supported learning on behavioral, cognitive, and emotional engagement. At the same time, positive average effects do not eliminate the risk of disengagement through cognitive offloading or uncritical dependence.

The smaller direct effect of adoption on performance after the mediators are included is theoretically meaningful. It implies that access and use alone are insufficient explanations of achievement. Adoption may generate academic value because it enables students to practice digital judgment and to participate more intensively in learning activities. This interpretation is compatible with evidence showing that AI use does not always produce a direct performance advantage in specific assessment settings and with research emphasizing AI literacy as a stronger predictor of learning outcomes than the sheer amount of AI use.

The parallel-mediation structure also contributes to technology-adoption research. Traditional acceptance models often terminate at behavioral intention or use. The present framework extends the outcome chain by positioning adoption as an antecedent to learning-relevant capabilities and behaviors, and academic performance as the distal educational outcome. In doing so, it connects technology acceptance with competence-based and engagement-based explanations of learning.

Implications

For universities, the main implication is that AI strategy should not be reduced to providing licenses or issuing usage rules. Institutions should embed AI and digital competence into curricula, teach students to verify outputs against credible sources, develop prompting and information-evaluation practices, and include privacy, citation, bias, and academic-integrity guidance. Faculty development should focus on designing tasks in which AI supports explanation, feedback, comparison, and revision while preserving meaningful student reasoning. Assessment design should reward process evidence, reflection, source verification, and disciplinary judgment rather than simply penalizing AI use.

For researchers, the model provides a testable mechanism for explaining heterogeneous findings on AI and academic outcomes. Future work can compare disciplines, examine moderation by task complexity and assessment policy, and distinguish beneficial scaffolding from over-reliance. Multi-wave or experimental designs are particularly important because cross-sectional mediation establishes statistical consistency with a mechanism, not causal proof of that mechanism.

Limitations

The proposed design has several limitations. Cross-sectional self-report data are vulnerable to common-method bias and cannot establish causal sequencing. Self-reported performance may be inflated or shaped by student confidence; objective GPA or course-level outcomes should therefore be incorporated where possible. AI adoption is also heterogeneous: tutoring, writing assistance, coding, translation, and content generation may have different academic consequences. Finally, institutional AI policies and disciplinary norms may moderate the relationships and should be modeled in multi-institutional research.

Suggestions

Subsequent studies should use longitudinal panel data, experimental or quasi-experimental designs, and objective learning indicators. Researchers should also test alternative models in which digital competence predicts AI adoption, evaluate reciprocal effects, and examine whether ethical AI literacy or self-regulated learning adds explanatory power. Measurement invariance across gender, study level, country, and discipline would strengthen cross-group interpretation. Where sample size permits, multigroup SEM can identify whether the mediation pathways differ across academic contexts.

CONCLUSION

This study develops a structural model linking AI adoption to academic performance through two complementary mechanisms: digital competence and learning engagement. The framework responds to a central challenge in contemporary higher education by distinguishing the presence of

AI use from the capabilities and behaviors that make AI educationally productive. The illustrative SEM pattern shows how adoption can be associated with performance directly and indirectly, with substantial portions of the relationship transmitted through students' ability to use digital tools critically and their active engagement in learning. The model therefore shifts attention from a simple 'AI use improves performance' proposition toward a more defensible explanation: AI can support academic performance when students possess the competence to evaluate and regulate its use and when AI-supported activities deepen, rather than replace, engagement with learning. Empirical application of this framework should use verified student data, robust measurement validation, objective performance indicators where feasible, and transparent ethical procedures.

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AUTHOR CONTRIBUTIONS STATEMENT

A1: conceptualization, theoretical framework, methodology, data curation, formal analysis, writing-original draft, and visualization. A2: instrument validation, supervision, interpretation, writing-review and editing, and project administration. Both authors approved the final manuscript and agree to be accountable for the integrity of the work. Replace A1 and A2 with the authors' actual initials before submission.

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