# AI ADOPTION, ACADEMIC SUCCESS AND CAREER READINESS: THE DUAL MEDIATING ROLES OF AI LITERACY AND CRITICAL THINKING SKILLS

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***Abstract**. Purpose – Anchored primarily in the Technology Acceptance Model (TAM), and extended with complementary insights from Social Cognitive Theory and Human Capital Theory, this study examines the impact of artificial intelligence (AI) adoption on university students' academic success and career readiness, proposing AI literacy and critical thinking skills as parallel mediating variables.*

***Design/methodology/approach** – A quantitative cross-sectional survey design was employed. Data were collected from 331 university students in Uzbekistan using a self-administered online questionnaire comprising 44 Likert-scale items. Partial Least Squares Structural Equation Modelling (PLS-SEM) was used for analysis, with bootstrapping (5,000 resamples) for significance testing of indirect effects.*

***Findings** – All 12 hypothesised relationships were supported. AI adoption positively and significantly predicted academic success, career readiness, AI literacy, and critical thinking. AI literacy and critical thinking each partially mediated the relationships between AI adoption and both outcome variables. AI literacy was the primary mediator for academic outcomes ($\beta = 0.123$), while critical thinking showed a marginally stronger indirect effect on career readiness ($\beta = 0.115$). The dual-mediation model explained 41.2% of variance in academic success and 38.7% in career readiness.*

***Originality/value** – This study contributes a novel dual-mediation model that simultaneously positions AI literacy and critical thinking as parallel mediators between AI adoption and two student outcomes. It extends TAM beyond adoption intention toward an explanatory performance model and provides empirical evidence from a higher education context undergoing rapid AI integration, offering practical guidance for universities, educators, and policymakers navigating responsible AI integration.*

***Keywords:** AI adoption, academic success, career readiness, AI literacy, critical thinking skills, higher education, PLS-SEM, mediation*

***Paper type:** Research article.*

## 1. Introduction

The integration of artificial intelligence (AI) into higher education has advanced rapidly, with universities deploying adaptive learning platforms, intelligent tutoring systems, and generative AI tools such as ChatGPT, Claude, and Gemini to transform how students access information, complete assignments, and develop academic skills (Bond et al., 2023; UNESCO, 2021). Student adoption has risen correspondingly: research across multiple national contexts indicates that the majority of university students now use AI regularly for writing assistance, literature summarisation, problem-solving, and language translation (Kasneci et al., 2023; Rudolph et al., 2023).

The World Economic Forum (2023) further notes that AI competency is increasingly expected in graduate labour markets, motivating adoption beyond the classroom. This proliferation has been matched by a rapid expansion of academic interest: a systematic review by Almatrafi et al. (2024) identified dozens of empirical and conceptual studies on AI literacy alone published between 2019 and 2023, underscoring how quickly both the research base and the practical stakes for universities have grown.

**1.1 Problem statement**

The practical problem motivating this study is straightforward but consequential: universities are investing substantially in AI-enabled infrastructure and are actively encouraging, or at minimum tolerating, widespread student use of generative AI tools, yet they are doing so without a settled evidence base for whether — and how — this investment translates into better academic and career outcomes for students (OECD, 2021; UNESCO, 2021). Decisions about curriculum redesign, AI-use policy, and resource allocation are, in many institutions, proceeding faster than the empirical literature that should inform them.

This uncertainty is well documented in the literature. A meta-analysis by Wang and Fan (2025), synthesising 51 empirical studies, found moderate positive effects of AI tools on students' learning performance; however, effects on higher-order thinking were weaker and highly context-dependent. Other scholars caution that over-reliance on AI-generated content may suppress deep cognitive engagement, academic integrity, and critical reasoning (Kasneci et al., 2023; Baidoo-Anu and Owusu Ansah, 2023). Similarly, while AI-related competencies are increasingly demanded in the labour market, empirical evidence directly linking university AI use to career preparedness remains sparse, with many graduates lacking the structured competencies needed to apply AI effectively in professional settings (Portocarrero Ramos et al., 2025).

**1.2 Research gap**

This inconsistency reflects a deeper conceptual gap: most studies treat AI adoption as a direct predictor of student outcomes without modelling the cognitive mechanisms through which adoption translates into educational benefits (Bond et al., 2023; Zawacki-Richter et al., 2019). Research has examined AI literacy — the capacity to understand, evaluate, and ethically use AI systems — as a mediator of tool effectiveness (Long and Magerko, 2020; Salhab and Aboushi, 2025), and critical thinking as a factor in AI-enhanced learning (Rudolph et al., 2023; Wang and Fan, 2025), but never both simultaneously within a single empirical model. This gap persists despite a fast-growing evidence base: Almatrafi et al.'s (2024) systematic review of 47 studies published between 2019 and 2023 found that the large majority of AI-literacy research either promotes the construct through interventions or conceptualises it theoretically, with only a small minority developing measurement instruments and fewer still embedding AI literacy within a broader structural model of student outcomes. Zhang et al.'s (2025) review of reviews similarly shows that AI-literacy scholarship has diversified conceptually — spanning functional, critical, and sociocultural perspectives — without converging on how the construct relates empirically to established outcome variables such as academic performance or employability. On the critical-thinking side, the recent development of an AI-specific critical-thinking scale (Lau et al., 2025) signals that the field is only now acquiring the measurement tools needed to test AI literacy and critical thinking jointly, rather than as isolated constructs.

Furthermore, career readiness has rarely been treated as a co-equal outcome alongside academic success, with much of the literature prioritising in-class performance while leaving employment preparation empirically underexamined (Makarius et al., 2020).

### 1.3 Purpose and contributions

The present study addresses this three-part gap by proposing and testing a dual-mediation model in which AI literacy and critical thinking serve as parallel mediators linking AI adoption to both academic success and career readiness. The model is anchored primarily in TAM (Davis, 1989), with Social Cognitive Theory (Bandura, 1986, 1997) and Human Capital Theory (Becker, 1993) drawn on as complementary, supporting lenses that extend TAM's explanatory reach from adoption behaviour to downstream cognitive and career outcomes. On this foundation, the study makes four contributions. First, it provides the first empirical test of a dual-mediation structure combining AI literacy and critical thinking in a single, simultaneously estimated model. Second, it extends TAM beyond adoption intention toward an explanatory performance model. Third, it generates evidence from Uzbekistan, an under-represented higher education context undergoing rapid digital transformation. Fourth, by including career readiness as a co-equal dependent variable, it bridges educational technology research and employability studies.

## 2. Theoretical background and hypothesis development

### 2.1 Theoretical foundations

This study is anchored in a single primary theoretical framework — the Technology Acceptance Model (TAM; Davis, 1989) — which explains AI adoption behaviour through perceived usefulness and perceived ease of use and provides the foundational basis for operationalising AI adoption as the study's independent variable. TAM was selected as the primary lens because it directly models the behavioural adoption construct at the centre of this study, and because extended TAM frameworks have been widely and successfully applied to understand technology adoption in educational settings generally (Venkatesh et al., 2003) and to the adoption of generative AI among university students specifically (Salhab and Aboushi, 2025). To extend TAM's explanatory reach beyond adoption itself — toward the cognitive mechanisms and career outcomes also modelled in this study — two complementary theories are drawn on in a supporting role.

First, Social Cognitive Theory (Bandura, 1986, 1997) supports the modelling of AI literacy and critical thinking as cognitive mediators. It explains how competencies — particularly self-efficacy — mediate the relationship between environmental stimuli (here, AI adoption) and behavioural outcomes: individuals do not passively receive environmental inputs, but process and interpret them through cognitive schemas. AI literacy and critical thinking represent precisely such mediating mechanisms, determining whether AI-generated information is used constructively or uncritically. Social Cognitive Theory is used here specifically to justify the mediating role of these two constructs, not as a co-equal alternative to TAM.

Second, Human Capital Theory (Becker, 1993) supports the inclusion of career readiness as a dependent variable. It provides the economic rationale for linking educational experiences, including AI adoption, to career outcomes, holding that investment in knowledge, skills, and competencies during education translates into enhanced productivity and employability. Human Capital Theory is drawn on specifically to justify treating AI literacy and critical thinking as value-added competencies that mediate the return on AI adoption for career readiness — again in a supporting, rather than primary, theoretical role.

### 2.2 Hypothesis development

Direct effects of AI adoption. Wang and Fan's (2025) meta-analysis confirmed a moderate positive effect of AI tools on learning performance, consistent with earlier evidence from Chen et al. (2022) and Zawacki-Richter et al. (2019) linking AI-assisted learning to enhanced student engagement and self-efficacy. Although not unconditional, the weight of evidence supports a direct positive association. This effect appears robust across delivery modes: Bond et al.'s (2023) meta-systematic review similarly reported a preponderance of positive associations between AI-supported instruction and measurable learning gains across primary, secondary, and higher-education settings. More recent evidence extends this pattern to generative AI specifically: Almatrafi et al. (2024) note that a majority of post-2022 studies frame active AI engagement as a precursor to improved academic functioning, even where the underlying mechanism is not explicitly modelled.

**H1.** AI adoption has a significant positive effect on students' academic success.

Academic engagement with AI tools exposes students to technologies increasingly demanded by employers in AI-augmented workplaces (World Economic Forum, 2023).

Portocarrero Ramos et al. (2025) demonstrated empirically that structured AI engagement during university studies is positively associated with graduate employability and career-relevant competencies. This relationship is reinforced by evidence that employers increasingly treat AI fluency as a baseline hiring criterion rather than a specialised skill (World Economic Forum, 2023), meaning academic AI engagement functions simultaneously as skill-building and as direct exposure to tools graduates will be expected to use professionally. Portocarrero Ramos et al.'s (2025) finding that structured, rather than incidental, AI engagement predicts employability strengthens the case for a direct hypothesised path from AI adoption to career readiness.

**H2.** AI adoption has a significant positive effect on students' career readiness.

AI adoption as antecedent of mediating variables. AI literacy is not innate; it develops through repeated engagement with AI systems that require users to evaluate accuracy, understand algorithmic limitations, and navigate responsible use (Long and Magerko, 2020). Gu and Ericson (2025) confirm that active use of AI tools is a key antecedent of AI literacy development. Deliberate AI engagement also creates opportunities to compare AI outputs with other sources, assess credibility, and engage in evidence-based reasoning, fostering reflective cognitive skills (Rudolph et al., 2023; Wang and Fan, 2025). This developmental account is corroborated by Almatrafi et al.'s (2024) systematic review, which found that most AI-literacy interventions in the 2019–2023 literature were built around structured, repeated AI engagement rather than passive exposure, and by Lau et al.'s (2025) validation work showing that frequency of AI use correlates positively with scores on a dedicated critical-thinking-in-AI-use scale. This evidence supports modelling AI adoption as a positive antecedent of both mediating variables, rather than treating AI literacy and critical thinking as pre-existing traits unrelated to actual AI engagement.

**H3.** AI adoption has a significant positive effect on students' AI literacy.

**H4.** AI adoption has a significant positive effect on students' critical thinking skills.

Effects of mediating variables on outcomes. Students with higher AI literacy use AI tools strategically — extracting relevant information and applying AI assistance to enhance rather than replace cognitive effort (Long and Magerko, 2020; Salhab and Aboushi, 2025). Employers in AI-driven industries increasingly require graduates who understand AI functioning, limitations, and ethical implications beyond mere tool proficiency (NACE, 2024; Portocarrero Ramos et al., 2025).

Zhang et al.'s (2025) review of reviews similarly concludes that, across conceptualisations of AI literacy, the functional dimension — the ability to use AI tools effectively for a given task — is the dimension most consistently linked to downstream performance outcomes in the reviewed literature, lending convergent support to a positive path from AI literacy to both academic success and career readiness.

**H5.** AI literacy has a significant positive effect on students' academic success.

**H6.** AI literacy has a significant positive effect on students' career readiness.

Critical thinking — encompassing evaluation, analysis, synthesis, and judgment — underpins deep learning (Facione, 2015). Wang and Fan (2025) confirmed that higher-order thinking skills moderated the academic benefit students derived from AI tools, while Rudolph et al. (2023) and the World Economic Forum (2023) highlight independent analytical reasoning as especially prized in AI-augmented professional contexts where employees must routinely evaluate automated recommendations and make consequential decisions under uncertainty. This is consistent with Lau et al.'s (2025) validation of a dedicated critical-thinking-in-AI-use scale, which found that higher scores predicted more accurate judgement in an AI-assisted fact-checking task — behavioural evidence that critical thinking translates into better-calibrated use of AI-derived information, a competency plausibly relevant to both academic performance and professional judgement.

**H7.** Critical thinking skills have a significant positive effect on students' academic success.

**H8.** Critical thinking skills have a significant positive effect on students' career readiness.

Mediation hypotheses. AI literacy provides the cognitive mechanism through which AI adoption translates into academic and career benefits; without sufficient AI literacy, adoption may yield limited or even negative outcomes such as over-reliance, academic dishonesty, or uncritical acceptance of flawed outputs (Baidoo-Anu and Owusu Ansah, 2023). Similarly, critical thinking is proposed as a mediating mechanism between AI adoption and student outcomes: students who engage reflectively with AI develop opportunities to exercise critical judgment (H4), and stronger critical thinking predicts both academic performance (H7) and career preparedness (H8; Rudolph et al., 2023). This dual-mediation logic is consistent with Wang and Fan's (2025) observation that the benefit of AI tools for learning is highly context-dependent, a pattern more readily explained by unmeasured mediating competencies — such as the AI literacy and critical thinking modelled here — than by AI adoption operating as a uniform, unconditional predictor.

**H9.** AI literacy mediates the relationship between AI adoption and academic success.

**H10.** AI literacy mediates the relationship between AI adoption and career readiness.

**H11.** Critical thinking skills mediate the relationship between AI adoption and academic success.

**H12.** Critical thinking skills mediate the relationship between AI adoption and career readiness.

## 3. Methodology

A quantitative cross-sectional explanatory design was employed, consistent with the study's objective of testing theoretically derived hypotheses and measuring the strength and direction of associations among precisely defined constructs (Collis and Hussey, 2021; Creswell and Creswell, 2018).

The philosophical positioning is positivist, with a deductive logic: theoretical propositions derived from the literature are subjected to empirical testing using structural equation modelling.

Primary data were collected through a self-administered online survey distributed between March and April 2026 via university communication channels, academic networks on social media platforms, and direct peer outreach. The survey targeted undergraduate and postgraduate students at New Uzbekistan University and affiliated higher education institutions across Uzbekistan. All participants provided informed consent prior to completion, yielding a final analytical sample of $n = 331$. As the survey was distributed through non-probability channels without a fixed distribution list, a conventional response rate cannot be calculated. Non-probability convenience sampling was justified on three grounds: the study objective is explanatory rather than descriptive, testing construct relationships rather than population parameters; convenience sampling is the dominant approach in AI-adoption and educational technology research (Demir and Uşak, 2025); and $n = 331$ exceeds the minimum threshold for stable PLS-SEM parameter estimation.

Data analysis was conducted using SPSS for descriptive and reliability analysis, and SmartPLS for structural equation modelling. The analytical sequence comprised: (1) descriptive statistics; (2) reliability analysis using Cronbach's alpha; (3) confirmatory factor analysis (CFA) to assess measurement model validity; and (4) structural model estimation to test all direct effects (H1–H8) and indirect mediation effects (H9–H12), with bootstrapping using 5,000 resamples (Hair et al., 2017). To address the risk of common method bias inherent in self-report designs (Podsakoff et al., 2003), Harman's single-factor test was conducted; the unrotated single factor accounted for less than 50% of total variance, indicating that common method bias does not invalidate the findings.

**4. Measures**

All constructs were operationalised as latent variables measured using multi-item, five-point Likert scales (1 = Strongly Disagree; 5 = Strongly Agree), adapted from validated instruments in prior studies to ensure conceptual alignment and measurement accuracy.

AI adoption (independent variable) was measured using eight items adapted from Davis (1989), Venkatesh et al. (2003), and Salhab and Aboushi (2025), capturing four dimensions drawn from TAM and the Unified Theory of Acceptance and Use of Technology (UTAUT): perceived usefulness (three items), perceived ease of use (two items), social influence (one item), facilitating conditions (one item), and behavioural intention to continue use (one item). Sample item: "Using AI tools improves my performance in academic tasks" ($\alpha = 0.84$; CR = 0.88).

AI literacy (mediating variable) was assessed using four items adapted from Long and Magerko (2020), Gu and Ericson (2025), and Salhab and Aboushi (2025), capturing awareness of AI versus non-AI systems, practical application of AI tools, appropriate tool selection, and ethical AI use. Sample item: "I always comply with ethical principles when using AI applications or products" ($\alpha = 0.81$; CR = 0.87).

Critical thinking skills (mediating variable) were measured using eleven items adapted from Facione (2015), Kasneci et al. (2023), and Rudolph et al. (2023), capturing contextualisation and implication awareness, application of new insights, verification and source evaluation, open-mindedness and perspective-seeking, evidence-based reasoning, and reflective self-regulation.

Several items incorporated AI-specific referents to capture critical thinking as it operates in AI-assisted academic contexts. Sample item: "When using AI-generated information, I consult additional sources to verify the information" ($\alpha = 0.88$; CR = 0.90).

Academic success (dependent variable 1) was operationalised using six items adapted from Zimmerman (2000), Bandura (1997), and Chen et al. (2022), capturing satisfaction with current performance, grade attainment relative to personal expectations, comparative academic standing among peers, and goal-oriented progress. Sample item: "I am satisfied with my academic performance in my program" ($\alpha = 0.79$; CR = 0.84).

Career readiness (dependent variable 2) was assessed using 15 items adapted from NACE (2024) and Portocarrero Ramos et al. (2025), spanning professional orientation, knowledge application and problem-solving, communication and interpersonal skills, learning orientation and adaptability, and professional self-awareness, conceptualised as a holistic, higher-order competency. Sample item: "I can apply the knowledge I learn in university to real-world problems" ($\alpha = 0.91$; CR = 0.93).

## 5. Data analysis and results

### 5.1 Respondent profile and descriptive statistics

The sample was gender-balanced (female 43.2%; male 42.9%), with the majority of respondents (54.7%) aged between 21 and 25 years, consistent with the typical university student profile. ChatGPT was the most widely used AI tool (29.3%), followed by Claude (21.1%) and Gemini (19.0%). A substantial proportion (39.3%) reported daily AI use, and 42.3% subscribed to a paid AI service — indicating a high level of AI integration into academic routines. Laptops were the primary study device for 45.0% of respondents.

Construct-level means indicated that AI literacy recorded the highest mean ($M = 4.00$, $SD = 1.04$), followed by AI adoption ($M = 3.92$), career readiness ($M = 3.74$), academic success ($M = 3.63$), and critical thinking ($M = 3.62$). Notably, item CTS10 ("Before using AI-generated information, I consider its possible implications or limitations") recorded the lowest mean across all constructs ($M = 3.32$, $SD = 1.39$), suggesting that critical evaluation of AI content prior to use remains a developmental area for students despite high overall AI adoption.

### 5.2 Measurement model

Convergent validity was assessed through item loadings, average variance extracted (AVE), and composite reliability (CR) following Hair et al. (2017). All standardised factor loadings exceeded the 0.60 threshold, ranging from 0.63 (ACS3) to 0.83 (AIL4), and were statistically significant at $p < 0.001$. CR values exceeded 0.84 for all constructs, and AVE values exceeded the 0.50 threshold recommended by Fornell and Larcker (1981), supporting convergent validity. The relatively lower loading for ACS3 ("Compared with other students in my program, I perform well academically"; $\lambda = 0.63$) is consistent with its high variability ($SD = 1.38$), suggesting that self-assessed relative academic standing is the most contested dimension of academic success. All items were nonetheless retained as loadings exceeded the minimum acceptable threshold.

Discriminant validity was assessed using the Heterotrait-Monotrait (HTMT) ratio criterion. All HTMT values fell below the conservative threshold of 0.85 (Kline, 2015), confirming that the five constructs are empirically distinct and that the measurement model adequately discriminates between them.

### 5.3 Structural model and hypothesis testing

The structural model was estimated using PLS-SEM in SmartPLS with bootstrapping (5,000 resamples) to estimate standard errors and confidence intervals for all path coefficients and mediation effects. The model demonstrated strong explanatory power: $R^2$ for academic success = 0.412 and for career readiness = 0.387, both substantially exceeding Cohen's (1988) large-effect threshold of $R^2 \geq 0.26$.

All eight direct hypotheses (H1–H8) were supported at $p < 0.001$. AI adoption exerted the strongest direct effect on AI literacy ($\beta = 0.447$), confirming that extensive and purposeful AI engagement is a powerful antecedent of AI literacy development. AI adoption also predicted critical thinking ($\beta = 0.381$), challenging the view that AI use necessarily erodes analytical reasoning. Both AI literacy ($\beta = 0.268$ on academic success; $\beta = 0.275$ on career readiness) and critical thinking ($\beta = 0.289$ on academic success; $\beta = 0.302$ on career readiness) positively and significantly predicted both outcomes, with critical thinking demonstrating a slightly stronger association with career readiness.

For mediation analysis, statistical significance was established when the 95% bias-corrected confidence interval (CI) for the indirect effect excluded zero (Hayes, 2018). All four mediation hypotheses (H9–H12) were supported, with confidence intervals for all indirect effects excluding zero. Because the direct effects of AI adoption on academic success and career readiness remained significant after mediators were included, the mediation is classified as partial rather than full. This finding indicates that AI adoption exerts both a direct influence on student outcomes and an indirect influence channelled through AI literacy and critical thinking.

The largest indirect effect was observed on the path AI adoption → AI literacy → academic success ($\beta = 0.123$), confirming AI literacy as the primary mediating mechanism for academic performance. The indirect effect of critical thinking on career readiness ($\beta = 0.115$) was marginally higher than on academic success ($\beta = 0.110$), aligning with theoretical expectations that analytical reasoning is especially consequential for professional preparedness.

## 6. Discussion

### 6.1 Theoretical implications

The study makes four theoretical contributions to the literature on AI adoption in higher education. First, it proposes and empirically validates a novel dual-mediation model that simultaneously positions AI literacy and critical thinking as parallel mediators between AI adoption and student outcomes. Previous research has examined these constructs individually or in separate frameworks (Long and Magerko, 2020; Facione, 2015; Kasneci et al., 2023), but not within a single, simultaneously estimated structural model. The dual-mediation structure provides a more complete and nuanced account of how AI adoption translates into academic and career benefits than prior single-mediator or direct-effects models.

Second, the study extends TAM (Davis, 1989) beyond its traditional focus on adoption intention by linking TAM-derived AI adoption constructs to downstream cognitive and performance outcomes. The inclusion of AI literacy and critical thinking as mediating variables enriches the TAM framework, moving it from a descriptive adoption model toward an explanatory performance model — a development increasingly called for in educational technology research (Demir and Uşak, 2025).

Third, the finding that AI adoption positively predicts critical thinking provides new empirical support for Social Cognitive Theory's core proposition that environmental stimuli and cognitive processes interact to shape behaviour. This result challenges the concern voiced by Kasneci et al. (2023) and Baidoo-Anu and Owusu Ansah (2023) that AI use necessarily erodes analytical thought; the evidence suggests instead that deliberate and reflective AI engagement is associated with stronger critical thinking competencies.

Fourth, by linking educational AI adoption to career readiness through Human Capital Theory, this study contributes an empirically tested labour-market perspective to a literature that has predominantly focused on in-class academic outcomes (Makarius et al., 2020; Portocarrero Ramos et al., 2025). The finding of partial, rather than full, mediation is theoretically important: it indicates that AI adoption operates through two distinct channels — a direct channel reflecting immediate utility of AI tools for task completion and skill exposure, and an indirect channel mediated by cognitive competencies developed through sustained AI engagement. This nuanced finding advances the field beyond simplistic input-output models.

Fifth, by evaluating AI literacy and critical thinking within a single model, the study responds directly to the gap identified in recent reviews: both Almatrafi et al. (2024) and Zhang et al. (2025) call for research that moves beyond conceptualising these constructs in isolation toward testing their joint explanatory power. The present findings — that both constructs partially and independently mediate the AI adoption–outcome relationship — provide one of the first empirical answers to that call, and suggest that future instrument development, such as Lau et al.'s (2025) AI-specific critical-thinking scale, should be paired with structural modelling rather than treated as a standalone measurement exercise.

**6.2 Practical implications**

The empirical confirmation that AI adoption alone does not guarantee improved student outcomes carries clear institutional responsibilities. Universities should establish mandatory AI literacy modules within first-year curricula, covering tool evaluation, algorithmic bias awareness, and ethical AI use — competencies the current sample demonstrated most variably. Institutional AI policies should move beyond acceptable-use guidelines toward structured skill-development pathways. Given that 42.3% of respondents already subscribe to paid AI services from personal funds, institutions should explore subsidised or centrally licensed AI tool access to reduce inequality in AI engagement quality.

For curriculum designers and educators, the finding that critical thinking mediates the path from AI adoption to career readiness suggests designing assessments that explicitly require students to interrogate, verify, and contextualise AI-generated content rather than merely consume it. The notably low mean for CTS10 ($M = 3.32$) signals an actionable pedagogical gap: pre-use evaluation of AI content should be an explicit, assessed component of learning tasks. Practical approaches include source triangulation exercises, structured reflection journals, and staged assignments in which AI use is permitted for ideation but prohibited for final argumentation.

Career services offices should incorporate AI competency self-assessment tools into graduate readiness programmes, helping students articulate their AI literacy and critical thinking skills to prospective employers. Employers are advised to revisit graduate recruitment criteria to assess not only AI tool proficiency but candidates' demonstrated capacity to evaluate AI outputs critically and apply AI responsibly within professional contexts — competencies empirically linked to career readiness in this study (Portocarrero Ramos et al., 2025; NACE, 2024).

Beyond its theoretical contribution, the study's findings carry direct implications for how AI adoption translates into educational benefit in practice. The dual-mediation results show that AI adoption's benefit for students is not automatic: it is realised specifically through the development of AI literacy and critical thinking, which together helped explain a substantial share of variance in both academic success (41.2%) and career readiness (38.7%). In practical terms, the educational value of AI investment is capped by how deliberately institutions cultivate these two competencies alongside adoption itself: granting students access to AI tools, without parallel investment in literacy and critical-thinking development, is likely to leave much of AI's potential educational benefit unrealised. This has direct implications for three groups: university administrators deciding how to allocate AI-related budgets, educators designing AI-integrated coursework, and career-services staff preparing students for AI-augmented labour markets.

Taken together, these findings position AI adoption as a genuine, but conditional, lever for improving both academic and career outcomes in higher education. The educational benefit of AI is neither guaranteed by mere access nor undermined by use per se; rather, it is contingent on the cognitive competencies that mediate how students translate AI engagement into learning and professional preparation. For institutions weighing whether and how to expand AI integration, this study's evidence suggests that the more consequential investment is not in AI infrastructure alone, but in the literacy- and critical-thinking-building structures that determine whether that infrastructure is used well.

**6.3 Limitations and future research**

This study has several limitations that future research should address. First, a non-probability convenience sample limits statistical generalisability; findings should be interpreted as theoretically generalisable to the dual-mediation model rather than as population estimates.

Second, the cross-sectional design precludes causal inference; longitudinal studies are needed to track how AI adoption, AI literacy, and critical thinking develop over the course of a degree programme and whether their effects on student outcomes strengthen over time. Third, all variables were measured through self-report instruments; future studies should supplement self-reported outcomes with objective data such as institutional GPA records, employer ratings, or standardised critical thinking assessments. Fourth, the sample was drawn primarily from one national higher education context; replication across different national and institutional settings would test the model's cross-cultural generalisability. Fifth, the AI literacy scale (four items) is relatively brief; future research should employ more comprehensive instruments capturing emerging dimensions such as prompt literacy, awareness of AI hallucination, and data privacy (Gu and Ericson, 2025).

Future research may also investigate whether demographic variables — field of study, gender, prior technology experience — moderate the relationships in the dual-mediation model, providing a more differentiated understanding of for whom AI adoption is most beneficial.

Qualitative methods, including interviews and focus groups, would enrich the quantitative findings by providing insight into the experiential and contextual factors shaping AI literacy and critical thinking development.

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