AI Literacy and Perceived Academic Performance: The Mediating Role of AI Self-Efficacy

Carlos Manosalvas-Vaca[1,2,*], David Sancho-Aguilera[1]

[1] *Universidad Estatal Amazónica, Puyo, Ecuador*
[2] *Universidad Internacional del Ecuador, Quito, Ecuador*

Abstract

This study examines whether AI self-efficacy mediates the relationship between AI literacy and perceived academic performance among 387 undergraduate students from public universities in Ecuador. Using a cross-sectional design and Partial Least Squares Structural Equation Modeling (PLS-SEM) with bootstrapping (5,000 subsamples) in SmartPLS 4, a single-mediator model was tested with validated instruments for all constructs. Results show that AI literacy is associated with both a significant direct path to perceived academic performance ($\beta = 0.252$, $p < .001$) and a significant indirect path through AI self-efficacy ($\beta = 0.372$, $p < .001$), a pattern consistent with complementary partial mediation. AI literacy accounts for 70.2% of the variance in AI self-efficacy ($R^2 = 0.702$), and together with AI self-efficacy it accounts for 44.9% of the variance in perceived academic performance ($R = 0.449$). Given the cross-sectional, single-source design, these associations should be interpreted as consistent with, rather than proof of, the hypothesized psychological mechanism. Overall, the findings suggest that AI competencies relate to perceived academic performance both directly and through students' confidence in their own capabilities, indicating that AI literacy programs in Latin American higher education may benefit from combining technical skill-building with deliberate efforts to reinforce students' AI-related self-beliefs.

Keywords

AI literacy, AI self-efficacy, Perceived academic performance, Mediation, PLS-SEM

1. Introduction

The rapid integration of artificial intelligence (AI) tools into higher education has fundamentally reshaped how students engage with academic tasks, access information, and manage their learning processes [1, 2]. Within this transformation, AI literacy, defined as a multidimensional competency encompassing awareness, use, evaluation, and ethical reasoning regarding AI systems [2], has emerged as a critical predictor of students' capacity to harness AI effectively in academic settings. Meta-analytic evidence confirms that integrating AI into educational environments has a significant positive effect on students' academic achievement [3]. Similarly, AI-enabled environments have been shown to substantially enhance learners' self-efficacy [4]. These converging bodies of evidence suggest that AI not only influences academic processes through direct instructional pathways but also operates through motivational and psychological mechanisms. Consistent with Bandura's social cognitive theory, students' beliefs about their own capabilities, particularly in relation to AI-mediated tasks, constitute a fundamental psychological channel linking technological engagement to performance outcomes [5].

Despite this growing body of evidence, substantial inconsistencies persist in the literature regarding how AI literacy translates into improved academic outcomes, revealing critical conceptual and empirical gaps. At the individual level, studies have failed to converge on a consistent pattern for the direct relationship between AI literacy and academic performance: Bećirović et al. [1] found that no AI literacy dimension, technical understanding, critical appraisal, or practical application, exerted a significant direct effect on academic performance, whereas Xiao et al. [6] and Shi et al. [7] reported significant direct

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*Corresponding author.
cmanosalvas@uea.edu.ec (C. Manosalvas-Vaca); dsancho@uea.edu.ec (D. Sancho-Aguilera)
0000-0002-7521-069X (C. Manosalvas-Vaca); 0000-0001-5625-4198 (D. Sancho-Aguilera)

associations between AI literacy and, respectively, educational attainment and writing performance. This divergence suggests that the pathway from AI literacy to academic outcomes may combine both a direct channel and mediating psychological mechanisms, rather than operating through either route alone. Recent work has begun to test self-efficacy as one such mediating pathway: Wang [8] demonstrated that academic self-efficacy mediates the relationship between generative AI literacy and academic achievement, and Dang and Nguyen [9] reported a comparable indirect pathway moderated by AI use duration. However, most of these studies model self-efficacy as either a full mediator or examine mediation without simultaneously testing whether a residual direct effect persists once the mediator is included, leaving unresolved whether AI literacy's influence on performance is fully channeled through self-efficacy or operates in parallel with it. Evidence from the adjacent domain of digital literacy reinforces the relevance of testing self-efficacy as a mediator without prematurely assuming full mediation: Zakir et al. [10] showed that self-efficacy, alongside other psychological variables, accounts for a substantial share of the digital literacy–performance relationship while a direct path remained relevant. Additionally, empirical evidence from higher education settings in Latin America remains notably scarce, thereby constraining the generalizability of current findings to diverse institutional and sociocultural contexts [11].

Against this background, the present study aims to examine the mediating role of AI self-efficacy in the relationship between AI literacy and perceived academic performance among university students. Specifically, this study addresses two research questions: (1) Does AI literacy predict perceived academic performance in higher education students, both directly and indirectly? (2) Does AI self-efficacy mediate the relationship between AI literacy and perceived academic performance, and does a direct effect persist once this mediator is accounted for? Perceived academic performance, rather than objective indicators such as grade point average or exam scores, was adopted as the outcome variable because self-reported performance captures students' own appraisal of how AI-related competencies translate into their academic experience, is less susceptible to the grading heterogeneity that complicates comparisons across disciplines and institutions, and has established construct validity in the Latin American higher education context [11]. To address these questions, a cross-sectional quantitative design was employed, using validated instruments, and the data were analyzed using partial least squares structural equation modeling (PLS-SEM) in SmartPLS 4, enabling simultaneous estimation of direct and indirect effects and nonparametric bootstrapping-based confidence intervals.

This study offers two interconnected contributions to the existing literature. Theoretically, it clarifies the mediating mechanism connecting AI literacy to perceived academic performance by explicitly testing whether AI self-efficacy fully or partially accounts for this relationship, addressing the ambiguity left by prior single-predictor and full-mediation designs [1, 8]. Practically, the findings are intended to inform faculty members, curriculum designers, and institutional policymakers on how to structure AI-related educational activities that simultaneously build students' technical competence and their confidence in using AI tools for academic tasks—contributing to more effective AI integration strategies, particularly in Latin American higher education contexts where rigorous empirical evidence on this phenomenon remains insufficient [11].

2. Literature Review

2.1. Theoretical Framework

Bandura's [12, 13] Social Cognitive Theory posits that individuals' beliefs about their own capabilities are among the most powerful determinants of behavior, effort, persistence, and ultimately performance. In educational contexts, self-efficacy shapes how students approach challenges, regulate their learning processes, and respond to setbacks. High self-efficacy is associated with greater cognitive engagement, deeper processing strategies, and higher academic achievement [8, 9]. In the context of AI-mediated learning, SCT provides a compelling framework for understanding why students who develop competence with AI tools may experience elevated confidence beliefs that in turn improve their academic outcomes. Crucially, SCT frames self-efficacy not merely as a trait but as a domain-specific, context-sensitive belief that can be cultivated through mastery experiences, vicarious learning, and social persuasion—all mechanisms activated in AI-supported educational environments [4, 5].

2.2. AI Literacy and Perceived Academic Performance (H1)

The relationship between AI literacy and academic performance has attracted growing empirical attention, yet findings remain notably inconsistent across methodological contexts. At the meta-analytic level, Dong et al. [3] reported an overall effect size of g = 0.924—a large, statistically significant positive effect of AI on academic achievement. This result, however, masks considerable heterogeneity: educational level, the role assigned to AI, intervention duration, and subject area all emerge as significant moderators, implying that AI's effect on academic performance is far from uniform and is conditioned by variables that most individual-level studies do not fully control [3].

At the individual level, the picture is more nuanced. Xiao et al. [6] confirmed a direct positive effect of AI literacy on educational attainment, with academic well-being serving as an additional pathway. Similarly, Shi et al. [7] found that AI literacy positively and significantly predicted writing performance, a specific academic outcome. In contrast, Bećirović et al. [1] found no significant direct effect of any AI literacy dimension on academic performance, a null finding that challenges the assumption of a straightforward AI literacy–performance link. Dang and Nguyen [9], conducting a mixed-methods study, similarly observed that AI literacy's relationship with academic achievement varied substantially depending on duration of AI use and academic year, reinforcing that boundary conditions moderate this relationship.

These inconsistencies converge on an important implication: the direct path from AI literacy to academic performance is not uniformly observed across contexts, and its magnitude may depend on whether mediating psychological mechanisms are simultaneously modeled. Additionally, most prior studies measure academic performance through grade point averages or exam scores, which are susceptible to institutional grading differences and contextual confounds; fewer studies use perceived academic performance as an outcome variable, despite its established construct validity and relevance to students' subjective learning experience [11]. This gap is particularly notable in Latin American higher education, where instrument validation for perceived academic performance has only recently begun to advance [11]. A plausible explanatory account for this context-dependent divergence concerns the differential maturity of AI adoption: in institutional settings where AI tools are already routine, their marginal contribution to performance may operate mainly through internalized confidence rather than through visibly novel skills, favoring mediated over direct pathways. In emerging-adoption contexts such as Ecuadorian public universities, by contrast, AI-related skills may still translate into perceived academic gains through immediately observable, skill-based channels that are independent of accumulated confidence beliefs, which would favor the persistence of a direct effect alongside any mediated one. This account, proposed specifically for the present study, is examined empirically in the results that follow.

H1: AI literacy has a significant positive effect on perceived academic performance.

2.3. The Mediating Role of AI Self-Efficacy (H2)

The role of self-efficacy as a bridge between AI competence and academic outcomes has received substantial empirical support in recent literature, making it one of the field's most theoretically fertile research directions. The first step of the mediation chain—from AI literacy to self-efficacy—has been established across multiple study designs and cultural contexts. Bewersdorff et al. [5], in a large-scale structural path model with 1,465 university students from the United States, the United Kingdom, and Germany, demonstrated that AI literacy, in conjunction with positive AI attitudes and AI use behavior, significantly predicts AI self-efficacy. Students who possessed greater competence in understanding and applying AI were more confident in their ability to engage effectively with AI-driven academic tasks. This finding is mirrored in Du et al.'s [14] structural equation modeling study with 318 Chinese K-12 teachers, which showed that AI literacy directly and significantly influenced self-efficacy in AI learning and perceptions of AI's social value, with downstream effects on behavioral learning intentions. Wang et al. [15] further showed that the satisfaction of psychological needs (autonomy, competence, and relatedness) shapes AI literacy through self-regulated learning strategies, linking competence beliefs to AI literacy acquisition in a bidirectional manner.

The second step, from self-efficacy to academic performance, has been equally well-documented. Wang [8] represents the most direct empirical test of this specific mediation: using structural equation modeling with 744 Chinese university students, the study demonstrated that academic self-efficacy fully mediates the effect of generative AI literacy on academic achievement, while critical thinking moderates the strength of the AI literacy–self-efficacy path. High-literacy students with elevated critical thinking skills exhibited the strongest self-efficacy gains, ultimately yielding the highest academic achievement. Zakir et al. [10], working in the adjacent domain of digital literacy, demonstrated a structurally equivalent parallel mediation model in which self-efficacy—alongside digital informal learning and digital competence—mediated the relationship between digital literacy and academic performance, accounting for a substantially greater proportion of variance than single-predictor specifications.

However, important limitations qualify this evidence. Bećirović et al. [1] found that while AI technical understanding and practical application positively influenced AI self-efficacy, self-efficacy itself failed to predict academic performance—a result the authors interpreted as suggesting that mediating paths between self-efficacy and performance require the presence of additional moderating or mediating variables. Dang and Nguyen [9] similarly found that self-efficacy's role was moderated by the duration of AI use, such that the relationship was significant only among students who had used AI tools for extended periods. These boundary conditions point to a meaningful gap: prior studies have not consistently tested whether self-efficacy fully absorbs the effect of AI literacy on performance or whether a direct effect persists alongside it, particularly outside East Asian and North American/European university contexts—a gap the present study directly addresses in a Latin American sample. In the present study, partial rather than full mediation is expected: because AI adoption among Ecuadorian public university students is comparatively recent, students may derive perceived academic benefits directly from newly acquired technical skills—such as using AI tools to draft, summarize, or check academic work—before those skills are fully internalized as stable confidence beliefs. A direct path is therefore considered plausible alongside the self-efficacy pathway, rather than self-efficacy being expected to fully absorb the relationship as observed in more AI-mature contexts [8].

H2: AI self-efficacy mediates the relationship between AI literacy and perceived academic performance.

3. Method

3.1. Research Design

This study employed a quantitative, cross-sectional, non-experimental design to examine the mediating role of AI self-efficacy in the relationship between AI literacy and perceived academic performance. A survey-based approach was selected as the primary data collection strategy, given its suitability for measuring latent psychological constructs across large samples and its widespread application in analogous structural models in the AI in education literature [1]. The proposed conceptual model, comprising one predictor (AI literacy), one mediator (AI self-efficacy), and one outcome (perceived academic performance), was estimated using Partial Least Squares Structural Equation Modeling (PLS-SEM), a technique recommended for exploratory theory testing when the primary research objective is predictive and the model involves multiple latent constructs [16].

3.2. Participants and Contextual Justification

The study was conducted with a sample of 387 university students enrolled in public higher education institutions in Ecuador. Participants were recruited across different academic disciplines and study years through an online questionnaire distributed through institutional channels. Inclusion criteria required active enrollment in a public university and self-reported prior experience using AI tools (e.g., ChatGPT, Copilot, or equivalent generative AI assistants) for academic purposes. Descriptive sociodemographic data were collected on gender, academic year, field of study, and frequency of AI tool use.

The focus on public universities in Ecuador is theoretically and empirically justified on several grounds. First, public higher education institutions in Latin America serve predominantly low- to middle-income student populations that have historically faced structural barriers to access to advanced technologies, making the equity implications of AI literacy particularly salient in this context [11]. Second, despite growing scholarly interest in AI's role in higher education, empirical evidence from Latin American public university settings remains scarce and fragmented: the majority of published studies have been conducted in East Asian, European, or North American contexts [5, 8, 9], with only recent work beginning to produce validated evidence from the region [11, 17]. This geographic gap limits the generalizability of existing theoretical models and leaves unanswered whether the psychological pathways linking AI literacy to academic outcomes operate equivalently in institutional contexts characterized by uneven AI infrastructure, heterogeneous digital readiness, and distinct pedagogical cultures. Third, Ecuador's national higher education system has undergone significant regulatory and technological reforms in recent years, with public universities increasingly integrating digital platforms into instructional delivery, making the student population both a relevant and timely target for AI literacy research.

3.3. Instruments

All constructs were measured using validated scales adapted from prior published research. Given that the original instruments were developed in English and the study was administered in Spanish, a standard forward-and-back translation protocol was applied: all items were independently translated from English into Spanish by two bilingual researchers, the Spanish versions were reconciled, and then back-translated into English by a third bilingual expert to verify semantic equivalence. Minor wording adjustments were made to ensure contextual clarity for the Ecuadorian university setting. All items were rated on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree).

AI literacy was measured using the 12-item scale developed and validated by Wang et al. [2], which operationalizes AI literacy across four theoretically grounded dimensions: Awareness (understanding of AI capabilities and limitations), Use (practical interaction with AI tools), Evaluation (critical assessment of AI outputs), and Ethics (awareness of AI's social and moral implications). This instrument was selected over longer alternatives (e.g., the 31-item SNAIL; [18]) due to its parsimony, its demonstrated applicability to non-specialist user populations, and the strong fit indices and reliability coefficients ($\alpha = .85\breve{}.91$ across dimensions) reported in the validation study. Its four-factor structure also aligns directly with the multidimensional conceptualization of AI literacy adopted throughout this paper's theoretical framework.

Self-efficacy toward AI-mediated academic tasks was measured using the 8-item AI self-efficacy scale developed by Bewersdorff et al. [5], originally constructed from the competency taxonomy proposed by Long and Magerko [19]. Items reflect students' confidence in their ability to understand, evaluate, and apply AI technologies in academic contexts (e.g., "I am confident that I can use AI tools effectively for my studies"). The scale demonstrated satisfactory internal consistency in the original validation ($\alpha = .83$) and has been applied across culturally diverse university samples, including students from the United States, the United Kingdom, and Germany [5], supporting its cross-cultural robustness.

Perceived academic performance was measured using the 18-item Student Perception of ChatGPT (SPC) instrument developed and validated by George-Reyes et al. [11], which captures students' perceptions of AI's contribution to their academic performance across communicative and analytical academic skills, including academic writing, digital communication, argumentation, critical thinking, synthesis, and problem-solving. For the purposes of the present model, all 18 items were specified as reflective indicators of a single, global perceived academic performance construct, consistent with the instrument's validated overall factor structure and with the parsimony required by a single-mediator specification.

3.4. Data Collection Procedure

Data were collected through a self-administered online questionnaire distributed via institutional email lists and the learning management systems of the participating universities over a four-week period. Participation was voluntary and anonymous; informed consent was obtained digitally from all participants prior to completing the survey.

Data were analyzed using PLS-SEM implemented in SmartPLS 4 [20]. The analysis proceeded in two sequential stages following the two-step procedure recommended by Hair et al. [16]. In the measurement model stage, the reliability and validity of all reflective constructs were assessed through: (a) internal consistency reliability using Cronbach's alpha (α) and composite reliability (CR), with thresholds of $\geq .70$; (b) convergent validity via average variance extracted (AVE $\geq .50$) and standardized outer loadings ($\geq .70$); and (c) discriminant validity using the Heterotrait–Monotrait (HTMT) ratio criterion [21], with a conservative threshold of HTMT $< .85$.

4. Results

4.1. Measurement Model Assessment

Prior to evaluating the structural relationships, the measurement model was assessed following the two-stage procedure recommended by Hair et al. [16], examining internal consistency reliability, convergent validity, and discriminant validity for the three reflective constructs included in the model: AI literacy, AI self-efficacy, and perceived academic performance.

Table 1 presents the reliability and convergent validity statistics for the three constructs retained in this model. Internal consistency was assessed through Cronbach's alpha (α), the more conservative composite reliability index rho_A, and the traditional composite reliability rho_C. All constructs exceeded the widely accepted threshold of .70 for all three reliability indices [16]. AI Literacy ($\alpha = .946$, rho_A = .955, rho_C = .953), Self-Efficacy ($\alpha = .938$, rho_A = .956, rho_C = .952), and Perceived Academic Performance ($\alpha = .974$, rho_A = .975, rho_C = .976) all indicate strong to excellent internal consistency, with Perceived Academic Performance showing the highest coefficients of the three, consistent with its comprehensive 18-item composition [11].

Table 1
Reliability and Convergent Validity Indicators.

Construct	α	rho_A	rho_C	AVE
AI Literacy	0.946	0.955	0.953	0.627
Perceived Academic Performance	0.974	0.975	0.976	0.694
Self-Efficacy	0.938	0.956	0.952	0.721

Convergent validity was confirmed for all constructs through the average variance extracted (AVE) criterion. All AVE values exceeded the threshold of .50 established by Fornell and Larcker [22]: AI Literacy (AVE = 0.627), Perceived Academic Performance (0.694), and Self-Efficacy (0.721). These results indicate that, on average, each construct explains more than half of the variance in its indicators, confirming adequate convergence of the items around their respective latent variables. Outer loadings for all indicators exceeded the recommended threshold of 0.70 [16], providing further item-level evidence of convergent validity.

Discriminant validity was assessed using the Heterotrait–Monotrait (HTMT) ratio of correlations [21], which is considered superior to the Fornell–Larcker criterion for detecting discriminant validity failures in PLS-SEM contexts. Table 2 presents the full HTMT matrix.

Two of the three HTMT ratios in this model fall comfortably below the conservative threshold of 0.85, supporting adequate discriminant validity between the constructs involved: the ratios between Perceived Academic Performance and AI Literacy (0.635) and between Perceived Academic Performance

Table 2
HTMT Ratio Matrix.

	AI Literacy	Perc. Acad. Perf.	Self-Efficacy
AI Literacy	—		
Perc. Academic Performance	0.635	—	
Self-Efficacy	0.869	0.678	—

and AI Self-Efficacy (0.678) confirm that these constructs are empirically distinguishable despite their theorized structural relationships. The third ratio, between AI Self-Efficacy and AI Literacy, marginally exceeds this threshold and is addressed separately below.

One HTMT value warrants specific interpretation: the ratio between Self-Efficacy and AI Literacy (0.869) marginally exceeds the 0.85 conservative threshold, though it remains below the more lenient 0.90 cutoff sometimes applied in applied PLS-SEM research. This slight overlap is theoretically interpretable: as demonstrated by Bewersdorff et al. [5], AI literacy and AI self-efficacy are conceptually proximal constructs, with competence in AI directly feeding into confidence beliefs. The structural model positions Self-Efficacy as an outcome of AI Literacy rather than as a parallel or redundant measure, and the substantial path coefficient from AI Literacy to Self-Efficacy ($\beta = .838$, $R^2 = .702$) further corroborates their directional, rather than conceptually confounded, relationship. Taken together, the discriminant validity evidence is considered sufficient to proceed with structural model estimation.

4.2. Structural Model

The structural model was evaluated following the two-stage assessment procedure recommended by Hair et al. [16], examining first the explanatory power of the model (R^2), then the statistical significance and relevance of the path coefficients, and finally the indirect effects through bootstrapping with 5,000 subsamples.

Figure 1: Structural model showing standardized path coefficients (β) with significance levels and explained variance (R^2) for AI literacy, AI self-efficacy, and perceived academic performance.

The model explains a substantial proportion of variance across both endogenous constructs. AI literacy accounts for 70.2% of the variance in AI self-efficacy ($R^2 = 0.702$), a substantial effect. Together, AI literacy and self-efficacy explain 44.9% of the variance in perceived academic performance ($R^2 = 0.449$), a moderate effect according to conventional social science benchmarks [16].

The direct path from AI literacy to perceived academic performance was positive and statistically significant ($\beta = 0.252$, $p < .001$), indicating that AI literacy predicts perceived academic performance even after accounting for the mediating effect of self-efficacy. H1 is therefore supported. Bootstrapping analysis also confirmed the significance of the indirect pathway: the indirect effect of AI literacy on perceived academic performance through AI self-efficacy was positive and significant ($\beta = 0.372$, SD = 0.062, $t = 6.002$, $p < .001$), supporting H2. AI literacy strongly predicts self-efficacy ($\beta = 0.838$,

$p < .001$), and self-efficacy, in turn, significantly predicts perceived academic performance ($\beta = 0.444$, $p < .001$).

Given that both the direct and indirect effects of AI literacy on perceived academic performance were statistically significant and had the same sign, the data support a pattern of complementary partial mediation [23]. The total effect of AI literacy on perceived academic performance, conventionally computed in PLS-SEM as the sum of the direct and indirect standardized path coefficients ($\beta = 0.252 + 0.372 = 0.624$), is reported here as a standard summary statistic rather than as a precise decomposition of the underlying relationship; this additive approach assumes linear, non-interacting paths and does not capture potential nonlinearities or interaction effects between the direct and mediated channels, which future research could examine explicitly. With this caveat, the total-effect estimate is consistent with a substantive role for AI self-efficacy in transmitting part of the influence of AI competencies onto perceived academic performance, while a meaningful direct channel also remains active. This pattern is consistent with AI literacy relating to perceived academic performance both directly, through cognitive and technical competencies that students can apply immediately to academic tasks, and indirectly, by strengthening students' beliefs in their own capabilities.

5. Discussion

This study examined whether AI self-efficacy mediates the relationship between AI literacy and perceived academic performance among university students in Ecuador. The results reveal a pattern of complementary partial mediation, in which AI literacy exerts both a direct influence on performance and an indirect influence channeled through self-efficacy. This discussion interprets each finding in light of existing empirical evidence and advances a theoretical account of why both direct and mediated effects can be expected in contexts of emerging AI adoption.

The significant direct path from AI literacy to perceived academic performance found in this study contrasts with Bećirović et al. [1], who found no significant direct effect of AI literacy on academic performance, but is consistent with Xiao et al. [6], who confirmed a direct positive effect of AI literacy on educational attainment; with Shi et al. [7], who found that AI literacy positively predicted writing performance; and with Wijaya [24], who documented a significant direct path from AI literacy to academic achievement. This pattern suggests that AI literacy, understood as a set of cognitive competencies for understanding, using, and evaluating AI systems, can translate into perceived academic gains through channels that are independent of self-efficacy, such as the direct application of AI-related skills to academic tasks, in addition to operating through psychological mechanisms. This interpretation is compatible with the meta-analytic evidence from Dong et al. [3], who reported an overall effect size of $g = 0.924$ for the AI–academic achievement relationship, while noting substantial heterogeneity attributable to the mediating structures included across studies. The contrast with Bećirović et al. [1] is instructive: differences in institutional context, in the AI literacy dimensions emphasized, and in whether a single or multiple mediators are modeled may jointly determine whether a residual direct effect is detectable, underscoring the value of testing partial rather than assuming full mediation.

The indirect effect of AI literacy on perceived performance through AI self-efficacy constitutes the strongest single pathway in the model and provides support for H2. The predictive strength of AI literacy on self-efficacy is consistent with the meta-analytic estimate reported by Ren et al. [4]. This path reflects a well-established mechanism grounded in Bandura's social cognitive theory: as students develop competencies in AI tools, they acquire mastery experiences that strengthen their belief in their own capability to perform academic tasks, which in turn elevates their perceived performance [8, 9]. Wang [8] demonstrated a comparable sequence, finding that self-efficacy fully mediated the relationship between GenAI literacy and academic achievement. Dang and Nguyen [9] similarly reported significant indirect effects of AI literacy through self-efficacy on academic outcomes among Vietnamese students, situating self-efficacy as an important psychological engine through which competence translates into performance. The magnitude of the AI literacy $\rightarrow$ AI self-efficacy path in the present study exceeds those reported in most prior single-country studies. One plausible, though speculative, explanation—not directly tested with the present data—is the relative novelty of AI tools in the Ecuadorian university context: in environments where AI exposure is relatively new, even modest literacy gains might produce pronounced gains in self-efficacy by providing students with mastery experiences that were previously inaccessible [5]. This interpretation should be treated as a hypothesis for future research rather than as a finding of the present study. It is broadly consistent with Du et al. [14], who found that AI literacy strongly predicted self-efficacy among K-12 teachers encountering AI tools for the first time. Unlike Wang [8], who found that self-efficacy fully mediated this relationship, the present study finds that self-efficacy operates alongside a significant direct effect, suggesting that in the Ecuadorian public university context AI competencies translate into perceived performance both through confidence-building and through more immediate, skill-based channels.

The joint presence of a significant direct effect and a significant indirect effect through self-efficacy defines a pattern of complementary partial mediation [23], which carries specific implications for the theoretical framing of AI literacy research. It implies that the influence of AI competencies on perceived academic performance is only partly channeled through psychological mechanisms: educators can expect that imparting AI skills will yield some direct academic benefit, but that these gains are substantially amplified when accompanied by growth in students' self-efficacy beliefs. This finding qualifies the conclusions of studies conducted in more AI-mature contexts, such as Wang [8], where self-efficacy fully absorbed the AI literacy–performance relationship, and instead resonates with Xiao et al. [6], who found that AI literacy exerted both direct and indirect effects on educational attainment through academic well-being, corroborating the view that in less AI-saturated institutional contexts, competence-based and psychological pathways can operate simultaneously rather than one substituting entirely for the other.

5.1. Implications

The context of this study adds important interpretive texture to these findings. Public universities serve a predominantly first-generation student population with heterogeneous prior exposure to digital technologies and limited institutional AI infrastructure [11, 17]. In this context, the substantial strength of self-efficacy as a mediator suggests that confidence-building may be a valuable intervention target: programs that combine AI literacy training with structured mastery opportunities, such as guided AI-assisted tasks with immediate performance feedback, could plausibly produce stronger gains in self-efficacy and, through it, perceived academic performance—though this expectation follows from cross-sectional associations and would need to be confirmed through intervention or longitudinal designs before being treated as established. At the same time, the persistence of a significant direct effect is consistent with technical AI literacy training itself, independent of its effect on students' confidence, contributing to perceived academic performance. With this caveat in mind, institutions may wish to avoid treating self-efficacy-building and technical skills training as substitutes, and instead consider AI literacy curricula that pursue both objectives concurrently.

6. Conclusion

This study demonstrates that AI literacy is associated with perceived academic performance among Ecuadorian university students both directly and through AI self-efficacy, a psychological pathway that partially, rather than fully, channels this relationship. The complementary partial mediation pattern observed indicates that AI competencies relate to perceived academic performance both by directly equipping students with applicable skills and by strengthening their beliefs in their own capabilities. The self-efficacy pathway proved to be the single strongest component of the total effect, consistent with meta-analytic evidence on the AI–self-efficacy relationship, while the persistence of a significant direct effect underscores that technical AI competence carries independent value for students' perceived academic performance. These findings carry potential implications for higher education policy in Latin America: AI literacy programs that focus exclusively on technical skill acquisition, without also cultivating students' confidence in using AI tools, may realize only part of their potential academic benefit. Building technical competence and cultivating AI self-efficacy together are the two conditions this cross-sectional study associates with the strongest observed relationship to perceived academic performance; whether they causally enable AI literacy to reach its fuller potential as a driver of academic performance remains to be established through longitudinal or experimental research.

6.1. Limitations and Future Research

Several limitations should be noted. First, the cross-sectional design precludes causal inference, and longitudinal replication would be needed to establish the temporal ordering of the constructs. Second, all variables are based on self-reported perceptions, and the use of perceived academic performance as the outcome, while theoretically justified and psychometrically validated, does not capture objective grade-based achievement; the relationship between perceived and actual performance warrants future investigation. Third, the sample is drawn exclusively from public universities in Ecuador, which constrains generalizability to other national contexts and to private higher education institutions. Fourth, data collection relied on procedural remedies commonly recommended to reduce common method bias, such as guaranteeing respondent anonymity and varying item presentation order; however, these remedies were not the object of a dedicated statistical test (e.g., Harman's single-factor test or a marker-variable approach), and the single-source cross-sectional design remains a potential confound that future studies should address directly. Fifth, this study modeled AI self-efficacy as the sole mediator; other psychological or motivational variables not examined here may account for part of the direct effect that remained significant, and future research should test additional mediating or moderating mechanisms, including a formal moderation analysis by frequency of AI use, which prior studies suggest can condition the strength of these relationships [9]. Sixth, measurement invariance across academic disciplines and academic years was not tested; given the declared heterogeneity of the sample, this omission leaves open whether the measurement model holds equivalently across subgroups, and future work should conduct multi-group invariance analyses before drawing comparative conclusions. Seventh, the translated instruments were not piloted prior to full administration; although a forward-and-back translation protocol with bilingual reconciliation was applied, a small-scale pilot test would have provided additional assurance of item comprehension in the Ecuadorian university context. Eighth, participants were recruited through institutional mailing lists on a self-selected basis, which may have overrepresented students with greater familiarity with or interest in artificial intelligence, potentially inflating the observed relationships between AI literacy and self-efficacy; probability-based or stratified sampling would help address this risk in future studies. Future research should also incorporate multiple informants, objective performance indicators, and experimental or longitudinal designs to validate the mediation structure identified here.

Declaration on Generative AI

During the preparation of this paper, the author used Claude (Anthropic) to verify that the manuscript complied with the formatting and submission requirements established by the IWSAI 2026 conference. After using this tool, the edition was reviewed by the author as needed, and he takes full responsibility for the final content.

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