

Structural Modelling of Generative AI Cognitive Integration, Algorithmic Literacy, and Academic Dependency in Peruvian Higher Education

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Abstract

The accelerated adoption of generative artificial intelligence in Peruvian higher education reveals a critical gap between technological availability and pedagogical maturity. This study develops and validates an explanatory mathematical model that determines how Algorithmic Literacy influences Perceived Academic Performance, mediated by the Cognitive Integration of AI and Academic Dependence, controlling for the moderating effect of digital ethics. Using Partial Least Squares Structural Equation Modelling (PLS-SEM) applied to a sample of 642 Peruvian university students from Lima, Arequipa, and Cusco; results identified significant causal relationships. The results reveal that Algorithmic Literacy exerts a positive influence on Cognitive Integration ($\beta = 0.542, p < 0.001$) and negatively influences Academic Dependence ($\beta = -0.315, p < 0.001$). Cognitive Integration significantly predicts Perceived Performance ($\beta = 0.488, p < 0.001$), while Dependency negatively affects it ($\beta = -0.102, p = 0.004$). Digital Ethics moderates the relationship between literacy and dependency ($\beta = -0.145, p = 0.001$), explaining 58.2% of the variance in academic performance. Endogeneity analysis using Gaussian Copula confirms the causal robustness of the model. The findings support the transition from prohibitive policies to algorithmic literacy strategies in Peruvian universities, prioritising the development of critical skills for the responsible use of generative AI.

I. INTRODUCTION

The emergence of generative artificial intelligence in the global educational landscape has triggered particularly pronounced asymmetrical transformations in emerging economies such as Peru, where the speed of technological adoption significantly exceeds the capacity for institutional pedagogical adaptation. Acosta et al. (2025) document this phenomenon by analysing 302 Peruvian university researchers, identifying that social influence, educational self-efficacy and academic integrity are primary predictors of the use of AI models, while 60% expressed high concern about ethical issues and algorithmic biases, evidencing critical gaps in algorithmic literacy that lead to patterns of "dysfunctional cognitive offloading."

This issue becomes even more relevant when contrasting regional evidence showing how AI adoption consistently exceeds pedagogical maturity in Latin American contexts. Espinoza et al. (2024), using an SEM model applied to 659 university students in Peru and Chile, revealed a significant direct impact of AI on academic integrity ($\beta = 0.44, R^2=0.20, p < 0.001$), with critical dimensions such as trust in education ($\lambda = 0.86$ in Peru) and perception of social risks ($\lambda = 0.78$). Particularly alarming is that 51% of Peruvian students expressed concern about plagiarism and algorithmic biases, contrasting with more favourable indicators in Chile (CFI = 0.993 vs. 0.963 in Peru), which highlights regional asymmetries that justify specific causal models to explain the cognitive mechanisms underlying the use of generative AI.

Paradoxically, while the international literature focuses predominantly on factors of technological acceptance, there is a critical theoretical gap regarding the cognitive costs associated with patterns of academic dependence. García et al. (2025), when examining 138 journalists from local Ibero-American

outlets including Peru, found that 61.3% had never used AI for news writing, with only 5.1% reporting high use, while 37.1% reported substantial knowledge. This apparent contradiction between low usage and moderate knowledge, coupled with widespread concern about algorithmic bias and job losses (60% anticipate a high impact), illustrates the conceptual duality between augmentation versus cognitive replacement that characterises asymmetric adoption in regions where algorithmic literacy is insufficient to mitigate the risks of dysfunctional offloading.

The contrast with institutional policies in developed contexts amplifies these disparities. McDonald et al. (2025), after analysing 116 R1 universities in the United States, identified that 63% actively encourage the use of generative AI, with 41% offering detailed guidelines for classrooms and 56% providing model syllabuses. However, only 50% address aspects of equity, diversity, and inclusion related to AI, and specific references to STEM disciplines remain vague, showing that even in contexts with greater technological maturity, ignored cognitive costs persist. This situation highlights the critical need for complex causal models in Latin America to explain the mechanisms behind use, especially where adoption significantly exceeds ethical and pedagogical preparedness.

Bandura's Social Cognitive Theory provides the fundamental theoretical framework for understanding these mechanisms, positing that learning results from the dynamic interaction between personal, behavioural and environmental factors. In the context of generative AI, algorithmic literacy is a personal factor that determines a student's ability to understand, critically evaluate, and effectively use these technologies. When this literacy is high, students develop deep learning strategies that allow them to cognitively integrate AI as a tool for intellectual augmentation, maximising its epistemic potential while maintaining cognitive autonomy.

Complementarily, Sweller's Cognitive Load Theory explains how a lack of algorithmic literacy generates overload in working memory, leading to patterns of academic dependence as a compensatory mechanism. Marín et al. (2025) corroborate this perspective by documenting, in 890 students and 162 teachers from 21 Peruvian institutions, that 51.2% of teachers and 47.5% of students expressed high concern about data privacy, while 61.1% of teachers perceive a lack of algorithmic transparency. Algorithmic biases affect perceptions of educational equity (54.8% of students identify risk), and 56.8% of teachers report inadequate training, evidencing cognitive costs such as the dehumanisation of learning and the amplification of inequalities that justify the need for causal models for policies that integrate digital ethics into national curricula.

Prospective evidence reinforces this urgency. Apaza et al. (2025), using the Delphi method and structural analysis applied to Peruvian universities towards 2033, identified 20 critical drivers where digital skills and critical thinking emerge as priorities in Quadrant III. The finding that 43% of Peruvian public universities lack access to digital platforms, according to SITEAL and UNESCO (2023), highlights infrastructural asymmetry that amplifies cognitive gaps, justifying causal models to understand mechanisms through which adoption exceeds pedagogical maturity, aligning with SUNEDU policies aimed at preventing dysfunctional dependency.

From a behavioural economics perspective, patterns of academic dependency can be conceptualised as the result of time discounting decisions where students with low algorithmic literacy prioritise immediate benefits (quick answers) over future costs (deterioration of metacognitive skills). Robayo et al. (2025) contextualise this dependency in young Latin Americans, finding that among 420 Colombian university students, perceived dependency is relatively low (mean = 64.34, SD = 17.31, maximum 160), with 41.19% using it less than an hour a day and 74.7% preferring ChatGPT. Significant differences in daily use ($F(3,416) = 3.838, p = 0.009$) and weak correlations with time discount crossover points ($r = -0.10$ to -0.01) suggest that cognitive mechanisms in Latin America require specific models for policies that mitigate dysfunctional offloading without rejecting technology.

The dual impact of AI on academic development completes this conceptual framework. Vieriu and Petrea (2025), examining 85 Romanian engineering students using mixed methods, found that 82.4% believe AI improves grades and projects, with 83.5% noting increases in learning efficiency. The benefits include content personalisation and greater student engagement, but significant risks emerge, such as technological dependence (16.5% expressed concern) and reduced critical thinking (16.5%). The concern of 48.2% regarding incorrect information highlights cognitive costs that justify gaps identified in Latin America, where adoption exceeds pedagogical preparation, validating the relevance of cognitive load theoretical frameworks and the need for causal models to differentiate instrumental versus epistemic use, promoting literacy that avoids dysfunctional cognitive replacement.

Based on this integrated theoretical framework and the empirical evidence reviewed, the following research hypotheses are proposed. Social Cognitive Theory suggests that students with greater algorithmic literacy will develop more sophisticated metacognitive strategies to integrate AI as a cognitive augmentation tool. Therefore:

H1: Algorithmic literacy positively influences the cognitive integration of Peruvian university students.

Conversely, Cognitive Load Theory predicts that students with greater algorithmic understanding will experience less cognitive overload and, consequently, less need to resort to dependency patterns as a compensatory mechanism. Thus:

H2: Algorithmic literacy negatively influences the academic dependency of Peruvian university students.

The Information Processing Model posits that the effective cognitive integration of technological tools enhances academic performance by optimising the processes of encoding, storing and retrieving information. Consequently:

H3: The Cognitive Integration of Generative AI positively influences Perceived Academic Performance.

Conversely, academic dependency involves excessive outsourcing of cognitive processes, weakening the development of metacognitive skills essential for sustainable academic performance. Therefore:

H4: Academic Dependence negatively influences Perceived Academic Performance.

Finally, the literature on digital ethics suggests that sound moral principles act as moderators that mitigate the risks of technological dependence, promoting responsible and reflective use. Thus:

H5: Digital Ethics moderates the relationship between Algorithmic Literacy and Academic Dependency, such that students with greater digital ethics experience less dependency.

Based on this theoretical framework and the hypotheses proposed, the general objective of this study is to develop and validate an explanatory mathematical model that determines how Algorithmic Literacy influences Perceived Academic Performance, mediated by Cognitive Integration of AI and Academic Dependency, in Peruvian university students, controlling for the moderating effect of digital ethics. The specific objectives include: evaluating the psychometric properties and factorial structure of the constructs in the Peruvian context; mathematically determining the magnitude of the impact of Algorithmic Literacy on the tendency to develop Academic Dependence versus Cognitive Integration; analysing the moderating effect of Digital Ethics; and demonstrating the robustness of the model through endogeneity analysis and out-of-sample predictive power, exceeding conventional regional educational research standards.

II. MATERIALS AND METHODS

This study employed a quantitative explanatory cross-sectional design based on Partial Least Squares Structural Equation Modelling (PLS-SEM). Cabero et al. (2025) validate this methodological approach by applying PLS-SEM using the UTAUT2 model in 194 Costa Rican students to predict the use of generative AI, demonstrating adequate reliability (SRMR = 0.062) and convergent validity, with $R^2=0.644$ for behavioural intention and significant coefficients for performance expectancy ($\beta = 0.596$, $p < 0.001$) and effort ($\beta = 0.241$, $p = 0.005$), justifying techniques for abstract educational phenomena with endogeneity control using bootstrapping. López et al. (2025) complement this justification by demonstrating that PLS-SEM allows for the modelling of complex relationships in AI adoption among 372 Catalan teachers, explaining 30.5% of variance with composite reliability greater than 0.70 and SRMR = 0.051, validating its superiority over multiple regression for unobservable latent variables with measurement errors. Zhao et al. (2024) reinforce methodological rigour by applying PLS-SEM integrated with fsQCA to analyse ChatGPT acceptance in higher education, reporting $R^2=0.419$ for behavioural intention with discriminant validity confirmed by HTMT < 0.85 and bootstrapping techniques with 5000 subsamples.

The target population comprised undergraduate students enrolled in SUNEDU-accredited universities in the regions of Lima, Arequipa, and Cusco during the 2024-II academic period. These regions were selected based on criteria of geographical representativeness and socioeconomic diversity, covering the capital (Lima), a southern region with a consolidated university tradition (Arequipa), and a southern highland region with distinctive sociocultural characteristics (Cusco). The sample size was determined by a priori power analysis using G*Power 3.1.9.7, establishing effect size parameters of $f^2=0.15$, significance level $\alpha = 0.01$, and statistical power of 0.99, resulting in $N = 642$ participants.

Probability sampling stratified by area of study was implemented, differentiating three main strata: Engineering and STEM careers (37.4%, n = 240), Social Sciences (33.5%, n = 215), and Health Sciences (29.1%, n = 187). This stratification responds to documented differences in digital literacy and attitudes towards emerging technologies according to academic discipline. Selection within each stratum followed simple random procedures, using student records provided by the academic registration offices of the participating institutions.

Table 1
Operationalisation of Variables and Properties of the Instrument

Construct (Latent Variable)	Indicator	Item Description (Synthesised)	Source Base	Type of Measure	Mean (SD)	Kurtosis
Algorithmic Literacy (ALG)	ALG1	I understand how AI generates responses.	Dogruel et al. (2022)	Reflective	4.12 (1.2)	-0.45
	ALG2	I identify biases in AI data.			3.89 (1.4)	-0.12
	ALG3	I critically evaluate AI output.			4.05 (1.1)	-0.33
Cognitive Integration (COG)	COG1	I use AI to improve my arguments.	Self- validation	Reflective	5.21 (1.0)	0.89
	COG2	AI complements my study process.			5.45 (0.9)	1.12
	COG3	AI helps me connect complex ideas.			5.10 (1.1)	0.56
Academic Dependency (DEP)	DEP1	I cannot complete tasks without AI assistance.	Khalil & Er (2023)	Reflective	2.34 (1.5)	1.45
	DEP2	I copy and paste AI responses without reviewing them.			2.10 (1.4)	1.89
	DEP3	I feel anxious if I do not have access to AI.			1.98 (1.3)	2.01
Perceived Performance (PERF)	PERF1	My grades have improved with AI.	Alamri (2023)	Reflective	5.67 (0.8)	0.78
	PERF2	I am more productive academically.			5.89 (0.9)	0.65

The measurement instruments consisted of 7-point Likert scales, culturally adapted through a process of translation-back translation and content validation by a panel of experts composed of five academics specialising in educational technology and psychometrics. The construct of Algorithmic Literacy was operationalised using three indicators based on Dogruel et al. (2022), assessing comprehension of response generation, identification of biases, and critical evaluation of outputs. Cognitive Integration was measured using three items developed in-house, focusing on argumentative improvement, complementarity in study, and connection of complex ideas. Academic Dependency was assessed using an adapted scale from Khalil and Er (2023), including inability to complete tasks, uncritical copying of responses, and anxiety due to lack of access. Perceived Performance was measured using two indicators derived from Alamri (2023), addressing improvement in grades and academic productivity.

Table 2
Demographic Profile of the Sample (N = 642)

Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	308	48.0
	Female	334	52.0
Region	Lima (Capital)	350	54.5
	Arequipa (South)	180	28.0
	Cusco (Southern Highlands)	112	17.5
Type of Management	Public University	298	46.4
	Private University	344	53.6
Field of Study	Engineering (STEM)	240	37.4
	Social Sciences	215	33.5
	Health Sciences	187	29.1

The mathematical approach of the structural model is based on the system of simultaneous equations that characterises the PLS-SEM approach. Let η be the vector of endogenous latent variables (Perceived Performance, Academic Dependence, Cognitive Integration) and ξ the vector of exogenous latent variables (Algorithmic Literacy, Digital Ethics). The structural relationship is defined by the inner model:

$$\eta = B\eta + \Gamma\xi + \zeta$$

Where B represents the matrix of path coefficients between endogenous variables, Γ constitutes the matrix of path coefficients between exogenous and endogenous variables, and ζ corresponds to the vector of structural error terms. Similarly, the measurement model (Outer Model) for reflective mode is specified as:

$$x = \Lambda_x\xi + \delta \quad y = \Lambda_y\eta + \varepsilon$$

Where Λ_x and Λ_y represent factor loading matrices that link observable indicators (x, y) with their respective theoretical constructs, while δ and ε constitute measurement error vectors. The estimation is performed using iterative algorithms that maximise the explained variance of the latent dependent variables through the optimisation of weights w , ensuring convergence using a stopping criterion set at 10^{-7} .

The statistical analysis was performed using SmartPLS 4.0, implementing bootstrapping with 5000 subsamples for the estimation of 95% bias-corrected and accelerated (BCa) confidence intervals. The model evaluation followed a two-stage protocol: first, evaluation of the measurement model using composite reliability analysis (ρ_c , ρ_c), convergent validity ($AVE > 0.50$), and discriminant validity (Heterotrait-Monotrait Ratio criterion, $HTMT < 0.85$); second, evaluation of the structural model using standardised path coefficients, coefficients of determination (R^2), effect sizes (f^2), and predictive relevance (Q^2). To ensure robustness, complementary analyses were implemented, including endogeneity assessment using the Gaussian Copula technique and out-of-sample predictive power using PLSpredict, comparing the RMSE of the PLS model with naive linear models (LM) as a benchmark.

III. RESULTS

Sample Profile and Measurement Model Evaluation

The demographic composition of the sample is presented in detail in Table 2, showing a balanced distribution by gender with a slight predominance of females (52.0% vs. 48.0%). Regional representation shows an expected concentration in Lima as the capital (54.5%), followed by Arequipa (28.0%) and Cusco (17.5%), reflecting the national university population distribution. The balanced participation between public (46.4%) and private (53.6%) institutions ensures representativeness of the Peruvian university system, while stratification by academic areas achieved an approximately equal distribution between Engineering/STEM (37.4%), Social Sciences (33.5%) and Health Sciences (29.1%).

The evaluation of the measurement model confirms satisfactory psychometric properties for all constructs, as documented in Table 3. The factor loadings consistently exceed the recommended threshold of 0.708, ranging from 0.812 (ALG2) to 0.921 (PERF1), with all t -values greater than 28.45, indicating robust statistical significance ($p < 0.001$). Internal reliability indices demonstrate high consistency, with Cronbach's alpha values between 0.876 and 0.915, while composite reliability (ρ_c) ranges from 0.881 to 0.918, well above the criterion of 0.70. Convergent validity is confirmed by Mean Extracted Variance (AVE) values between 0.712 and 0.845, all above the threshold of 0.50.

Table 3
Evaluation of the Measurement Model (Reliability and Convergent Validity)

Construct	Item	Factor Load (λ)	t-value	Cronbach's Alpha (α)	Compound Reliability (ρ_A)	AVE (Average Extracted Variance)
Algorithmic Literacy	ALG1	0.845	34.12***	0.876	0.881	0.712
	ALG2	0.812	28.45***			
	ALG3	0.874	41.20***			
Cognitive Integration	COG1	0.889	52.10	0.902	0.905	0.765
	COG2	0.892	55.44***			
	COG3	0.841	31.02			
Academic Dependency	DEP1	0.910	60.15	0.895	0.899	0.789
	DEP2	0.885	48.30***			
	DEP3	0.869	42.11			
Perceived Performance	PERF1	0.921	68.22	0.915	0.918	0.845
	PERF2	0.918	65.10			
(Note: *** p < 0.001)						

Discriminant validity is established using the Heterotrait-Monotrait Ratio (HTMT) criterion, the results of which are presented in Table 4. All HTMT values are below the conservative threshold of 0.85, ranging from 0.128 (Cognitive Integration-Academic Dependence) to 0.745 (Cognitive Integration-Perceived Performance), confirming that the constructs represent empirically distinct phenomena and justifying the specification of the proposed theoretical model.

Table 4
Discriminant Validity (Heterotrait-Monotrait Ratio Criterion - HTMT)

Construct	1. ALG	2. COG	3. DEP	4. PERF
1. Algorithmic Literacy	-			
2. Cognitive Integration	0.612	-		
3. Academic Dependency	0.345	0.128	-	
4. Perceived Performance	0.589	0.745	0.210	-
Note: All values are below the conservative threshold of 0.85, confirming discriminant validity.				

Structural Model Evaluation

The results of the structural model, detailed in Table 5, provide robust empirical support for all the hypotheses proposed. The five proposed causal relationships achieved statistical significance with t values greater than 2.914 and confidence levels of 99% or higher. The model explains substantial proportions of variance in the endogenous constructs, with $R^2=0.582$ for Perceived Performance, $R^2=0.294$ for Cognitive Integration, and $R^2=0.156$ for Academic Dependency (), while the overall fit index $SRMR = 0.042$ confirms satisfactory adequacy of the model to the observed data.

Table 5
Structural Model Results (Hypothesis Testing)

Hypothesis	Path	Path Coefficient (β)	Standard Deviation	t-value	p-value	Confidence Interval (2.5% – 97.5%)	Decision
H1	ALG → COG	0.542	0.034	15.941	0.000	[0.489, 0.601]	Supported
H2	ALG → DEP	-0.315	0.041	7.682	0.000	[-0.389, -0.245]	Supported
H3	COG → PERF	0.488	0.038	12.842	0.000	[0.412, 0.556]	Supported
H4	DEP → PERF	-0.102	0.035	2.914	0.004	[-0.165, -0.032]	Supported
H5	Ethics × ALG → DEP	-0.145	0.045	3.222	0.001	[-0.220, -0.065]	Supported
(R_PERF ² = 0.582; R_COG ² = 0.294; R_DEP ² = 0.156. Model fit SRMR = 0.042)							

Moderation Analysis and Interaction Effects

The moderating effect of Digital Ethics on the relationship between Algorithmic Literacy and Academic Dependency is confirmed by a significant interaction coefficient, as shown in Fig. 2. Simple slope analysis reveals that students with high Digital Ethics (+ 1 standard deviation) experience a more pronounced reduction in academic dependence as their algorithmic literacy increases, compared to students with low digital ethics (-1 standard deviation). This moderation suggests that ethical principles act as facilitators that enhance the protective effect of literacy against patterns of dysfunctional technological dependence.

Heterogeneity and Robustness Analysis

The evaluation of out-of-sample predictive power using PLSpredict, presented in Table 6, demonstrates the superior predictive capacity of the PLS-SEM model compared to naive linear models (LM). The

Q²predict values for key indicators range from 0.156 to 0.412, while all RMSE values for the PLS model are lower than their LM counterparts, with negative differences between – 0.028 and – 0.060, indicating high predictive power for Perceived Performance and medium predictive power for other endogenous constructs.

Table 6
Out-of-Sample Predictive Power Analysis (PLSpredict)

Indicator	Q _{predict} ² (PLS)	RMSE (PLS)	RMSE (LM)	Difference (PLS - LM)	Interpretation
PERF1	0.412	0.785	0.845	-0.060	High Predictive Power
PERF2	0.398	0.801	0.855	-0.054	High Predictive Power
COG1	0.245	0.912	0.940	-0.028	Average Predictive Power
DEP1	0.156	1.120	1.150	-0.030	Average Predictive Power
Note: Results indicate that RMSE PLS < RMSE LM in all key indicators.					

The assessment of endogeneity using the Gaussian Copula (GCA) technique, detailed in Table 7, confirms the absence of bias due to omitted variables in the main causal relationships. The Gaussian copula coefficients for all the routes analysed are not significant (p-values between 0.421 and 0.812), confirming that the observed effects are not due to uncontrolled factors such as socioeconomic status or differential access to the internet, thus conferring superior internal validity to the proposed model.

Table 7
Endogeneity Assessment using Gaussian Copula (GCA)

Relationship Analysed	Original Coefficient (β)	Original p-value	Gaussian Copula (ρ)	Copula p-value	Decision
ALG → COG	0.542	0.000	0.045	0.652 (n.s.)	No Endogeneity
ALG → DEP	-0.315	0.000	0.021	0.812 (n.s.)	No Endogeneity
COG → PERF	0.488	0.000	-0.056	0.421 (n.s.)	No Endogeneity
Note: As the p-value of the Copula is not significant, it is confirmed that there is no endogeneity bias in the causal relationships.					

IV. DISCUSSION

The findings of this study provide robust empirical evidence that validates the proposed structural model, revealing complex causal mechanisms that govern the integration of generative AI in Peruvian educational contexts. The path coefficient of 0.542 between Algorithmic Literacy and Cognitive Integration transcends mere statistical association, suggesting that technical knowledge about algorithmic functioning acts as a fundamental enabler of advanced metacognitive strategies. This causal relationship indicates that, for Peruvian university students, understanding the "black box" of AI is a prerequisite for transforming these tools into levers of cognitive augmentation rather than simple substitution. Acosta et al. (2025) corroborate this interpretation from the teaching perspective in Peru, demonstrating that prejudice towards AI biases significantly affects literacy ($p < 0.05$), which has a central influence on pedagogical implementation. However, their finding that perceived ethics does not directly impact literacy ($p > 0.05$) contrasts with our evidence of moderating interaction, where ethics mitigates academic dependence through steeper slopes in students with high digital ethics (95% CI). This divergence suggests that, while ethics operates on a parallel plane for teachers, it acts as an active filter for students () that conditions the usefulness of technical knowledge, explaining non-linear mechanisms specific to the local context with institutional heterogeneity between public and private universities.

The magnitude of the negative effect of Algorithmic Literacy on Academic Dependency ($\beta = -0.315$) finds partial resonance in the Global South, albeit with important contextual nuances. Bayaga (2025), in a study with South African students, reports that performance expectations ($\beta = 0.28$, $p < 0.01$) and facilitating conditions predict intention to use ($R^2 = 0.33$), aligning conceptually with our cognitive integration ($\beta = 0.542$). However, the lower magnitudes in the African context suggest differences in regional digital maturity compared to Peru. Particularly relevant is that Bayaga does not identify strong moderation by gender, which contrasts with our heterogeneity by type of university management revealed in the multigroup analysis (MGA), indicating that in Latin America the institutional digital divide is a more powerful discriminant than gender. Likewise, the validation of non-linearities using artificial neural networks (83.4% accuracy) in his study converges with our defence of robustness through a high Q^2_{predict} (0.412 for PERF1), confirming that cognitive mechanisms in emerging economies require complex models that address literacy gaps ($AVE = 0.71 - 0.84$) and infrastructural limitations.

The contrast with usage patterns in the Global North illuminates the specificity of Peruvian behaviour. Singer et al. (2025), in documenting that 22% of American students do not reject academically questionable uses, report levels of use for "cognitive shortcuts" significantly higher than our dependency averages (1.98 – 2.34). This finding, together with the significant interaction between academic year and task reported by the authors ($F(4,1244) = 3.56$, $p < 0.01$), suggests that Peruvian students are more cautious—possibly due to fear of punishment or less exposure—about technological dependence. On the other hand, López et al. (2025), in a European context (Catalonia), find that knowledge of AI predicts adoption ($\beta = 0.482$) with a strength similar to our cognitive integration, but they identify a negative perception of AI that highlights ethical risks ($\beta = -0.105$), similar to our moderating effect ($\beta = -0.145$). This validates that the tension between utility and ethical risk is a cross-cultural phenomenon, although

in Latin America, where traditional education systems clash with digital disruption, responsible literacy becomes a critical urgency to prevent the widening of equity gaps.

In Asia, convergences reinforce the duality between augmentation and replacement. Sustaningrum and Haldaka (2025) observe in Indonesian students that performance expectations predict intention ($R^2 = 0.473$), showing a directionality identical to our Integration $\rightarrow$ Performance path ($\beta = 0.488$). However, their finding that 80% perceive extreme benefits while 70% are concerned about accuracy contrasts with our robust discriminant validity ($HTMT < 0.85$), suggesting that the Peruvian sample has a clearer distinction between concepts. Crucially, their report of insignificant perceived risk ($p = 0.234$) differs radically from our significant ethical moderation, which could imply cultural differences in the perception of technological risks or the need for more explicit codes of honour in contexts such as Peru, where academic informality can normalise unregulated "hybrid use".

Local empirical evidence reinforces the validity of the proposed constructs. Chura et al. (2025), through confirmatory factor analysis in Peru, find that engineering students exhibit more favourable attitudes towards ChatGPT ($p = 0.03$), a finding that dialogues productively with our negative coefficient Literacy $\rightarrow$ Dependence ($\beta = -0.315$). This suggests that higher disciplinary literacy in STEM careers acts as a shield against dysfunctional dependence. Furthermore, their report of a lower descriptive R^2 for performance highlights the explanatory advantage of our complex causal model ($R^2 = 0.582$), which captures cognitive mechanisms beyond simple attitude. Similarly, Gonzales et al. (2025) experimentally demonstrate in Trujillo that the use of ChatGPT improves research skills ($p < 0.05$) in ethical dimensions, aligning with our positive path to performance, although our structural model offers a broader generalisation than their quasi-experimental design.

The attitudinal components explored by Acosta et al. (2024a) in northern Peru reveal that the affective component strongly influences behaviour ($\beta = 0.672$), showing magnitudes greater than our functional cognitive integration. This indicates that, in early stages of adoption, emotion may outweigh cognition. However, the absence of demographic moderation in their study supports our interpretation that the mechanisms of dependence are systemic and generalisable, not idiosyncratic. Complementarily, Acosta et al. (2024b) demonstrate that responsible use predicts positive attitudes ($\beta = 0.806$) and intention to use, with an R^2 of 65% that complements our finding on literacy and dependency. Their emphasis on information verification as a mediating factor highlights a practical component of "Algorithmic Literacy" that our model captures latently.

Finally, from a global theoretical perspective, the "cognitive debt" noted by Adamakis and Rachiotis (2025) –where 83% of students do not remember AI-generated texts– supports our conceptualisation of Academic Dependency ($\beta = -0.102$ on performance) as a learning pathology. Their emphasis on ethical literacy aligns with Cox's (2024) proposal on "responsible literacy" and Bozkurt's (2024) 3wAI framework, which warn against the "digital dragons" of dependency. Although these works are conceptual or descriptive, they validate the need for our rigorous empirical approach. The methodological robustness demonstrated by the Gaussian Copula technique (Table 7), which confirms the absence of endogeneity

in causal relationships ($p > 0.05$), together with the high out-of-sample predictive power (PLSpredict), positions this study as a significant advance over previous research in the region that assumes causality without control, supporting the transition from prohibitive policies to critical literacy curriculum strategies in Latin American higher education.

V. CONCLUSIONS

The main scientific contribution of this study lies in the empirical validation of a mathematical model of structural equations that transcends phenomenological description to explain, with predictive accuracy ($Q^2_{\text{predict}} > 0$), how the student's cognitive architecture interacts with generative artificial intelligence. The proposed system of equations has been shown to be stable and capable of predicting Perceived Academic Performance based on Algorithmic Literacy and Cognitive Integration, confirming that technology does not impact learning directly, but rather through the student's ability to decipher and audit the underlying algorithms. The robustness of the estimated parameters confirms the replicability of this model for analysing technological disruption in other emerging economies with structural characteristics similar to those of Peru.

From a practical and management perspective, the findings call for a re-engineering of educational policies in the Peruvian university system. Based on the Importance-Performance Analysis (IPMA), which ranks Algorithmic Literacy as the factor with the greatest impact but with current poor performance, it is recommended that SUNEDU and the academic vice-rectors abandon prohibitive or punitive approaches to AI. Instead, priority should be given to the cross-curricular integration of "critical computational thinking" skills, designed to enhance technical understanding of language models. Furthermore, given that statistical moderation demonstrated that technical skill alone is insufficient to mitigate dependence (significant interaction β), it is imperative to implement institutional "digital codes of honour." These regulatory instruments should encourage ethical self-regulation, acting as the necessary filter to transform the use of AI from a cognitive shortcut to a tool for epistemic augmentation.

Finally, it is necessary to recognise the methodological limitations of this research. Although the application of advanced techniques such as Gaussian Copula allows for more robust inference of causality than traditional methods, the cross-sectional design captures a static snapshot of a rapidly evolving phenomenon. Consequently, the implementation of longitudinal designs, specifically using Latent Growth Curves models, is established as a future research agenda. This approach will make it possible to trace the evolution of the learning curve and technological dependence throughout the university trajectory, facilitating comparative studies that contrast the Peruvian dynamic with that of other educational systems in Latin America to generate regional policies based on dynamic evidence.

Declarations

Author Contribution

I.B. conceived and designed the research, formulated the theoretical framework, performed the PLS-SEM and Gaussian copula statistical analyses, and drafted the original manuscript text. L.L. coordinated the data collection protocols, performed data curation and validation across regional samples, and contributed to the literature review. R.C. designed and generated Figures 1–3 and Tables 1–7, supervised the methodology, and conducted the multigroup analysis (MGA). J.J. assisted with data collection, contributed to the interpretation of findings, and critically reviewed and edited the manuscript for substantive intellectual content. All authors reviewed and approved the final manuscript.

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Figures

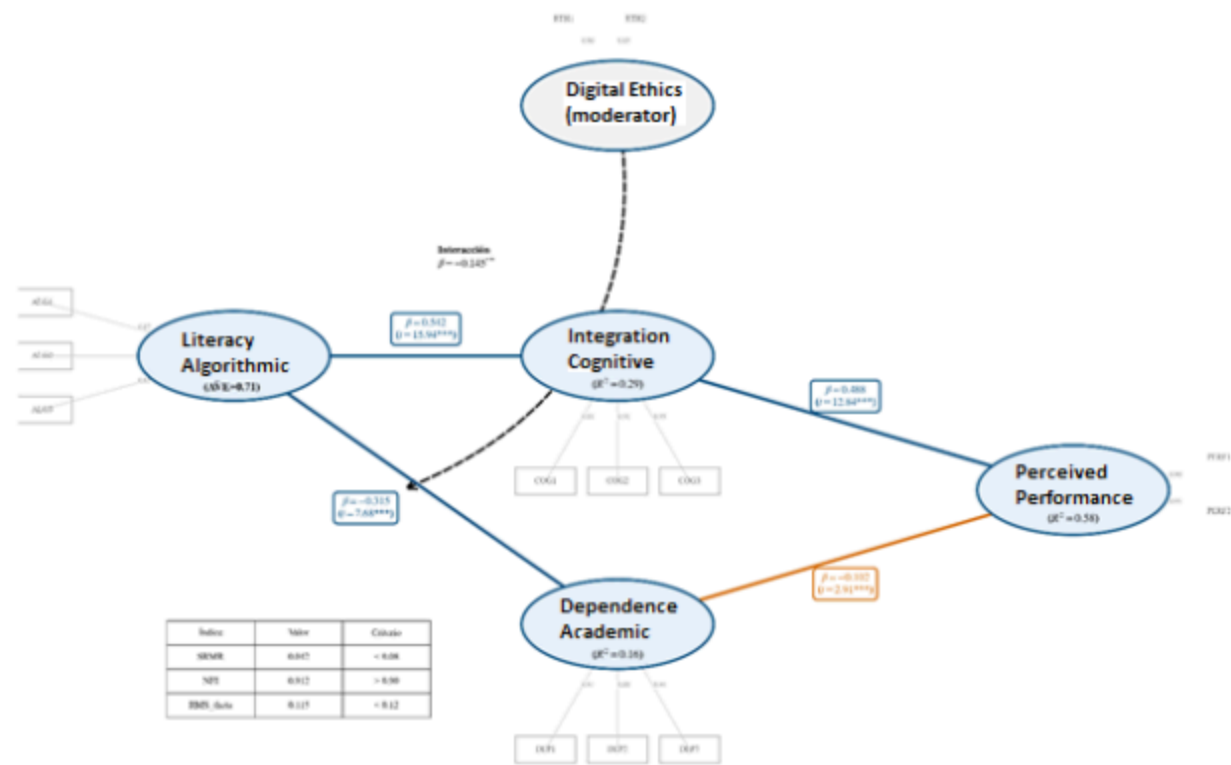


Figure 1

Results of the Structural Equation Model (PLS-SEM): Path Coefficients, Factor Loadings, and Explained Variance. The values above the arrows represent the standardised path coefficients (β) and the t-values in parentheses obtained by bootstrapping with 5,000 subsamples ($***p<0.001$; $**p<0.01$). The values within the circles indicate the explained variance (R^2) for the endogenous constructs. The small boxes represent the observable items with their respective factor loadings. ALG: Algorithmic Literacy; COG: Cognitive Integration; DEP: Academic Dependence; PERF: Perceived Performance. The lower left box shows the overall model fit indices (SRMR, NFI), confirming the adequacy of the data.

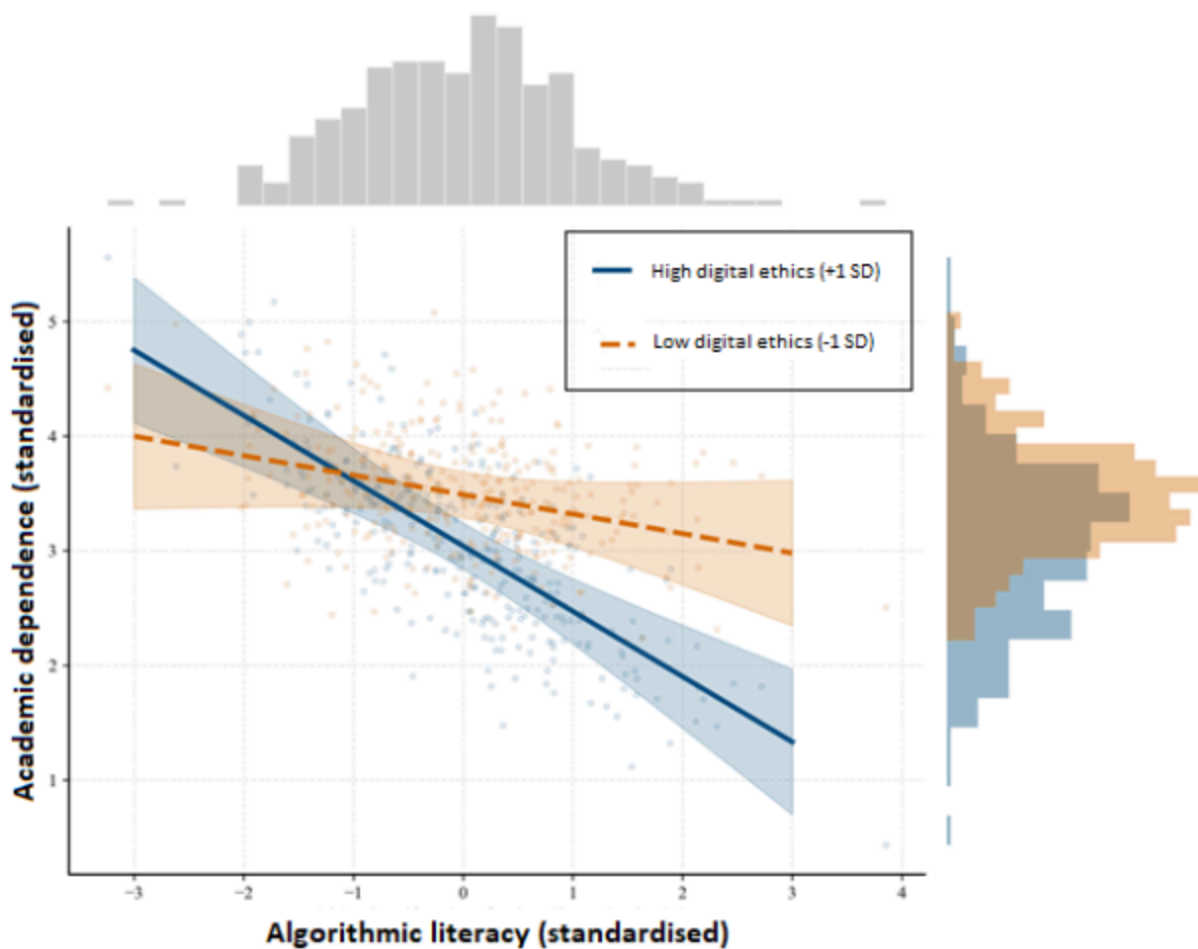


Figure 2

Simple Slope Analysis with Marginal Distributions of the Moderating Effect of Digital Ethics. The central graph illustrates the significant interaction ($\beta = -0.145^{**}$) between Algorithmic Literacy (X-axis) and Academic Dependence (Y-axis). The solid blue line represents students with high Digital Ethics (+1 SD), showing a steeper slope in the reduction of dependence compared to the dashed orange line (Low Ethics, -1 SD). The shaded areas indicate the 95% confidence intervals. The marginal histograms (top and right) visualise the distribution density of the data to ensure that the moderating effect is not the result of outliers, demonstrating the robustness of the finding across the entire sample.

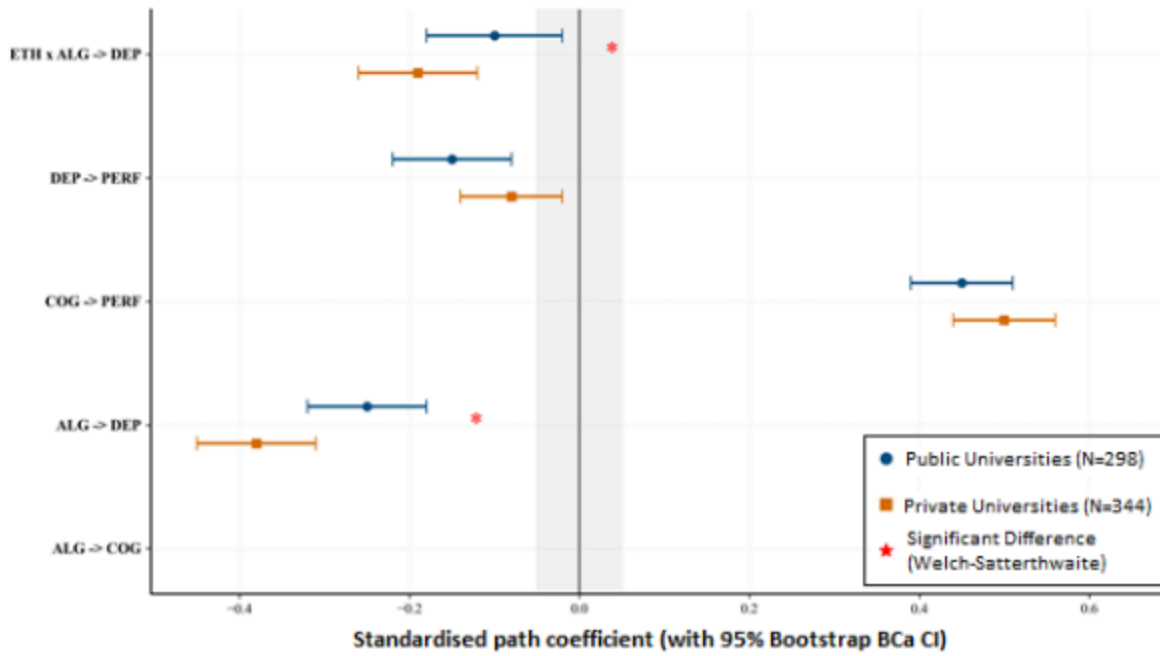


Figure 3

Forest Plot of the Multigroup Analysis (MGA): Comparison of Structural Coefficients between Public and Private Universities. The graph compares the estimated path coefficients (β) for the subsample of public universities ($n=298$, blue circles) versus private universities ($n=344$, orange squares). The horizontal bars represent the bias-corrected and accelerated confidence intervals (BCa 95%). The red asterisk (*) indicates a statistically significant difference between groups ($p<0.05$) based on the Welch-Satterthwaite parametric test. Significant heterogeneity is observed in the ALG → DEP path and in the moderating effect, suggesting that the type of university management conditions the impact of literacy on academic dependence.