Academic Procrastination and Functional Dependence on Generative Artificial Intelligence among University Students

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Abstract

This study followed an explanatory sequential mixed-methods design (DEXPLIS) to determine the relationship between academic procrastination and functional dependence on generative artificial intelligence (GenAI) among university students, and to explain this relationship from the perspective of university professors. In the quantitative phase, a probabilistic sample of 240 students was calculated from a population of 636 undergraduates of a public university in Ancash, Peru; the instruments showed excellent reliability (Cronbach's alpha = .972 for academic procrastination and .958 for functional dependence on GenAI) and, given a non-normal distribution (Kolmogorov-Smirnov, $p < .001$), Spearman's rho revealed a strong, positive, and significant correlation between academic procrastination and functional dependence on GenAI (rho = .733, $p < .001$), as well as between its two dimensions, self-regulation difficulty (rho = .735, $p < .001$) and postponement of activities (rho = .708, $p < .001$), and functional dependence. In the qualitative phase, semi-structured interviews with 15 professors (more than five years of experience), analyzed through open, axial, and selective coding, identified seven converging categories, with cognitive delegation as the central mechanism linking postponement and self-regulation deficits to functional dependence. These integrated quantitative and qualitative findings support strategies for critical AI literacy, self-regulated learning, and process-based assessment in higher education.

Keywords

Academic procrastination, Generative artificial intelligence, Functional dependence, Higher education, Mixed methods

1. Introduction

Internationally, generative artificial intelligence (GenAI) has rapidly become one of the most widely adopted digital resources in higher education, supporting students in drafting, summarizing, translating, and organizing academic information [1, 2]. However, the problem is not the use of GenAI itself, but its excessive or uncritical use: intensive reliance on AI-based dialogue systems can reduce critical thinking, weaken academic self-regulation, and diminish learner autonomy when the technology replaces, rather than supports, cognitive effort, a process described internationally as cognitive offloading [3, 4]. Academic procrastination, defined as the irrational tendency to postpone academic tasks despite the negative consequences this delay may generate [5], has likewise been consistently associated with self-regulation deficits and low intrinsic motivation across the international literature.

In Latin America, this global concern has acquired its own body of evidence. Studies conducted in Ecuador have documented consequences of AI dependence on critical skills and autonomous learning among university students [6], as well as predictive associations between attitudes toward AI and

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technology dependency [7], while research in Peru has examined academic self-efficacy and dependence on artificial intelligence in university samples [8]. These regional studies suggest that functional dependence on GenAI is not merely an imported concern from international literature, but an emerging, locally documented phenomenon that requires context-specific evidence rather than direct extrapolation from studies conducted in different educational systems.

Within Peru specifically, the problem takes on particular relevance. Peruvian researchers validated one of the region's academic procrastination scales more than a decade ago [9], establishing a local precedent for measuring this construct, and more recent qualitative work conducted at a Peruvian public university has begun to conceptualize functional dependence on artificial intelligence as a form of cognitive disruption in academic practice [10]. Yet most Peruvian universities, particularly public regional institutions outside the capital, still lack institutional frameworks for the pedagogical use of GenAI comparable to those emerging in metropolitan or private universities, even as students increasingly rely on these tools under academic and time pressure. This gap between rapid technology adoption and slower institutional response defines the problematic reality addressed by this study, situated in a public university in the region of Ancash, Peru.

Recent evidence indicates that procrastination is also a relevant predictor of dependence on ChatGPT, since students who postpone their tasks tend to use generative AI as a quick, last-minute compensatory resource [11, 12]. Quantitative studies have examined this association among students [11], and qualitative studies have explored the dimensions of functional dependence on AI [10] and professors' concerns about its ethical and pedagogical use [13], but there is limited research, in Peru or elsewhere, integrating quantitative evidence from students with qualitative explanations from professors within a single explanatory design.

Consequently, this study follows a mixed approach with an explanatory sequential design (DEXPLIS), in which a quantitative phase was first developed and then complemented with a qualitative phase to obtain a broader understanding of the phenomenon under study [14, 15]. The general objective was to determine the relationship between academic procrastination and functional dependence on generative AI among students of a public university in Ancash, Peru, and to explain this relationship from the perspective of university professors. Specifically, the study sought to determine the relationship between academic self-regulation difficulty and functional dependence on generative AI, to determine the relationship between postponement of academic activities and functional dependence on generative AI, to describe the levels of both variables, and to analyze, through the perspective of university professors, the pedagogical, ethical, and academic reasons that explain these quantitative results.

This dual focus is timely: bibliometric evidence shows a steadily growing number of academic publications on procrastination over the last decade, reflecting increasing scientific interest in the phenomenon [16], at the same time that GenAI adoption in higher education, in Peru and internationally, has expanded far faster than the institutional frameworks needed to guide its academic use. Addressing both processes jointly, rather than in isolation, is therefore necessary to understand how longstanding self-regulation difficulties interact with a genuinely new technological affordance, and to move beyond single-method accounts that capture either the magnitude of the relationship or its underlying reasons, but rarely both.

2. Theoretical Framework

2.1. Academic Procrastination and Self-Regulation

Academic procrastination is an irrational tendency to delay academic responsibilities, representing a self-regulation deficit associated with both personal dispositions and contextual factors [5, 17]. It is mainly explained by motivation rather than the reverse: low achievement value, low self-determination, low intrinsic motivation, and high delay discounting are associated with higher procrastination [18, 19, 20], and chronic procrastination has been linked to higher anxiety and reduced academic performance [21]. Validated instruments distinguish an academic self-regulation dimension from a postponement-of-activities dimension, both reliable in university samples [22, 9]. From self-determination theory, procrastination can be understood as a consequence of unmet needs for competence, autonomy, and relatedness [23, 24, 25, 26, 27, 28], since a strong sense of competence predicts intrinsic motivation, autonomy-supportive teaching is associated with greater engagement, and peer relatedness has been shown to mediate students' motivation and engagement even beyond the classroom, for instance in interprofessional education settings, suggesting that fostering these three needs could reduce both procrastination and functional dependence on generative AI.

2.2. Functional Dependence on Generative AI and the Role of Professors

Functional dependence on AI is the tendency to repeatedly delegate cognitive control to an external technological resource, accepting its responses without critical verification, a construct conceptualized by Garcia Castro et al. [10]; its consequences for critical skills and autonomous learning have been documented separately in the region [6]. This process is explainable through the Unified Theory of Acceptance and Use of Technology [29]. Validated dependence scales [30] confirm that dependence on generative AI is associated with inert thinking [12], low academic self-efficacy [8, 31], and academic stress [31, 32], while poorly calibrated trust in AI-generated responses has been documented experimentally [33, 34]. Systematic reviews link over-reliance on AI dialogue systems to reduced critical thinking [4, 35], while cautioning that this phenomenon is an emerging pattern requiring monitoring rather than an established addiction [36, 37]. ChatGPT dependence has been directly associated with procrastination and burnout, and experimental interventions show it can reduce academic performance over time [38, 39, 40, 41, 42]. University professors play a central role in guiding a balanced use of GenAI: qualitative studies across continents show that professors consistently prioritize ethics, transparency, confidentiality, and human oversight [13, 43, 44, 45], and critical AI literacy has been proposed as a competency framework combining technical skills with ethical judgment and self-regulation [2, 46, 47, 48, 49, 7, 50]. Curriculum-level applications of self-determination theory to AI education, and inclusive design approaches for AI literacy, further suggest that institutions can deliberately structure autonomy, competence, and social support around AI use rather than leaving it to individual students [51, 52], an argument reinforced by community-of-inquiry frameworks that call for sustained cognitive, social, and teaching presence to prevent an excessive dependence on technological tools in online and distance education [53].

3. Method

This study followed a mixed approach with an explanatory sequential design (DEXPLIS) [14, 15], in which a quantitative phase was first developed and subsequently complemented with a qualitative phase to explain the quantitative results. In the quantitative phase, the population consisted of 636 undergraduate students of a public university located in the region of Ancash, Peru. A probabilistic sample was calculated by applying the statistical formula for finite populations [54], $n = [N \times Z^2 \times p \times q]/[d^2 \times (N - 1) + Z^2 \times p \times q]$, considering $N = 636$, a 95% confidence level ($Z = 1.96$), a success and failure probability of $p = q = 0.5$ (maximum variance, adopted in the absence of prior estimates of the population proportion), and a margin of error of $d = 0.05$. The computation yielded $n = 239.7$, rounded to a final sample of 240 undergraduate students, selected through simple random sampling. All 240 selected students completed the instruments, and no questionnaire was discarded for incompleteness. Academic procrastination was measured with a Likert-type scale composed of two dimensions, self-regulation difficulty and postponement of activities (ten items each, range $10 - 50$ per dimension and $20 - 100$ total), adapted from the Academic Procrastination Scale [22, 9], with self-regulation items reverse-scored so that higher scores indicate greater difficulty. Functional dependence on generative AI was measured with an academic adaptation of a dependence-on-AI scale (twenty items, range 20-100), informed by the dimensions proposed by Garcia Castro et al. [10] and by validated scales of dependence on ChatGPT [12, 30]. Both instruments were reviewed through expert judgment and a pilot test, and internal consistency was estimated using Cronbach's alpha [55]. Given that the sample exceeded 50 participants, the Kolmogorov-Smirnov test with Lilliefors correction was used to examine normality rather than the Shapiro-Wilk test, and Spearman's rho was used to test the relationships, with significance set at $p < .05$ (two-tailed). In the qualitative phase, semi-structured interviews, structured around eight open questions covering the general use of GenAI, its use for postponed tasks, the boundary between support and dependence, self-regulation difficulties, critical verification, academic integrity, assessment redesign, and formative strategies, were conducted with 15 university professors with more than five years of teaching experience, purposively selected across twelve disciplinary areas, with the number of professors per area indicated in parentheses: Education (2), Law (2), Civil Engineering (2), Systems Engineering (1), Accounting (1), Psychology (1), Communication (1), Administration (1), Humanities (1), Social Sciences (1), Applied Mathematics (1), and Professional Ethics (1). Disciplinary breadth was deliberately prioritized over within-discipline depth in order to establish whether the phenomenon was reported transversally across fields rather than being confined to a particular epistemic culture. Consistent with the sequential logic of the DEXPLIS design, the interview guide was constructed after the quantitative results had been obtained and analyzed, specifically in order to explain the associations identified in the first phase; the two phases did not overlap in time. Data collection ceased at the fifteenth interview upon reaching theoretical saturation: no new categories emerged after the thirteenth interview, and the two subsequent interviews yielded only variations within categories already established, indicating that the capacity to generate new conceptual properties had been exhausted. The decision to stop was therefore governed by a saturation criterion rather than by participant availability. Interviews were analyzed manually, without the use of CAQDAS software, following open, axial, and selective coding, identifying recurrent categories and their interrelations. Transcripts were coded independently by two researchers, and discrepancies in category assignment were resolved through discussion until consensus was reached; no formal inter-coder reliability statistic was computed, a limitation acknowledged below. Participants in both phases received information about the purpose of the study and provided informed consent; anonymity and confidentiality were guaranteed, participation was voluntary, and participants could withdraw at any time without consequence, in accordance with the Declaration of Helsinki and the European Code of Conduct for Research Integrity [56]. The study was conducted as independent research and was not affiliated with an institutional program requiring formal review by a research ethics committee; consequently, no institutional approval code is available. No identifying data, sensitive personal information, or academic records were collected, and no intervention of any kind was applied to participants. In accordance with a confidentiality agreement with the participating institution, its name is withheld and it is identified throughout as a public university in the region of Ancash, Peru.

4. Results

This section first presents the quantitative results (reliability, descriptive statistics, normality, and Spearman correlations) obtained from the 240 university students, and then the qualitative results obtained from the 15 university professors.

Table 1
Reliability, Descriptive Statistics, and Kolmogorov-Smirnov Normality Test for Academic Procrastination and Functional Dependence on Generative AI (N = 240).

Variable	M	SD	Skew.	Kurt.	KS (p)	alpha
Academic procrastination	71.72	21.85	-0.540	-0.793	<.001	.972
Functional dependence on generative AI	66.72	21.52	-0.363	-0.993	<.001	.958
Self-regulation difficulty	35.69	11.15	-0.523	-0.826	<.001	
Postponement of activities	36.03	11.15	-0.547	-0.799	<.001	

Note. Academic procrastination and functional dependence range 20-100; their dimensions range 10-50. Cronbach's alpha is reported separately for each variable rather than for a single combined instrument. Given the sample size ($N = 240 > 50$), the Kolmogorov-Smirnov (KS) test with Lilliefors correction was used instead of the Shapiro-Wilk test to examine normality; all distributions departed significantly from normality ($p < .001$), which justified the use of Spearman's rho.

The mean scores of academic procrastination and functional dependence on generative AI were located above the theoretical midpoint of their scales, suggesting a moderate-to-high level for both variables and their dimensions, consistent with a non-normal, negatively skewed distribution. The alpha coefficients obtained (.972 and .958) indicate very high internal consistency. Tavakol and Dennick [55] caution that values above .90 may signal item redundancy rather than optimal reliability, since near-paraphrastic items inflate the coefficient without adding informational content. Given that both instruments comprise a substantial number of items addressing closely related behavioral manifestations, a degree of semantic overlap between items cannot be ruled out; item-reduction analyses are therefore recommended for subsequent applications of these instruments.

Table 2
Spearman Correlations between Academic Procrastination, its Dimensions, and Functional Dependence on Generative AI (N = 240).

Variable	**1**	**2**	**3**	**4**
1. Academic procrastination	1.000			
2. Functional dependence on generative AI	.733**	1.000		
3. Self-regulation difficulty	.979**	.735**	1.000	
4. Postponement of activities	.978**	.708**	.915**	1.000

Note. ** $p < .001$ (two-tailed). Spearman's rho revealed a strong, positive, and statistically significant correlation between academic procrastination and functional dependence on generative AI (rho $= .733$, $p < .001$). Both self-regulation difficulty (rho $= .735$, $p < .001$) and postponement of activities (rho $= .708$, $p < .001$) were strongly and significantly related to functional dependence, indicating that students who report greater self-regulation difficulty and more frequent postponement tend to present higher functional dependence on generative AI. The correlations between academic procrastination and its two subscales (rho $= .979$ for self-regulation difficulty and rho $= .978$ for postponement of activities) are part–whole relationships, given that the total score is the arithmetic sum of the two dimensions ($35.69 + 36.03 = 71.72$). These coefficients are mathematically expected and should not be interpreted as independent empirical findings.

As shown in Table 3, all seven categories reached high analytical convergence across the 15 professors interviewed (15/15 for six categories and 14/15 for weak verification of AI-generated content), from disciplines as diverse as Law, Systems Engineering, Humanities, Psychology, and Professional Ethics, which reflects a structured interview guide anchored to these themes and a convergent cross-disciplinary pattern rather than isolated opinions. Selective coding identified cognitive delegation as the central category: professors described that when postponement (time pressure) meets self-regulation deficits (poor planning), students increasingly delegate not only drafting but also decisions, procedures, and judgment to generative AI, which in turn weakens verification and raises academic integrity risks. Disciplinary nuances were also observed: in technical fields (Systems and Civil Engineering, Applied Mathematics) professors emphasized students' inability to reconstruct or explain a procedure, while in Humanities, Communication, and Social Sciences the concern centered on loss of personal voice and interpretation, in Law and Tax Law on the loss of normative grounding, in Psychology on AI as an anxiety-avoidance mechanism, and in Professional Ethics on the transfer of moral responsibility to a machine. Professors converged on recommending process-based assessment (portfolios, oral defense, progressive evidence) and institutional AI-literacy training as the main levers to convert functional dependence back into critical, self-regulated use.

Table 3
Qualitative Categories Emerging from the Semi-Structured Interviews with University Professors (n = 15).

Category	Professors (n/15)	Illustrative excerpt (translated)
GenAI as a compensatory resource for postponed tasks	15/15	"GenAI was used as a quick way out of procrastination" (D02)
Cognitive delegation	15/15	"The AI is making decisions for the student" (D03)
Self-regulation deficits	15/15	"Lack of planning... and difficulty breaking a task into stages" (D01)
Weak verification of AI-generated content	14/15	"Some trust generated citations even without a DOI or a matching title" (D09)
Academic integrity risks	15/15	"Risks include plagiarism, opacity, bias, and loss of academic merit" (D15)
Assessment redesign toward process and traceability	15/15	"The final product must show traceability" (D14)
Critical AI literacy	15/15	"The key competency is not avoiding AI, but using it without losing one's own judgment" (D03)

5. Discussion

The general objective of this study was to determine the relationship between academic procrastination and functional dependence on generative AI, and to explain it from the professors' perspective. The strong, positive correlation found (rho $= .733$, $p < .001$) is consistent with previous evidence reporting procrastination as a relevant factor contributing to ChatGPT dependence [11], with Ye et al. [12], who report inert thinking as an outcome associated with reliance on generative AI, and with Yu et al. [40], who validated a scale of problematic ChatGPT use documenting patterns of problematic engagement rather than that specific cognitive outcome. The qualitative data explain this association: professors described that postponement creates time pressure under which students seek AI as a rapid, complete solution ("GenAI as a compensatory resource"), which converges with quantitative and qualitative evidence on ChatGPT dependence among procrastinating students [39].

The strong association between self-regulation difficulty and functional dependence (rho $= .735$, $p < .001$) is consistent with the conceptualization of functional dependence proposed by Garcia Castro et al. [10], who describe operational technological need as the category that converts instrumental use into dependence when self-regulation resources are limited, and with the notion of cognitive offloading [3]. The professors' central category, cognitive delegation, refines this conceptualization: dependence is not merely frequent use, but an accompanying loss of the student's capacity to explain, reconstruct, or justify what generative AI produced, which is also consistent with experimental evidence on poorly calibrated trust in AI systems [33].

From the perspective of university professors, the priority given to ethics, transparency, and human oversight [13, 43] was echoed in the interviews through the academic integrity risk category, and the professors' recommendation to redesign assessment toward process and traceability is aligned with recent policy analyses calling for human-centered, transparent institutional AI policies [44]. Taken together, these results suggest that generative AI is not problematic per se; the pattern of concern is one in which its use co-occurs with reduced planning, cognitive effort, and autonomous academic production, particularly among students with lower self-regulation and higher postponement, and that critical AI literacy and process-based assessment are the levers identified by both the quantitative and the qualitative evidence to address it [31, 7].

An additional contribution of the qualitative phase is that the cognitive delegation mechanism was not confined to a single disciplinary field. Professors in technical areas such as Systems Engineering, Civil Engineering, and Applied Mathematics, in Humanities and Communication, in Law and Tax Law, in Psychology, and in Professional Ethics converged on describing the same underlying process, even though the surface manifestations differed: an unexplainable procedure in engineering, a lost personal voice in writing-intensive fields, an ungrounded legal argument in Law, an anxiety-avoidance pattern in Psychology, and a diffusion of moral responsibility in Ethics. These preliminary observations suggest cognitive delegation as a possible transversal explanatory category rather than a discipline-specific artifact. Given that nine of the twelve disciplines were represented by a single professor and only three by two, this cross-disciplinary pattern should be read as indicative rather than established, and warrants confirmation with a larger within-discipline sample. At the same time, the specific manifestations identified by each professor offer concrete, discipline-sensitive entry points for redesigning assessment, consistent with calls for critical AI literacy tailored to different learner and disciplinary contexts [2].

6. Limitations

Several limitations should be considered when interpreting these findings.

First, the quantitative phase relies on a cross-sectional correlational design and therefore cannot establish directionality between academic procrastination and functional dependence on generative AI. Reverse causality is plausible, in that students who already rely heavily on AI tools may subsequently develop weaker self-regulatory capacity rather than the converse, and third-variable confounding cannot be excluded. The associations reported here should accordingly be read as co-occurrence rather than as evidence of a causal mechanism.

Second, both constructs were measured through self-report Likert-type scales completed by the same participants at a single point in time, which introduces the risk of common method bias. No common method variance test was conducted, and part of the shared variance observed may therefore be attributable to method artifacts rather than to genuine construct overlap.

Third, the adapted twenty-item functional dependence instrument was reviewed through expert judgment and a pilot test and showed high internal consistency, but no confirmatory factor analysis was performed. High reliability does not establish construct or dimensional validity, and the factor structure of the adapted instrument in this population therefore remains unverified.

Fourth, the bivariate analysis does not control for potential covariates such as year of study, prior academic performance, course workload, or previous experience with AI tools, any of which could independently influence both variables.

Fifth, the quantitative sample was drawn entirely from a single public university in the region of Ancash. The findings may not generalize to private universities, metropolitan institutions, or different disciplinary compositions, and should be read as a situated case rather than as a nationally representative account.

Sixth, the qualitative sample was purposive rather than random, and nine of the twelve disciplines were represented by a single professor, with only three represented by two. Cross-disciplinary convergence patterns should therefore be treated as preliminary. Finally, although transcripts were coded independently by two researchers with discrepancies resolved by consensus, no formal inter-coder reliability statistic was computed.

These limitations delineate an agenda for further research: longitudinal or cross-lagged panel designs to test temporal precedence, as modeled by Huang et al. [36]; confirmatory factor analysis of the adapted instrument; multivariate models incorporating academic and demographic covariates; and multi-institutional sampling across public and private universities.

7. Conclusion

University students of a public university in Ancash, Peru, presented moderate-to-high levels of academic procrastination and functional dependence on generative AI, strongly and significantly correlated (rho $= .733$, $p < .001$), with both procrastination dimensions, self-regulation difficulty and postponement of activities, strongly related to functional dependence. University professors, interviewed across twelve disciplines, explained this relationship through seven converging categories, with cognitive delegation acting as the central category linking postponement and self-regulation deficits to functional dependence, weak verification, and academic integrity risks.

These integrated findings indicate that generative AI does not constitute a problem in itself; the pattern of concern is one in which its use co-occurs with reduced planning, cognitive effort, and autonomous academic production, particularly among students with lower self-regulation and a higher tendency to postpone academic tasks. Because the quantitative phase relies on a cross-sectional correlational design, these associations should be read as co-occurrence and not as evidence of a causal mechanism. Consequently, it is recommended to strengthen critical AI literacy, redesign evaluation activities toward authentic reflection and traceability of the academic process, as recommended convergently by the professors interviewed, and establish institutional criteria for the transparent and responsible use of generative AI in higher education.

Declaration on Generative AI

During the preparation of this manuscript, the authors used a generative AI tool for language editing purposes, that is, to improve grammar and clarity. The authors reviewed and edited the resulting text and take full responsibility for the publication's content.

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