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Generative AI and Autonomous Learning in Higher Education: A Systematic Review

Inteligencia Artificial Generativa y Aprendizaje Autónomo en Educación Superior: Una Revisión Sistemática

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Abstract

This systematic review examined empirical evidence on generative artificial intelligence (GenAI) and autonomous learning among university students, focusing on planning, monitoring, self-evaluation, metacognition, and implications for engineering education. Following PRISMA 2020 reporting guidance, 60 author-supplied full-text documents were assessed. 8 duplicates were removed, 52 records were screened, 26 full texts were evaluated, and 7 primary studies (cumulative N = 1,469) met the eligibility criteria. Findings were narratively synthesized and appraised using domains adapted from the Mixed Methods Appraisal Tool. Observational studies reported positive associations between academic GenAI use and autonomy-related processes, but did not establish causation. A randomized trial found improved self-regulated learning and higher-order thinking when ChatGPT provided guidance rather than direct answers. Feedback studies identified benefits for monitoring alongside risks of inaccurate or context-insensitive responses. No included study specifically examined Civil Engineering. Overall, GenAI may scaffold autonomous learning when instruction requires independent attempts, verification, justification, and reflection; unguided reliance may instead displace cognitive effort.

Keywords: generative artificial intelligence, autonomous learning, self-regulated learning.

Resumen

Esta revisión sistemática examinó la evidencia empírica sobre inteligencia artificial generativa (GenAI) y aprendizaje autónomo entre estudiantes universitarios, centrándose en la planificación, el monitoreo, la autoevaluación, la metacognición y las implicaciones para la educación en ingeniería. Siguiendo las directrices de informes PRISMA 2020, se evaluaron 60 documentos de texto completo proporcionados por los autores. Se eliminaron 8 duplicados, se examinaron 52 registros, se evaluaron 26 textos completos y 7 estudios primarios (N acumulativo = 1469) cumplieron los criterios de elegibilidad. Los hallazgos se sintetizaron narrativamente y se evaluaron utilizando dominios adaptados de la Herramienta de Evaluación de Métodos Mixtos. Los estudios observacionales informaron asociaciones positivas entre el uso académico de GenAI y los procesos relacionados con la autonomía, pero no establecieron causalidad. Un ensayo aleatorio encontró una mejora en el aprendizaje autorregulado y el pensamiento de orden superior cuando ChatGPT proporcionó orientación en lugar de respuestas directas. Los estudios de retroalimentación identificaron beneficios para el monitoreo junto con riesgos de respuestas inexactas o insensibles al contexto. Ningún estudio incluido examinó específicamente la Ingeniería Civil. En general, la IA generativa puede facilitar el aprendizaje autónomo cuando la instrucción requiere intentos independientes, verificación, justificación y reflexión; por el contrario, la dependencia sin guía puede desplazar el esfuerzo cognitivo.

Palabras clave: inteligencia artificial generativa, aprendizaje autónomo, aprendizaje autorregulado.

Introduction

Generative artificial intelligence (GenAI), particularly large language models, can generate explanations, practice activities, code, and feedback in response to natural-language requests. Its rapid adoption in universities has created opportunities for personalized assistance alongside concerns about reliability, dependence, and academic integrity (Dwivedi et al., 2023; Kasneci et al., 2023; United Nations Educational, Scientific and Cultural Organization [UNESCO], 2023). The educational question is not only whether GenAI improves task completion, but whether it strengthens students' ability to learn independently.

Autonomous learning involves decisions about goals, resources, strategies, and evaluation (Holec, 1981; Little, 1991). Self-directed learning emphasizes learner initiative (Knowles, 1975), whereas self-regulated learning (SRL) describes interacting processes of planning, monitoring, and reflection (Pintrich, 2004; Zimmerman, 2000). These constructs differ, but each requires learners to retain responsibility for their decisions.

GenAI can help students decompose tasks, generate practice questions, compare explanations, and review drafts. Immediate access to tailored feedback may facilitate self-regulation (Ogunleye et al., 2024; Qian, 2025). However, obtaining an AI-generated plan or correction is not equivalent to developing the ability to plan or self-correct independently. The same technology can also replace the reasoning it is intended to support. When students accept unverified output or delegate complete tasks, apparent productivity may conceal reduced monitoring and judgment. These risks reinforce calls for transparent use, AI literacy, and critical verification (Chan & Hu, 2023; Farrokhnia et al., 2024).

Emerging studies report positive associations between GenAI and autonomy: Cardenas-Sinche et al., (2026) in Peru, Essel et al., (2026) in Ghana, and Monar et al., (2026) in Ecuador. Their cross-sectional designs, however, cannot establish whether GenAI enhances autonomy or more autonomous students use it strategically. More informative causal evidence comes from Lee et al., (2024), whose randomized trial compared conventional ChatGPT with a guidance-based version that encouraged initial attempts and provided hints. Guided use improved SRL, higher-order thinking, and knowledge construction. Feedback research likewise suggests benefits that depend on disciplinary accuracy and educator oversight (Leiva-Guerrero et al., 2026).

Reviews identify personalization, feedback, and regulatory support as recurring opportunities, but also describe heterogeneity, overreliance, and ethical risks (Achuthan, 2025; Amofa et al., 2025; Batista et al., 2024; Castillo-Martínez et al., 2024). The distinction between cognitive support and cognitive substitution is therefore central to interpreting outcomes. This distinction is especially important in engineering, where students must justify assumptions, validate calculations, and transfer strategies to unfamiliar problems. Evidence specific to engineering disciplines remains limited, and extrapolation to Civil Engineering requires caution.

This systematic review therefore asked: what empirical evidence links academic GenAI use to autonomous learning processes in higher education, under what pedagogical conditions are outcomes favorable or adverse, and what can reasonably be inferred for engineering education?

Methodology

The review followed PRISMA 2020 reporting guidance (Page et al., 2021) and used narrative thematic synthesis. Meta-analysis was not appropriate because designs, constructs, measures, and reported outcomes were

heterogeneous. Primary empirical studies involving university students were the unit of analysis. Reviews and conceptual papers informed contextual discussion but were excluded from the evidence synthesis to prevent double counting.

The authors supplied 60 full-text documents previously collected from academic literature on GenAI, autonomous learning, and higher education. Database-specific exports and original search logs were unavailable. Accordingly, Figure 1 transparently reports selection from the supplied corpus rather than retrospectively inventing database yields. This limits the reproducibility and comprehensiveness of the search.

The following conceptual string summarized the topical eligibility logic; it should not be interpreted as a documented database search executed identically across platforms:

("generative artificial intelligence" OR GenAI OR ChatGPT OR "large language model*") AND ("autonomous learning" OR "self-regulated learning" OR "self-directed learning" OR metacognition OR planning OR monitoring OR "self-evaluation") AND ("higher education" OR universit* OR undergraduate OR engineering)

The eligibility period was 2023–2026, with articles published in English, Spanish, or Portuguese and full text available.

Table 1
PICOS criteria and inclusion/exclusion rules

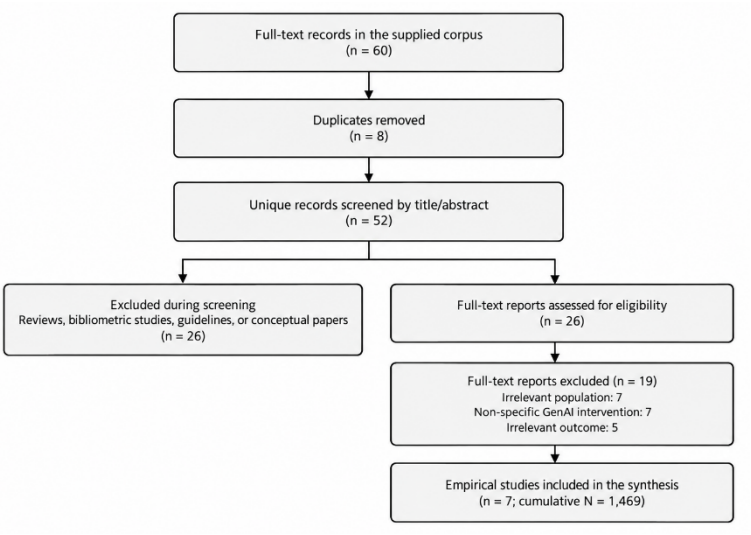
Component	Inclusion	Exclusion
Population	Higher-education students (undergraduate or graduate); engineering studies were retained when available.	Faculty members without direct student data; basic education; non-university participants.
Intervention/exposure	Academic use of GenAI or generative systems (e.g., ChatGPT, GPT-4o, GPT-3.5, RAG systems with LLMs).	Non-generative AI without an identifiable GenAI component; analytics/algorithms without generative interaction.
Comparison	Conventional use, another mode of GenAI use, absence of a control group, or correlational analysis, depending on the design.	A comparator was not required when the empirical design was observational or qualitative.
Outcomes	Autonomous/self-regulated learning; planning, management, monitoring, feedback, self-evaluation, metacognition, agency, or independent thinking related to autonomy.	Performance, acceptance, or ethics as the sole outcome without a connection to autonomy or learning regulation.
Design	Primary quantitative, qualitative, or mixed-method empirical studies with student data.	Reviews, meta-analyses, bibliometric studies, editorials, guidelines, conceptual essays, and duplicates.
Period/language	2023-2026; Spanish, English, or Portuguese; full text available.	Outside the period or insufficient information to determine eligibility.

Note: PICOS = population, intervention/exposure, comparison, outcomes, and study design. *Source:* authors' eligibility framework, informed by Page et al., (2021).

Of the 60 documents, 8 duplicates were removed. Of 52 unique records screened, 26 secondary, conceptual, or other non-primary publications were excluded; 26 reports underwent full-text assessment.

19 full texts were excluded: 7 for ineligible populations, 7 for lacking an identifiable generative-AI exposure, and 5 for lacking autonomy-related outcomes. 7 primary studies involving 1,469 participants were retained (Figure 1).

Figure 1
PRISMA 2020-guided selection flow for the supplied document corpus



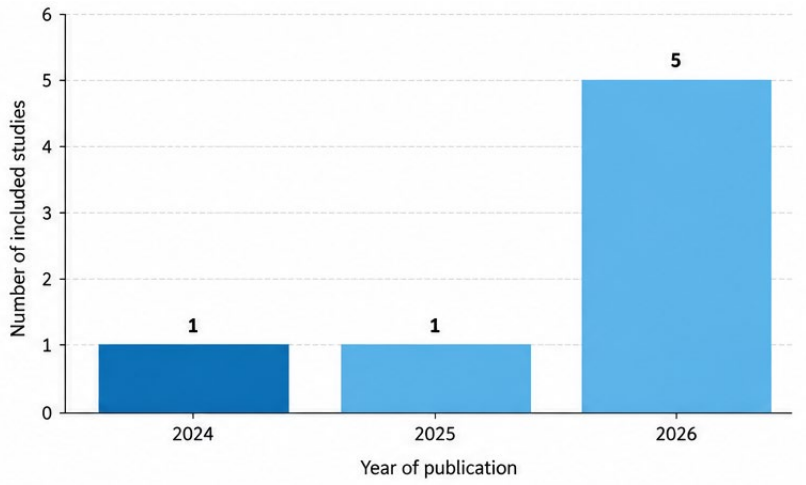
Source: authors' preparation from the supplied 60-document corpus, guided by Page et al., (2021).

From each included study, the authors extracted year, location, sample, design, GenAI use, autonomy-related outcomes, findings, and limitations. Quantitative associations and relevant qualitative themes were retained as reported. Synthesis categories were planning/management; monitoring/feedback; self-evaluation/metacognition; and agency/personalization. Dependence, unreliable output, and cognitive substitution formed a cross-cutting risk theme.

Methodological confidence was assessed qualitatively using selected domains adapted from the MMAT (Hong et al., 2018), including design adequacy, measurement, confounding, and interpretive support. High, moderate, or low judgments informed the weight assigned to findings; they were not presented as formal MMAT summary scores.

Results and discussion

Figure 2
Publication years of the seven included empirical studies



Source: authors' calculation from the seven included studies.

The 7 studies appeared in 2024 (n = 1), 2025 (n = 1), and 2026 (n = 5). Together, they involved 1,469 participants, with individual samples ranging from 27 to 969. 3 studies were correlational, 2 examined implementation or comparative experiences, 1 was uncontrolled quasi-experimental, and 1 was randomized. Consequently, most

findings support association or interpretation rather than causal claims. Figure 2 shows that five of seven studies were published in 2026, underscoring the recency of this evidence. Table 2 then distinguishes the designs, outcomes, and inference limits of each primary study.

Table 2
Characteristics of the seven included empirical studies

Study	Setting / design	GenAI / autonomy-related focus	Principal evidence / caution
Amzalag et al., (2025)	Israel; n = 68; qualitative comparison	GenAI-supported vs. conventional teaching; agency	Exploration and flexibility vs. instructional structure; one course.
Cardenas-Sinche et al., (2026)	Peru; n = 148; cross-sectional	Academic ChatGPT use; autonomy, planning, time management	Autonomy r = .838; planning r = .799; time r = .813; tasks r = .630 (all $p < .001$). Self-report; non-causal.
Essel et al., (2026)	Ghana; n = 969; cross-sectional	GenAI perceptions; learning autonomy	r = .871; R^2 = .758; high shared variance, self-report, non-causal.
Juárez (2026)	Spain; n = 52; uncontrolled quasi-experiment	PathRAG + GPT-3.5 Turbo; participation, adaptive pathways	Positive perceived participation and usefulness; no control group, short duration.
Lee et al., (2024)	Taiwan; n = 61; randomized trial	Guided vs. direct-answer ChatGPT; SRL, higher-order thinking	Guidance improved measured outcomes; limited to a chemistry course.
Leiva-Guerrero et al., (2026)	Chile; n = 144; qualitative/exploratory	GPT-4o feedback in Moodle; monitoring, revision	Rapid feedback; occasional contextual errors and impersonal tone; no controlled comparison.
Monar et al., (2026)	Ecuador; n = 27; correlational	Academic GenAI use; learning process / regulation	Overall r = .893; mode of use mattered; small n and inconsistent reporting.

Note: GenAI = generative artificial intelligence; SRL = self-regulated learning; HOTS = higher-order thinking skills. *Source:* authors' synthesis of the seven original studies cited in this table.

Planning was most directly assessed by Cardenas-Sinche et al., (2026): academic ChatGPT use correlated with planning (r = .799), time management (r = .813), and task execution (r = .630). These associations do not establish directionality; students with stronger pre-existing SRL may use GenAI more purposefully. Among engineering students, Amzalag et al., (2025) found that GenAI-supported learning enabled exploration and flexibility, while conventional teaching offered structure. Their findings favor guided choice rather than the removal of instructional support.

Leiva-Guerrero et al., (2026) used GPT-4o to provide rapid feedback through Moodle. Automated responses created opportunities to review and revise work but sometimes lacked disciplinary context or a sufficiently personal tone. Juárez (2026) reported favorable experiences with PathRAG-assisted adaptive pathways, although the small sample, short intervention, and absence of a control group restrict attribution of the results to GenAI. The strongest design was Lee et al.,'s (2024) randomized comparison. When ChatGPT required students to attempt problems before receiving hints, SRL, higher-order thinking, and knowledge construction improved relative to conventional ChatGPT use. The comparison supports guided interaction within the studied course, not universal effects across disciplines.

Monar et al., (2026) reported a strong overall association with learning processes (r = .893), but subgroup analyses suggested that mode of use may be more informative than frequency. Its small sample (n = 27) and reporting inconsistencies warrant caution. Essel et al., (2026) found a strong association between GenAI

perceptions and learning autonomy (r = .871; R^2 = .758). Because both variables were self-reported in a cross-sectional survey, the unusually large explained variance should not be interpreted causally. Across studies, the benefits of personalization depend on students' capacity to question, verify, or reject generated suggestions. Table 3 synthesizes these enabling conditions and risks.

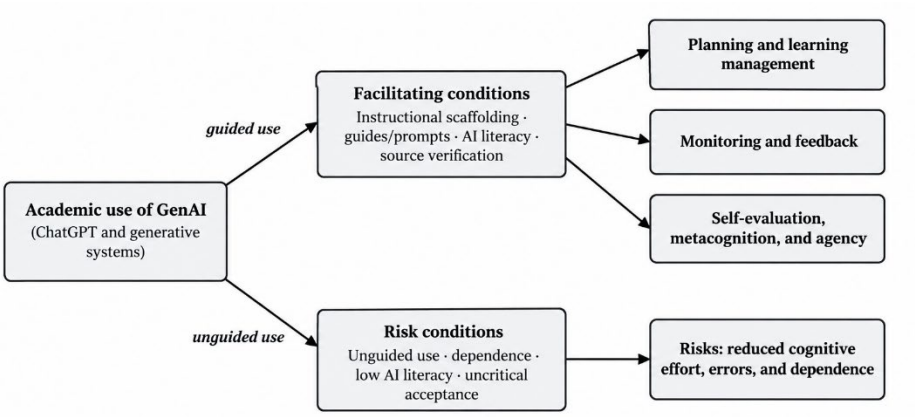
Table 3
Thematic synthesis of opportunities, conditions, and risks

Dimension	Favorable evidence	Necessary conditions	Risks / cautions	Main studies
Planning and management	Strong associations with planning and time management; greater flexibility and exploration.	Explicit goals, sequences, rubrics, and student responsibility.	Confusing productivity with autonomy; causality not demonstrated in surveys.	Amzalag et al., (2025). Cardenas-Sinche et al., (2026).
Monitoring and feedback	Rapid, repeatable, personalized feedback; support for revising products.	Quality criteria, disciplinary contextualization, and instructor supervision.	Errors, decontextualization, impersonal tone, and overconfidence.	Juárez (2026). Leiva-Guerrero et al., (2026).
Self-evaluation and metacognition	Better outcomes when ChatGPT guides with hints and requires a prior attempt.	Prompts that request explanation, justification, verification, and reflection.	Direct answers may replace reasoning and reduce cognitive effort.	Lee et al., (2024). Monar et al., (2026).
Agency and personalization	Favorable perceptions associated with greater autonomy; adaptive pathways.	AI literacy, equitable access, and the ability to reject/review suggestions.	Dependence, uncritical acceptance, and digital-skills gaps.	Essel et al., (2026). Juárez (2026).
Engineering	GenAI promotes autonomy and exploration in an engineering course.	Authentic problems, technical verification, and combination with instructional structure.	Limited disciplinary evidence; no studies specific to Civil Engineering.	Amzalag et al., (2025). (Indirect evidence from other studies).

Source: authors' thematic synthesis of the seven included empirical studies.

The synthesis identifies pedagogical design and verification as recurring conditions rather than proven statistical moderators. Figure 3 illustrates this interpretive distinction between guided support and uncritical delegation.

Figure 3
Interpretive framework of conditions associated with GenAI-supported autonomous learning



Source: authors' synthesis; conceptual model, not a tested moderator.

The conceptual framework is consistent with observed differences in study designs and outcomes but does not establish causal pathways across all studies. Table 4 therefore grades the confidence warranted by each empirical contribution.

Table 4
Methodological confidence appraisal of included studies

Study	Overall confidence	Main strength	Main threat to inference
Amzalag et al., (2025)	Moderate	Rich comparison of experiences among engineering students.	Qualitative evidence from a single course.
Cardenas-Sinche et al., (2026)	Moderate	Random sample and analysis by autonomy dimensions.	Cross-sectional design and self-report.
Essel et al., (2026)	Moderate	Large sample and explicit statistical model.	Exceptionally high explained variance; common-method and non-causal design.
Juárez (2026)	Moderate	Authentic intervention with a GenAI-based adaptive system.	No control group, short duration, and instruments not fully validated.
Lee et al., (2024)	High	Randomized trial directly comparing two modes of ChatGPT use.	Moderate sample and a single course/discipline.
Leiva-Guerrero et al., (2026)	Moderate	Prior validation of the prompt and real-world application in two courses.	No control group and outcomes focused on the feedback experience.
Monar et al., (2026)	Low	Explores differences between intensity and mode of use.	n=27 and inconsistencies between overall findings and specific analyses.

Note: judgments are qualitative interpretive appraisals adapted from MMAT domains, not validated MMAT percentage scores.
Source: authors' appraisal of the seven included studies (Hong et al., 2018).

Only one included study specifically centered on engineering students, and another included an electromechanical-engineering context. No included study focused exclusively on Civil Engineering; extrapolation to that discipline is therefore uncertain. Taken together, the findings do not support the equation 'more GenAI use = more autonomy.' Positive outcomes depend on what students do with the tool and whether they retain control of planning, verification, and reflection. Lee et al., (2024) offer the most direct evidence that altering assistance from answers to hints can change learning outcomes.

The correlations from Peru and Ghana are compatible with different explanations: GenAI might support regulation, already autonomous students might be more strategic users, or motivation and AI literacy might influence both variables (Cardenas-Sinche et al., 2026; Essel et al., 2026). Observational findings should therefore remain explicitly non-causal. The Ecuadorian study further suggests that raw usage counts can obscure contrasting behaviors, such as copying an answer versus requesting a hint and independently checking a solution (Monar et al., 2026). Future research should classify the quality and purpose of interactions. Secondary evidence is broadly consistent: Achuthan (2025) reported favorable AI-related associations with self-regulation, but included technologies beyond GenAI. Reviews of generative systems similarly describe benefits for tutoring and feedback alongside risks of inaccuracy and dependence (Amofa et al., 2025; Ogunleye et al., 2024; Qian, 2025).

Feedback may shorten the cycle between performance and adjustment (Leiva-Guerrero et al., 2026), but metacognitive benefit requires students to compare responses against explicit criteria, diagnose errors, and justify changes. Automated correction alone does not demonstrate independent learning. The engineering comparison by Amzalag et al., (2025) likewise shows that autonomy and instructional structure need not compete. Instructor-designed criteria and progressive withdrawal of assistance may preserve learner agency while reducing unsupported dependence. For engineering tasks, a defensible integration sequence is to state assumptions, attempt a solution independently, request hints or counterexamples, verify outputs against calculations and standards, and document revisions. This is a pedagogical recommendation inferred from the synthesis, not a tested Civil Engineering intervention.

Disciplinary transfer remains untested. Civil Engineering research should examine authentic tasks in structures, hydraulics, geotechnics, or construction management and assess how students justify decisions and solve new problems without AI assistance. More rigorous outcome measurement should combine self-report with interaction logs, revisions, error detection, independent transfer tests, and longitudinal follow-up to distinguish perceived autonomy from demonstrated competence.

AI literacy is also an equity issue: in the Ghanaian sample, 54.8% reported no prior AI experience and 31.2% low AI literacy (Essel et al., 2026). Learners need instruction in verification, uncertainty, privacy, and responsible refusal of unsuitable outputs. Autonomy-supportive integration should prioritize agency and competence rather than convenience. This principle is consistent with self-determination theory (Deci & Ryan, 2000), although the reviewed studies do not establish a common motivational mechanism.

Limitations include the absence of auditable database-specific search records, the small and recent evidence base, diverse outcome measures, predominance of cross-sectional self-reports, and no Civil Engineering-specific study. These constraints preclude pooled-effect estimation and strong disciplinary or causal generalization. Future trials should compare direct answers, graduated hints, and criteria-based feedback, using objective measures of monitoring, transfer, and unassisted performance. Table 5 translates the current synthesis into tentative instructional principles.

Table 5

Practical principles for autonomy-supportive GenAI integration

Principle	Teaching application	Observable indicator
Attempt before assistance	Require an initial solution or self-generated explanation before opening ChatGPT.	Evidence of the student's prior reasoning is available.
Hints before answers	Configure prompts or tutors to provide questions, hints, and counterexamples.	The student completes missing steps and explains decisions.
Mandatory verification	Compare outputs with primary sources, standards, calculations, or disciplinary software.	GenAI errors and the sources used to correct them are documented.

Criteria-based feedback	Link the generative response to a rubric or explicit list of criteria.	The student identifies which criterion improves and how.
Metacognitive reflection	Close the activity with questions about strategy, error, and transfer.	The student describes what changed in the way the problem was solved.
Transfer assessment	Include later tasks without GenAI or with restricted support.	Performance is maintained as technological assistance decreases.

Note: these principles are practical inferences, not interventions directly tested across the seven studies. *Source:* authors' synthesis of reviewed evidence.

Conclusions

The seven included studies suggest that GenAI can facilitate planning, feedback, and exploration, but most evidence is observational or perception-based. The randomized trial by Lee et al., (2024) provides stronger, context-specific evidence favoring guidance-based ChatGPT over direct-response use for SRL and higher-order thinking. Benefits appear conditional on pedagogy: independent attempts, hints, verification, and reflection may preserve cognitive agency, whereas uncritical delegation can undermine it. Higher education institutions should therefore couple GenAI access with AI literacy and authentic assessment. No included study established an effect in Civil Engineering. Future longitudinal and experimental research should assess demonstrated autonomy and transfer without assistance in authentic engineering tasks.

Author contributions

Proposed CRediT statement (subject to confirmation by all authors): Jaime Canal-Apaza—conceptualization, methodology, writing–original draft; Martín Eduardo Gonzales Laguna—investigation, data curation, formal analysis; Jose Luis Chambilla-Quispe—investigation, validation, visualization; Jorge Lizandro Choque-Quispe—formal analysis, visualization, writing–review and editing. All authors should verify their actual contributions, approve the final manuscript, and accept responsibility for the work before submission.

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