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Systematic Review

AI-Augmented Experiential Pedagogies for Transversal Competencies in Engineering and STEM Higher Education: A Systematic Review for Sustainable-Development Education

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Abstract

Engineering education must develop transversal competencies that overlap with those targeted by education for sustainable development, and artificial intelligence (AI), particularly generative AI, is entering the experiential pedagogies that develop them. Following PRISMA 2020, we searched Web of Science, Scopus, and IEEE Xplore (last searched 31 October 2026), screened 1506 records with human screeners and an AI model as an independent second screener, and assessed 436 full texts. We included 323 studies, of which 153 primary studies combined AI, an experiential pedagogy, and a transversal competency. AI was used mostly as a tutor or co-creative partner in project-based learning; role-play partners, feedback on interpersonal processes, and drama were rare. Only 60 studies compared groups on performance or validated measures, mostly without randomization and while AI was available, and comparisons favored AI less often in studies meeting more MMAT criteria (50% vs. 85%). Certainty was low to very low. Structured AI use was more often associated with comparative gains than unconstrained use, an exploratory pattern, not a demonstrated effect. Sustainability links were explicit in 15% of studies, and no study assessed sustainability competences with an established framework. The review was not registered; it was funded by Lucian Blaga University of Sibiu.

Keywords: artificial intelligence; generative AI; engineering education; transversal competencies; experiential learning; project-based learning; role-play; education for sustainable development; systematic review; PRISMA

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1. Introduction

1.1. Transversal Competencies, Engineering Education, and Sustainable Development

The 2030 Agenda frames education as both a goal and an enabler of sustainable development: Target 4.7 asks that all learners acquire the knowledge and skills needed to promote sustainable development, and Target 4.4 asks for a substantial increase in the number of young people and adults with relevant skills for decent work [1]. Engineers sit at the center of this agenda, because the infrastructure, energy, production and digital systems on which most of the Sustainable Development Goals (SDGs) depend are designed, built and operated by them [2]. Frameworks of education for sustainable development (ESD) therefore converge on a set of competencies that go well beyond technical knowledge: systems and critical thinking, anticipatory and strategic thinking, collaboration, self-awareness, and the ability to act under complexity and uncertainty [3–6].

These sustainability competencies overlap substantially with what engineering-education research calls transversal competencies (also termed soft, generic or 21st-century skills): communication, collaboration and teamwork, creativity, critical thinking, problem solving, self-regulation, emotional intelligence and empathy, adaptability, and ethical responsibility [7–9]. The overlap is explicit in the main reference frameworks. The European GreenComp framework groups 12 sustainability competences into four areas (embodying sustainability values, embracing complexity, envisioning sustainable futures and acting for sustainability) and names critical thinking, problem framing, adaptability, exploratory thinking, collective action and individual initiative among them [6]. The key competencies in sustainability proposed by Wiek et al. and updated by Brundiers et al. add interpersonal, intrapersonal and integrated problem-solving competence to systems thinking, futures, values and strategic competence [4,5]. Employer and graduate studies repeatedly report that engineering graduates are technically well prepared but under-prepared in exactly these areas, and that the gap matters for employability and career sustainability [10–14]. Developing transversal competencies is therefore not a peripheral add-on to engineering curricula; it is part of what makes engineering education a lever for sustainable development.

The overlap is, however, partial, and its limits matter for any claim that transversal-competency research serves ESD. Table 1 maps the transversal competencies coded in this review onto both sustainability frameworks and distinguishes core correspondences (the transversal competency is a constituent of the sustainability competence) from partial ones (it contributes to, but does not constitute, the competence). Most transversal competencies have a core counterpart: critical thinking and problem solving correspond to the GreenComp area 'embracing complexity' and to integrated problem-solving; collaboration and communication to collective action and interpersonal competence; self-regulation to individual initiative and intrapersonal competence; ethical responsibility to values thinking and fairness; and creativity to exploratory thinking. Several sustainability competences have no core counterpart among the transversal competencies: systems thinking, futures literacy or anticipatory thinking, strategic and implementation competence, political agency and promoting nature; some of them are reached only partially, for example, futures literacy through creativity or political agency through communication. The crosswalk is conceptual. Overlap between a transversal and a sustainability competence does not mean that a study targeting the transversal-competency targets, measures, or develops the sustainability competence, and we therefore keep these levels apart in the analysis (Section 3.5).

Table 1. Crosswalk between the transversal competencies coded in this review and two sustainability-competence frameworks.

Transversal Competency	GreenComp Competences	Key Competencies in Sustainability	Shared Focus
Critical thinking	Critical thinking (core); problem framing (partial)	Values thinking, integrated problem-solving (partial)	Evaluating claims, assumptions and evidence, including AI output
Problem solving	Problem framing (core); exploratory thinking (partial)	Integrated problem-solving (core); strategic, implementation (partial)	Framing and solving open-ended, ill-structured problems
Collaboration/ teamwork	Collective action (core)	Interpersonal (core); implementation (partial)	Working with others towards shared goals
Creativity	Exploratory thinking (core); futures literacy (partial)	Futures thinking (partial)	Generating novel alternatives and possibilities

Table 1. *Cont.*

Transversal Competency	GreenComp Competences	Key Competencies in Sustainability	Shared Focus
Communication	Collective action, political agency (partial)	Interpersonal (core)	Exchanging, explaining and negotiating perspectives
Self-regulation/ metacognition	Individual initiative (core)	Intrapersonal (core)	Planning, monitoring and reflecting on one's own learning
Ethics/responsibility	Supporting fairness (core); valuing sustainability (partial)	Values thinking (core)	Applying norms and values to technical decisions
Emotional intelligence/empathy	Supporting fairness, promoting nature (partial)	Interpersonal, intrapersonal (core)	Recognizing and managing one's own and others' emotions
Adaptability	Adaptability (core)	Intrapersonal (partial)	Acting under uncertainty and change

GreenComp: European sustainability-competence framework [6]; KCS: key competencies in sustainability [4,5]. Core: the transversal competency is a constituent of the sustainability competence; partial: it contributes to, but does not constitute, the competence. Sustainability competences without a core counterpart: systems thinking (both frameworks), futures literacy/futures thinking, strategic thinking, implementation, political agency and promoting nature (the last four are reached at most partially). The mapping is conceptual and does not imply that a study targeting a transversal-competency targets or develops the corresponding sustainability competence.

1.2. Experiential Pedagogies as Vehicles for Transversal Competencies

Transversal competencies are difficult to teach through lectures and examinations alone. They are developed mainly through experience: learners act in an authentic or simulated situation, reflect on what happened, conceptualize, and try again [15,16]. A family of alternative and experiential pedagogies operationalizes this logic in engineering and STEM higher education. Project-, problem- and challenge-based learning (PBL) organizes learning around open-ended, team-based problems and is one of the most frequently reported vehicles for teamwork, communication and problem-solving skills [17–19]. Design-thinking structures human-centered problem solving around empathy, ideation, prototyping and testing and has been linked to creative and entrepreneurial competencies [20–22]. Role-play, applied drama and improvisation, building on the work of Spolin, Boal and Heathcote, train communication, empathy and conflict management by having students rehearse professional interactions [23–30]. Games and gamification, simulation, and immersive virtual, augmented, and extended reality (VR/AR/XR) place students in rich scenarios that would be costly or impossible to stage in reality, although immersion also adds cognitive load that must be managed [31–35].

What these approaches share is that they are resource-intensive. They need carefully designed scenarios, credible counterparts to interact with, timely and individual feedback, and facilitators who can observe and debrief many students at once. These are precisely the bottlenecks that artificial intelligence (AI) promises to relieve.

1.3. Artificial Intelligence in Engineering and STEM Education

AI has been part of STEM education for more than a decade, mainly in the form of intelligent tutoring systems, adaptive learning environments, learning analytics, and automated assessment [36–40]. Since the public release of ChatGPT in late 2022, generative AI and large language models (LLMs) have changed the scale and the nature of this presence: students and teachers now have general-purpose conversational systems that can

explain, generate text, code, and images, play roles, and give feedback on demand [41–44]. Engineering-education research has responded quickly, initially with a strong focus on assessment integrity and on AI as a tutor for technical content [44,45]. Guidance from international bodies stresses that generative AI should be introduced in ways that protect human agency, equity and the development of higher-order competencies [46].

The relationship between AI and transversal competencies is ambivalent. On one side, conversational agents can act as tireless rehearsal partners for communication and interview practice; generative AI can author role-play scenarios and case studies at low cost; and multimodal systems can give feedback on presentations and collaboration [47–50]. On the other side, recent experimental evidence suggests that unrestricted access to generative AI can reduce learners' own cognitive effort, impair learning when the support is withdrawn, and narrow the diversity of creative output [51–53]. Whether AI strengthens or erodes transversal competencies may therefore depend less on the technology itself than on how it is embedded in the pedagogy.

1.4. Research Gap, Aim and Research Questions

Existing reviews cover AI in STEM education in general [36,39], generative AI in higher education [42,43], LLMs in computing education [44], generative AI and transversal competencies across disciplines [54], and design thinking and AI [55]. Our own search also retrieved 30 reviews that touch the topic more closely, and they are included in this review as secondary evidence. Each of them, however, is bounded by a single technology, outcome, pedagogy or discipline: chatbots and generative AI in engineering education [56], conversational agents [57], AI in immersive or XR environments [58–60], adaptive or serious games [61,62], technologies for assessment and feedback [63], generative AI and creative thinking [64,65], emerging technologies in project-based learning [66], human–generative-AI interaction in active learning in STEM [67], AI-supported language and communication training for engineers [68] and innovative mathematics courses in engineering [69]. None of them maps the whole range of experiential formats against all types of AI and against the transversal-competency outcomes measured in engineering and STEM higher education, and none relates these outcomes to sustainability-competence frameworks. As a result, we do not know which roles AI actually plays across role-play, design thinking, PBL, games and immersive simulation; which competencies these AI-augmented activities target and how they are measured; how robust the evidence is; and whether the research connects to the sustainable-development agenda that motivates competency-based engineering education.

This systematic review addresses that gap. Its aim is to map and critically appraise the empirical and conceptual literature on AI-augmented experiential pedagogies for transversal competencies in engineering and STEM/STEAM higher education, and to derive implications for sustainable-development education. Five research questions guide the review:

- RQ1. What are the characteristics of research on AI-augmented experiential and alternative pedagogies for transversal competencies in engineering and STEM/STEAM higher education (publication trends, contexts, disciplines and study designs)?
- RQ2. Which roles does AI play, and through which mechanisms does it augment experiential pedagogies such as role-play, drama and improvisation, design thinking, games and gamification, immersive environments, simulation, and project-, problem-, or challenge-based learning?
- RQ3. Which transversal competencies are targeted, how are they measured, and what outcomes are reported?
- RQ4. What is the methodological quality of this evidence?

- RQ5. Which risks and challenges are reported, to what extent is this research explicitly linked to sustainable development and education for sustainable development (SDG 4), and which gaps should future research address?

The review contributes a PRISMA 2020-compliant, multi-database map of a field that has emerged almost entirely since 2024, in which studies that combine AI, an experiential pedagogy and a transversal competency are reported separately from adjacent and contextual literature; explicit and reproducible rules for coding outcomes, AI-use structure and methodological quality; a quality- and certainty-weighted reading of the comparative evidence; and a crosswalk between transversal and sustainability competences that separates conceptual overlap from what studies actually target and measure.

2. Materials and Methods

2.1. Review Design

This systematic review was conducted and is reported in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 statement [70]. The completed PRISMA 2020 checklist and PRISMA 2020 for Abstracts checklist are provided in Table S6 (PRISMA 2020 checklists), and the PRISMA 2020 flow diagram is shown in Figure 1 (an editable version on the official PRISMA template is included as File S7 (PRISMA 2020 flow diagram)). The search is reported following PRISMA-S [71], and the synthesis of quantitative findings follows the Synthesis Without Meta-analysis (SWiM) guideline [72]. Because interventions, outcomes and instruments were too heterogeneous for statistical pooling, the synthesis combines descriptive mapping, direction-of-effect summaries and thematic synthesis, complemented by analyses of consistency across databases and retrieval stages.

The review was not registered in PROSPERO, the Open Science Framework, or any other register, and no separate protocol was published. The eligibility criteria, screening codes, and extraction form were defined before screening and are provided in full in the Supplementary Materials (Document S1: Search log and field definitions; Table S2: Screening and extraction data; Document S3: Screening, extraction and appraisal protocols). Four amendments were made during the review and peer review, all reported here and in Document S1 (Search log and field definitions): (i) additional full-text retrieval efforts for reports not obtained in the first search (Section 2.5); (ii) exclusion of systematic reviews from the outcome synthesis to avoid double counting (Section 2.8); (iii) extension of the search to Scopus and IEEE Xplore, with a reliability benchmark of the AI-assisted screening and a description of non-retrieved reports; and (iv) an independent assessment of a sample of records removed by the field filter, and coding of all primary studies with the explicit outcome, AI-use and appraisal rules in Sections 2.6 and 2.7 and Document S3 (Screening, extraction and appraisal protocols). Eligibility criteria and screening codes were not changed after results were known; the coding in amendment (iv) replaced the earlier outcome coding for all studies, so that the same rules apply throughout. Because amendments (iii) and (iv) were made after a first synthesis had been completed, they could have been influenced by knowledge of the earlier results; this risk is discussed as a limitation (Section 4.7).

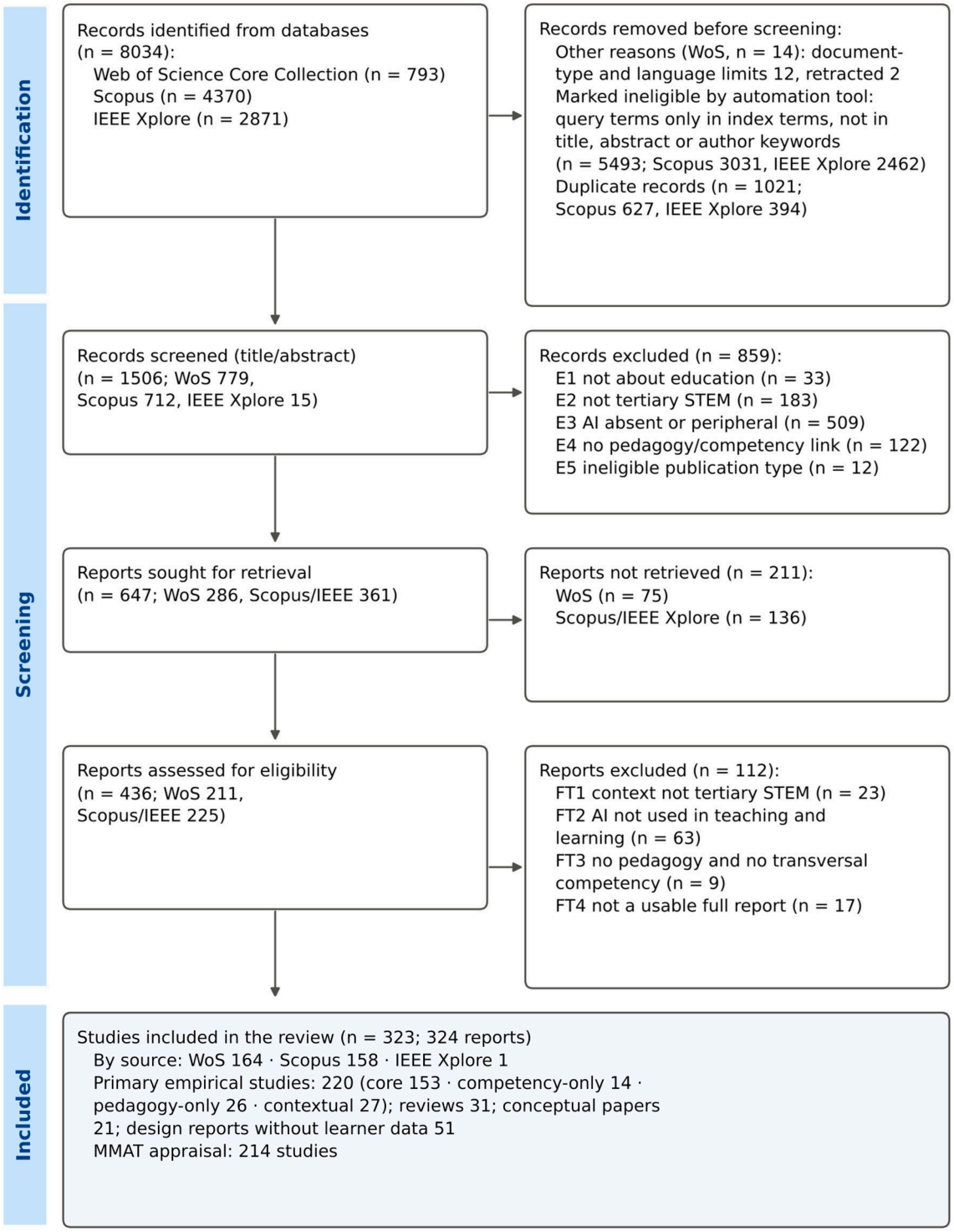

Figure 1. PRISMA 2020 flow diagram of the selection process.

2.2. Information Sources and Search Strategy

Three bibliographic databases were searched. The WoS Core Collection was searched on 7 October 2026 through the institutional subscription of Lucian Blaga University of Sibiu (editions SCI-EXPANDED, SSCI, A&HCI, ESCI, CPCI-S, CPCI-SSH, BKCI-S, BKCI-SSH and IC); Scopus and IEEE Xplore were searched on 31 October 2026. The databases were chosen for complementary coverage: WoS as a curated multidisciplinary index of the main engineering-education journals and the IEEE and ACM education conference series (e.g., FIE, EDUCON and SIGCSE); Scopus for its broader coverage of conference proceedings,

regional journals and publishers outside the WoS selection; and IEEE Xplore as the primary source for engineering and computing-education conference papers. Methodological studies show that no single database is sufficient for a systematic review and that combinations of databases are needed to reach adequate recall [73–75], and that coverage differs substantially between WoS and Scopus, particularly for conference papers [76]. Publication years were limited to 2015–2026, a window that covers the decade of conversational agents, intelligent tutoring systems, and AI-enabled immersive environments that preceded generative AI, as well as the rapid growth of generative-AI applications since 2022.

The query combined four concept blocks: AI technologies (#1); alternative and experiential pedagogies (#2); transversal competencies (#3); and the engineering/STEM/STEAM higher-education context (#4). The final search, #1 AND (#2 OR #3) AND #4, was run as a single combined query (Table 2). The pedagogy and competency blocks were joined with OR because terminology at this intersection is not yet consolidated, so that studies describing either an experiential format or a transversal-competency outcome were captured. The competency block deliberately used umbrella terms (soft, transversal, generic, 21st-century, professional and employability skills) and the interpersonal and creative competencies most closely associated with experiential pedagogies; generic cognitive terms such as "critical thinking", "problem solving" and "communication" were not added because, in combination with the AI and engineering blocks, they would mainly retrieve studies on technical problem solving and AI-assisted programming without an experiential component. Studies reporting these competencies could still enter through the pedagogy block or through the umbrella terms. The consequence of this choice was not quantified, because no sensitivity search with these terms was run, but its direction is predictable: studies of AI and critical thinking, problem solving, or communication that use none of the pedagogy or umbrella terms were not retrieved, so the corpus over-represents studies in which these competencies are embedded in an experiential format, and the small competency-only class (Section 3.1) does not indicate how much research on AI and these competencies exists (Section 4.7). In WoS, results were refined to articles, review articles, proceedings papers, and early-access items in English, which yielded 781 records exported as full records with cited references.

Table 2. Web of Science Core Collection search strategy (7 October 2026). Equivalent Scopus and IEEE Xplore strings are given in Document S1 (Search log and field definitions).

Set	Concept	Search String	Results
#1	AI technologies, 2015–2026	TS = ("artificial intelligence" OR AI OR "generative AI" OR GenAI OR "large language model*" OR LLM* OR ChatGPT OR chatbot* OR "conversational agent*" OR "pedagogical agent*" OR "virtual agent*" OR "intelligent tutoring system*" OR "affective computing" OR "emotion recognition" OR "AI-based" OR "AI-powered" OR "AI-enhanced" OR "AI-assisted" OR "AI-driven") AND PY = (2015–2026)	678,471
#2	Alternative/ experiential pedagogies	TS = ("role-play*" OR "role play*" OR roleplay* OR "drama-based" OR "applied drama" OR "process drama" OR "educational drama" OR "drama pedagog*" OR theatr* OR theater* OR improvis* OR "design thinking" OR "design-based learning" OR gamif* OR "serious game*" OR "game-based learning" OR "educational game*" OR "virtual reality" OR "augmented reality" OR "mixed reality" OR "extended reality" OR metaverse OR "immersive learning" OR "immersive environment*" OR "simulation-based learning" OR "simulation-based training" OR "experiential learning" OR "problem-based learning" OR "project-based learning" OR "challenge-based learning")	436,547

Table 2. *Cont.*

Set	Concept	Search String	Results
#3	Transversal competencies	TS = (“soft skill*” OR “transversal competenc*” OR “transversal skill*” OR “generic skill*” OR “21st century skill*” OR “21st-century skill*” OR “twenty-first century skill*” OR “professional skill*” OR “employability skill*” OR “interpersonal skill*” OR “communication skill*” OR “collaboration skill*” OR teamwork OR creativity OR “creative thinking” OR “emotional intelligence” OR empathy OR adaptability)	416,184
#4	Engineering/ STEM/STEAM higher-education context	TS = (“engineering education” OR “engineering student*” OR “engineering course*” OR “engineering curricul*” OR “engineering program*” OR “STEM education” OR “STEM learning” OR “STEM student*” OR “STEM course*” OR “STEM discipline*” OR “STEAM education” OR “STEAM learning” OR “STEAM approach*” OR “science technology engineering” OR “technical education” OR “technical universit*” OR polytechnic* OR “computing education” OR “computer science student*”)	87,073
#5	Combined	#1 AND (#2 OR #3) AND #4	793
	Refined	Document types: article, review article, proceedings paper, early access; language: English	781

TS = topic field (title, abstract, author keywords, Keywords Plus); PY = publication year; * = truncation. Generic cognitive terms (“critical thinking”, “problem solving” and “communication” other than “communication skill*”) were deliberately not included in #3; see Sections 2.2 and 4.7.

The same blocks were translated into Scopus (TITLE-ABS-KEY, with document-type, language and year limits) and IEEE Xplore (Command Search, with wildcards replaced by explicit singular and plural forms because of its limit of 10 wildcards per search); the full strings are given in Document S1 (Search log and field definitions). The databases search different fields (Table 3): the WoS topic field covers title, abstract, author keywords, and Keywords Plus (terms derived algorithmically from the titles of cited references); Scopus TITLE-ABS-KEY adds index keywords, including controlled vocabularies such as Compendex terms; and IEEE Xplore metadata searches add IEEE and INSPEC index terms. Index keywords assign broad terms such as “engineering education” or “artificial intelligence” to many records in which the concepts are not substantive: of the 4370 Scopus records, 4281 matched the query when index keywords were included, but only 1339 matched in the title, abstract, or author keywords. We therefore re-applied the query with a script to the title, abstract, and author keywords of every exported Scopus and IEEE Xplore record and marked non-matching records as ineligible by an automation tool, as PRISMA 2020 provides [70]. The script, which reproduces the Boolean structure, truncations, and case-sensitive acronyms of the query, is provided as executable code with its input and output files in File S8 (Field filter and analysis code). This field definition is stricter than the WoS topic field, which retains Keywords Plus. Applied to the WoS corpus, the filter retained 694 of the 779 screened records and 140 of the 145 studies included from the WoS search (96.6%); the five studies it would have missed entered WoS only through Keywords Plus. To estimate how many eligible records the filter removed in Scopus and IEEE Xplore, two authors independently screened a random sample of 300 of the 5493 removed records (166 Scopus, 134 IEEE Xplore, proportional to database) with the normal title/abstract criteria, and the third author resolved disagreements. The two screeners forwarded 12 and 10 of the 300 records to full-text assessment, agreed on 292 decisions (97.3%; $\kappa = 0.62$, lower than the percentage agreement because few records were forwarded) and on the exclusion code in 279 of 285 joint exclusions; the third author resolved the 8 disagreements (2 forwarded, 6 excluded). In total, 9 of the 300 records (3.0%; Wilson 95% CI 1.6–5.6%)

would have been forwarded to full-text assessment (6 of 166 Scopus and 3 of 134 IEEE Xplore records), compared with 361 of the 727 records that passed the filter (49.7%). Extrapolated to the 5493 removed records, this corresponds to about 165 records (95% CI 87–308), or roughly 31% (19–46%) of all Scopus and IEEE Xplore records that would have reached full-text assessment. The forwarded records were recent conference papers and journal articles on AI-supported project-based learning, gamification, simulation, critical thinking, and reflection in undergraduate engineering and computing, i.e., of the same kind as the included studies; they are listed with both screeners' decisions in Table S4 (Non-retrieved reports and field-filter assessment), sheet S4b. If the same proportion of forwarded records were eligible as among the Scopus and IEEE Xplore records that passed the filter (159 of 361, 44%), the filter would have removed about 73 eligible studies (roughly 38–136). We retained the filter for three reasons. First, it gives the three databases a comparable field definition; without it, Scopus and IEEE Xplore would have been searched in controlled vocabularies that the WoS search did not use. Second, its precision is very different on the two sides: half of the records it retained reached full-text assessment, compared with 3% of those it removed, so screening all 5493 removed records would have added about 5300 screening decisions for an estimated 165 forwarded records. Third, the removed eligible records are of the same kind as those included (recent conference papers on AI-supported project-based learning, gamification and simulation), and adding 80 studies of this kind through later retrieval did not change the direction of any finding (Section 3.6), although this cannot show that the removed records would not have done so. We nevertheless treat the removed records as a limitation of coverage (Section 4.7), not as evidence that the filtered corpus is complete. The remaining records were deduplicated against WoS and against each other by DOI and normalized title. IEEE Xplore added only 15 unique records, because 394 of its 409 eligible records (96.3%) were already indexed in WoS or Scopus. No registers, websites, or citation searching were used.

Table 3. Fields searched, search yield, and contribution of each database.

	Web of Science	Scopus	IEEE Xplore	Total
Fields searched	TS: title, abstract, author keywords, Keywords Plus	TITLE-ABS-KEY: title, abstract, author keywords, index keywords (incl. controlled terms)	Command Search: title, abstract, author keywords, IEEE and INSPEC index terms	
Fields used for eligibility (field filter)	as searched (no filter)	title, abstract, author keywords [a]	title, abstract, author keywords [a]	
Date of search	7 October 2026	31 October 2026	31 October 2026	
Records identified	793	4370	2871	8034
Removed for other reasons [c]	14	—	—	14
Marked ineligible by automation tool [a]	—	3031	2462	5493
Duplicates removed	—	627	394	1021
Records screened	779	712	15	1506
Reports sought	286	356	5	647
Reports retrieved	211	223	2	436

Table 3. *Cont.*

	Web of Science	Scopus	IEEE Xplore	Total
Included studies (database of first identification)	164	158	1	323
Included studies indexed in the database (unique) [b]	164 (8)	314 (119)	94 (1)	323

[a] Records in which the query terms matched only index terms (controlled vocabulary) and not the title, abstract, or author keywords; identified by the script in File S8 (Field filter and analysis code) and checked on a random sample of 300 removed records (Section 2.2). [b] A study can be indexed in several databases (Section 3.1); in parentheses, studies found only in that database. [c] WoS document-type and language refinement (n = 12) and retracted records (n = 2).

2.3. Eligibility Criteria

Records were eligible when four criteria were met. C1 (context): tertiary education (university, college, polytechnic or tertiary vocational programs) or the professional training of engineers, in engineering, computing/IT or other STEM/STEAM disciplines, with architecture and design counted as STEAM; mixed samples that included tertiary STEM students were eligible. C2 (AI component): an AI technology was used in the teaching and learning process (for example, generative AI and LLMs, chatbots and conversational or pedagogical agents, intelligent tutoring systems, AI-driven feedback or learning analytics, affective computing, and AI-driven characters in simulations, games or VR), or the paper was a review or framework about such use. C3 (pedagogy or competency): the AI was embedded in, or studied together with, an alternative or experiential pedagogy (role-play; drama, theatre or improvisation; design thinking; games and gamification; VR/AR/MR/XR; simulation; experiential learning; problem-, project- or challenge-based learning; hackathons and studio learning), or the study targeted, measured or substantively discussed transversal competencies. C4 (publication type): an empirical study of any design, a design or implementation report, a systematic, scoping or bibliometric review, or a substantive conceptual or framework paper.

At title/abstract level, records were excluded with the first applicable code: E1, not about education or learning; E2, only K-12 pupils, only non-STEM disciplines or the general public; E3, AI absent or peripheral, or AI only the subject taught (e.g., an AI course) with no AI tool used in the pedagogy; E4, no link to an experiential pedagogy or to transversal competencies (e.g., AI used only for automated grading of technical answers, dropout prediction or plagiarism detection); E5, ineligible publication type (editorial, front matter, abstract-only, erratum, retracted). At full-text level, the corresponding codes were FT1 (context not tertiary STEM/STEAM), FT2 (AI not used in teaching and learning), FT3 (no experiential pedagogy and no transversal competency), FT4 (not a usable full report), and FT5 (duplicate report).

2.4. Selection Process

Two records marked as retracted in WoS were removed before screening; no duplicates were found among the 781 exported WoS records. All 1506 records (779 from WoS and 727 from Scopus and IEEE Xplore) were screened on title, abstract, keywords, source, and document type by one human reviewer and an AI model (Claude, Anthropic), working independently. For each database, the records were divided between two authors (V.G. and A.-M.M.), who entered their decisions (include, exclude with code, or unsure) in a screening workbook in which the AI decisions were hidden until all human decisions had been completed. The AI model screened all records against the same written criteria (Document S1: Search log and field definitions); records it judged uncertain were forwarded

to full-text assessment rather than excluded. For the WoS records, its 168 initially uncertain decisions were re-assessed in a second pass before the workbook was given to the human reviewers, so the agreement statistics compare the final AI decisions with the human decisions. For the agreement analysis, "include" and "unsure" were both treated as a decision to retrieve the full text.

Human and AI decisions agreed for 755 of 779 WoS records (96.9%; Cohen's $\kappa = 0.93$ [77], almost perfect agreement [78]; $\kappa = 0.94$ and 0.93 for the two authors' sets) and for 705 of 727 Scopus and IEEE Xplore records (97.0%; $\kappa = 0.94$ for both authors' sets). All 46 disagreements were resolved by the third author (G.M.M.), who forwarded 23 records to full-text assessment and excluded 23. No record was excluded by the AI model alone. Overall, 859 records were excluded at this stage (E1 = 33; E2 = 183; E3 = 509; E4 = 122; E5 = 12) and 646 reports were sought for retrieval, plus one report identified by the audit described below (647 in total).

The use of an AI model as the second screener follows a design that has become common as evidence on large language models in evidence synthesis accumulates. Single human screening misses a non-negligible share of eligible studies [79], while recent evaluations report high but variable agreement between GPT-class models and human reviewers, with sensitivity that depends on the clarity of the criteria [80,81]. We therefore used the AI model only as an independent second screener whose decisions could forward but never exclude a record on their own, and we benchmarked it against a conventional second human screener. A second author re-screened a random 10% sample of the WoS records (n = 78; 39 from each author's set) without access to earlier decisions. Agreement between the two human screeners was 94.9% ($\kappa = 0.89$), compared with 96.2% ($\kappa = 0.92$) between the second human screener and the AI model, and the two human screeners agreed on the exclusion code in 42 of 44 jointly excluded records. In addition, the third author re-assessed a random sample of 50 records that both the human screener and the AI had excluded; one (2.0%; Wilson 95% CI 0.4–10.5% [82]) was judged borderline and was sought at full text, but could not be retrieved. In this sample, the AI model was as consistent with an independent human screener as a second human was. The benchmark is small, however: with 78 records, the confidence intervals of the κ values overlap widely, and the audit of 50 joint exclusions cannot exclude a miss rate of up to about 10%. We therefore interpret these results as evidence that the AI-assisted screening did not perform worse than conventional single human screening, not as evidence that it was equivalent to full dual human screening. All agreement statistics are summarized in Table 4.

Table 4. Reliability of the AI-assisted steps and extent of human verification.

Step	Comparison	n	Agreement	κ	Resolution or Outcome
Title/abstract screening, WoS records	Human (VG or AMM) vs. AI	779 records	96.9%	0.93	24 disagreements resolved by GMM (12 forwarded, 12 excluded)
Title/abstract screening, Scopus/IEEE Xplore records	Human (VG or AMM) vs. AI	727 records	97.0%	0.94	22 disagreements resolved by GMM (11 forwarded, 11 excluded)
Screening benchmark	Second human vs. first human	78 records (random 10%)	94.9%	0.89	Same exclusion code in 42 of 44 joint exclusions

Table 4. *Cont.*

Step	Comparison	n	Agreement	κ	Resolution or Outcome
Screening benchmark	Second human vs. AI	78 records	96.2%	0.92	—
Audit of joint human–AI exclusions	Re-assessment by GMM	50 records (random)	49 of 50 confirmed	—	1 borderline (2.0%; 95% CI 0.4–10.5) sought at full text
Field filter: removed records	Two authors, independently (VG, AMM)	300 records (random sample of 5493)	97.3% (code: 97.9%)	0.62	8 disagreements resolved by GMM; 9 records (3.0%; 95% CI 1.6–5.6) would go to full text
Full-text exclusions, WoS reports (first search)	Two authors, independently (VG, AMM)	44 reports	88.6% (code: 89.7%)	—	5 disagreements resolved by GMM; all exclusions confirmed
Full-text exclusions, Scopus/IEEE Xplore reports (first search)	Two authors, independently (VG, AMM)	42 reports	90.5% (code: 89.5%)	—	4 disagreements resolved by GMM; all exclusions confirmed
Full-text exclusions, later retrieval (repeated searches)	Two authors, independently (VG, AMM)	10 reports	90.0% (code: 77.8%)	—	1 disagreement resolved by GMM; all exclusions confirmed
Full-text exclusions, later retrieval (library requests)	Two authors, independently (VG, AMM)	16 reports	87.5% (code: 85.7%)	—	2 disagreements resolved by GMM; all exclusions confirmed
Data extraction, WoS studies (first set)	Author verification of AI extraction	936 field values (117 studies)	94.8% unchanged	—	49 corrections; independent double-check of 24 studies: 97.4% agreement
Data extraction, WoS studies (second set)	Author verification of AI extraction	224 field values (28 studies)	92.0% unchanged	—	18 corrections; double-check of 6 studies: 97.9% agreement
Data extraction, Scopus/IEEE Xplore studies	Author verification of AI extraction	784 field values (98 studies)	95.8% unchanged	—	33 corrections; independent double-check of 20 studies: 97.5% agreement
Extraction and coding, studies from library requests	Author verification of AI extraction and coding	904 values (55 studies)	95.9% unchanged	—	37 values corrected

Table 4. *Cont.*

Step	Comparison	n	Agreement	κ	Resolution or Outcome
Coding of outcomes, AI-use structure and MMAT (all primary studies)	Independent double-check by a second author	296 values (49 studies, random 20%)	92.6%	—	98 corrections in total (Table S2: Screening and extraction data, sheets S2k–S2l)
MMAT calibration	Two authors, independently	105 judgements (15 studies)	84.8%	0.75	Consensus decision rules fixed
MMAT calibration	AI vs. author consensus	105 judgements	88.6%	0.81	Calibrated rules applied to all studies

VG, AMM, GMM: the three authors. κ: Cohen's kappa. AI: Claude (Anthropic). Agreement for screening is on the binary decision (retrieve full text vs. exclude).

2.5. Full-Text Retrieval and Eligibility Assessment

Full texts were sought through the authors' institutional subscriptions, legal open-access sources (publisher websites, institutional and subject repositories, preprint servers and conference proceedings archives) and reference-manager look-ups (Zotero open-access look-up). Reports that could not be obtained in the first search were searched for again individually with the same sources and finally requested through the library of Lucian Blaga University of Sibiu; retrieval closed on 5 November 2026. These later efforts yielded 106 further reports (19 from the WoS search and 87 from the Scopus and IEEE Xplore searches). In total, 436 of 647 reports (67.4%) were retrieved, and 211 (32.6%) were not: 75 of 286 from the WoS search and 136 of 361 from the Scopus and IEEE Xplore searches. Most non-retrieved reports were conference papers (FIE, EDUCON, ISEC, ASEE and other proceedings) without open-access versions and outside the university's subscriptions. Study investigators were not contacted: with 211 outstanding reports, most of them recent conference papers, individual requests could not have been completed and verified within the time frame of the review, and replies would have been incomplete and selective. The non-retrieved reports are listed in Table S4 (Non-retrieved reports and field-filter assessment). Because they could not be assessed, their eligibility, findings, and methodological quality are unknown, and the review's conclusions apply to the retrieved literature (Sections 3.6 and 4.7).

For each retrieved report, the AI model extracted the eligibility facts and proposed a decision with a code and rationale. Every proposed exclusion was assessed independently against the full text by two authors (V.G. and A.-M.M.), and disagreements were resolved by G.M.M. Across all 112 proposed exclusions, the two authors agreed on the decision for 100 reports (89.3%) and on the exclusion code for 88 of the 100 jointly excluded reports (88.0%); agreement for each retrieval stage is given in Table 4. G.M.M. confirmed exclusion in all disputed cases. Proposed inclusions were confirmed by the author who verified the data extraction for that study (Section 2.6). In total, 112 reports were excluded (FT1 = 23; FT2 = 63; FT3 = 9; FT4 = 17), and 324 reports of 323 studies were included; one study was reported in two papers [83,84], which were treated as a single study. One retrieved report had been retracted by its publisher after publication; it was excluded as an unusable report (FT4), consistent with the removal of retracted records before screening (Section 2.2), and it is listed with the other excluded reports in Table S2 (Screening and extraction data) but not cited. Reports that might appear to meet the inclusion criteria but were excluded include an extended abstract of a comparative study of interactive AI feedback on STEM students' writing, which reported no group sizes or statistics (FT4) [85], and a poster on AI agents that simulate users with disabilities in software-engineering education, which reported no

evaluation method or data (FT4) [86]. All excluded reports are listed with their codes and rationales in Table S2 (Screening and extraction data). The selection process is summarized in Figure 1.

2.6. Data Extraction

A structured extraction form (Document S3: Screening, extraction and appraisal protocols) recorded the country, educational level, discipline, number of participants, intervention duration, study design, presence of a comparison group, AI tools, the primary AI role, and a one- to two-sentence description of the augmentation mechanism and the pedagogies involved (several codes allowed). For each transversal competency targeted, it recorded the type of measure (validated scale, self-report survey, performance rubric or test, qualitative, not measured), the direction of the reported result (positive, mixed, no effect, negative, not measured), and the supporting evidence. It also recorded other outcomes (e.g., engagement, motivation, knowledge), the risks and challenges reported by the authors, any explicit link to sustainability, the SDGs or ESD, and the authors' stated limitations. Primary AI roles were coded as tutor/assistant, role-play or simulated partner, scenario/content generator, feedback/assessment, co-creative partner, analytics/affective sensing, agent inside VR or a game, or other.

The AI model completed a first-pass extraction for every included study from the full text, recording only information reported in the text. Each extraction record was then verified against the full text by one author, with the studies divided equally among the three authors, focusing on the eight fields that feed the synthesis (design, comparison group, sample size, AI role, pedagogies, competency outcomes, sustainability link, and quality appraisal). For the first 117 WoS studies, the verifiers corrected 49 of the 936 verified field values (5.2%) in 33 studies. A random 20% sample of these studies (24 studies, eight from each author's set) was verified again by a second author working independently; the two verifiers agreed on 187 of 192 field values (97.4%), and the five discrepancies (four corrections made by only one verifier and one partial overlap) were resolved by adopting the correction. The remaining 28 WoS studies were verified with the same procedure; the verifiers corrected 18 of 224 field values (8.0%) in 16 studies, and the independent double-check of six of these studies (21%) agreed on 47 of 48 values (97.9%). The 98 studies from Scopus and IEEE Xplore were verified with the same procedure; the verifiers corrected 33 of the 784 verified field values (4.2%) in 30 studies, most often MMAT ratings (23 corrections), followed by sample size (5) and design (3), and confirmed the eligibility of all 98 studies. The independent double-check of 20 studies (20%, stratified by verifier) agreed on 156 of 160 field values (97.5%), and the four discrepancies (three corrections made only by the second verifier and one only by the first) were resolved by adopting the correction. Reports obtained in the later retrieval efforts were extracted and verified with the same procedure. The author verification of the coding of all primary studies (below) led to 98 corrections of extraction, outcome, AI-use and MMAT values, all listed in Table S2 (Screening and extraction data; sheets S2k and S2l). Study investigators were not contacted to obtain or confirm data.

All primary studies were coded from the full text with an explicit protocol (Document S3: Screening, extraction and appraisal protocols). Every coded value was verified by one author against the full text, and a random 20% of studies were checked independently by a second author (274 of 296 values agreed across 49 studies, 92.6%). The protocol fixed four sets of rules. First, each study was assigned a scope class: core (AI used in teaching and learning inside an experiential pedagogy, with at least one transversal competency targeted or measured), competency-only (AI and a transversal competency, no experiential pedagogy), pedagogy-only (AI inside an experiential pedagogy, no transversal competency

targeted or measured), or contextual (reviews, conceptual papers, design reports without learner data and surveys of general AI use not tied to a designed learning activity). Second, each outcome record was coded by type of measure, type of contrast, time point, whether AI was available when the competency was assessed, and direction, with the rules in Table 5; statistics and effect sizes were copied as reported. Third, the organization of AI use was classified as structured, unconstrained, both, or unclear, with the operational definitions in Table 5. Fourth, the MMAT rating rules were made explicit (Section 2.7). Records were created for every combination of competency, measure, and contrast; when a study reported both a between-group and a within-group result, both were recorded; subscales of one instrument measuring the same competency were aggregated with the 'mixed' rule; the immediate post-test was the main time point and any delayed follow-up was recorded separately.

Table 5. Rules for coding outcome records and AI-use structure.

Element	Rule
Scope class	Core: AI used in teaching/learning inside an experiential pedagogy and ≥1 transversal competency targeted or measured. Competency-only: AI and a competency, no experiential pedagogy. Pedagogy-only: AI in an experiential pedagogy, no competency. Contextual: reviews, conceptual papers, design reports without learner data, surveys of general AI use.
Type of measure	Performance (rubric, test, expert rating of product or behavior); validated self-report (published scale or reported validity/reliability); non-validated self-report (author-made items); qualitative; not measured.
Type of contrast	Between-group (AI condition vs. no-AI, historical or alternative-AI comparator); within-group (pre–post in the AI group); correlational; descriptive (post-only, no contrast). Between- and within-group results of one study are recorded separately.
Positive	Significant difference ($p < 0.05$ or CI excluding the null) favoring the AI condition or significant improvement; without a test, an improvement reported by the authors without contrary evidence (flagged "no inferential test").
Negative	Significant difference favoring the comparator or significant decline; without a test, deterioration reported without contrary evidence.
Non-significant	Test reported and not significant; not interpreted as evidence of no effect (no-effect only with an equivalence test or CI-based argument; none found).
Mixed	Within one record (aggregated subscales, items, groups or time points), results in different directions, or qualitative reports of both benefits and harms.
Multiple measures and time points	One record per competency × measure × contrast; subscales of one instrument aggregated with the mixed rule; immediate post-test as main record, delayed follow-up recorded separately.
AI at assessment	With AI (assessed task or product produced while AI was available); without AI (e.g., closed test, transfer or delayed test without AI); unclear.
AI-use structure	Structured: ≥1 explicit constraint on how, when, or for what AI is used (phase restriction, solution-withholding, verification or justification, sequencing after own attempt, usage limits, instructor-curated output). Unconstrained: open on-demand access or AI produces the core generative/problem-solving output. Both: structure varied within the study. Unclear: not reported.

Rules applied to all primary studies; the full protocol is provided in Document S3 (Screening, extraction and appraisal protocols).

2.7. Quality Appraisal

The methodological quality of primary studies with learner outcome data was appraised with the Mixed-Methods Appraisal Tool (MMAT), version 2018 [87]. Single-group pre–post studies were appraised as non-randomized studies and cross-sectional surveys as

quantitative descriptive studies; case studies and experience reports were appraised in the category that matched the data they reported. Following the MMAT guidance, "yes" was used when the report gave information showing that a criterion was met, "no" only when the report gave information showing that it was not met (a demonstrated weakness, for example, confounders reported but not controlled, a non-response rate above 20% or an analysis reported and inappropriate), and "can't tell" whenever the information needed to judge the criterion was not reported. Missing information was therefore never rated "no", and a short justification was recorded for every "no" rating. For mixed-methods studies, the qualitative component and the quantitative component were each appraised with the criteria of their own category, in addition to the five mixed-methods criteria; criterion 5.5 was rated "yes" only if both components met their criteria. Of the 323 studies, 214 were appraised; the others were reviews, conceptual papers, design reports, or reports without learner outcome data. In line with the MMAT guidance, no overall score was calculated; results are reported per criterion, separately for demonstrated weaknesses and reporting gaps, and as the number of criteria met.

Two authors (V.G. and A.-M.M.) first appraised a calibration sample of 15 studies (three per MMAT category) independently, without seeing the AI ratings. They agreed on 89 of 105 judgements (84.8%; $\kappa = 0.75$) and resolved the remaining ones by consensus, with G.M.M. for two studies; the consensus also fixed shared decision rules (e.g., "yes" only for explicit reporting; blinding rated "can't tell" when not mentioned; an analysis that is not described at all rated "can't tell" after the re-coding, to align with the MMAT guidance). The first-pass AI ratings matched the consensus ratings in 93 of 105 judgements (88.6%; $\kappa = 0.81$). The calibrated rules were then given to the AI model for all studies and applied by each author when verifying the AI proposals for the remaining studies in their set. Quality ratings were not used to exclude studies but to weight the interpretation of outcome evidence (Section 2.8).

2.8. Synthesis Methods

The synthesis followed the five research questions and was stratified by scope class: findings for core studies are reported separately from competency-only and pedagogy-only studies, and contextual literature (reviews, conceptual papers and design reports) is used only descriptively and in the Discussion. For RQ1, study characteristics were summarized with frequencies, separately for core primary studies, other primary studies, and contextual literature. For RQ2, an evidence map cross-tabulated the primary AI role against the pedagogies in primary studies, and the extracted mechanisms were grouped by the stage of the experiential activity at which AI intervened. For RQ3, outcome records from core and competency-only primary studies were synthesized by direction of effect [72,88], separately by type of contrast (between-group, within-group, correlational, descriptive) and type of measure (performance, validated self-report, non-validated self-report, qualitative). Non-significant results were reported as such and not as evidence of no effect. Comparative evidence was defined as between-group records with a performance or validated self-report measure; within this subset, we separated records with and without an inferential test, records assessed while AI was available from those assessed without AI, and immediate from delayed outcomes, and we tabulated reported effect sizes and confidence intervals without pooling them (Section 3.3). For the structured-versus-unconstrained hypothesis, all comparative records were tabulated by AI-use structure, including those that do not fit the hypothesis. For RQ4, MMAT ratings were summarized per criterion, and the direction of comparative outcomes was compared across studies meeting 0–1, 2, and 3–5 criteria to examine how methodological quality relates to the findings. The certainty of each main finding was rated with GRADE guidance for narrative syntheses without a single effect

estimate [89]: evidence from non-randomized designs started at low certainty and evidence from randomized designs at high certainty, and was rated down for risk of bias (MMAT), inconsistency, indirectness (for example, outcomes assessed while AI was available), imprecision (few or small studies) and suspected publication bias (Section 3.4). For RQ5, reported risks were counted by category, explicit links to sustainability were classified by their nature, and the targeted competencies were related to sustainability competences at three levels: conceptual correspondence (Table 1), competencies targeted or measured, and competencies with comparative evidence of development. Descriptive analyses were run in Python (pandas, matplotlib); the analysis code is provided in File S8 (Field filter and analysis code).

Two further analyses examined whether the findings were consistent across databases and retrieval stages (Section 3.6); neither can show that the findings hold for the reports that were not retrieved or for the records removed by the field filter. A database-robustness analysis compared key indicators between the WoS corpus and the studies added from Scopus and IEEE Xplore, and the studies obtained through the later retrieval efforts were compared with those retrieved first. A dictionary-based comparison of titles, abstracts and keywords between included studies and non-retrieved reports was retained only as a description of the non-retrieved literature: because abstracts do not reveal findings or methodological quality, this comparison cannot show that non-retrieval did not bias the results.

2.9. Bibliometric Mapping

To situate the included studies within the wider literature, an author-keyword co-occurrence map was built for the 243 studies retrieved in the first search (minimum four occurrences; the 80 studies obtained through later retrieval efforts are not included in this map), and author-keyword, co-citation and country co-authorship maps of the screened WoS corpus (n = 779) are provided in File S5 (VOSviewer maps). Keywords were harmonized with a thesaurus (e.g., merging singular and plural forms and synonyms such as "generative AI" and "GenAI"). Co-occurrence counts were normalized with the association strength [90], and maps were built with the VOS mapping technique and Leiden clustering (resolution 1) [91,92], as implemented in VOSviewer (1.6.20) [93] and, for the map of the included studies, in the open-source networkanalysis library developed by the same group. Map and network files are provided for reproduction in VOSviewer.

2.10. Use of Generative AI

In line with the journal's policy, an AI model (Claude, Anthropic; Opus 5.5 and Sonnet 5.5 models, accessed through the Claude desktop application, October 2026) was used in this review for (i) acting as the second, independent reviewer in title/abstract screening; (ii) proposing full-text eligibility decisions; (iii) first-pass data extraction and MMAT appraisal proposals; (iv) writing the Python code for the field-harmonization filter, deduplication, descriptive statistics, figures and bibliometric maps; and (v) drafting support and language editing of the manuscript. The protocols given to the model are provided in Document S3 (Screening, extraction and appraisal protocols). All AI outputs were checked by the authors as described in Sections 2.4–2.7 and Table 4: no record was excluded, no extracted value was retained without human verification, and every disagreement between the AI model and a human reviewer was resolved by a human author. The authors take full responsibility for the content of this publication.

3. Results

3.1. Characteristics of the Included Studies (RQ1)

The 323 included studies comprise 220 primary empirical studies (153 core, 14 competency-only, 26 pedagogy-only, and 27 contextual surveys) and 103 contributions without learner outcome data (31 reviews, 21 conceptual papers, and 51 design reports); they are grouped in Table 6 and listed individually in Appendix A (Table A1). The field is very recent: 276 studies (85.4%) were published in 2025 or 2026 (Figure 2). Generative AI was the AI technology in 252 studies (78.0%), and in 117 of the 153 core studies (76.5%); ChatGPT was named in 142 studies. The few earlier studies used rule-based or case-based virtual characters, knowledge-based feedback systems, adaptive engines, or classical machine learning [94,95].

Table 6. Characteristics of the included studies by scope class.

Characteristic	Category	Core Primary, n (%) (n = 153)	Other Primary, n (%) (n = 67)	Contextual Literature, n (%) (n = 103)
Publication year	2018–2023	2 (1.3)	5 (7.5)	5 (4.9)
	2024	15 (9.8)	11 (16.4)	9 (8.7)
	2025	75 (49.0)	23 (34.3)	49 (47.6)
	2026 (January–October)	61 (39.9)	28 (41.8)	40 (38.8)
Publication type	Journal article	64 (41.8)	34 (50.7)	33 (32.0)
	Conference paper	89 (58.2)	33 (49.3)	55 (53.4)
	Review	0 (0.0)	0 (0.0)	15 (14.6)
Study design	Randomized or crossover experiment	12 (7.8)	3 (4.5)	0 (0.0)
	Quasi-experiment	38 (24.8)	8 (11.9)	1 (1.0)
	Single-group pre–post	12 (7.8)	3 (4.5)	0 (0.0)
	Mixed methods	41 (26.8)	15 (22.4)	0 (0.0)
	Qualitative	13 (8.5)	7 (10.4)	1 (1.0)
	Cross-sectional survey	8 (5.2)	25 (37.3)	1 (1.0)
	Case study or experience report	29 (19.0)	6 (9.0)	6 (5.8)
	Design or implementation report	0 (0.0)	0 (0.0)	43 (41.7)
	Systematic, scoping or bibliometric review	0 (0.0)	0 (0.0)	31 (30.1)
	Conceptual or framework paper	0 (0.0)	0 (0.0)	20 (19.4)
Sample size	Median (IQR) [a]	64 (33–118)	83 (36–180)	12 (4–20)
Educational level	Undergraduate	113 (73.9)	41 (61.2)	37 (35.9)
	Postgraduate	12 (7.8)	4 (6.0)	4 (3.9)
	Mixed	7 (4.6)	11 (16.4)	27 (26.2)
	Not reported	21 (13.7)	11 (16.4)	33 (32.0)
Discipline	Computing and software engineering	57 (37.3)	25 (37.3)	31 (30.1)
	Electrical and electronic engineering	21 (13.7)	5 (7.5)	12 (11.7)
	Engineering (general or several)	21 (13.7)	14 (20.9)	26 (25.2)
	Mechanical, industrial, manufacturing	22 (14.4)	9 (13.4)	12 (11.7)
	Chemical, biological, materials	17 (11.1)	3 (4.5)	4 (3.9)
	Civil engineering and architecture	6 (3.9)	3 (4.5)	4 (3.9)
	Design, STEAM and arts	6 (3.9)	0 (0.0)	6 (5.8)
	Sciences and mathematics	3 (2.0)	4 (6.0)	4 (3.9)
	STEM (general)	0 (0.0)	4 (6.0)	4 (3.9)
AI technology	Generative AI	117 (76.5)	54 (80.6)	81 (78.6)
	Other AI (non-generative)	36 (23.5)	13 (19.4)	22 (21.4)

Table 6. *Cont.*

Characteristic	Category	Core Primary, n (%) (n = 153)	Other Primary, n (%) (n = 67)	Contextual Literature, n (%) (n = 103)
Primary AI role	Tutor or assistant	60 (39.2)	33 (49.3)	31 (30.1)
	Co-creative partner	37 (24.2)	6 (9.0)	19 (18.4)
	Feedback or assessment	16 (10.5)	7 (10.4)	14 (13.6)
	Scenario or content generator	12 (7.8)	7 (10.4)	10 (9.7)
	Role-play or simulated partner	14 (9.2)	0 (0.0)	5 (4.9)
	Agent inside VR or a game	4 (2.6)	10 (14.9)	5 (4.9)
	Analytics or affective sensing	4 (2.6)	0 (0.0)	7 (6.8)
	Several or other roles	6 (3.9)	4 (6.0)	12 (11.7)
AI-use structure	Structured	92 (60.1)	20 (29.9)	18 (17.5)
	Unconstrained	38 (24.8)	19 (28.4)	2 (1.9)
	Both compared	3 (2.0)	1 (1.5)	0 (0.0)
	Unclear or n/a	20 (13.1)	27 (40.3)	83 (80.6)
Pedagogy	Project-, problem- or challenge-based	112 (73.2)	10 (14.9)	68 (66.0)
	Collaborative learning	95 (62.1)	8 (11.9)	43 (41.7)
	Experiential learning (general)	58 (37.9)	19 (28.4)	42 (40.8)
	Simulation	43 (28.1)	15 (22.4)	54 (52.4)
	Games and gamification	24 (15.7)	13 (19.4)	30 (29.1)
	Immersive VR/AR/XR	16 (10.5)	12 (17.9)	33 (32.0)
	Flipped or blended	20 (13.1)	4 (6.0)	17 (16.5)
	Role-play	22 (14.4)	4 (6.0)	13 (12.6)
	Design thinking	21 (13.7)	2 (3.0)	16 (15.5)
	Drama, theatre, improvisation	1 (0.7)	0 (0.0)	0 (0.0)
Explicit sustainability/ SDG link	Yes	27 (17.6)	3 (4.5)	20 (19.4)

Percentages refer to the studies in the column. Pedagogy counts overlap because a study can report several. Core: AI used inside an experiential pedagogy with a transversal-competency targeted or measured; other primary: competency-only, pedagogy-only and contextual surveys; contextual literature: reviews, conceptual papers and design reports without learner outcome data. [a] Of studies that reported a sample size.

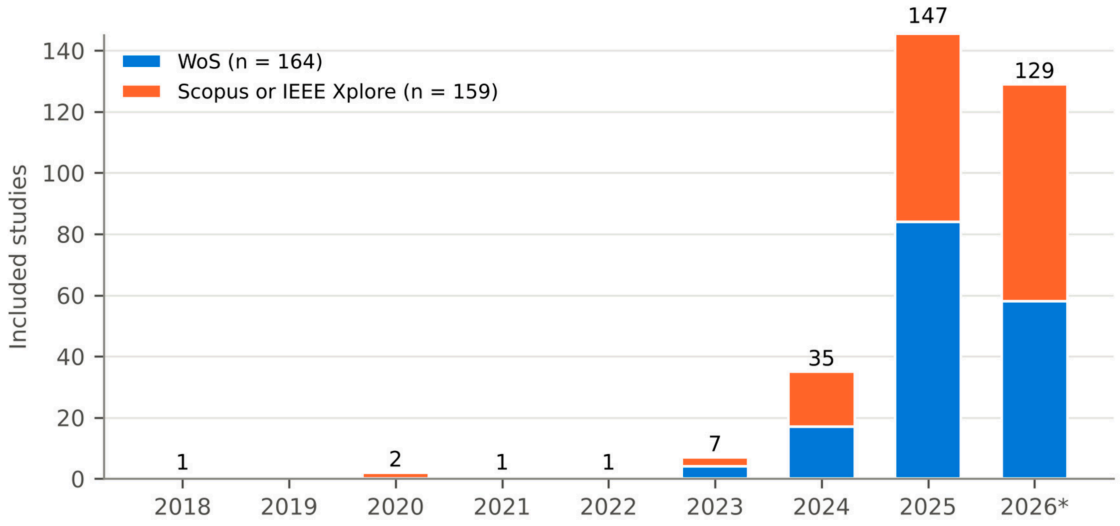

Figure 2. Included studies by publication year and database of first identification. Data for 2026 cover January to October (*).

The three databases contributed differently (Figure 3). WoS indexed 164 of the included studies (50.8%), Scopus 314 (97.2%), and IEEE Xplore 94 (29.1%); 119 studies were found

only in Scopus, 8 only in WoS, and 1 only in IEEE Xplore. Most studies added from Scopus were recent conference papers and journal articles from regional or specialized venues, consistent with known differences in coverage [76].

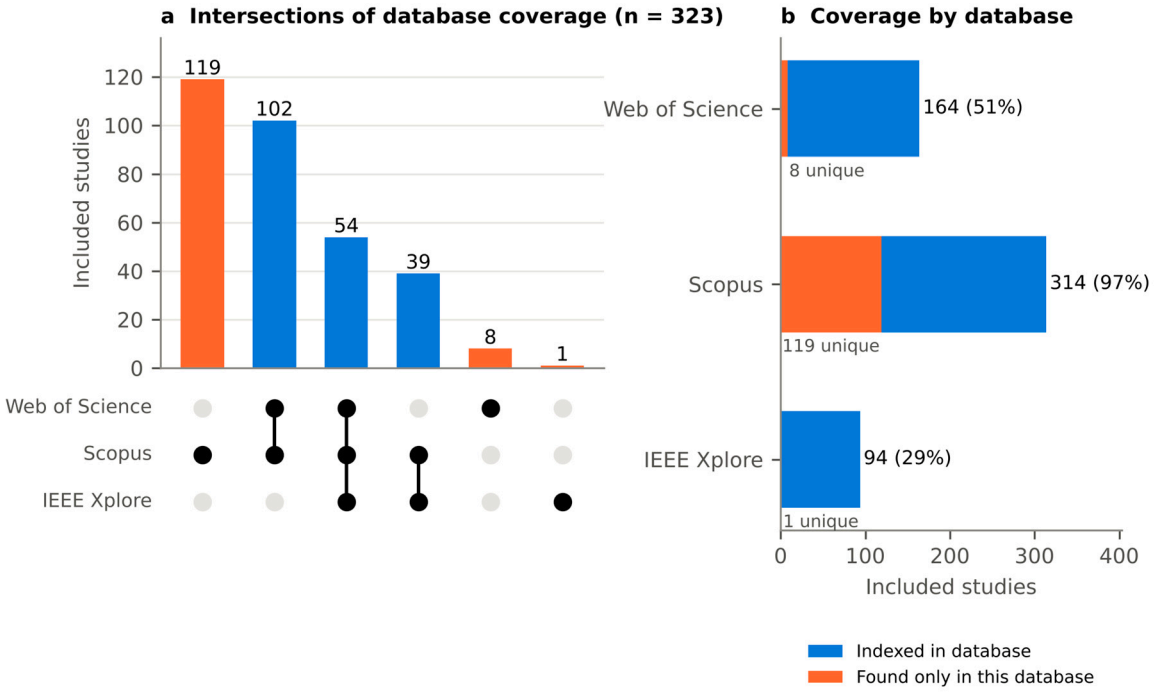

Figure 3. Database coverage of the included studies: (**a**) intersections of the three databases (UpSet plot); (**b**) number of included studies indexed in each database and found only in that database.

The studies came from 63 countries, led by China (48), the USA (46), Mexico (21), India (17), the UK (11) and Spain (11). Most core studies involved undergraduates (113 of 153). Computing and software engineering dominated (113 studies; 35.0%), followed by general or multidisciplinary engineering (61), mechanical, industrial and manufacturing (43), electrical and electronic (38) and chemical, biological and materials engineering (24); design and STEAM programs contributed 12 studies.

Designs differed by scope class. Among the 153 core studies, mixed-methods studies (41), quasi-experiments (38), case studies and experience reports (29), qualitative studies (13), single-group pre–post studies (12) and randomized or crossover experiments (12) predominated, whereas the other primary studies were mostly cross-sectional surveys (25 of 67). Of the 220 primary studies, 63 compared an AI condition with a concurrent no-AI control, 23 with a historical cohort and 6 with an alternative AI condition; baseline equivalence was reported in 27 of the comparative studies and not reported in 61. Among the core studies that reported a sample size, the median was 64 participants (interquartile range 33–118).

The keyword co-occurrence map of the 243 studies retrieved in the first search (Figure 4) shows seven clusters: a computing-education cluster that links large language models with project-based learning, gamification, adaptive learning, intelligent tutoring, learning analytics and teamwork; an immersive-learning cluster around artificial intelligence with virtual, augmented and extended reality, personalized learning, feedback and assessment; a generative-AI cluster that connects engineering and higher education with design thinking, creativity, critical thinking and challenge-based learning; a pedagogical cluster around STEM education, active, experiential and collaborative learning and CDIO; a ChatGPT cluster linked to software and chemical engineering and game-based learning; a smaller cluster that joins AI in education with human–AI collaboration, STEAM and AI literacy; and

problem-based learning as a separate node. The keywords "sustainability" and "sustainable development" did not reach the four-occurrence threshold. The map does not include the 80 studies obtained through later retrieval efforts, but their keywords follow the same structure: 61 of them reported author keywords, 55 of these (90%, compared with 87% of the studies retrieved first) used at least one keyword of the map, and their keywords were distributed across the same clusters in similar proportions.

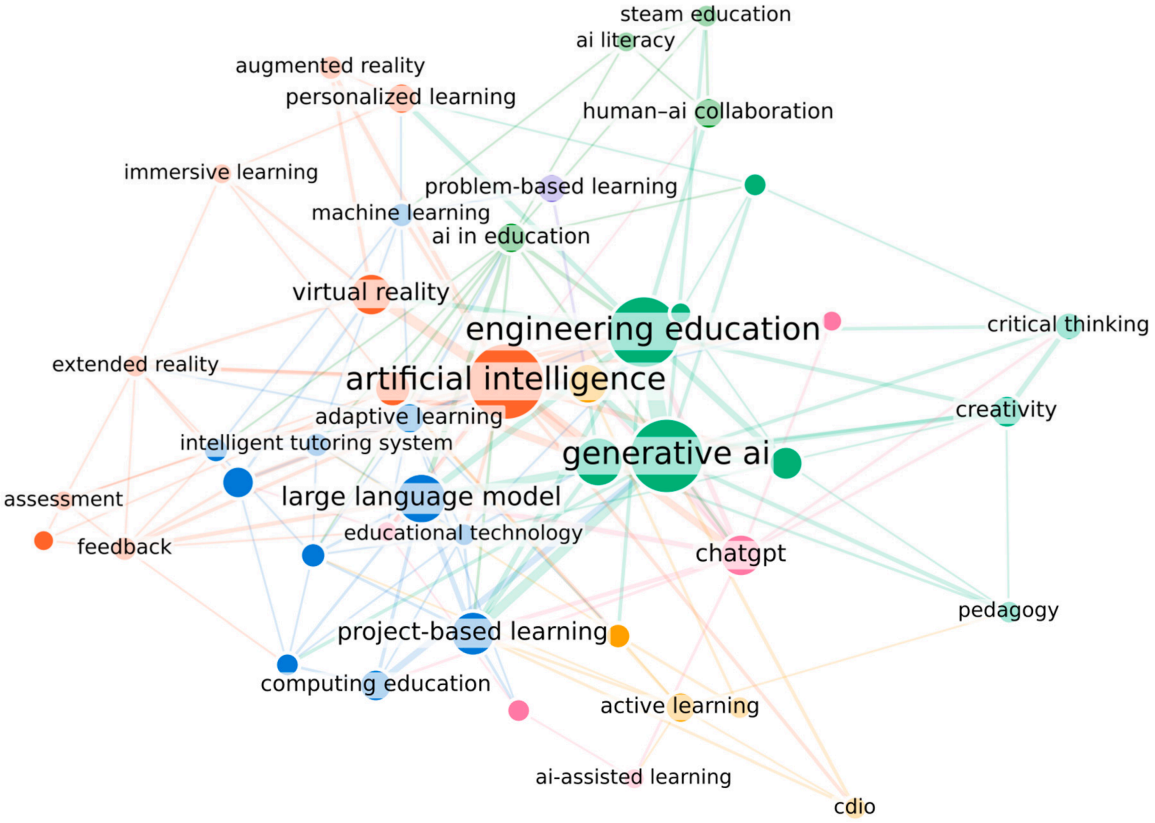

Figure 4. Author-keyword co-occurrence map of the 243 studies retrieved in the first search (keywords with at least four occurrences; the keywords of the 80 studies obtained later fall into the same clusters, Section 3.1; association-strength normalization, VOS layout and Leiden clustering). Node size reflects occurrences; colors indicate clusters; overlapping labels are omitted.

3.2. Roles and Mechanisms of AI in Experiential Pedagogies (RQ2)

In the 153 core studies, AI most often acted as a tutor or assistant (60) or as a co-creative partner (37); feedback and assessment (16), role-play or simulated partner (14), scenario or content generator (12), analytics or affective sensing (4), and agents inside VR or games (4) were less frequent. Project-, problem- and challenge-based learning was the most frequent pedagogy (112), usually combined with collaborative learning (95), followed by experiential learning in a broader sense (58), simulation (43), role-play (22), games (24), flipped or blended formats (20), design thinking (21) and immersive VR/AR/XR (16); drama, theatre and improvisation appeared in a single study [96]. AI use was structured in 92 core studies, unconstrained in 38, contrasted in 3 and unclear in 20; the most common structuring features were phase restriction, verification requirements, solution-withholding tutors and sequencing AI after students' own attempts.

The evidence map of primary studies (Figure 5) shows that the corpus is concentrated in two cells: AI tutors and co-creative partners inside team projects. Role-play partners were almost always paired with role-play and simulation, and embodied agents with VR.

AI as a feedback instrument for collaboration, communication, or emotional expression during experiential activities remained rare.

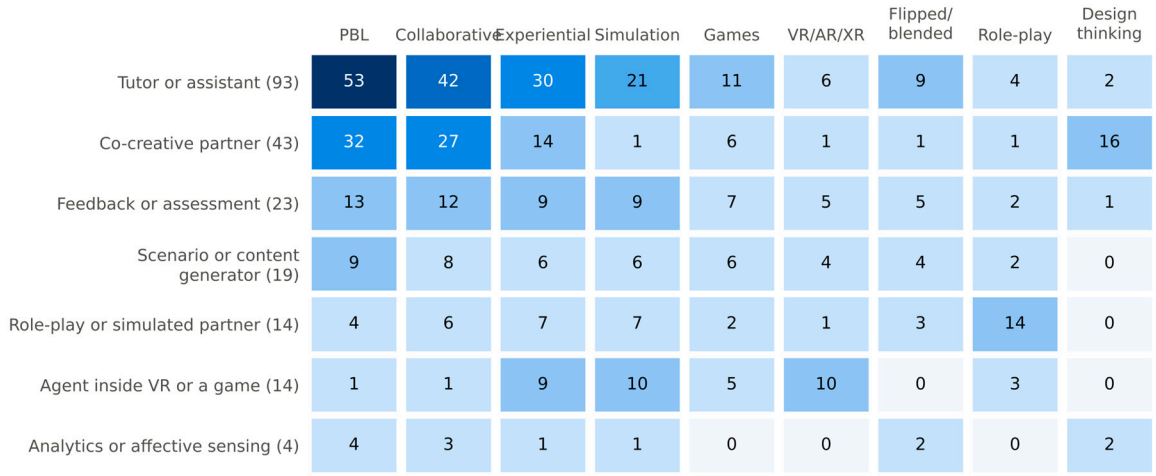

Figure 5. Evidence map of the primary AI role by pedagogy in primary empirical studies (reviews, conceptual papers and design reports excluded). Cells show the number of studies; a study can use several pedagogies; row totals in parentheses; darker cells indicate a higher number of studies.

Reading the extracted mechanisms across studies, AI entered experiential pedagogies at five points of the learning activity (Figure 6).

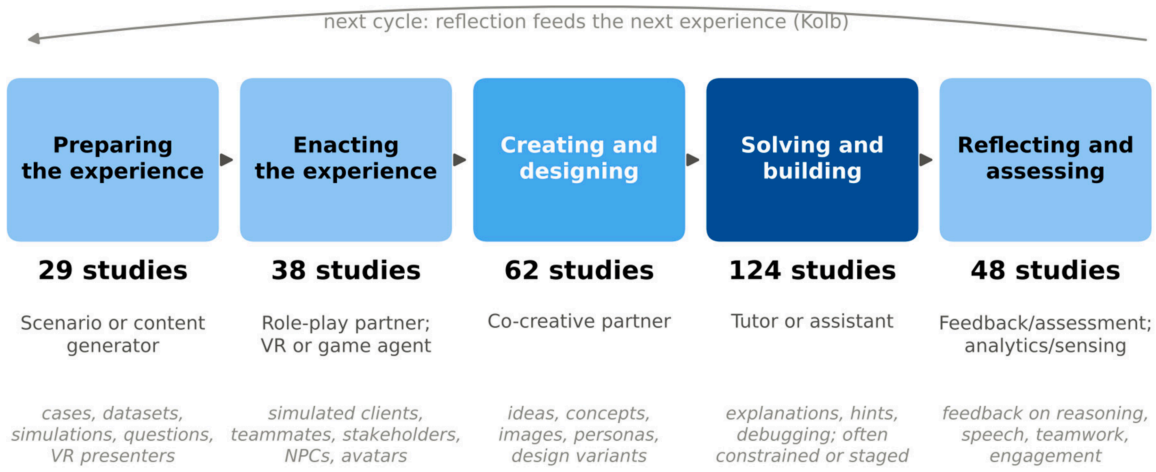

Figure 6. Where AI enters the experiential activity: a synthesis of the included studies by primary AI role. Counts are studies; studies with several or other roles are not included in the figure (their roles are listed in Table A1).

Preparing the experience. Generative AI was used to author the materials that experiential activities depend on: animated narrative videos with embedded questions for collaborative problem solving [97], personalized programming challenges in a gamified platform [98], theoretical content and simulations converted by student teams into AR learning objects [99], interactive web simulations generated by instructors through natural-language "vibe coding" [100], and VR presenters generated from lecture notes [101]. In several studies, the generation itself became the learning activity: students prompted LLMs to turn engineering-ethics cases into branching role-play games and then debugged them for bias [102], critiqued an LLM-derived process model against their own derivation and laboratory data [103], and competed to detect errors in Copilot's answers about requirements and modelling [104]. Studies from Scopus and IEEE Xplore extend this pattern: instructors

used ChatGPT to draft a full role-play case study with rubrics and teaching guide [105], generative AI built a red-team/blue-team network attack-and-defense sandbox [106], AI-generated disaster videos anchored PBL discussions in fire-protection engineering [107], and student teams prompted ChatGPT to fabricate datasets that other teams then had to detect [108].

Enacting the experience. Here AI replaced or extended the human counterpart of a role-play. LLM-based simulated clients and stakeholders let software-engineering students practice requirements interviews [109,110]; custom GPT chatbots played an industry consultant and an academic examiner in a process-safety capstone [111]; Gemini acted as a conversation partner in engineering-English role-plays [112]; AI-simulated students with confused, passive, or aggressive personas trained graduate teaching assistants [113]; and ChatGPT played a defensive teammate [114] or a teammate in four teamwork scenarios, scoring each response [115]. Multi-agent classrooms combined a Socratic AI professor with a skeptical AI peer [116], and a role-play mystery game used generative AI as game host and characters [117]. In immersive settings, embodied AI teaching assistants and voice agents guided students inside VR and mixed-reality physics, programming and fabrication environments [118–120], while non-player characters [94], an LLM game-show host and opponent [121] and LLM expert avatars [122] populated virtual offices, games and laboratories. Further examples include an LLM-powered buyer inside a VR trade fair who questioned textile-engineering students about their fabrics [123], LLM agents playing frontend, backend and QA teammates with conflicting goals whom the student had to lead [124], an AI avatar that asked students to justify their drone design in VR [125], an AI machinist in a VR workshop [126] and students interviewing AI-simulated historical scientists and patients [127].

Creating and designing. As a co-creative partner, AI generated ideas, concepts and artefacts during team projects and design thinking: in creative ideation for products and services [83,84], robotics design projects [128], entrepreneurial product development in which ChatGPT acted as a "quasi-member" of each team chat [129], a timed engineering design challenge [130], and design-thinking projects in which teams used AI to enrich empathy maps, ideas and storyboards [131,132]. Several studies show students deciding deliberately where AI belongs: design teams used AI as a tool or as a "teammate" in ideation but kept it out of empathy and user research [133]; project teams asked an LLM to impersonate expert stakeholders [134] or to act as a co-requirements analyst whose output they compared with their own [135]. The single drama-related study used ChatGPT and DALL-E in speculative co-design workshops in which groups jointly negotiated prompts and narratives [96]. Similar uses appeared in product design, where image generators produced wearable concepts that teams critiqued [136], in studio design briefs with standardized prompt templates [137], and in design-thinking projects in which teams compared AI-generated solutions with their own only after completing all phases [138].

Solving and building. The most common role was an on-demand tutor during project work: explaining concepts, suggesting approaches, and debugging code or hardware at each phase of CDIO or PBL projects [139–141]. Several designs deliberately constrained this support. A custom GPT tutor was instructed not to give direct answers [142]; a coding assistant gave graduated hints rather than solutions [143]; an inquiry tool capped the dialogue at ten turns and turned students' predictions into questions [144]; a two-by-two experiment compared individual with shared accounts and restricted with unrestricted use [145]; a programming course faded educator scaffolding step by step while students logged their prompts [146]; and a GPT-based aid was inserted only at the reflective-observation and abstract-conceptualization stages of Kolb's cycle [147]. Other courses required prompt logs and an individual oral defense [148,149] or asked students to check an AI diagnosis against

their own laboratory evidence [150]. In simulations and virtual laboratories, adaptive engines and AI tutors were coupled to the simulation state [151,152]. Further constrained designs included a PLC debugging agent that guided hierarchical troubleshooting without giving solutions [153], a RAG chatbot in a management simulation game that gave hints rather than decisions [154], AI used under explicit guidelines as cognitive scaffolding in experiential modelling [155], and an in-game Minecraft assistant with step-specific hints [156].

Reflecting and assessing. A smaller group of studies used AI to close the experiential loop. LLMs summarized peer-assessment comments into constructive reports [157], produced individual contribution summaries from Git data to support team discussion [158], helped students prepare peer feedback that they then delivered orally and empathetically [159], and scored public-speaking performances from multimodal recordings [160]. Multi-agent systems gave criterion-based feedback on capstone proposals [161], LLMs gave feedback on professional-language tasks [162], and real-time corrections in mixed-reality engineering scenarios [163]; explainable machine-learning models and an AI assistant gave personalized feedback in PBL laboratory modules [164], and interaction logs fed dashboards with a predicted creativity index [165]. Emotion-aware tutoring appeared only in conceptual form [166]. Further examples include a machine-learning classifier that rated the quality of students' empathy comments and nudged them to improve [167], speech recognition that replaced the human pseudo-pilot and checked air-traffic-control phraseology in real time [168], a rule-based checker for team DFMEA reports [169], and affective sensing of team discussions through a telepresence robot [170] or of students acting as workers in a human–cobot cell [171].

Across these stages, a recurrent design principle was to make students verify, justify, and own what the AI produced: logging and defending prompts, comparing AI output with their own work, and restricting AI to specific phases. Whether this principle matters for outcomes is examined below.

3.3. Transversal Competencies, Measures and Outcomes (RQ3)

The outcome synthesis is based on 560 outcome records from the 153 core and 14 competency-only primary studies (521 and 39 records, respectively); pedagogy-only and contextual studies contributed no or only incidental competency records and are not part of the synthesis. Critical thinking and problem solving were the most frequently targeted competencies (69 and 72 studies), followed by collaboration (75), creativity (63), communication (46) and self-regulation (40); ethics (22), adaptability (11), emotional intelligence and empathy (9) and systems thinking (6) remained the least addressed.

Most evidence was not comparative (Figure 7a). Of all records, 268 were descriptive (post-only reports, percentages agreeing or qualitative accounts without contrast), 48 within-group pre–post changes, 12 correlational, and 154 between-group contrasts; 78 records concerned competencies that were targeted but not measured. By measure, 154 records were qualitative, 112 used non-validated self-report, 172 used performance assessments, and 44 used validated self-report instruments. Descriptive and within-group records were predominantly positive (183 of 268 and 30 of 48), but they cannot separate the contribution of AI from that of the course, the pedagogy, the instructor, or time; we therefore report them as improvements reported by the authors, not as evidence that AI caused the improvement.

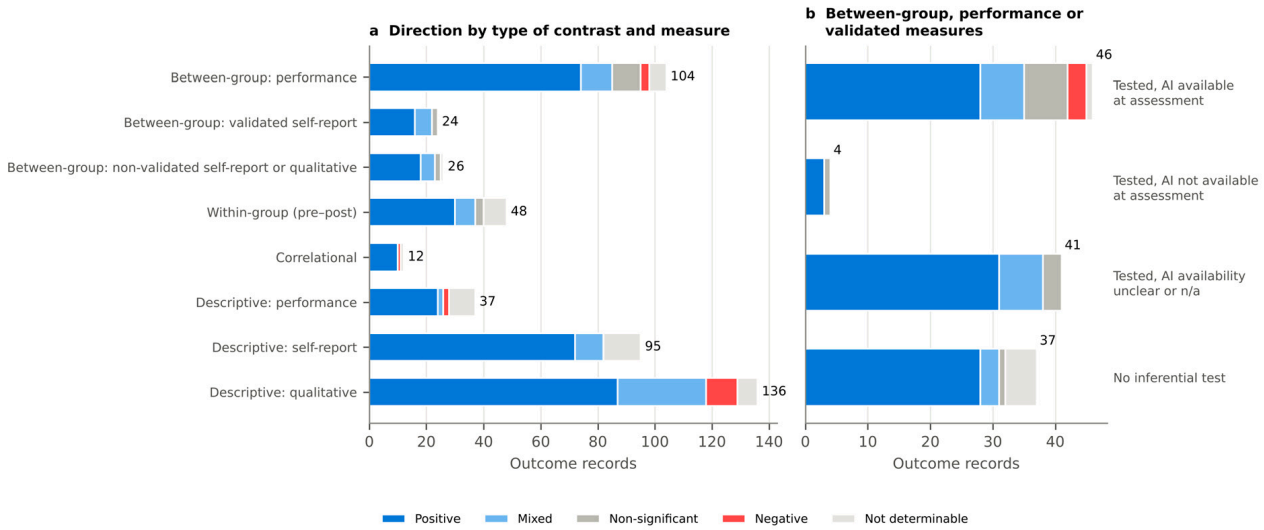

Figure 7. Direction of competency outcome records in core and competency-only primary studies: (**a**) by type of contrast and measure; (**b**) comparative records (between-group, performance or validated self-report measures) by inferential testing and by whether AI was available when the competency was assessed.

Comparative evidence came from 128 between-group records with performance or validated self-report measures in 60 studies (Table 7). Of these records, 91 were supported by an inferential test: 62 favored the AI condition, 14 were mixed, 11 were non-significant, 3 favored the comparator, and in 1 the direction could not be determined because the reported group means contradicted the authors' interpretation of the test (semantic divergence of ideas [83]); the other 37 records reported differences without a test. Most comparisons were non-randomized (intact classes or historical cohorts) and rarely adjusted for baseline differences (Section 3.4), so even significant differences show an association between the AI-supported course and the outcome rather than causal effectiveness. Effect sizes were reported for 50 of the 128 comparative records (22 studies) and confidence intervals for 40 (52 and 41 of all 154 between-group records), in heterogeneous metrics (d, g, η^2, r); they are listed in Table 7, rounded to two decimals, but were not pooled. Two further features limit what this evidence shows about learners' competencies. First, 68 of the 128 comparative records assessed a task or product that students completed while AI was available, so they measure AI-assisted performance; only 9 records, from 7 studies, assessed students without AI [111,112,123,156,172–174], and for the remainder this was unclear or not applicable. Second, only one study followed students up after six months [175] and one surveyed them at the end of the semester after a four-day activity [176]; neither had a comparison group. The evidence therefore concerns performance during or at the end of AI-supported activities, not the sustained development of competencies once AI support is removed.

Table 7. Comparative evidence: between-group outcome records with performance or validated self-report measures in core and competency-only primary studies.

Study	Design, n; Comparator	Structure; AI Role; Pedagogy	Competency Outcomes (Measure; AI at Assessment: Direction)	ES (as Reported)
Acuna et al. (2025) [149]	MM, n = 112; H	S; Tutor; PBL, GAM, DT, EXP, COL	Communication (P, AI: ±); Communication (P, AI: +); Communication (P, AI: ±); Communication (P*, AI: ?); Other (P, AI: +)	—

Table 7. *Cont.*

Study	Design, n; Comparator	Structure; AI Role; Pedagogy	Competency Outcomes (Measure; AI at Assessment: Direction)	ES (as Reported)
Appiah-Kubi (2026) † [137]	MM, n = 130; C	U; Co-creator; PBL	Creativity (P, AI: ±); Creativity (P, AI: +); Creativity (P*, AI: +)	$\eta^2 = 0.48$
Bai et al. (2026) [164]	RCT, n = 131; C	?; Feedback; PBL, EXP, SIM	Creativity (P: +); Creativity (P*, AI: ?); Self-regulation (V*: +); Self-regulation (P*, AI: +); Collaboration/teamwork (P*, AI: +); Other (P: +)	—
Balta-Salvador et al. (2026) [83]	RCT, n = 51; C	U; Co-creator; DT	Creativity (P, AI: ±); Creativity (P, AI: ?); Creativity (P, AI: ns)	r = 0.36 (novelty); r = 0.34 (text elaboration); $\eta p^2 = 0.13$ (novelty AI main effect)
Behara et al. (2026) [165]	CS, n = 450; H	S; Analytics; DT, PBL, COL, FB	Creativity (P*, AI: +); Communication (P, AI: +); Ethics/responsibility (P, AI: +); Collaboration/teamwork (P, AI: +)	—
Bharadwaj et al. (2025) † [177]	RCT, n = 64; C	S; Role-play partner; RP, EXP	Communication (P: +); Collaboration/teamwork (P: +); Adaptability (P: +); Creativity (P: +); Emotional intelligence/empathy (P: +)	$\eta^2 = 0.64$
Binkhonain et al. (2026) [110]	MM, n = 69; C	S; Role-play partner; RP, EXP, COL	Communication (P, AI: +)	—
Burgos-López and Ruiz-Cantisani (2025) † [138]	CS, n = 67; ?	S; Co-creator; DT, PBL, COL	Creativity (P, AI: −); Problem solving (P*, AI: ±)	—
Cahyono et al. (2025) † [178]	MM, n = 25; C	U; Co-creator; DT, EXP, XR	Creativity (V: +)	g = 1.46
Chen et al. (2026) † [179]	QE, n = 180; H	S; Tutor; PBL, EXP	Problem solving (P, AI: +); Ethics/responsibility (P, AI: +); Creativity (P, AI: +)	—
Dai et al. (2024) † [180]	MM, n = 593; H	U; Analytics; DT, PBL, COL	Other (V: ±); Collaboration/teamwork (V: +)	—
Das (2025) † [181]	CS, n = 24; C	S; Tutor; EXP	Communication (P*, AI: ±)	—
Dinu (2025) [182]	QE, n = 60; C	U; Tutor; PBL	Problem solving (P, AI: +)	—
Ge et al. (2026) [116]	QE, n = 87; C	S; Role-play partner; PBL, SIM, RP, FB	Problem solving (P: +); Problem solving (P: +)	g = 0.58; g = 0.77
Gee et al. (2026) [113]	QE, n = 266; C	S; Role-play partner; RP, SIM, EXP	Communication (P*, AI: +); Adaptability (P*, AI: +)	—

Table 7. *Cont.*

Study	Design, n; Comparator	Structure; AI Role; Pedagogy	Competency Outcomes (Measure; AI at Assessment: Direction)	ES (as Reported)
Guerrero-Chirinos et al. (2026) † [183]	QE, n = 71; C	S; Feedback; PBL, COL	Problem solving (P: +)	—
Guo et al. (2025) [128]	RCT, n = 113; C	S; Co-creator; PBL, COL	Creativity (P: +)	—
Han et al. (2025) † [173]	QE, n = 86 (30 experimental + 56 control); H	S; Scenario generator; PBL, SIM	Problem solving (P*, noAI: +)	—
Han et al. (2026) † [184]	MM, n = 376; C	S; Tutor; PBL, COL	Collaboration/teamwork (V, AI: +); Self-regulation (V, AI: +); Problem solving (P, AI: +)	d = 0.71; d = 0.84; d = 0.52; d = 0.67; d = 0.78; d = 0.93
Hare et al. (2023) † [174]	QE, n = 55 (13 + 20 + 14 + 8 across 4 comparison groups); A	U; Tutor; GAM, SIM	Problem solving (P, noAI: ns); Problem solving (P, noAI: +); Problem solving (P*, noAI: ?)	—
Honig et al. (2024) [111]	MM, n = 41; H	S; Role-play partner; RP, SIM, EXP, COL	Critical thinking (P*, noAI: +)	—
Jantassova et al. (2026) [162]	QE, n = 122; C	S; Feedback; PBL, RP, DT, GAM, FB, COL	Communication (P: +)	—
Ji et al. (2025) [129]	QE, n = 36; C	S; Co-creator; PBL, COL	Creativity (P, AI: ±); Critical thinking (V: ±)	—
Kavitha et al. (2026) † [172]	QE, n = 130; C	S; Scenario generator; GAM, COL	Problem solving (P, noAI: +)	—
Keith et al. (2025) [103]	MM, n = 130; H	S; Scenario generator; EXP, PBL, COL	Problem solving (P, AI: ns); Problem solving (P: ns)	—
La Scala et al. (2025) † [185]	QE, n = 72; C	S; Co-creator; DT, COL	Creativity (P, AI: +)	d = 0.94
Lei et al. (2025) [140]	QE, n = 76; C	U; Tutor; PBL, COL	Creativity (V: ±); Other (V: +); Collaboration/teamwork (V: ns); Critical thinking (V: +); Problem solving (V: ±)	—
Li et al. (2025) [144]	RCT, n = 62; A	B; Tutor; COL	Creativity (V: +); Problem solving (V: +); Critical thinking (V: +)	$\eta p^2 = 0.45$; $\eta p^2 = 0.50$; $\eta p^2 = 0.52$
Li et al. (2026) † [186]	QE, n = 71; C	U; Tutor; PBL, DT, EXP	Creativity (P, AI: +); Systems thinking (P, AI: +); Other (P, AI: +); Problem solving (P, AI: ns); Other (V: +); Other (V: +)	$\eta^2 = 0.11$; $\eta^2 = 0.09$; $\eta^2 = 0.02$; $\eta^2 = 0.08$; $\eta^2 = 0.10$
Lin et al. (2025) [147]	RCT, n = 74; C	S; Tutor; EXP, COL, PBL	Self-regulation (V: +); Collaboration/teamwork (P, AI: ±)	d = 1.20
Liu (2025) † [187]	QE, n = 180; C	S; Tutor; PBL, SIM, COL	Creativity (P, AI: +)	d = 1.19

Table 7. *Cont.*

Study	Design, n; Comparator	Structure; AI Role; Pedagogy	Competency Outcomes (Measure; AI at Assessment: Direction)	ES (as Reported)
Liu (2026) † [188]	QE, n = 120 (62 experimental; 58 control); C	S; Feedback; PBL, EXP, FB	Critical thinking (P, AI: +); Communication (P, AI: +)	d = 0.89; η^2 = 0.17; d = 2.07; d = 1.54; η^2 = 0.37
Lojo et al. (2025) [109]	RCT, n = 120; C	S; Role-play partner; RP, SIM	Communication (P*, AI: ?)	—
Lytovchenko et al. (2025) † [189]	QE, n = 27; C	U; Tutor; PBL, COL	Creativity (P, AI: −); Communication (P, AI: −)	—
Maalek (2024) [190]	CS, n = n.r.; H	S; Tutor; PBL	Problem solving (P*, AI: +)	—
Mallika et al. (2026) † [191]	CS, n = 65; C	U; Other; PBL, DT, SIM, COL	Problem solving (P*, AI: +); Critical thinking (P*, AI: +); Collaboration/teamwork (P*, AI: +)	—
Manipatruni et al. (2026) [112]	QE, n = 36; C	S; Role-play partner; RP, FB	Communication (P*, noAI: +)	—
Mariño et al. (2025) [192]	MM, n = 180; C	?; Co-creator; PBL, EXP, COL	Communication (P*: +); Communication (P*: +); Critical thinking (P*: ?)	—
Meng et al. (2026) † [193]	RCT, n = 120; C	U; Tutor; PBL, SIM, COL, FB	Problem solving (P*: +); Other (P*, AI: +)	—
Mitrovic et al. (2025) † [167]	QE, n = 103; H	S; Feedback; EXP, PBL	Emotional intelligence/empathy (V: +); Self-regulation (P, AI: ns)	—
Mosquera-Navarro et al. (2026) † [194]	QE, n = 144; C	S; Tutor; PBL, COL	Problem solving (P, AI: +)	—
Nieto-Jalil et al. (2026) † [155]	QE, n = 84; C	S; Tutor; EXP	Problem solving (P*: +); Communication (P*: +); Critical thinking (P*: +)	—
Núñez et al. (2024) [195]	QE, n = 44; C	?; Other; PBL, DT, COL	Problem solving (P*: +)	—
Omeh et al. (2025) [141]	QE, n = 87; C	S; Tutor; PBL, COL	Other (V: +); Other (V: +); Other (P: +)	η^2 = 0.69; η^2 = 0.69; η^2 = 0.52
Pasalkar et al. (2025) [143]	QE, n = 50; C	S; Tutor; GAM	Problem solving (P*, AI: +)	—
Pi et al. (2026) [196]	RCT, n = 92; C	B; Scenario generator; —	Creativity (P: ±); Creativity (P: ±); Creativity (P: ns)	ηp^2 = 0.02 (main effect); ηp^2 = 0.08 (interaction)
Qi et al. (2026) † [197]	QE, n = 90; C	S; Co-creator; PBL, COL	Problem solving (P, AI: ns); Critical thinking (P, AI: +); Systems thinking (P, AI: +); Communication (P, AI: +)	d = 0.40; d = 1.12; d = 1.06; d = 1.02

Table 7. *Cont.*

Study	Design, n; Comparator	Structure; AI Role; Pedagogy	Competency Outcomes (Measure; AI at Assessment: Direction)	ES (as Reported)
Sadik (2025) † [198]	CS, n = 35; H	S; Tutor; PBL, GAM, COL	Problem solving (P*, AI: +)	—
Sheela et al. (2025) [199]	MM, n = 107; H	?; Tutor; XR, SIM, PBL, EXP	Collaboration/teamwork (P: +); Other (P: +)	—
Sinnari (2026) [200]	QE, n = 29; H	U; Co-creator; PBL, COL	Creativity (V, AI: ns); Other (V, AI: ±)	r = 0.30; r = 0.33; r = 0.34
Sun et al. (2026) † [201]	QE, n = 90; H	S; Tutor; PBL, RP, SIM, COL, FB	Problem solving (P, AI: +)	d = 1.35
Syahri et al. (2025) † [202]	QE, n = n.r.; C	S; Tutor; PBL, COL	Critical thinking (P: +)	—
van Dijk and Zaytsev (2026) † [203]	MM, n = 38; C	U; Tutor; PBL	Problem solving (P*, AI: ns)	—
Wang et al. (2026) † [156]	RCT, n = 40; C	U; VR/game agent; GAM, EXP, PBL	Problem solving (P*, AI: ±); Problem solving (P*, noAI: +)	—
Yang (2025) † [204]	RCT, n = 60 (30 experimental, 30 control); C	S; VR/game agent; XR, SIM	Problem solving (P: +)	—
Yang and Gai (2026) † [123]	RCT, n = 60; C	S; VR/game agent; XR, SIM, RP, EXP	Communication (P, noAI: +)	—
Yi et al. (2025) [145]	MM, n = 120; A	B; Tutor; PBL, COL	Collaboration/teamwork (V: ±); Other (P, AI: +); Problem solving (P, AI: +); Problem solving (P, AI: ns)	η^2 = 0.11; d = 0.91; d = 0.85; d = 0.55; d = 0.48; η^2 = 0.35; η^2 = 0.09
Zhang et al. (2026) † [205]	RCT, n = 120; C	U; Tutor; PBL, COL, EXP, SIM	Collaboration/teamwork (P*, AI: +); Adaptability (P*, AI: +)	—
Zhu (2026) † [206]	QE, n = n.r.; C	S; Tutor; SIM, EXP, PBL, FB	Problem solving (P*: +)	—
Zhu and Xu (2026) † [207]	QE, n = 88; C	?; Other; PBL	Creativity (P: +)	—

P performance assessment; V validated self-report. + favors AI condition (significant, or reported improvement where no test); ± mixed; ns non-significant; − favors comparator; ? not determinable. * no inferential test reported. AI: assessed while AI was available; noAI: assessed without AI. Structure: S structured, U unconstrained, B both conditions compared, ? unclear. Comparator: C concurrent no-AI control, H historical cohort, A alternative AI condition. ES: effect sizes as reported by the authors (not recomputed), rounded to two decimals; confidence intervals are given in Table S2 (Screening and extraction data; sheet S2i). † Study identified in Scopus or IEEE Xplore or obtained through later retrieval efforts.

Within the comparative subset, results differed by competency (Table 8). For communication, most comparisons in which AI served as a rehearsal partner or feedback source favored the AI condition, including a VR trade-fair buyer assessed in an oral test without AI [123] and AI role-play partners for engineering English and requirements interviews [110,112,162], but one team-level comparison favored the comparator [189]. For problem solving and critical thinking, comparisons mostly favored AI-supported

PBL [116,182,183,194,201,202], but nearly all assessed products produced with AI, several used historical cohorts, and four records were non-significant [103,145,186]. Creativity was the most contested outcome: positive comparisons [128,137,186,187] were balanced by mixed, non-significant, or negative ones [83,138,189,196,200]. Evidence for collaboration, self-regulation, ethics, empathy, adaptability, and systems thinking came from one to five studies each.

Table 8. Summary of main findings and certainty of evidence (GRADE for narrative synthesis).

Finding	Evidence Base	Direction	Main Concerns	Certainty
Communication improves when AI acts as rehearsal partner or feedback source	39 studies measured it (3 randomized); tested records: 2 mixed, 13 positive, 1 negative	Mostly favors AI; one comparison favors the comparator	RoB serious; IND (mostly assessed with AI available); IMP	Low
Problem solving in AI-supported project work	63 studies measured it (6 randomized); tested records: 1 mixed, 19 positive, 7 non-significant, 1 negative	Mostly favors AI for AI-assisted task performance; a substantial minority non-significant	RoB serious (historical or intact groups); IND serious (assessed with AI); PB suspected	Low (AI-assisted performance); very low (unaided competency)
Critical thinking	57 studies measured it (2 randomized); tested records: 7 positive, 3 mixed	Mostly favors AI	RoB serious; IMP serious (few comparative studies); IND	Very low
Creativity	53 studies measured it (9 randomized); tested records: 9 mixed, 14 positive, 5 non-significant, 1 not determinable, 2 negative	Inconsistent: gains, mixed, null and negative results	INC serious; RoB; IND	Very low
Collaboration and teamwork	57 studies measured it (4 randomized); tested records: 10 positive, 2 mixed, 1 non-significant	Mostly favors AI; some mixed and non-significant results	RoB serious; INC; IMP; IND	Very low
Self-regulation, ethics, empathy, adaptability, systems thinking	One to three tested comparative studies per competency	Mostly favors AI	IMP very serious; RoB	Very low
Structured AI use yields more benefit than unconstrained use	4 studies varying structure within one design; cross-study comparison of 26 structured and 10 unconstrained studies with tested comparisons	Pattern favors structured use, with counterexamples	Indirect (cross-study, confounded); heterogeneous constraints; IMP; classification depends on reporting	Very low (hypothesis)
Competencies persist once AI support is removed	7 comparative studies assessed without AI; follow-up in 2 studies, none with a comparison group	Too little evidence to judge	IMP very serious; IND	Very low/ insufficient

Table 8. *Cont.*

Finding	Evidence Base	Direction	Main Concerns	Certainty
Development of sustainability competences (GreenComp, key competencies)	No study targeted or measured them; implicit sustainability learning was not assessed	—	—	No evidence

Certainty: high, moderate, low or very low (GRADE). Evidence from non-randomized designs started at low certainty. RoB risk of bias (MMAT); IND indirectness (e.g., assessed with AI available, immediate outcomes only); INC inconsistency; IMP imprecision (few or small studies); PB suspected publication bias.

Outside the comparative subset, qualitative findings described both benefits and costs. Students reported reduced direct communication between teammates when they consulted generative AI before each other [208], collaborative interaction was less comprehensive in an AI-supported condition [147], and students feared that constant AI availability would reduce independent troubleshooting and peer explanation [209]. Beyond transversal competencies, comparative studies frequently reported higher engagement, motivation, and knowledge [94,116,141,144,201,210].

3.4. Methodological Quality (RQ4)

Of the 214 appraised studies, 59 (27.6%) met none of the five category-specific criteria, 50 met one, 42 met two, 42 met three, and 21 met four or five (median 1; Figure 8a). Across all category-specific ratings, 351 were "yes", 612 "can't tell", and 107 "no": most criteria could not be judged because the information was not reported, whereas demonstrated weaknesses were concentrated in a few criteria. A total of 100 studies had at least one demonstrated weakness, and 107 had reporting gaps only.

Demonstrated weaknesses concerned mainly confounding in non-randomized studies (criterion 3.4 rated "no" in 36 of 56, mostly intact or historical groups without adjustment), the quality of mixed-methods components (5.5 "no" in 36 of 62) and non-response in surveys (4.4 "no" in 8 of 53). Reporting gaps dominated elsewhere: the representativeness of participants and the appropriateness of measures could not be judged in most non-randomized studies (52 and 41 of 56), and among the 19 randomized studies the randomization procedure was adequately described in 4 and blinding of assessors reported in 2. In the 62 mixed-methods studies, the separately appraised quantitative components were weaker than the qualitative ones (116 of 310 quantitative ratings "yes" vs. 198 of 310 qualitative ratings).

The appraisal changed how the outcome evidence should be read (Figure 8b). Among comparative records from studies meeting 0–1 MMAT criteria, 46 of 54 (85%) favored the AI condition, and among those from studies meeting two criteria, 20 of 26 (77%); among records from the 17 studies meeting three or more criteria, 24 of 48 (50%) did, while 10 were mixed, 9 non-significant and 2 negative. The more completely a study reported its methods, the less favorable its findings were; we therefore gave most weight to these studies and rated down the certainty of all findings for risk of bias (Table 8).

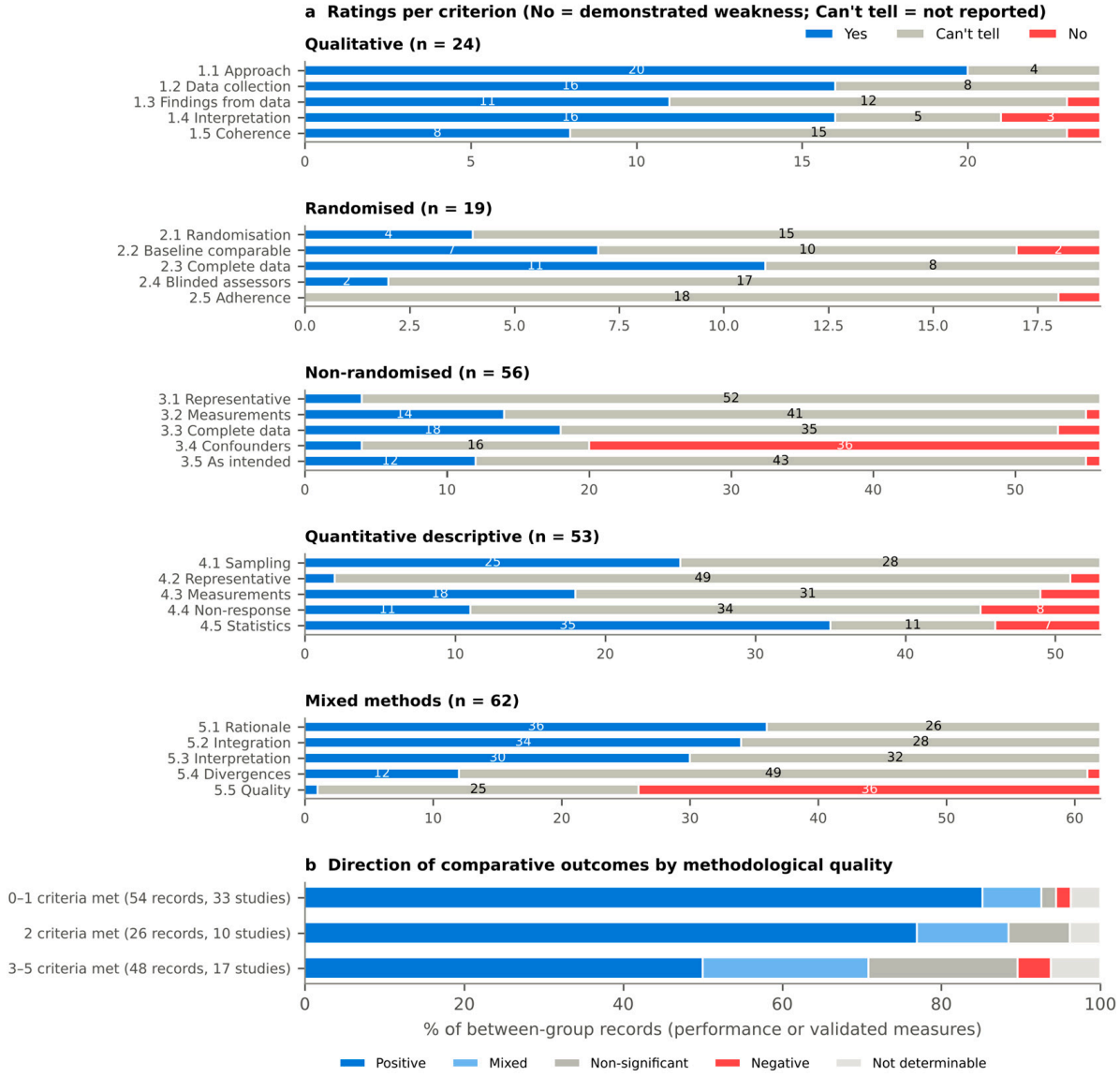

Figure 8. Methodological quality (MMAT 2018): (**a**) ratings per criterion in each study category; "no" indicates a demonstrated weakness and "can't tell" missing information; (**b**) direction of comparative outcome records (between-group, performance or validated measures) by the number of MMAT criteria met by the study.

3.5. Risks, Links to Sustainable Development and Gaps (RQ5)

The included studies reported a consistent set of risks (Figure 9): inaccurate or hallucinated output (142 studies) and over-reliance on AI (145) were the most frequent concerns, followed by bias and ethical issues (112), academic integrity (98), cost and infrastructure (75), equity and access (75), technical problems (78), teacher readiness and workload (73), privacy and data protection (77) and reduced human interaction (39).

Only 50 studies (15.5%) linked their work explicitly to sustainability, the SDGs, or ESD, and these links were mostly thin. In most of them, sustainability was the content or context of the student projects, for example solar-powered or recycled-material designs, water–energy–food laboratories, biobased materials, waste-management simulations, zero-waste fashion, a green-transition game project or SDG-themed games [131,142,192,198,211–217]. In others, the AI-augmented approach itself was framed as a contribution to SDG 4 or to "sustainable" teaching quality in terms of scalability, efficiency, or inclusion [99,116,126,164,218–220], and several reviews mapped technologies to SDG targets [66,221–224]. Sustainability-

related learning outcomes were assessed in only three studies: as part of course learning outcomes or a design-thinking sub-competency [131,149] and, most substantively, in an environmental-engineering laboratory in which students using an AI assistant made ecology-first design decisions more often than the comparison cohort [179]. We found no study that assessed sustainability competencies with an established framework such as GreenComp or the key competencies in sustainability [4–6].

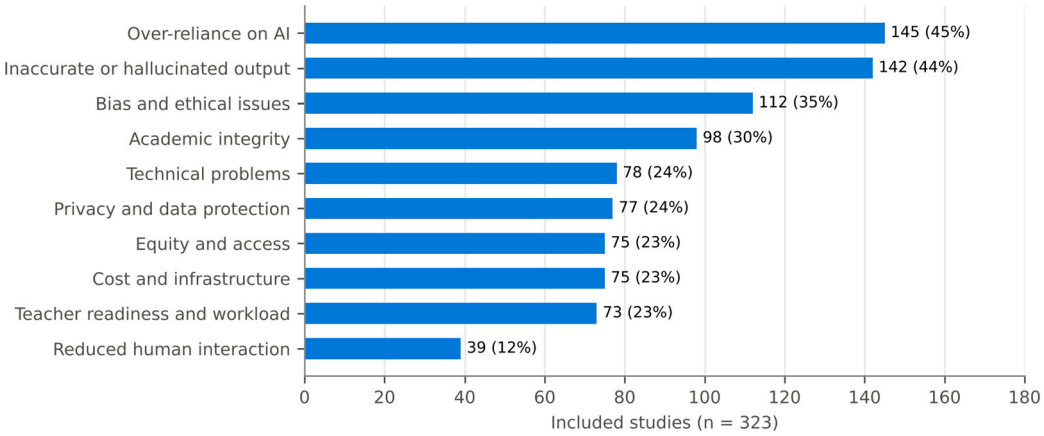

Figure 9. Risks and challenges reported in the included studies (n = 323; a study can report several).

We distinguish three levels when relating the included research to sustainability competencies (Figure 10). At the level of conceptual overlap, the transversal competencies studied most often have core counterparts in GreenComp's critical thinking, problem framing, exploratory thinking, and collective action, and in the interpersonal and integrated problem-solving competencies. At the level of targeting and measurement, however, no included study targeted or measured a sustainability competence as defined by GreenComp or the key competencies in sustainability; studies targeted transversal competencies, and systems thinking was targeted in 6 studies and measured in 4. At the level of demonstrated development, comparative tested gains existed for only a few transversal competencies (Figure 10, row labels), all measured while AI was available and none followed up. Within the retrieved corpus, therefore, the evidence that AI-augmented experiential pedagogies develop sustainability competences is indirect at best: it rests on conceptual overlap with transversal competencies, not on sustainability-competence outcomes.

Taken together, the evidence map, the outcome synthesis, the quality appraisal and the crosswalk reveal six gaps in the retrieved literature. (i) Drama, theatre and improvisation are virtually absent (one study). (ii) Empathy, emotional intelligence, adaptability and ethical responsibility are less studied than communication, creativity or problem solving, and no study targets sustainability competences such as futures, strategic or systems thinking with an established framework. (iii) AI is rarely used to observe, assess, or give feedback on the experiential process itself. (iv) Comparative designs are a minority, mostly non-randomized and rarely adjusted for confounders. (v) Competencies are almost always assessed while AI is available and immediately after the course, so the sustained development of learners' own competencies is untested. (vi) Links to sustainable development are mostly rhetorical, and evidence from design-oriented STEAM programs and from Africa remains limited.

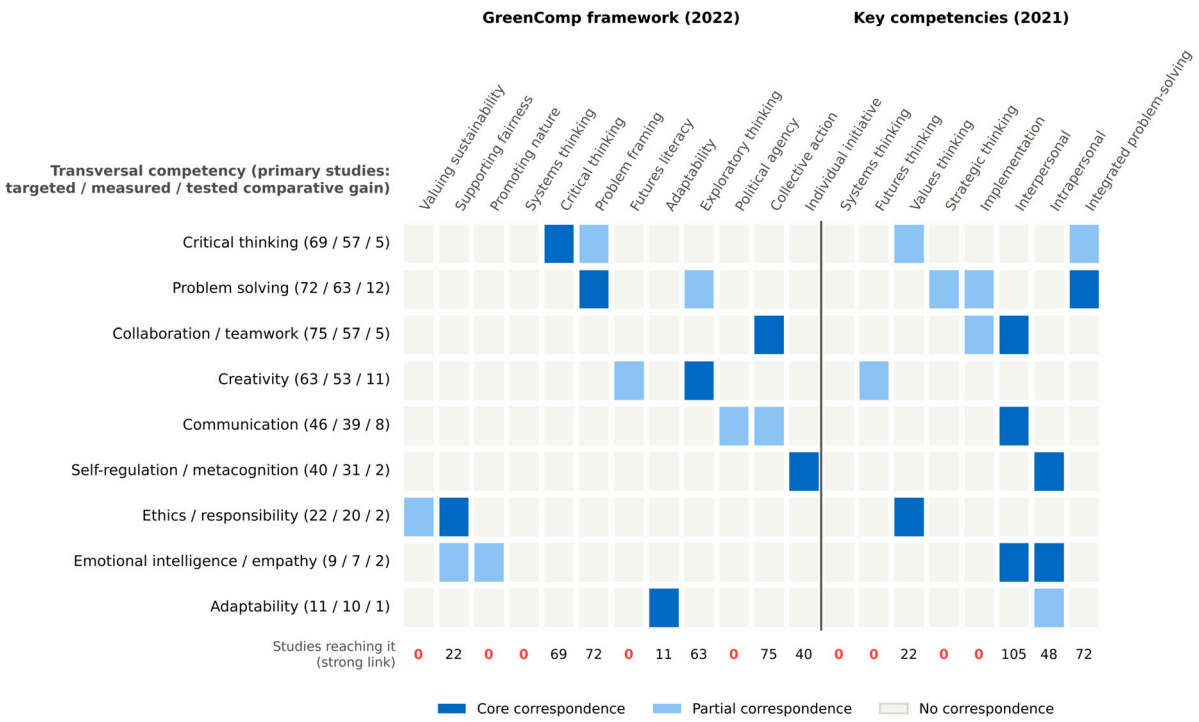

Figure 10. Crosswalk between the transversal competencies coded in this review and two sustainability-competence frameworks. Row labels give the number of core and competency-only primary studies that targeted/measured/showed a tested comparative gain (between-group, performance or validated measure) for each competency; the bottom row gives the number of studies that target a competency with a core conceptual correspondence. Correspondences are conceptual (Table 1); no study targeted or measured the sustainability competences themselves.

3.6. Consistency Across Databases and Retrieval Stages, and Non-Retrieved Reports

The main descriptive findings were similar across databases and retrieval efforts (Figure 11a): in every subset, AI was used mainly as a tutor or co-creator within PBL, role-play partners and drama were rare, and explicit sustainability links were found in a minority of studies. The 80 studies obtained through the later retrieval efforts differed from the 243 retrieved first, but not in a consistent direction. The 25 studies found by the repeated individual searches were more often contextual (12 of 25) and less often core (9 of 25) than those retrieved first (48.6% core); 25 of their 27 measured outcome records were qualitative or non-validated self-reports, and 5 of their 13 appraised studies met no MMAT criterion (38.5% vs. 30.3%). The 55 studies obtained through the library, in contrast, resembled the earlier corpus in scope (26 core, 47.3%), met more MMAT criteria (median 2 vs. 1; 4 of 36 met none) and contributed 22 comparative records from 10 studies, 19 of which favored the AI condition. Adding these 80 studies to the 243 retrieved first (an increase of 33%) did not change the direction or certainty of any finding in Table 8, and the quality gradient in Section 3.4 was present in both sets. This shows consistency within the retrieved literature only; it does not show that the findings would hold for the reports that could not be retrieved or for the records removed by the field filter.

The 211 reports that remained non-retrieved after all retrieval efforts were compared with the included studies at title, abstract, and keyword level (Figure 11b). They mention similar pedagogies and competencies (differences of at most 6.1 percentage points), are far more often conference papers (81% vs. 54%), mention generative AI less often (47% vs. 60%), and mention a comparison group somewhat less often (8% vs. 12%). This comparison describes what the missing literature is about; similar abstracts do not imply similar findings or similar methodological quality. The later retrieval efforts show that

reports which were harder to obtain can differ from earlier ones in either direction: one set was weaker in design and reporting, the other was not. We therefore cannot predict whether the non-retrieved reports would strengthen or weaken the findings, or whether the quality profile in Section 3.4 over- or underestimates that of all eligible reports. The conclusions of this review apply to the retrieved literature, and the certainty ratings in Table 8 were not raised based on these comparisons.

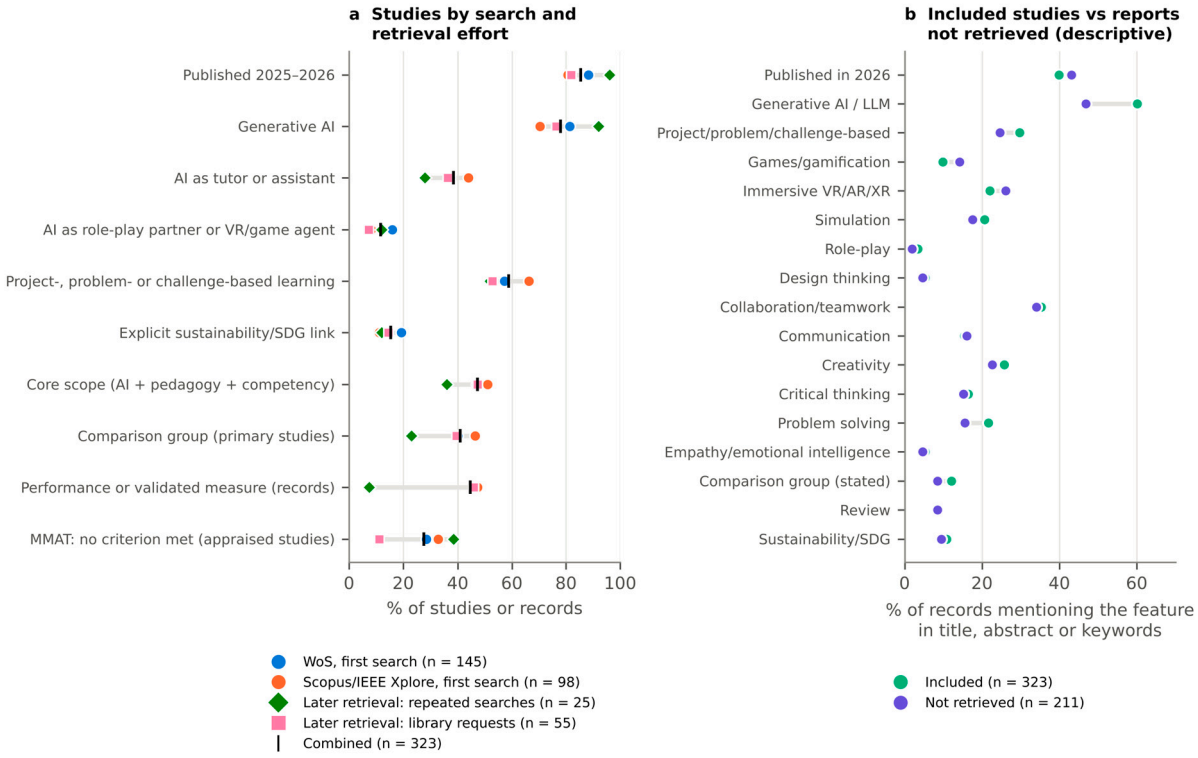

Figure 11. Consistency across databases and retrieval stages, and non-retrieved reports: (**a**) key indicators in the studies from the WoS search and from the Scopus and IEEE Xplore search retrieved in the first search, in the studies obtained through later retrieval efforts (repeated individual searches; library requests), and in all 323 studies; (**b**) features of the 323 included studies and of the 211 reports that could not be retrieved, coded from titles, abstracts and keywords with the same dictionaries (descriptive only; conference papers 54% vs. 81%, reported in Table S4 (Non-retrieved reports and field-filter assessment), sheet S4a2).

4. Discussion

4.1. Principal Findings

This review mapped 323 studies on AI in experiential pedagogies for transversal competencies in engineering and STEM higher education, of which 153 primary studies combined all three elements. Four findings stand out. First, the field is new and dominated by generative AI. Second, AI is mostly inserted where it is easiest to insert, as a tutor or co-creator inside team projects, rather than where experiential pedagogies are most resource-hungry: in playing the counterpart of a role-play, in generating rich scenarios, and in giving feedback on the interpersonal process. Third, the evidence on competency outcomes is thin and of low to very low certainty: only 60 studies compared groups on performance or validated measures, most assessed students while AI was available, almost none followed them up, the share of favorable comparisons fell as methodological quality rose, and most designs could not support causal conclusions. Fourth, the research is largely disconnected from sustainable development: links are mostly rhetorical, and no study targeted or measured sustainability competences.

These findings extend earlier reviews. Reviews of AI in STEM education described a field organized around tutoring, prediction and assessment [36,39], and reviews of generative AI in higher education focused on opportunities, integrity and general learning outcomes [41–43]. The reviews included in our corpus are consistent with these findings while covering narrower slices of the field. They report mostly positive but methodologically limited evidence, often without formal quality appraisal, for chatbots and generative AI in engineering education [56] and in active STEM learning [67]; find generative AI generally supportive of divergent thinking but weak for originality and complex design thinking [64]; observe that guided or customized generative AI outperformed unguided general-purpose use [67]; and flag that critical thinking and transfer were not assessed in AI–XR studies [58] and that soft skills in serious games lack standardized metrics [62]. A recent cross-disciplinary review linked generative AI to transversal competencies [54], but not to the pedagogies through which these competencies are developed. By focusing on that intersection in engineering and STEM, this review shows that the experiential setting changes both the opportunities and the risks of AI.

4.2. Structure Matters: A Review-Generated Hypothesis

We examined whether the way AI use was organized relates to comparative outcomes, using the operational definitions in Table 5: AI use was structured when the design imposed at least one explicit constraint on how, when, or for what students used AI (phase restriction, solution-withholding, verification requirements, sequencing after students' own attempts, usage limits, or instructor-curated output), and unconstrained when students had open access during the task, or AI produced the core generative or problem-solving output. All comparative records are tabulated by structure in Table 7. Of the tested comparative records (between-group, performance or validated measures), those from structured designs favored the AI condition in 40 of 50 (80%; 26 studies) and those from unconstrained designs in 12 of 26 (46%; 10 studies). Unconstrained designs more often produced mixed, non-significant, or negative results, notably for creativity and communication [83,140,189,200]. The pattern has clear counterexamples: structured designs also produced non-significant or negative results [103,138,167,197], and some unconstrained designs reported gains [137,178,182,193,205]. The comparison is also confounded, because structured and unconstrained studies differ in discipline, task, sample, comparator, and quality, and the classification depends on how completely the AI use was reported. The structured category is also heterogeneous. Because a design was classified as structured if it imposed at least one constraint, the category groups light constraints, such as asking students to log their prompts, with designs that combine several constraints, such as phase-specific tutors that withhold solutions and pose Socratic questions. Among the 26 structured studies with tested comparisons, the most frequent constraints were phase restriction (11 studies), verification or justification requirements (9) and instructor-curated output (9), followed by solution-withholding (5), sequencing after students' own attempts (5) and usage limits (2); 13 studies used one constraint and 13 combined two or more. The share of records favoring AI did not increase with the number of constraints (17 of 21 records, 81%, with one constraint; 23 of 29, 79%, with two or more), so the data do not support a dose–response reading, and the numbers are too small to compare types of constraint. The remaining 15 of the 91 tested records came from studies that compared both conditions (10) or did not report how AI use was organized (5). Only 4 studies varied the organization of AI use within one design: in a 2 × 2 quasi-experiment, individual access produced better collaboration and project outcomes than shared access, whereas restricted and unrestricted use did not differ significantly on project scores [145]; in a randomized study, an inquiry tool that capped and staged the dialogue outperformed unrestricted ChatGPT on higher-

order thinking [144]; in a laboratory experiment, editing AI-generated notes gave mixed creativity results compared with using them unchanged or taking one's own notes [196]; and in a reflection activity, dynamically generated AI questions were compared with fixed questions [225]. We therefore present the contrast as an exploratory, hypothesis-generating comparison of very low certainty, which future studies should test by varying structure within the same course rather than by comparing AI with no AI, specifying which constraint is varied (e.g., phase restriction, solution-withholding or verification) and how intensively it is applied. It is consistent with an included review reporting that guided generative AI outperformed unguided use [67], and with evidence outside engineering that unrestricted generative AI can reduce cognitive effort and self-regulation [51–53].

For experiential pedagogies, this suggests a working principle that future studies should test rather than assume: AI should add friction and feedback to the experience, not remove the experience; because nearly all outcomes were assessed with AI available, it should also be tested whether such designs leave students more capable when AI is withdrawn. In role-play, an AI counterpart may be valuable because it reacts, resists, and gives feedback, as with simulated clients, consultants, teammates, buyers and students [109–111,113,114,123,124]. In design and project work, AI appears most useful when students must evaluate, justify, and adapt its output, as in studies that required prompt logs, oral defenses, or comparison with students' own work [103,135,138,148–150]. The fact that design students in one study chose not to use AI for empathy and user research [133] illustrates that learners themselves can recognize which parts of the experience must remain human.

4.3. The Missing Half: Interpersonal Competencies and Drama Pedagogy

The competencies that experiential pedagogies are best known for developing, namely communication, empathy, emotional intelligence, conflict management and adaptability [26–30], are the least represented in AI-augmented research. Empathy and emotional intelligence were addressed in 8 primary studies and measured with a validated instrument in one, and drama, theatre, and improvisation appeared in a single study. At the same time, outside engineering education, AI conversational partners for speaking practice, AI-based role-play for soft skills and multimodal feedback on presentations are well developed [47–50], and the few engineering studies that used AI as a role-play partner reported mostly positive communication outcomes [109,110,112,113,123].

Drama pedagogy offers concrete structures into which AI could be inserted without displacing what makes drama educative. In process drama, the teacher works "in role" to build an unfolding fictional situation with the group [226]; in Heathcote's mantle of the expert, students take on the responsibility of a fictional expert team commissioned by a client [25]; and in Boal's forum theatre, spectators step into a scene to try alternative ways of resolving an oppression or conflict [24]. Each of these structures has an obvious place for an AI counterpart: an LLM can act as a teacher-in-role or as the client who commissions an engineering team, or it can play the antagonist in a forum scene about a contested infrastructure project, such as a community objecting to a dam or a waste-treatment plant, and vary its arguments across repetitions. What AI cannot provide is the embodied, co-present encounter with other people: voice, gesture, timing, risk-taking in front of peers, and the facilitated debrief in which meaning is negotiated. A realistic division of labor is therefore that AI supplies scenario variety, a responsive counterpart for rehearsal and feedback between sessions, while the human group and facilitator keep the embodied enactment and the reflection. Such designs would also address the interpersonal, normative and strategic dimensions of sustainability competencies, which require learners to understand and negotiate conflicting perspectives [4,5].

The near absence of drama should nevertheless be interpreted with caution. Studies of drama with engineering students often describe their context as a course or a program rather than in the topic terms of our context block (e.g., "engineering education"), and some may therefore have been missed by the search. The gap is real in the sense that no included study combined AI with drama pedagogy for engineers, but its size may be overstated.

4.4. Implications for Education for Sustainable Development

Transversal competencies and sustainability competencies overlap, but only partly (Table 1), and the review shows that the overlap is currently conceptual rather than empirical. Sustainability appears mostly as project content or as rhetorical framing of the innovation; only three studies assessed sustainability-related learning outcomes, and none targeted or measured sustainability competences with an established framework. The absence of explicit references to GreenComp or to the key competencies in sustainability should not, however, be read as evidence that sustainability learning was absent. Engineering projects often require students to reflect on socio-technical systems, trade-offs, and affected stakeholders even when the authors describe the activity as open-ended problem solving in a specific context, and our coding captured only explicit links and framework-based assessment. The gap is therefore one of design and measurement: such learning may occur, but it is rarely an explicit objective and is not assessed in a way that would allow it to be identified. For sustainable-development education, four implications follow.

First, AI-augmented experiential activities should be designed around sustainability problems and explicitly aligned with sustainability competencies. Generative AI is well suited to the competencies that the field currently ignores: it can generate alternative future scenarios for futures literacy, model the downstream consequences of a design for systems thinking, and voice the conflicting positions of affected stakeholders for strategic and normative competence, for example, in a design challenge on energy, water, or circular production. Second, outcomes should be assessed with instruments derived from sustainability frameworks, such as GreenComp-based rubrics, alongside generic transversal-competency measures, so that claims about ESD rest on ESD outcomes. Third, the social dimension of sustainability includes equity. The evidence base is concentrated in computing education and in well-resourced institutions, and cost, infrastructure, and access were reported as challenges in about a quarter of the studies; AI-augmented pedagogy should not widen the gap between institutions and students who can afford reliable AI tools and those who cannot [46,227,228]. Fourth, the reported risks of over-reliance, inaccurate output, bias, and reduced human interaction are themselves threats to the quality of education (SDG 4). Making students verify and critique AI output, as many included studies did, is both a safeguard and a learning outcome in its own right, closely related to the critical and normative thinking that ESD seeks to develop.

4.5. Implications for Practice

For engineering educators, the reviewed studies suggest five design principles, which should be read as informed hypotheses rather than evidence-based rules. (1) Define the role of AI explicitly for each phase of the experiential activity, rather than giving open access throughout. (2) Use AI where it relieves the real bottlenecks of experiential pedagogy: generating varied scenarios, acting as a responsive counterpart in rehearsal, and giving timely feedback. (3) Protect the generative and interpersonal core of the activity, such as idea generation, empathy work, and teamwork, by sequencing AI after students' own attempts. (4) Require students to verify, justify, and document their use of AI through prompt logs, comparisons, or oral defenses, and assess this critical engagement. (5) Assess

transversal competencies directly, with rubrics or validated instruments, and not only through satisfaction surveys.

4.6. Research Agenda

The gaps identified in Section 3.5 translate into a research agenda. Research should (i) test AI-augmented drama, improvisation and role-play for interpersonal competencies in engineering, with AI generating scenarios and playing counterparts while human facilitators keep the embodied debrief; (ii) target empathy, emotional intelligence, adaptability and ethical competencies and, explicitly, the sustainability competences of systems, futures and strategic thinking, which are central to ESD but almost absent so far; (iii) use comparative designs that vary the structure of AI use within the same course, and not only AI with no AI, to test the hypothesis formulated in Section 4.2, and assess students without AI and at follow-up to separate AI-assisted performance from competency development; (iv) measure competencies with validated instruments or performance assessments, including instruments derived from GreenComp, control for confounders and follow students after the course to test retention once AI support is removed; (v) explore AI for observing and giving feedback on the experiential process itself, including multimodal and affective feedback, under strict privacy and consent safeguards; and (vi) broaden the evidence to design-oriented STEAM programs and to institutions in Africa and other under-represented regions.

4.7. Limitations

This review has several limitations. First, the protocol was not registered, although the eligibility criteria, codes, and extraction form were fixed before screening and are provided in full; the extension of the search to Scopus and IEEE Xplore was an amendment made during the review, and it used unchanged criteria and procedures. The explicit outcome, AI-use and appraisal rules (amendment iv) were, however, formulated during peer review, after a first synthesis had been completed, and could therefore have been influenced by knowledge of the earlier results; to limit this risk, they were applied to all studies, and the earlier coding is retained in Table S2 (Screening and extraction data) for comparison. Second, three databases were searched, but the ACM Digital Library, ERIC, and gray literature were not, and no citation searching was performed. The small number of unique studies contributed by IEEE Xplore (one) suggests that further sources would add mostly similar studies, but relevant work may have been missed and its findings are unknown. Third, the field-harmonization filter applied to Scopus and IEEE Xplore records may have excluded relevant records indexed only through controlled vocabulary; on the WoS corpus, it would have missed 5 of 145 included studies (3.4%), all retrieved through Keywords Plus, and the independent assessment of 300 removed Scopus and IEEE Xplore records found that 9 (3.0%; 95% CI 1.6–5.6%) would have been forwarded to full-text assessment, which corresponds to about 165 records (95% CI 87–308) across all removed records. About 73 eligible studies (roughly 38–136) may therefore be missing, mainly recent conference papers similar to those included. Adding 80 such studies through later retrieval did not change the direction of any finding, but this cannot show how the removed studies would have affected the results: they could change the counts and proportions reported here, and studies indexed only through controlled vocabulary are under-represented. Fourth, the competency block of the search did not include generic cognitive terms such as “critical thinking”, “problem solving” or “communication” (Section 2.2). Studies that measured these competencies entered the corpus only if they also mentioned an experiential pedagogy, a broader soft-skills term, or an interpersonal or creative competency, so studies of AI and critical thinking or problem solving outside experiential settings are under-represented. Because the query required an experiential-pedagogy term (#2) or a competency term

(#3), this also explains why the competency-only class is small (14 primary studies): such studies entered only when they used a broader term such as "soft skills" or named an interpersonal or creative competency. The effect of this choice on the size and composition of the corpus was not quantified, because no sensitivity search with these terms was run; it shifts the corpus towards studies in which these competencies are embedded in experiential formats, so the findings on critical thinking and problem solving refer mainly to such settings. Similarly, the context block may have missed studies that describe engineering courses without using engineering-education terms.

Fifth, 211 of the 647 reports sought (32.6%) could not be retrieved despite repeated searches and library requests, mostly conference papers without open-access versions; study authors were not contacted. Conference papers are a principal outlet of engineering-education research (54% of the included studies and 81% of the non-retrieved reports), and the abstracts compared in Figure 11b reveal neither effect directions nor methodological rigor. Their findings and methodological quality are unknown. Non-retrieval may therefore have biased the results in either direction, and the reports obtained through the later retrieval efforts, which were weaker in one set and not in the other, do not allow us to predict that direction; the conclusions apply to the retrieved literature only. Only English-language publications were included, and many included studies are conference papers with limited methodological detail, which constrains both extraction and appraisal.

Sixth, an AI model was used as the second reviewer in screening and for first-pass extraction and appraisal. We mitigated the associated risks by keeping AI decisions hidden from human screeners, by benchmarking the AI model against a second human screener, by auditing jointly excluded records, by having two authors independently assess every full-text exclusion, by having every extraction record verified by an author with a double-check of a 20% sample, and by calibrating MMAT ratings between two authors and by re-coding and verifying all primary studies with explicit rules (Table 4). For studies whose full text was read through an open-access web version, numbers were verified against the published article. Nevertheless, title and abstract screening involved one human reviewer and the AI model per record; inclusions at full-text level were confirmed by one author rather than two; the AI model and the human verifiers may share blind spots; and verification of AI proposals is not identical to fully independent dual extraction. The procedure as a whole is therefore not equivalent to independent dual human review, particularly for subtle pedagogical judgements such as whether an activity qualifies as role-play, simulation or experiential learning. Finally, the synthesis coded one primary AI role per study and relied on direction-of-effect counting, which ignores effect sizes and sample sizes, and the classification of AI-use structure depends on how completely studies reported it; counts of positive outcomes should not be read as evidence of effectiveness, especially given the low methodological quality and the likelihood of publication bias towards positive results.

5. Conclusions

AI is entering experiential engineering education quickly, but mostly through the easiest door: as a tutor and co-creator inside team projects. Its most distinctive potential for transversal-competency development, namely playing credible counterparts in role-play and simulation, generating rich scenarios and giving feedback on the interpersonal process, remains under-explored, and drama-based approaches are almost absent. The outcome evidence is of low to very low certainty. It is dominated by descriptive and self-report data; most comparisons were non-randomized, so reported improvements cannot be read as causal effects; comparative studies mostly assessed students while AI was available; and better-reported studies found fewer benefits. Studies with structured AI use more often reported comparative gains than studies with unconstrained use, but this is an exploratory

cross-study pattern across heterogeneous interventions, with counterexamples and confounding, not a demonstrated effect. These conclusions apply to the retrieved literature: about a third of the reports sought could not be retrieved, and the field filter may have removed eligible studies.

For education for sustainable development, the review identifies an opportunity rather than an established contribution. AI-augmented experiential pedagogies could help engineering programs develop collaborative, critical, and ethical competencies that overlap with sustainability competences, but the retrieved studies have not yet targeted or measured sustainability competences, and none has shown that competencies persist once AI support is removed. Future research should test how AI should be used in experiential learning, for whom and with which lasting effects, and should assess sustainability competences directly.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/su182312170/s1, Document S1: Search log and field definitions (search log (PRISMA-S) for WoS, Scopus and IEEE Xplore (Table S1), field definitions and field-harmonization filter, retrieval and amendments); Table S2: Screening and extraction data (1506 screened records with human and AI decisions; full-text decisions for 436 reports; extraction, outcome records, AI-use structure and MMAT ratings with justifications for the 323 included studies; author corrections and agreement statistics; sheets S1_Search (WoS search log), S2a–S2a2 (title/abstract screening), S2b–S2b5 (full-text retrieval and decisions), S2c–S2c2 (extraction), S2h (study-level coding), S2i (outcome records), S2j (MMAT ratings), S2d–S2d2 and S2e–S2e2 (superseded outcome coding and MMAT ratings), S2f–S2f2 and S2k–S2l (author corrections) and S2g (agreement statistics)); Document S3: Screening, extraction and appraisal protocols (protocols for screening, full-text assessment, extraction, outcome coding and MMAT appraisal); Table S4: Non-retrieved reports and field-filter assessment (reports not retrieved (n = 211) and the title/abstract comparison (sheets S4a and S4a2), and independent assessment of 300 records removed by the field filter (sheets S4b and S4b2)); File S5: VOSviewer maps (map 1, author keywords of the screened WoS corpus; map 2, author keywords of the 243 studies retrieved in the first search, shown in Figure 4; map 3, co-citation; map 4, country co-authorship) with their network and thesaurus files; Table S6: PRISMA 2020 checklists (completed PRISMA 2020 checklist and PRISMA 2020 for Abstracts checklist); File S7: PRISMA 2020 flow diagram (editable version of Figure 1); File S8: Field filter and analysis code (executable field filter, sampling script and analysis code with input and output files). References [70,71,87] are cited in the Supplementary Materials.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial intelligence
AR	Augmented reality
CDIO	Conceive–Design–Implement–Operate
ESD	Education for sustainable development
GenAI	Generative artificial intelligence
LLM	Large language model
MMAT	Mixed-Methods Appraisal Tool
PBL	Project-, problem- or challenge-based learning
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
SDG	Sustainable-Development Goal
STEM	Science, technology, engineering and mathematics
STEAM	Science, technology, engineering, arts and mathematics
SWiM	Synthesis Without Meta-analysis
VR	Virtual reality
WoS	Web of Science
XR	Extended reality

Appendix A

Table A1 lists the 323 included studies grouped by scope class and study type (core, competency-only and pedagogy-only primary studies; contextual surveys; reviews; conceptual papers; design or implementation reports), alphabetically within each group, with their main coded characteristics; studies identified in Scopus or IEEE Xplore or obtained through later retrieval efforts are marked with †. Full extraction data are provided in Table S2 (Screening and extraction data).

Table A1. Characteristics of the 323 included studies.

Study	Country	Discipline	Design	Scope	AI Role; Structure	Pedagogy	Competencies
Core primary studies (n = 153)							
Acuna et al. (2025) [149]	Colombia	Chem./Bio./Mat.	MM, n = 112	Core	Tutor; S	PBL, GAM, DT, EXP, COL	CMb±, CMb+, CMb±, CMb?, OTb+, CMd+, TWb?, TWd+, CRd+, PSd+, ADd+
Adorni and Grosso (2025) † [229]	Italy	Engineering	CS	Core	Co-creator; S	PBL, COL, DT	TWd+, CTd+
Aggrawal et al. (2024) [114]	USA	Computing/SE	QUAL, n = 46	Core	Role-play partner; S	RP, SIM, EXP, PBL, COL	TWd+, TWd?, TWd?
Alshayji et al. (2025) † [176]	USA	Engineering	MM, n = 30 (21 students, 9 staff)	Core	Tutor; S	PBL, COL	ETd±, ETd+, CTd+, CTd?
Alvarez et al. (2026) † [230]	Mexico	Sci./Math.	SURV, n = 51	Core	Role-play partner; S	PBL, XR, RP, COL	CMd+, CM nm
Alvarez et al. (2026) † [125]	Mexico	EE	MM, n = 54	Core	Feedback; S	XR, SIM, PBL, EXP	OTd+, CTd+, SRd+
Alvarez et al. (2026) † [231]	Mexico	Mech./Ind.	MM, n = 62	Core	Tutor; U	PBL, EXP, SIM	PSd?, PSw+
Appiah-Kubi (2026) † [137]	Ghana	Design/STEAM	MM, n = 130	Core	Co-creator; U	PBL	CRb±, CRb+, CRb+, CRr+, CRd±, ETd?
Ariza et al. (2026) [232]	Colombia	Computing/SE	MM, n = 119	Core	Tutor; ?	PBL, SIM, EXP	TWd+, TWd±, CTd−, CRd+
Bai et al. (2026) [164]	China	Civil/Arch.	RCT, n = 131	Core	Feedback; ?	PBL, EXP, SIM	CRb+, CRb?, SRb+, SRb+, TWb+, PSd+, OTb+, CT nm, ST nm
Balakayeva et al. (2026) † [233]	Kazakhstan	Computing/SE	MM, n = 83	Core	Tutor; S	PBL, COL	SRd+, PSd+, TWd+, CMd+, CRd+, OTd+, SRd+, TWd+, CMd+, PSd+, OTd+, CT nm
Behara et al. (2026) [165]	South Africa	EE	CS, n = 450	Core	Analytics; S	DT, PBL, COL, FB	CRb+, CRw+, CMb+, ETb+, TWb+

Table A1. *Cont.*

Study	Country	Discipline	Design	Scope	AI Role; Structure	Pedagogy	Competencies
Bento (2025) † [234]	Mexico	Computing/SE	MM, n = 30 (22 survey respondents)	Core	Co-creator; U	GAM, PBL, COL	TWd±, PSd+
Bento et al. (2026) [235]	Mexico	Computing/SE	CS, n = 25	Core	Tutor; U	PBL, COL	TW nm, CTd±, CRd+
Bharadwaj et al. (2025) † [177]	India	Computing/SE	RCT, n = 64	Core	Role-play partner; S	RP, EXP	CMb+, TWb+, ADb+, CRb+, EIb+, EIw+
Binkhonain et al. (2026) [110]	Saudi Arabia	Computing/SE	MM, n = 69	Core	Role-play partner; S	RP, EXP, COL	CMb+, EIbns, CMb±, TWb+
Boluda-Prieto et al. (2026) [236]	Spain	Mech./Ind.	CS, n = 47	Core	Tutor; S	PBL, COL, EXP	PSd?, TW nm
Burgos-López and Ruiz-Cantisani (2025) † [138]	Mexico	Mech./Ind.	CS, n = 67	Core	Co-creator; S	DT, PBL, COL	CRb−, CRd−, PSb±, OTd−
Cahyono et al. (2025) † [178]	Indonesia	Design/STEAM	MM, n = 25	Core	Co-creator; U	DT, EXP, XR	CRd+, CRb+
Chandrasekaran (2026) † [237]	India	Computing/SE	QE, n = 139	Core	Tutor; U	EXP, COL, PBL	CTd+, CMd+, TWd+, ETd±
Chans et al. (2025) [132]	Mexico	Chem./Bio./Mat.	PP, n = 9	Core	Co-creator; S	DT, PBL, COL	CRw±, CRw±, EIw±
Chen et al. (2026) † [179]	China	Chem./Bio./Mat.	QE, n = 180	Core	Tutor; S	PBL, EXP	PSb+, ETb+, CRb+, PSd+, ETd+
Ciolacu et al. (2024) † [238]	Romania	EE	MM, n = 44	Core	Co-creator; S	PBL, SIM, EXP	TWd+, PSd+, SRd+, CRd+
Colaco et al. (2026) [239]	India	EE	PP, n = 60	Core	Tutor; S	SIM, EXP, COL	CTw+, PSw+, TWw+, CR nm
Cruz-Alcantar et al. (2026) [150]	Mexico	Mech./Ind.	CS, n = 31	Core	Tutor; S	EXP, COL	CTd?, CMd?, ADd?, OTd?, OTd?

Table A1. *Cont.*

Study	Country	Discipline	Design	Scope	AI Role; Structure	Pedagogy	Competencies
Dai et al. (2024) † [180]	n.r.	Engineering	MM, n = 593	Core	Analytics; U	DT, PBL, COL	OTb±, TWb+, TWd+, SR nm
Deng et al. (2025) † [240]	UK	Engineering	MM, n = 16	Core	Co-creator; U	DT, PBL	CRd+, CTd±
Dinu (2025) [182]	Romania	Engineering	QE, n = 60	Core	Tutor; U	PBL	PSb+
Ferrao et al. (2025) [158]	Brazil	Computing/SE	CS, n = 65	Core	Feedback; S	PBL, COL	TWd+
Filcik et al. (2025) [241]	USA	Computing/SE	CS, n = 544	Core	Co-creator; S	PBL	CRd+, PSd+, ETd+
Fodouop Kouam (2025) † [242]	France	Computing/SE	MM, n = 120	Core	Tutor; ?	XR, SIM, COL	TW nm, SR nm
Fouh (2026) [243]	USA	Computing/SE	SURV, n = 42	Core	Tutor; U	PBL, COL, FB	OTwns, SRw+, CM nm, TW nm, ET nm, CT nm
Fujs et al. (2026) [244]	n.r.	Computing/SE	SURV, n = 23	Core	Tutor; U	PBL, COL	TWd?
Garcia-Huertes and Bragós (2025) † [245]	Spain	EE	CS	Core	Co-creator; S	PBL, DT, COL	CTw+, PSw+, CRw?, CMw+, PSd+
Ge et al. (2026) [116]	China	EE	QE, n = 87	Core	Role-play partner; S	PBL, SIM, RP, FB	PSb+, PSb+, PSr+
Gee et al. (2026) [113]	USA	Computing/SE	QE, n = 266	Core	Role-play partner; S	RP, SIM, EXP	CMb+, CMb+, ADb+
Gianni et al. (2025) [246]	Greece	Computing/SE	RCT, n = 20	Core	Feedback; S	GAM, XR, COL	TW nm
Girmay et al. (2026) † [247]	Finland	Chem./Bio./Mat.	MM, n = 13	Core	Scenario generator; S	XR, SIM	CTd+
Gonzalez-Guerra et al. (2025) [248]	Mexico	Computing/SE	QE, n = 124	Core	Tutor; S	GAM, COL	PSd+

Table A1. *Cont.*

Study	Country	Discipline	Design	Scope	AI Role; Structure	Pedagogy	Competencies
Grey (2025) [102]	UK	Engineering	QUAL, n = 80	Core	Scenario generator; S	RP, GAM, PBL, EXP	ETd+
Grigore and Turcu (2025) † [249]	Romania	Mech./Ind.	QUAL, n = 43	Core	VR/game agent; S	XR, SIM, EXP	PS nm, CR nm, CT nm
Guerrero-Chirinos et al. (2026) † [183]	Ecuador	Sci./Math.	QE, n = 71	Core	Feedback; S	PBL, COL	PSb+, PSw+, PSr+, SRr+
Gül et al. (2024) † [250]	Turkey	Civil/Arch.	MM, n = 18	Core	Co-creator; U	DT, EXP	CRd+
Guo et al. (2025) [128]	China	EE	RCT, n = 113	Core	Co-creator; S	PBL, COL	CRb+, CRw+
Hakiki et al. (2026) † [251]	Indonesia	Computing/SE	PP, n = 234	Core	Feedback; ?	XR, SIM, FB, EXP	OTw+, TWd+, PSd+
Han et al. (2025) † [173]	China	Engineering	QE, n = 86 (30 experimental + 56 control)	Core	Scenario generator; S	PBL, SIM	PSb+, CRd+
Han et al. (2026) † [184]	multi-country	Computing/SE	MM, n = 376	Core	Tutor; S	PBL, COL	TWb+, SRb+, PSb+
Hare et al. (2023) † [174]	USA	Engineering	QE, n = 55 (13 + 20 + 14 + 8 across 4 comparison groups)	Core	Tutor; U	GAM, SIM	PSbns, PSb+, PSb?
Ho et al. (2025) † [252]	Canada	Computing/SE	CS, n = ~230 (60 teams)	Core	Co-creator; U	PBL, COL, EXP	TWd+, ETd+, CTd+, SRd±
Hodgkinson (2025) † [253]	USA	Mech./Ind.	QUAL, n = 97	Core	Scenario generator; S	EXP, PBL, COL	CTd+, PSd+, TW nm
Honig et al. (2024) [111]	Australia	Chem./Bio./Mat.	MM, n = 41	Core	Role-play partner; S	RP, SIM, EXP, COL	CTb+, CTd+, TWd+
Hu et al. (2025) [115]	China	Computing/SE	QUAL, n = 72	Core	Role-play partner; S	RP, SIM, GAM, EXP	TWd+

Table A1. *Cont.*

Study	Country	Discipline	Design	Scope	AI Role; Structure	Pedagogy	Competencies
Hu et al. (2025) † [254]	China	Mech./Ind.	PP, n = 39	Core	Tutor; U	SIM, PBL, COL, FB	TWw+, CR nm, PS nm
Jaramillo-Fierro et al. (2026) [99]	Ecuador	Chem./Bio./Mat.	PP, n = 106	Core	Scenario generator; S	PBL, XR, COL, EXP, FB	OTw+, CTd±, TW nm, CR nm, PS nm, CM nm
Ji et al. (2025) [129]	China	Computing/SE	QE, n = 36	Core	Co-creator; S	PBL, COL	CRb±, CRd±, CTb±, CTw±, CTd±
Karoglou et al. (2025) [152]	Greece	Chem./Bio./Mat.	PP, n = 10	Core	Tutor; ?	XR, SIM, EXP	OTd+, SR nm
Kavitha et al. (2026) † [172]	India	EE	QE, n = 130	Core	Scenario generator; S	GAM, COL	PSb+, TWd+, CTd+, PSd+, SRd+
Keith et al. (2025) [103]	UK	Chem./Bio./Mat.	MM, n = 130	Core	Scenario generator; S	EXP, PBL, COL	CTd+, CTd?, CTd+, ETd+, PSbns, PSbns
Khan et al. (2026) † [255]	Singapore	Design/STEAM	MM, n = 454 (end-of-term survey respondents of 558 invited; 550+ students enrolled)	Core	Co-creator; U	DT, PBL, COL	CRd+, TWd−
Kharrufa et al. (2026) [213]	UK	Computing/SE	MM, n = 39	Core	Tutor; S	PBL, COL	CTd+, PSd+, TWd±, OTd±
Kinto-Ramírez et al. (2025) [97]	Mexico	Chem./Bio./Mat.	QE, n = 29	Core	Scenario generator; S	PBL, COL, FB	SRb+, CTb+, TWb+, CMb+
La Scala et al. (2025) † [185]	Tunisia	Engineering	QE, n = 72	Core	Co-creator; S	DT, COL	CRb+, CTb+
Lavado-Anguera et al. (2025) [256]	Spain	Computing/SE	CS, n = 302 (42 survey)	Core	Tutor; S	PBL, COL	CRd±, CTd−, OT nm, OT nm
Lei et al. (2025) [140]	China	Computing/SE	QE, n = 76	Core	Tutor; U	PBL, COL	CRb±, OTb+, TWbns, CTb+, PSb±

Table A1. *Cont.*

Study	Country	Discipline	Design	Scope	AI Role; Structure	Pedagogy	Competencies
Li et al. (2025) [117]	China	Chem./Bio./Mat.	MM, n = 92	Core	Role-play partner; S	RP, GAM, COL, PBL, FB	PSd+, TWd+, PSd±, TWd±
Li et al. (2025) [144]	Taiwan	EE	RCT, n = 62	Core	Tutor; B	COL	CRb+, PSb+, CTb+
Li et al. (2025) † [257]	China	Chem./Bio./Mat.	MM, n = 29 (195 enrolled in course; 29 analyzed in clustering/ENA)	Core	Co-creator; S	PBL, COL, GAM, RP	TWd+, PSd+, CRd+
Li et al. (2026) † [186]	China	EE	QE, n = 71	Core	Tutor; U	PBL, DT, EXP	CRb+, STb+, OTb+, PSbns, OTb+, OTb+, SRd+, SRw+, PSd+, CTd−
Lin et al. (2025) [147]	Taiwan	Computing/SE	RCT, n = 74	Core	Tutor; S	EXP, COL, PBL	SRb+, TWb±
Littell (2025) † [258]	USA	Engineering	CS, n = 25	Core	Role-play partner; S	RP, SIM	CMd+, EI nm
Liu (2025) † [187]	China	Engineering	QE, n = 180	Core	Tutor; S	PBL, SIM, COL	CRb+, PS nm
Liu (2026) † [188]	China	EE	QE, n = 120 (62 experimental; 58 control)	Core	Feedback; S	PBL, EXP, FB	CTb+, CMb+
Liu and Zainol (2026) † [259]	China	Design/STEAM	QE, n = 642	Core	Feedback; S	PBL, COL	TW nm, CR nm, OTr+
Lojo et al. (2025) [109]	n.r.	Computing/SE	RCT, n = 120	Core	Role-play partner; S	RP, SIM	CMb+, CMb?
Loo et al. (2025) [139]	UK	EE	SURV, n = 119	Core	Tutor; U	PBL, EXP, RP, COL, FB	CTd+, OTd+, TWd+
Lytovchenko et al. (2025) † [189]	Ukraine	Engineering	QE, n = 27	Core	Tutor; U	PBL, COL	CRb−, CMb−
Lytovchenko et al. (2026) [260]	n.r.	Engineering	MM, n = 92	Core	Role-play partner; ?	RP, COL	—

Table A1. *Cont.*

Study	Country	Discipline	Design	Scope	AI Role; Structure	Pedagogy	Competencies
Maalek (2024) [190]	Germany	Civil/Arch.	CS	Core	Tutor; S	PBL	PSd+, PSb+, TWd+, LD nm, CM nm, SR nm, CT nm
Majgaard (2024) † [217]	Denmark	Computing/SE	QUAL, n = 36	Core	Co-creator; U	PBL, GAM, EXP, COL	CRd+, CTd+, ETd+
Mallika et al. (2026) † [191]	India	EE	CS, n = 65	Core	Other; U	PBL, DT, SIM, COL	PSb+, CTb+, TWb+, PSd+, TWd+, CMd+, TWd+
Manipatruni et al. (2026) [112]	India	EE	QE, n = 36	Core	Role-play partner; S	RP, FB	CMw+, CMb+, CMd+
Mariño et al. (2025) [192]	Spain	EE	MM, n = 180	Core	Co-creator; ?	PBL, EXP, COL	CMb+, CMb+, CTb?, CTd+, CMw+, SR nm
Meenakshi and Kavitha (2026) † [169]	India	EE	CS, n = 140	Core	Feedback; S	GAM, PBL, RP, SIM	CRd+, PSd+, ST nm, TW nm, OTd+
Meissner et al. (2026) † [261]	Germany	Computing/SE	MM, n = 12	Core	Tutor; U	GAM	SRd±, SRd+
Mejia et al. (2025) [262]	USA	Computing/SE	QUAL, n = 127	Core	Tutor; U	PBL, COL	PSd+, CRd±, TW nm, CM nm, CT nm
Mendonça et al. (2025) [134]	Brazil	Computing/SE	CS, n = 29	Core	Co-creator; S	PBL, COL	CRd+, TWd+, OT nm
Meng et al. (2026) † [193]	China	Computing/SE	RCT, n = 120	Core	Tutor; U	PBL, SIM, COL, FB	PSb+, CRb+, PSb+, SRb+, OTb+
Mnaoui et al. (2022) † [168]	Morocco	Mech./Ind.	CS, n = 12	Core	Feedback; S	SIM, EXP	CMw+, CMd+
Mosquera-Navarro et al. (2026) † [194]	Colombia	Mech./Ind.	QE, n = 144	Core	Tutor; S	PBL, COL	PSb+, CR nm
Murali et al. (2024) † [263]	India	Computing/SE	QE, n = 65	Core	Tutor; U	SIM, EXP	CT nm, PS nm
Nakajima et al. (2026) † [175]	Japan	EE	MM, n = 83	Core	Co-creator; U	EXP	CRd+, CRd+, CRd+, CTd+, CTd+, SRd?, TWd+, ETd+

Table A1. *Cont.*

Study	Country	Discipline	Design	Scope	AI Role; Structure	Pedagogy	Competencies
Nathaniel et al. (2025) [146]	Nigeria	Computing/SE	MM, n = 25	Core	Tutor; S	PBL	PSw+, CTw±, CRw±, CTd±, SRd+, TWd+
Navarro-Arcas et al. (2025) [212]	Spain	Mech./Ind.	MM, n = 48	Core	Co-creator; U	PBL, GAM, COL	OTd+, ADd+, PSd+, CMd+, ETd+, ETd+, CTd+
Nieto-Jalil et al. (2026) † [155]	Mexico	Sci./Math.	QE, n = 84	Core	Tutor; S	EXP	PSb+, CMb+, CTb+, SR nm
Núñez et al. (2024) [195]	Colombia	Computing/SE	QE, n = 44	Core	Other; ?	PBL, DT, COL	TW nm, PSb+
Nutzmann et al. (2024) † [264]	Germany	Mech./Ind.	CS, n = 29	Core	Co-creator; ?	COL	CRd+, ETd?, ETd+
Omeh et al. (2025) [141]	Nigeria	Computing/SE	QE, n = 87	Core	Tutor; S	PBL, COL	OTb+, OTb+, OTb+, CT nm, CR nm
Oran et al. (2024) [265]	Brazil	Computing/SE	SURV, n = 35	Core	Co-creator; S	PBL, COL	CTd±, CTd+, TWd±, CRd−
Pasalkar et al. (2025) [143]	India	Computing/SE	QE, n = 50	Core	Tutor; S	GAM	PSb+, PSw+
Pozos et al. (2025) [148]	Mexico	EE	CS, n = 29	Core	Tutor; S	PBL, COL	TWd+, PSd+, CM nm
Qi et al. (2026) † [197]	China	Engineering	QE, n = 90	Core	Co-creator; S	PBL, COL	PSbns, CTb+, STb+, CMb+
Ramírez-Cedillo et al. (2024) † [171]	Mexico	Mech./Ind.	CS, n = 6	Core	Analytics; ?	SIM, EXP, PBL	EI nm
Ramos and Condotta (2024) † [266]	Brazil	Chem./Bio./Mat.	CS, n = 42	Core	Scenario generator; S	PBL, RP, SIM, COL	CMd+, TWd+, PSd+
Rehman et al. (2025) [163]	UAE; Saudi Arabia; Qatar; Oman	Engineering	MM, n = 300	Core	Feedback; ?	XR, SIM, COL	CMw+, CMd+, CMd+, TWd+

Table A1. *Cont.*

Study	Country	Discipline	Design	Scope	AI Role; Structure	Pedagogy	Competencies
Robol et al. (2025) † [267]	USA	EE	MM, n = 21 (17 completed baseline survey)	Core	Tutor; U	PBL	SRd?, PSr+
Rong et al. (2025) † [225]	USA	Chem./Bio./Mat.	QUAL, n = 38	Core	Tutor; B	EXP, RP, PBL, COL	SRb±, TWb±
Roy et al. (2025) [268]	USA	Computing/SE	CS, n = 84	Core	Co-creator; S	PBL, COL, EXP	CTw+, CTw+, ADw+, ADd?, PS nm
Ruiz-Rojas et al. (2026) [269]	Ecuador	Computing/SE	QUAL, n = 20	Core	Co-creator; S	PBL, GAM	CRd+, SRd+, SRd±, TWd±, OTd±
Ryan et al. (2025) † [270]	USA	Engineering	QUAL, n = 106	Core	Feedback; ?	PBL, COL	OTd±, TWd±
Sadik (2025) † [198]	USA	Computing/SE	CS, n = 35	Core	Tutor; S	PBL, GAM, COL	PSb+, SRd±, CTd±, CRd±, CMd+, ETd?
Sajadi et al. (2024) [157]	USA	Engineering	QUAL, n = 118	Core	Feedback; S	PBL, COL	TW nm
Saleh et al. (2025) † [271]	United Arab Emirates	Computing/SE	QE, n = 30	Core	Feedback; S	GAM, FB, SIM, PBL	PSd+
Salomon et al. (2025) [208]	Canada	Computing/SE	MM, n = 341	Core	Tutor; U	PBL, COL	TWd±
Shao et al. (2026) † [106]	China	Computing/SE	PP, n = 260	Core	Scenario generator; ?	SIM, COL, FB	CMw?, SRw?, OTw?, PS nm
Sheela et al. (2025) [199]	India	Engineering	MM, n = 107	Core	Tutor; ?	XR, SIM, PBL, EXP	ETb+, TWb+, OTb+, EId+, EId+
Shi et al. (2026) † [272]	China	EE	SURV, n = 125	Core	Other; ?	PBL	CRr+
Shigi et al. (2025) [273]	Japan	Engineering	CS, n = 1	Core	Role-play partner; S	RP, EXP	CMd+, CMd+, SRd?
Shinn et al. (2026) † [274]	Thailand	Computing/SE	SURV, n = 108	Core	Scenario generator; S	COL, EXP, PBL	TWr+, ADr+

Table A1. *Cont.*

Study	Country	Discipline	Design	Scope	AI Role; Structure	Pedagogy	Competencies
Sinnari (2026) [200]	Saudi Arabia	Computing/SE	QE, n = 29	Core	Co-creator; U	PBL, COL	CRbns, OTb±, CRd+, TWd+, ADd+, OTd+
Sodhi and Lieber (2026) † [275]	USA	Mech./Ind.	PP, n = 89 (survey respondents)	Core	Co-creator; S	PBL, EXP	CMd+, CR nm
Steimel and Lee (2025) † [276]	USA	Chem./Bio./Mat.	QE, n = 39	Core	Other; ?	PBL, EXP, SIM, COL	CT nm, PS nm, TW nm
Stoeva et al. (2026) † [277]	Bulgaria	Computing/SE	CS, n = 64	Core	Co-creator; U	DT, PBL, COL	CRd+, STd+, TWd+, CTd±
Sun et al. (2026) † [201]	China	Computing/SE	QE, n = 90	Core	Tutor; S	PBL, RP, SIM, COL, FB	PSb+, AD nm, TW nm, CT nm
Syahri et al. (2025) † [202]	Indonesia	Mech./Ind.	QE	Core	Tutor; S	PBL, COL	CTb+
Tani et al. (2026) † [154]	Finland	Mech./Ind.	MM, n = 143	Core	Tutor; S	GAM, SIM, PBL, COL	PSr?, TWd+, SR nm, LD nm
Thompson and Fishlock (2024) † [136]	UK	Design/STEAM	CS, n = 35	Core	Co-creator; S	PBL, DT, COL, FB	CRd+
Tiwari et al. (2025) [135]	India	Computing/SE	CS, n = 46	Core	Co-creator; S	EXP	CTd+
Tong et al. (2026) † [278]	China	Computing/SE	QE, n = 600	Core	Tutor; U	PBL	PS nm, SR nm
Torta et al. (2025) † [279]	Netherlands	Mech./Ind.	MM, n = 20	Core	Tutor; U	PBL, SIM, COL, EXP	CTd+
Tsakalerou et al. (2026) [130]	Kazakhstan	Civil/Arch.	QE, n = 12 teams (individual n not reported)	Core	Co-creator; U	DT, PBL, EXP, COL	CRbns, CRwns, PSwns, PSd−
Tunc (2025) † [280]	Türkiye	Computing/SE	MM, n = 57	Core	Co-creator; S	PBL, EXP	CTd+, ETd−, PSd±
Turcios-Esquivel et al. (2025) [131]	Mexico	Engineering	PP, n = 56	Core	Co-creator; S	DT, PBL, EXP, COL	CRd+, TWd+, PSd+, EId+, OTw+, OTd+

Table A1. *Cont.*

Study	Country	Discipline	Design	Scope	AI Role; Structure	Pedagogy	Competencies
van Dijk and Zaytsev (2026) † [203]	Netherlands	Computing/SE	MM, n = 38	Core	Tutor; U	PBL	PSbns, CTd±
Viadero-Monasterio et al. (2026) [281]	Spain	Mech./Ind.	QE, n = 132	Core	Tutor; S	FB, PBL, COL	CTd±, CMd+, PSd+, TW nm, ET nm
Virkki et al. (2026) † [282]	Finland	Computing/SE	MM, n = 87 (pre–post survey); 73 (intervention reflections)	Core	Tutor; S	EXP	CTw±, CTd+
Wang et al. (2025) † [283]	Canada	Chem./Bio./Mat.	MM, n = 5	Core	Scenario generator; ?	XR, SIM, GAM, EXP	TW nm, CM nm
Wang et al. (2026) † [156]	USA	Engineering	RCT, n = 40	Core	VR/game agent; U	GAM, EXP, PBL	PSb±, PSb+
Willems et al. (2025) [133]	Singapore	Civil/Arch.	QUAL, n = 13	Core	Co-creator; S	DT, PBL, COL, GAM	SRd+, CTd+
Wu (2026) † [153]	China	Mech./Ind.	QE	Core	Tutor; S	PBL, COL, SIM	PSw+, STd?, TW nm, SR nm
Yang (2025) † [204]	China	Mech./Ind.	RCT, n = 60 (30 experimental, 30 control)	Core	VR/game agent; S	XR, SIM	PSb+
Yang and Gai (2026) † [123]	China	Chem./Bio./Mat.	RCT, n = 60	Core	VR/game agent; S	XR, SIM, RP, EXP	CMb+, CMw+
Yao et al. (2025) † [284]	China	Mech./Ind.	CS	Core	Feedback; S	PBL, FB, COL	SRw?, TWw?, CTw?, CMw?
Yi et al. (2025) [145]	China	Civil/Arch.	MM, n = 120	Core	Tutor; B	PBL, COL	TWb±, TWd±, CTd+, OTb+, SRd+, PSb+, PSbns
Yu et al. (2025) [96]	UK	Design/STEAM	QUAL	Core	Co-creator; S	DT, COL, DR	CRd+, TWd±, CTd+

Table A1. *Cont.*

Study	Country	Discipline	Design	Scope	AI Role; Structure	Pedagogy	Competencies
Yunes-Rojas et al. (2025) [285]	Mexico	Computing/SE	PP, n = 10	Core	Feedback; S	GAM, COL, EXP	SRd+, PSd+, TWd+, TWd+
Yunes-Rojas et al. (2026) † [286]	Dominican Republic; Mexico	Chem./Bio./Mat.	PP, n = 22	Core	Tutor; S	COL, EXP, PBL, XR	SRd+, PSd+, TWd+, CMd+
Zamora-Hernández et al. (2025) [142]	Mexico	Computing/SE	PP, n = 17	Core	Tutor; S	PBL	CTd?
Zangari et al. (2025) [287]	USA	Computing/SE	MM, n = 19	Core	Other; ?	PBL, COL	CR nm, CT nm, CM nm
Zhang et al. (2025) † [288]	China	Mech./Ind.	CS	Core	Analytics; ?	PBL, COL, FB	OTb+, CR nm, TW nm
Zhang et al. (2026) † [205]	China	Mech./Ind.	RCT, n = 120	Core	Tutor; U	PBL, COL, EXP, SIM	TWb+, TWb+, TWd−, ADb+, ADb+, CRb+, CTd−, ETd−
Zhu (2026) † [206]	China	EE	QE	Core	Tutor; S	SIM, EXP, PBL, FB	PSb+, CTd+, CRd+
Zhu and Xu (2026) † [207]	China	Computing/SE	QE, n = 88	Core	Other; ?	PBL	CRb+, TWb+, ADb+
Zolezzi et al. (2025) † [289]	Italy	Computing/SE	SURV, n = 102	Core	Tutor; S	GAM, PBL	SRd±, PSd+
Competency-only primary studies (n = 14)							
Adauto-Medina et al. (2026) [290]	Peru	EE	SURV, n = 158	Comp.	Tutor; ?	—	CMr+, CMd?
Amzalag et al. (2025) [291]	Israel	Computing/SE	QUAL, n = 68	Comp.	Tutor; U	FB	SRb±, CTb±
Balta-Salvador et al. (2026) [83]	Spain	Mech./Ind.	RCT, n = 51	Comp.	Co-creator; U	DT	CRb±, CRb?, CRbns, CRd?
Boudia and Krismadinata (2024) † [292]	Algeria	Computing/SE	MM, n = 62	Comp.	Tutor; U	PBL	SRd±, ETd?

Table A1. *Cont.*

Study	Country	Discipline	Design	Scope	AI Role; Structure	Pedagogy	Competencies
Cebon et al. (2024) [159]	Australia	Engineering	MM, n = 70	Comp.	Feedback; U	COL	CMd?, CMd±, EId+, CT nm
Das (2025) † [181]	USA	Chem./Bio./Mat.	CS, n = 24	Comp.	Tutor; S	EXP	CMb±
Datta (2026) † [293]	USA	Computing/SE	CS, n = 129 undergraduate; 65 graduate	Comp.	Scenario generator; S	GAM	CMd+, CTd?
Jantassova et al. (2026) [162]	Kazakhstan	Engineering	QE, n = 122	Comp.	Feedback; S	PBL, RP, DT, GAM, FB, COL	CMb+, CMw+, CMd+
Klopper et al. (2025) [294]	South Africa	EE	SURV, n = 6	Comp.	Tutor; S	—	CMd+, CMd±, PSd+, CTd±
Lai and Karrobi (2025) † [295]	USA	Chem./Bio./Mat.	MM, n = 83	Comp.	Tutor; S	—	CMd+
López-Vargas et al. (2026) [296]	n.r.	Computing/SE	MM, n = 340	Comp.	Tutor; U	RP, EXP	PSr−, PSd?, ETd?, ETd?
Mitrovic et al. (2025) † [167]	New Zealand	Computing/SE	QE, n = 103	Comp.	Feedback; S	EXP, PBL	EIb+, EIw+, SRbns, SRd+
Pi et al. (2026) [196]	China	Mech./Ind.	RCT, n = 92	Comp.	Scenario generator; B	—	CRb±, CRb±, CRbns
Wijesinghe et al. (2025) † [297]	USA	Civil/Arch.	QUAL, n = 13	Comp.	Scenario generator; S	—	CTd±, CRd−, ETd±
Pedagogy-only primary studies (n = 26)							
Ajibade et al. (2026) † [126]	Nigeria	Mech./Ind.	QE, n = 30	Ped.	VR/game agent; S	XR, SIM, EXP, COL	PS nm, TW nm, CT nm
Alipour et al. (2025) [118]	USA	Sci./Math.	MM, n = 10	Ped.	VR/game agent; U	XR, EXP	—
Alkhatib et al. (2025) † [298]	USA	Computing/SE	CS, n = 10	Ped.	Feedback; S	EXP, SIM	—

Table A1. *Cont.*

Study	Country	Discipline	Design	Scope	AI Role; Structure	Pedagogy	Competencies
Alvarez et al. (2025) [299]	Mexico	EE	SURV, n = 55	Ped.	Tutor; U	XR, SIM, EXP	—
Blazauskas et al. (2025) [101]	Lithuania	Computing/SE	SURV, n = 28	Ped.	Scenario generator; S	XR	—
Bosman et al. (2023) † [300]	USA	Mech./Ind.	MM, n = 120	Ped.	VR/game agent; U	RP, SIM, GAM, EXP	—
Breivik (2026) † [301]	Norway	Computing/SE	MM, n = 170 (survey respondents of ~300 enrolled)	Ped.	Tutor; U	PBL, EXP	SRd±
Cheon et al. (2026) [120]	USA	Computing/SE	MM, n = 24	Ped.	VR/game agent; U	XR, SIM, EXP	—
Cinar et al. (2024) [119]	UK; Ireland	Computing/SE	QE, n = 48	Ped.	VR/game agent; S	XR, SIM, GAM, EXP	—
Gulec et al. (2021) [94]	Türkiye; Ireland	Computing/SE	RCT, n = 32	Ped.	VR/game agent; S	XR, SIM, RP	OTb+, OTw+
Hu (2026) † [302]	Taiwan	STEM	PP, n = 32	Ped.	Co-creator; S	PBL, EXP, COL	—
Hurme et al. (2026) † [303]	Finland	Sci./Math.	QE, n = 80 (26 + 26 + 14 + 14 across 4 course realizations)	Ped.	Tutor; S	SIM, EXP	—
Karoglou et al. (2025) [304]	Greece	Chem./Bio./Mat.	CS, n = 10	Ped.	Tutor; S	XR, SIM, EXP, PBL	—
Kataoka et al. (2026) † [305]	Japan	Computing/SE	QE, n = 94	Ped.	Co-creator; U	PBL	ST nm, CT nm
Kelly et al. (2024) † [306]	USA	Computing/SE	MM, n = 23	Ped.	Scenario generator; S	GAM, FB	—
Kelly et al. (2025) [121]	USA	Computing/SE	MM, n = 25	Ped.	VR/game agent; S	GAM	—

Table A1. *Cont.*

Study	Country	Discipline	Design	Scope	AI Role; Structure	Pedagogy	Competencies
Kusam et al. (2024) [307]	USA	Computing/SE	PP, n = 42	Ped.	Tutor; S	PBL, EXP	—
Mezzaro et al. (2024) [308]	Germany	Computing/SE	MM, n = 37	Ped.	Tutor; U	GAM	—
Mogianesi et al. (2025) † [309]	Italy	Sci./Math.	QE, n = 12	Ped.	VR/game agent; S	SIM	—
Narayanan and Kumaravel (2024) † [310]	India	Computing/SE	CS, n = 200	Ped.	Feedback; ?	GAM	—
Patel et al. (2025) [311]	USA	Computing/SE	CS, n = 42 ratings (number of students not reported)	Ped.	Tutor; U	EXP, SIM	—
Patel et al. (2026) † [312]	India	Computing/SE	MM, n = 200	Ped.	Feedback; ?	GAM	—
Perez et al. (2025) † [313]	USA	Mech./Ind.	MM, n = 97	Ped.	VR/game agent; U	XR, SIM, EXP	—
Sunday et al. (2023) [314]	Nigeria	Computing/SE	SURV, n = 103	Ped.	VR/game agent; S	XR, GAM	—
Yarleque et al. (2025) [98]	Peru	Computing/SE	PP, n = 60	Ped.	Scenario generator; ?	GAM, PBL	OTw+, OTw+
Yuan (2026) † [210]	China	Mech./Ind.	QE, n = 120	Ped.	Other; ?	XR, SIM	—
Contextual primary studies (surveys of general AI use) (n = 27)							
Alghamdi (2025) [315]	Saudi Arabia	Sci./Math.	SURV, n = 405	Ctx	Tutor; ?	—	CTd+, CTr+, CRd+, CRr+
Chen et al. (2025) [316]	China	Computing/SE	SURV, n = 990	Ctx	Tutor; ?	COL	CMr+, ADr+, TWr+

Table A1. *Cont.*

Study	Country	Discipline	Design	Scope	AI Role; Structure	Pedagogy	Competencies
Cloux et al. (2025) † [317]	France	Engineering	MM, n = 51 students; 3 teachers	Ctx	Tutor; U	COL	CTd?, PSd?, TWd?
Deng et al. (2026) [318]	n.r.	Engineering	SURV, n = 966	Ctx	Tutor; ?	—	CRr+, OTr+
Estigoy et al. (2026) † [319]	China	Engineering	SURV, n = 345	Ctx	Tutor; ?	—	CRd±, CTd+, CMd+, ETd?
Giray and Aquino (2024) † [320]	Philippines	Engineering	QUAL, n = 144	Ctx	Tutor; U	—	CTd−, CRd−, PSd+
Guo et al. (2026) [321]	China	Engineering	SURV, n = 729	Ctx	Co-creator; ?	—	CTr+, CRr+
Guo et al. (2026) † [322]	China	Engineering	SURV, n = 989	Ctx	Tutor; ?	—	CRr+
Hasan et al. (2026) † [323]	Bangladesh	STEM	MM, n = 407	Ctx	Tutor; U	—	TWd+, CTd±, CRd−, PSd+
Hayudini et al. (2025) † [324]	Philippines	STEM	QUAL, n = 16	Ctx	Tutor; ?	PBL, GAM, COL, EXP	OTd+, CTd+, ETd+
Husin (2026) † [325]	Indonesia	Engineering	SURV, n = 435	Ctx	Tutor; ?	—	SRr+, CRrns
Jammeli et al. (2024) † [326]	Hungary; Tunisia; France; and others	Engineering	SURV, n = 129	Ctx	Tutor; U	—	EIbns, EIb−, EIr−
Krupansky et al. (2025) [327]	USA	Engineering	QUAL, n = 13	Ctx	Other; ?	—	CRd?, ETd?, CTd?
Liu et al. (2026) [328]	China	Engineering	SURV, n = 8426	Ctx	Co-creator; ?	—	CRr+, CTr+

Table A1. *Cont.*

Study	Country	Discipline	Design	Scope	AI Role; Structure	Pedagogy	Competencies
Mohamad et al. (2026) † [329]	Lebanon; Jordan; Saudi Arabia; Morocco; Egypt; Oman; Qatar; United Arab Emirates	Computing/SE	QUAL, n = 300	Ctx	Feedback; ?	XR, SIM, EXP, COL	OTd?, CMd+, TWd+, PSd+
Osadcha et al. (2025) † [330]	Multinational	Computing/SE	SURV, n = 55	Ctx	Tutor; ?	—	—
Quince et al. (2026) [209]	Australia	Computing/SE	QUAL, n = 48	Ctx	Tutor; ?	—	—
Rahardjo et al. (2026) † [220]	Australia	Civil/Arch.	SURV, n = 162	Ctx	Tutor; ?	—	PSd+, TWd?, CTd?, OTd+
Reyes (2026) † [331]	Philippines	Mech./Ind.	SURV, n = 50	Ctx	Scenario generator; ?	SIM	—
Sánchez-Ruiz et al. (2023) [332]	Spain	Mech./Ind.	SURV, n = 110	Ctx	Tutor; ?	FB, GAM	CTd?, PSd?, TWd?
Shabunina et al. (2023) † [333]	Ukraine	EE	SURV, n = 35	Ctx	Tutor; ?	—	—
Sinkus and Ozola (2024) † [334]	Latvia	Engineering	SURV, n = 137	Ctx	Tutor; ?	—	ETd?
Synekop et al. (2024) † [335]	Ukraine	Engineering	SURV, n = 82	Ctx	Tutor; ?	—	CMd±, CTd+, CRd+, TWd+
Szuta (2026) † [336]	Poland	Civil/Arch.	SURV, n = 191 (55 + 55 architecture across two years; 43 architecture + 38 electrical engineering master's)	Ctx	Tutor; U	—	CMd±

Table A1. *Cont.*

Study	Country	Discipline	Design	Scope	AI Role; Structure	Pedagogy	Competencies
Tan et al. (2026) [337]	China	STEM	SURV, n = 634	Ctx	Other; ?	—	CRr±, OTr+, CRr+
Tei-Narh et al. (2026) [338]	Ghana	Mech./Ind.	SURV, n = 394	Ctx	Co-creator; ?	—	CTr+, CRr+
Zhou et al. (2025) [339]	China	EE	SURV, n = 804	Ctx	Other; ?	—	CRr+, CTr+
Contextual literature: reviews (n = 31)							
Abdelsattar et al. (2025) † [340]	n.r.	Civil/Arch.	REV	Ctx	Scenario generator; ?	PBL, COL, DT	—
Aldossary et al. (2026) † [68]	—	Engineering	REV	Ctx	Tutor; ?	PBL, FB, GAM, SIM	—
Almasri (2026) † [341]	—	Engineering	REV	Ctx	Tutor; ?	PBL, SIM, XR, EXP, COL, FB, GAM	—
Arif et al. (2026) [62]	—	Computing/SE	REV	Ctx	Analytics; ?	GAM, XR, SIM, RP, EXP	—
Baba (2026) [342]	—	Mech./Ind.	REV	Ctx	Other; ?	EXP, SIM, XR, PBL, GAM	—
Badalov and Movsumova (2025) † [224]	—	Engineering	REV	Ctx	Tutor; ?	SIM, DT, PBL, EXP	—
Badaoui et al. (2026) [343]	—	Engineering	REV	Ctx	Other; ?	PBL, XR, GAM, COL, FB	—
Balart et al. (2025) † [344]	—	Engineering	REV	Ctx	Other; ?	PBL, SIM, GAM, COL	—
Bin Qushem et al. (2025) [345]	—	Computing/SE	REV	Ctx	Analytics; ?	PBL, GAM, XR	—
Cai et al. (2026) † [69]	—	Sci./Math.	REV	Ctx	Tutor; ?	PBL, GAM, FB, XR, COL, EXP, DT	—

Table A1. *Cont.*

Study	Country	Discipline	Design	Scope	AI Role; Structure	Pedagogy	Competencies
Dahal et al. (2026) [346]	—	Design/STEAM	REV	Ctx	Co-creator; ?	PBL, EXP, DT, SIM, COL	—
Fang (2026) † [347]	—	Design/STEAM	REV	Ctx	Co-creator; ?	PBL	—
Guo (2026) [64]	—	Design/STEAM	REV	Ctx	Co-creator; ?	PBL, DT, COL	—
Hosny et al. (2026) [223]	—	Civil/Arch.	REV	Ctx	Other; ?	XR, SIM, EXP, PBL, COL, GAM, FB	—
Jadeja et al. (2025) † [348]	—	Engineering	REV	Ctx	Tutor; ?	DT, GAM	—
Li et al. (2026) [65]	—	Design/STEAM	REV	Ctx	Co-creator; ?	PBL, DT, COL	—
Liu et al. (2026) [58]	—	STEM	REV	Ctx	Feedback; ?	XR, SIM, RP	—
Mishra et al. (2025) [57]	—	Engineering	REV	Ctx	Role-play partner; ?	RP, SIM, XR, GAM	—
Mulamba et al. (2025) [60]	—	Chem./Bio./Mat.	REV	Ctx	Tutor; ?	XR, SIM, EXP, PBL	—
Nedungadi et al. (2026) [221]	—	STEM	REV	Ctx	Other; ?	XR, GAM, SIM, PBL, EXP	—
Ntunka et al. (2024) [66]	—	Computing/SE	REV	Ctx	Other; ?	PBL, XR, DT, SIM	—
Ojetunde et al. (2026) [59]	—	Sci./Math.	REV	Ctx	VR/game agent; ?	XR, RP	—
Otto et al. (2025) [67]	—	Computing/SE	REV	Ctx	Co-creator; ?	PBL, COL, RP, SIM, FB	—
Pacheco-Olea et al. (2026) [222]	—	Computing/SE	REV	Ctx	Other; ?	XR, SIM, GAM, PBL, FB, COL	—
Quartulli et al. (2026) [61]	—	Computing/SE	REV	Ctx	Tutor; ?	GAM, XR, SIM	—

Table A1. *Cont.*

Study	Country	Discipline	Design	Scope	AI Role; Structure	Pedagogy	Competencies
Sembey et al. (2024) [63]	—	Computing/SE	REV	Ctx	Feedback; ?	SIM, XR, GAM, COL	—
Shaw et al. (2025) † [349]	—	Engineering	REV	Ctx	Tutor; ?	PBL, COL	—
Siddhpura et al. (2020) † [350]	—	Engineering	REV	Ctx	Tutor; ?	XR, SIM, COL, FB	—
Souza and Debs (2024) † [351]	—	Engineering	REV	Ctx	Analytics; ?	GAM, FB, PBL, SIM	—
Staneviciene et al. (2026) [56]	—	Computing/SE	REV	Ctx	Tutor; ?	FB, GAM, PBL	—
Sypsas et al. (2026) † [352]	—	Computing/SE	REV	Ctx	Tutor; ?	SIM, XR	—
Contextual literature: conceptual and framework papers (n = 21)							
Assaf et al. (2024) † [353]	—	Engineering	CONC	Ctx	Tutor; ?	PBL, EXP, SIM, COL	—
Balart et al. (2025) [354]	USA	Engineering	CONC	Ctx	Tutor; ?	PBL, SIM, GAM, COL, EXP	—
Calonge et al. (2026) † [355]	n.r.	Computing/SE	CONC	Ctx	Co-creator; ?	COL, PBL	—
Dignam et al. (2025) [166]	—	EE	CONC	Ctx	Analytics; ?	EXP, PBL, COL	—
Dubey et al. (2026) † [356]	n.r.	Engineering	CONC	Ctx	Co-creator; ?	DT, PBL, EXP, COL	—
Friesel (2025) † [357]	—	Engineering	CONC	Ctx	Other; ?	—	—
Karim et al. (2025) † [358]	Malaysia	Civil/Arch.	CONC	Ctx	Feedback; ?	PBL	—

Table A1. *Cont.*

Study	Country	Discipline	Design	Scope	AI Role; Structure	Pedagogy	Competencies
López Zapata and Cajaleón Flores (2018) † [359]	Peru	Mech./Ind.	CONC	Ctx	Feedback; ?	GAM, SIM, COL	—
Lourenço et al. (2025) [218]	—	EE	CONC	Ctx	Tutor; ?	GAM, XR, SIM, PBL, EXP, FB	—
Malathy et al. (2024) † [360]	India	Engineering	CONC	Ctx	Tutor; ?	—	—
Mamatjan et al. (2025) [361]	Canada	Computing/SE	CONC	Ctx	Tutor; ?	PBL, EXP, SIM, COL	—
Marquez et al. (2023) [215]	n.r.	Chem./Bio./Mat.	CONC	Ctx	Co-creator; ?	PBL, EXP, COL	—
Nikolic et al. (2025) † [362]	Australia	Engineering	CONC	Ctx	Co-creator; ?	PBL	—
Patlins (2025) † [363]	Latvia; Poland; Slovenia	EE	CONC	Ctx	Other; S	RP, COL, PBL, FB	—
Pereira et al. (2025) † [364]	Brazil	Engineering	CONC	Ctx	Tutor; ?	PBL	—
Shabalala (2024) † [365]	—	STEM	CONC	Ctx	Tutor; ?	XR, SIM, COL	—
Taylor (2026) † [366]	South Africa	Computing/SE	CONC	Ctx	Other; ?	—	—
Tshikolu et al. (2025) [219]	DR Congo	Computing/SE	QUAL	Ctx	Tutor; ?	PBL, EXP, SIM	—
Wang and Wang (2025) † [367]	China	Computing/SE	CONC	Ctx	Scenario generator; ?	PBL, SIM, DT, FB	—
Zhan and Wang (2024) † [368]	—	EE	CONC	Ctx	Feedback; ?	PBL, EXP, SIM, COL	—

Table A1. *Cont.*

Study	Country	Discipline	Design	Scope	AI Role; Structure	Pedagogy	Competencies
Zhong et al. (2026) † [369]	n.r.	Engineering	CONC	Ctx	Co-creator; S	PBL, EXP	—
Contextual literature: design or implementation reports (n = 51)							
Abdelfattah et al. (2023) † [370]	Egypt	Computing/SE	DES	Ctx	Co-creator; S	EXP, PBL	—
Adib et al. (2026) † [371]	USA	EE	DES	Ctx	Feedback; ?	GAM, XR, SIM, COL, EXP	—
Al Kalbani et al. (2025) [211]	UAE	EE	DES	Ctx	Co-creator; ?	PBL, SIM, EXP	—
Alex (2025) † [372]	France	Mech./Ind.	DES	Ctx	Scenario generator; ?	XR, SIM, EXP	—
Aparicio-Téllez et al. (2026) † [108]	Spain	Sci./Math.	DES	Ctx	Scenario generator; ?	PBL, COL	—
Ayora et al. (2025) [104]	Spain	Computing/SE	DES	Ctx	Scenario generator; ?	GAM, COL, PBL	—
Cao (2026) † [373]	China	EE	DES	Ctx	Tutor; S	SIM, EXP, XR	—
Chen et al. (2025) [374]	UK	Computing/SE	CS	Ctx	Co-creator; S	PBL, RP, COL	—
Chen et al. (2025) [375]	China	Computing/SE	CS	Ctx	Co-creator; S	PBL, COL	—
Danahy (2025) † [376]	USA	Engineering	DES	Ctx	Role-play partner; S	DT, RP, SIM, COL	—
Diona et al. (2025) [377]	Philippines	Computing/SE	SURV	Ctx	Tutor; S	SIM, EXP, GAM, COL	—
Douss et al. (2026) † [378]	Tunisia	Computing/SE	DES	Ctx	Feedback; S	PBL, COL	—
Durrani et al. (2025) [379]	UAE	Computing/SE	DES	Ctx	Co-creator; ?	PBL, EXP, SIM	—

Table A1. *Cont.*

Study	Country	Discipline	Design	Scope	AI Role; Structure	Pedagogy	Competencies
Gradone et al. (2025) † [380]	USA	Engineering	DES	Ctx	Tutor; ?	EXP, PBL, COL	—
Hang et al. (2026) † [124]	n.r.	Computing/SE	DES	Ctx	Role-play partner; ?	RP, SIM, EXP, PBL, COL	—
Harsh et al. (2025) [160]	India	Engineering	CS	Ctx	Feedback; ?	EXP	—
Hasan et al. (2025) [381]	China; Mexico	EE	DES	Ctx	Tutor; ?	EXP	—
Hochstetter-Diez et al. (2025) [382]	Peru; Chile	Computing/SE	DES	Ctx	Feedback; ?	—	—
Jahnke (2025) † [383]	USA	Engineering	DES	Ctx	Co-creator; S	DT	—
Kajal et al. (2026) † [384]	India	EE	DES	Ctx	Feedback; U	SIM	—
Kamoun and Iqbal (2025) † [105]	n.r.	Computing/SE	DES	Ctx	Scenario generator; ?	EXP, RP, PBL	—
Kumar et al. (2026) † [385]	n.r.	Mech./Ind.	DES	Ctx	Tutor; ?	SIM, DT, EXP	—
Li et al. (2025) † [386]	China	Engineering	DES	Ctx	Tutor; ?	PBL	—
Li et al. (2026) † [107]	China	Mech./Ind.	DES	Ctx	Scenario generator; ?	PBL, XR, SIM, FB, GAM, COL	—
Lim et al. (2025) † [387]	Australia	Chem./Bio./Mat.	CS	Ctx	Analytics; S	DT, PBL, COL	—
Lin et al. (2025) † [388]	USA	Mech./Ind.	QE	Ctx	VR/game agent; S	XR, EXP, SIM, GAM	—
Long et al. (2025) [389]	Greece	Computing/SE	DES	Ctx	Tutor; ?	XR, EXP	—

Table A1. *Cont.*

Study	Country	Discipline	Design	Scope	AI Role; Structure	Pedagogy	Competencies
Loo et al. (2025) [390]	UK	EE	DES	Ctx	Tutor; ?	PBL, COL, GAM, FB	—
Luo et al. (2025) † [391]	China	STEM	DES	Ctx	Scenario generator; ?	XR, SIM, GAM, RP, COL, FB, PBL	—
Maalaoui and Samet (2025) † [392]	Tunisia	Computing/SE	DES	Ctx	Tutor; S	PBL	—
Manzo and Sakib (2026) † [393]	USA	Mech./Ind.	DES	Ctx	Tutor; S	SIM, PBL, GAM	—
McGregor (2026) † [394]	South Africa	Mech./Ind.	DES	Ctx	Co-creator; S	EXP	—
Mosovsky et al. (2026) † [127]	USA	Chem./Bio./Mat.	DES	Ctx	Role-play partner; ?	RP, SIM, PBL	—
Mushtaq et al. (2025) [161]	UK; UAE; Pakistan; Qatar	Computing/SE	CS	Ctx	Feedback; ?	PBL	—
Neely et al. (2025) [395]	USA	Computing/SE	DES	Ctx	VR/game agent; ?	XR, SIM, PBL, EXP	—
Paul et al. (2025) † [396]	Canada	Engineering	DES	Ctx	Other; U	PBL, COL	—
Peng et al. (2026) † [397]	China	Mech./Ind.	DES	Ctx	Scenario generator; ?	XR, SIM	—
Pereira et al. (2024) [398]	Spain	Computing/SE	DES	Ctx	Role-play partner; ?	RP, SIM, PBL	—
Plappert et al. (2020) † [95]	Germany	Mech./Ind.	DES	Ctx	Feedback; ?	PBL	—
Ponce et al. (2026) [122]	USA; Mexico	Mech./Ind.	DES	Ctx	VR/game agent; ?	XR, SIM, GAM, EXP	—

Table A1. *Cont.*

Study	Country	Discipline	Design	Scope	AI Role; Structure	Pedagogy	Competencies
Prince et al. (2025) † [399]	India	Engineering	DES	Ctx	Feedback; S	SIM	—
Shehadeh et al. (2026) [214]	Jordan	EE	DES	Ctx	Feedback; ?	XR, SIM, PBL, EXP	—
Sockalingam et al. (2025) † [170]	Singapore	Design/STEAM	DES	Ctx	Analytics; ?	PBL, COL, GAM, XR, DT, FB	—
Starling and Tian (2025) † [400]	USA	Engineering	DES	Ctx	Co-creator; S	PBL, COL	—
Tarasak et al. (2026) [100]	Thailand	EE	DES	Ctx	Scenario generator; ?	SIM	—
Torres et al. (2025) † [401]	Mexico	Computing/SE	DES	Ctx	Analytics; ?	PBL, COL	—
Tripepi et al. (2026) [402]	USA	Sci./Math.	CS	Ctx	Other; S	EXP, PBL	—
Turkin et al. (2026) † [403]	Ukraine	Computing/SE	DES	Ctx	Tutor; ?	SIM	—
Veselá et al. (2024) † [216]	Czech Republic	Design/STEAM	DES	Ctx	Co-creator; ?	DT, PBL, EXP	—
Yahyaeian et al. (2025) [404]	USA	Mech./Ind.	DES	Ctx	VR/game agent; ?	XR, SIM, EXP	—
Zhang (2026) [151]	China	Civil/Arch.	DES	Ctx	Tutor; ?	SIM, EXP	—

Design: RCT randomized or crossover experiment; QE quasi-experiment; PP single-group pre–post; MM mixed methods; QUAL qualitative; SURV cross-sectional survey; CS case study or experience report; DES design or implementation report; REV review; CONC conceptual. Scope: Core, Comp. competency-only, Ped. pedagogy-only, Ctx contextual. Structure: S structured, U unconstrained, B both compared, ? unclear or n/a. Pedagogy: PBL project-, problem- or challenge-based; COL collaborative; EXP experiential; SIM simulation; GAM games/gamification; XR immersive VR/AR/XR; RP role-play; FB flipped/blended; DT design thinking; DR drama/improvisation. Competencies: CM communication; TW collaboration/teamwork; CR creativity; CT critical thinking; PS problem solving; SR self-regulation/metacognition; EI emotional intelligence/empathy; AD adaptability; ET ethics/responsibility; LD leadership; ST systems thinking; OT other; contrast: b between-group, w within-group, r correlational, d descriptive; direction: + positive, ± mixed, ns non-significant, − negative, ? not determinable, nm targeted but not measured. n.r. not reported; — not applicable. † Study identified in Scopus or IEEE Xplore or obtained through later retrieval efforts.

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