

Artificial Intelligence-Assisted Learning and Epistemic Agency: A Critical Scoping Review and Conceptual Synthesis of Psychological Responses and Epistemic Dependence*

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ABSTRACT

Artificial intelligence-assisted learning can improve academic performance while simultaneously weakening the learner's role in understanding, evaluation, and judgment. This study presents a critical scoping review and conceptual synthesis of psychological responses to artificial intelligence-assisted learning and their implications for human epistemic agency. Structured searches of Scopus and the Education Resources Information Center identified 32 empirical studies published between 2022 and 2026. Because 38 of 106 reports sought for retrieval were inaccessible, the corpus is treated as a bounded empirical baseline rather than an exhaustive census of the literature. Two broad trajectories emerged. Active and regulated use was associated with higher self-efficacy, confidence, perceived competence, feedback engagement, and metacognitive monitoring. In contrast, unregulated automation was associated with dependency, overreliance, anxiety, self-doubt, and uncertainty about competence. Philosophically, these patterns support a distinction between epistemic scaffolding and epistemic substitution. Drawing on Sosa's virtue epistemology, scaffolding occurs when artificial intelligence contributes to task accuracy while the learner's adroitness remains causally relevant to success, preserving apt performance. Substitution occurs when an output is accurate but its success is no longer attributable to the learner's competence, rendering the performance epistemically inapt. Cognitive offloading helps explain the transition between these modes. No included study directly measured the impostor phenomenon using a validated impostor instrument; it is therefore reframed as a Competence Attribution Ambiguity Hypothesis rather than an established empirical effect. Responsible artificial intelligence use in education requires calibrated dependence, active metacognitive control, and preservation of human epistemic agency.

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Intruduction

Artificial intelligence (AI) has rapidly become embedded in learning, writing, feedback, assessment, and academic support. Generative AI and large language models (LLMs) can provide explanations, generate ideas, revise text, and support complex academic tasks. Recent reviews document substantial educational benefits alongside concerns about accuracy, academic integrity, overreliance, and the quality of learning produced through AI assistance (Batista et al., 2024; Kasneci et al., 2023; Lo, 2023; Tlili et al., 2023). AI is also entering student-support and mental health-related environments, extending questions of reliance and human judgment beyond conventional classroom tasks (Olla et al., 2025).

These technologies, however, should not be treated as epistemically equivalent. Autoregressive LLMs such as ChatGPT generate outputs through probabilistic next-token prediction and do not possess human-like truth commitment or understanding (Bender et al., 2021; Hicks et al., 2024). Traditional intelligent tutoring systems typically rely on explicit learner models, rule-based mechanisms, or probabilistic knowledge-tracing procedures to adapt instruction, whereas automated writing evaluation systems primarily provide linguistic, syntactic, or feedback-oriented support. This distinction matters because the epistemic risks of persuasive confabulation, uncritical reliance, and extensive cognitive offloading are especially salient when generative systems produce explanations, arguments, or complete academic outputs.

The central problem is therefore not simply whether AI improves performance. A learner may produce an accurate, fluent, or persuasive output with substantial AI assistance while lacking the understanding required to evaluate, justify, or defend it. This creates a distinction between successful task performance and epistemic achievement. As AI increasingly mediates access to explanations and academic judgments, an important philosophical question emerges: when does AI extend human competence, and when does it begin to substitute for the cognitive activity through which knowledge and intellectual responsibility are achieved?

This question concerns human epistemic agency. In AI-assisted learning, learners may remain active epistemic agents who formulate questions, evaluate generated information, detect errors, revise outputs, and assume responsibility for final judgments. Alternatively, they may increasingly delegate these activities to the system. Jose et al. (2025) argue that generative AI is reshaping epistemic authority in learning environments by altering relationships among knowledge, justification, learners, teachers, and technological systems. The educational significance of AI therefore depends not only on what the technology enables learners to produce, but also on whether learners remain meaningfully involved in the epistemic processes underlying that production.

Psychological responses to AI-assisted learning are relevant to this problem because they can reveal how learners perceive their own competence and participation. AI assistance may strengthen self-efficacy, confidence, and perceived competence when it supports understanding, feedback interpretation, and independent task completion. The same assistance

may also generate self-doubt, anxiety, dependency, or uncertainty when learners cannot determine whether successful performance reflects their own ability or the contribution of the system. These responses should not be interpreted as direct measures of epistemic agency, but they provide an empirical basis for examining how learners experience competence, reliance, and ownership in AI-assisted achievement.

The impostor phenomenon represents a narrower issue within this broader competence-attribution problem. It involves persistent doubts about personal competence and difficulty internalizing achievement despite evidence of success (Bravata et al., 2020). Its relevance in higher education is well established (Yang et al., 2024), but direct empirical evidence linking AI-assisted learning to the impostor phenomenon remains insufficient. Self-doubt, anxiety, or authenticity concerns should therefore not be treated as equivalent to validated impostor experiences. In the present study, the impostor phenomenon is positioned instead as a theoretical hypothesis of competence-attribution ambiguity: AI-assisted success may make it more difficult for learners to determine whether achievement reflects their own competence or algorithmic contribution. This hypothesis requires direct future testing with validated psychometric instruments.

Existing scholarship remains divided between empirical research on the psychological effects of AI-assisted learning and philosophical work on epistemic authority, understanding, and human judgment. Educational reviews have largely emphasized applications, performance, implementation, and academic integrity (Batista et al., 2024; Lo, 2023), while philosophical analyses have questioned whether fluent generative systems should be treated as reliable epistemic authorities (Hicks et al., 2024; Jose et al., 2025). What remains underdeveloped is a framework that connects empirical patterns of confidence, self-efficacy, perceived competence, self-doubt, and dependence with the philosophical question of whether AI assistance preserves or displaces human epistemic competence.

The present study addresses this gap through a critical scoping review and conceptual synthesis. The empirical literature is treated as a structured, bounded corpus for identifying recurring psychological and behavioral patterns rather than as an exhaustive statistical census. These patterns are then used to develop a philosophical distinction between epistemic scaffolding, in which AI supports performance while learners retain meaningful epistemic control, and epistemic substitution, in which successful performance becomes increasingly detached from the learner's own competence. This distinction provides a basis for examining how AI-assisted success can remain epistemically attributable to the learner rather than merely technologically produced.

Accordingly, this study addresses four questions: (1) What competence-related psychological responses have been reported in AI-assisted learning? (2) What patterns distinguish active, regulated AI use from unregulated automation and dependence? (3) How do these patterns relate to competence attribution, cognitive offloading, and epistemic dependence? and (4) What conceptual conditions distinguish epistemic scaffolding from

epistemic substitution in AI-assisted learning? By integrating a structured empirical corpus with philosophical analysis, the study aims to clarify when AI functions as an extension of human epistemic agency and when it begins to displace the competence required for epistemic achievement.

Methodology

This study employed a critical scoping review and conceptual synthesis to map competence-related psychological responses to artificial intelligence (AI)-assisted learning and to use the resulting empirical corpus as a structured basis for philosophical analysis. The review was guided by the scoping review framework of [Arksey and O'Malley \(2005\)](#) and its methodological refinements by [Levac et al. \(2010\)](#), including identification of the research questions, identification of relevant studies, study selection, data charting, and synthesis of findings. PRISMA-based flow reporting was retained solely to provide transparency regarding identification, screening, retrieval, and corpus construction, consistent with reporting principles for scoping reviews ([Tricco et al., 2018](#)). No prospective protocol was registered. The study does not claim to provide an exhaustive statistical census of the literature; rather, it develops a bounded empirical corpus for critical and philosophical synthesis.

The empirical scope centered on competence-related psychological responses explicitly represented in the original search strategy, including self-doubt, academic confidence, academic or writing self-efficacy, perceived competence, and exploratory terms related to the impostor phenomenon. Additional responses—including anxiety, stress, dependency, overreliance, and authenticity concerns—were charted when they were reported within otherwise eligible studies and were relevant to competence attribution or epistemic agency. Impostor-related search terms were retained because they formed part of the original search strategy; however, the revised synthesis does not treat the impostor phenomenon as an established empirical outcome unless it was directly assessed. Instead, its relevance is considered conceptually in the subsequent theoretical synthesis.

Studies were eligible if they were published in English between 2017 and 2026; examined AI or AI-based educational technologies; assessed at least one competence-related psychological construct represented in the search strategy; were situated in educational, academic, counseling, student-support, or related mental health contexts; and reported primary empirical findings. Quantitative, qualitative, mixed-methods, experimental, quasi-experimental, and survey designs were eligible. Studies were excluded if they were purely technical, addressed only general AI adoption or behavioral intention, did not examine a predefined competence-related psychological construct, lacked primary empirical findings or sufficient methodological information, or were duplicates. Reports for which full text could not be retrieved were recorded separately as reports not retrieved and were not counted among full-text exclusions.

Scopus and the Education Resources Information Center (ERIC) were searched because they provide complementary coverage: Scopus offers broad interdisciplinary indexing, whereas ERIC provides education-specific coverage. These databases were not assumed to provide complete retrieval of the relevant literature. The omission of other potentially relevant databases, including PsycINFO and Web of Science Core Collection, is therefore treated as a boundary of the evidence base rather than as evidence of comprehensive database coverage. The final search was conducted on May 2, 2026, and no records were added afterward. Search terms combined three clusters addressing AI technologies, competence-related psychological constructs, and educational or support contexts. The complete database-specific search strings are presented in Table 1. Search reporting followed PRISMA-S conventions where applicable (Rethlefsen et al., 2021).

Table 1. Search strings used in Scopus and ERIC.

Database	Search Field and Search String	Limits/filters
Scopus	TITLE-ABS-KEY(("artificial intelligence" OR "generative AI" OR ChatGPT OR "large language model*" OR "AI writing tool*" OR "AI writing assistant*" OR "AI-assisted learning" OR "intelligent tutoring system*" OR "mental health chatbot*" OR "conversational agent*" OR "AI literacy") AND ("impostor*" OR "imposter*" OR "self-doubt" OR "self doubt" OR "academic confidence" OR "academic self-efficacy" OR "writing self-efficacy" OR "perceived competence") AND (student* OR learner* OR academic* OR educat* OR counsel* OR "mental health")) AND PUBYEAR > 2016	Publication year: 2017–2026
ERIC	("artificial intelligence" OR "generative AI" OR ChatGPT OR "large language model" OR "large language models" OR "AI writing tool" OR "AI writing tools" OR "AI writing assistant" OR "AI writing assistants" OR "AI-assisted learning" OR "intelligent tutoring system" OR "intelligent tutoring systems" OR "mental health chatbot" OR "mental health chatbots" OR "conversational agent" OR "conversational agents" OR "AI literacy") AND ("impostor" OR "imposter" OR "impostor syndrome" OR "imposter syndrome" OR "impostor phenomenon" OR "imposter phenomenon" OR "self-doubt" OR "self doubt" OR "academic confidence" OR "academic self-efficacy" OR "writing self-efficacy" OR "perceived competence") AND (student OR students OR learner OR learners OR academic OR academics OR education OR educational OR educator OR educators OR counseling OR counselling OR counselor OR counsellor OR "mental health")	Publication date: last ten years; peer-reviewed only; journal articles and research reports

All retrieved records were exported to reference-management software and screened using Rayyan (Ouzzani et al., 2016). Duplicates were removed before title and abstract screening. Two reviewers independently screened titles and abstracts against the eligibility criteria and

then assessed available full texts. Disagreements were resolved through discussion and consensus. Of the 106 reports sought for full-text retrieval, 38 (35.8%) could not be accessed through the institutional and open-access channels available to the review team. This retrieval ceiling represents a material boundary of the evidence base and may have introduced non-random retrieval bias. Accordingly, the 32 included studies are interpreted as a structured scoping corpus rather than an exhaustive representation of all eligible research. Figure 1 transparently reports the identification, screening, retrieval, eligibility, and final corpus-construction process.

For analytical purposes, AI technologies were differentiated by their dominant functional architecture. Generative and autoregressive systems, including large language model-based chatbots such as ChatGPT, generate probabilistic outputs and may produce extended explanations, arguments, or text. Intelligent tutoring and adaptive systems use explicit learner or mastery models, including rule-based or probabilistic knowledge-tracing mechanisms, to personalize instruction. Automated writing evaluation and feedback systems primarily provide linguistic, syntactic, corrective, or evaluative feedback. Related detection tools were classified separately where necessary. This distinction was retained because epistemic risks such as persuasive confabulation, extensive cognitive offloading, and end-to-end delegation of reasoning are especially relevant to generative systems and should not automatically be generalized to all forms of educational AI.

Data were charted using a standardized form covering author and year, country, study design, population, AI technology, educational context, primary competence-related construct, additional co-reported psychological responses, measurement instrument, key findings, methodological limitations, and relevance to the research questions. Additional psychological responses not explicitly included in the search terms were charted only when reported within studies that had already satisfied the eligibility criteria. Methodological quality was critically appraised using the Mixed Methods Appraisal Tool 2018 (Hong et al., 2018). Although formal quality appraisal is not mandatory in conventional scoping reviews, it was retained here because the study adopts a critical scoping orientation. Appraisal results were not used to exclude studies but informed the interpretation of evidentiary strength. Study characteristics are summarized in Supplementary Table 1 and appraisal results in Supplementary Table 2.

Synthesis proceeded in two stages. First, the empirical corpus was descriptively mapped by technology, population, psychological construct, and mode of AI engagement. Recurrent patterns were then organized into two higher-order trajectories: active and regulated AI use, in which learners remained engaged in evaluation, feedback processing, metacognitive monitoring, and task regulation; and unregulated automation and dependence, in which AI use was accompanied by extensive reliance, reduced independent engagement, uncertainty about competence, or related adverse responses. These categories were used as interpretive groupings rather than causal classifications.

Second, the mapped patterns were subjected to conceptual synthesis in relation to epistemic agency, epistemic dependence, cognitive offloading, competence attribution, authorship, and responsibility. This philosophical stage examined the conditions under which AI assistance could be interpreted as epistemic scaffolding, preserving meaningful human competence and judgment, or as epistemic substitution, in which successful performance becomes increasingly detached from the learner's own epistemic contribution. The conceptual synthesis did not alter study eligibility, data extraction, or the empirical corpus; it provided the normative framework through which the mapped evidence was interpreted.

Results

The search identified 259 records, comprising 217 from Scopus and 42 from ERIC. After removing 44 duplicates, 215 records underwent title and abstract screening, of which 109 were excluded. Of the 106 reports sought for full-text retrieval, 38 (35.8%) could not be accessed through the institutional and open-access channels available to the review team. Sixty-eight full-text articles were therefore assessed for eligibility. Thirty-six were excluded: 20 did not examine the predefined competence-related psychological constructs, 13 provided only contextual or supporting evidence, and three lacked primary empirical findings. The final scoping corpus comprised 32 empirical studies (Figure 1). Because more than one-third of reports sought for retrieval were unavailable, the corpus is interpreted as a bounded empirical baseline rather than an exhaustive representation of the literature.

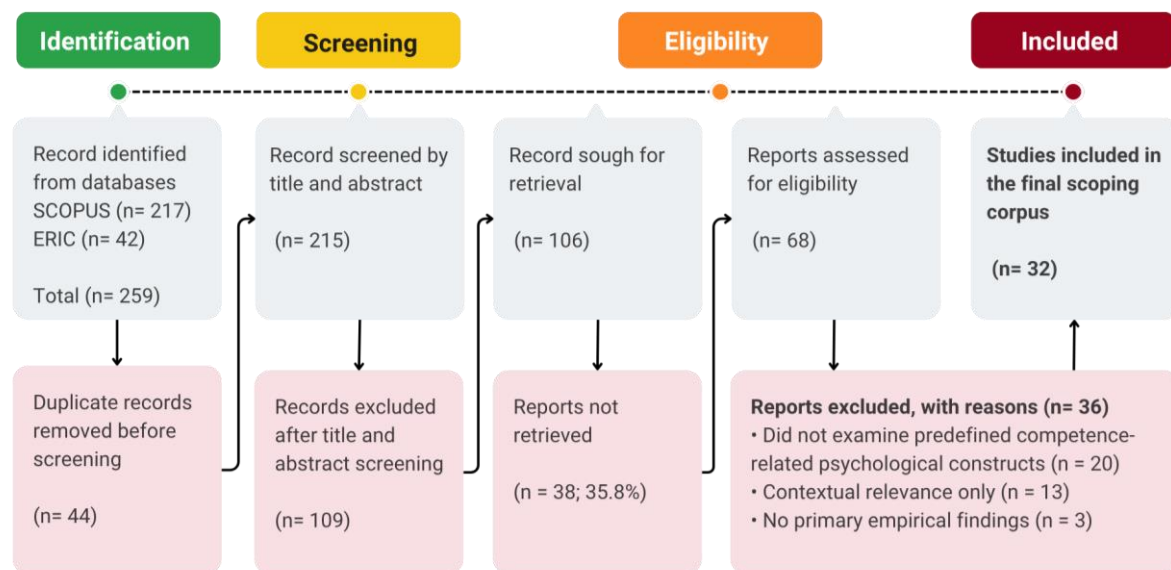


Figure 1. PRISMA-ScR-informed flow of study identification, screening, retrieval, eligibility assessment, and scoping corpus construction.

The included studies were published between 2022 and 2026, although the search covered 2017–2026. Most appeared in 2025 and 2026. Research was concentrated in higher education and included undergraduate and postgraduate students, pre-service teachers, engineering and

nursing students, language learners, and international students. Writing-related settings were particularly common, including EFL/L2 writing, academic and argumentative writing, research writing, technical report writing, and digital storytelling. Evidence from counseling and mental health-related contexts was comparatively limited and primarily concerned anxiety, stress, self-doubt, perceived competence, and related psychological responses rather than clinical outcomes.

The technologies represented in the corpus were heterogeneous. Generative AI and large language model-based systems, including ChatGPT and related writing assistants, were the most prominent. Non-generative educational AI, including educational chatbots, adaptive systems, and automated feedback technologies, was also represented, although system architecture was not always reported in sufficient detail to classify individual tools confidently as intelligent tutoring systems or automated writing evaluation systems. These technologies were analyzed separately where their functional differences were relevant because the forms of learner engagement and potential for extensive delegation differed across systems.

Methodological appraisal indicated that most studies met the relevant design-specific criteria of the Mixed Methods Appraisal Tool. Recurring concerns included incomplete reporting of confounding control, potential non-response bias, reliance on self-report measures, short intervention periods, and limited reporting of sampling procedures or measurement validity. Study characteristics are summarized in Supplementary Table 1, and quality appraisal results are presented in Supplementary Table 2.

Across the corpus, two broad empirical trajectories were evident. The first was active and regulated AI use. In this trajectory, AI supported idea generation, revision, feedback interpretation, task clarification, and other learning activities while learners remained actively engaged in evaluation and regulation. These studies reported higher self-efficacy, writing confidence, perceived competence, feedback engagement, and related constructive responses (Lee et al., 2025; Maeng, 2025; Song et al., 2026; Yang et al., 2025). Studies examining AI literacy, metacognitive strategies, and feedback literacy similarly indicated that more reflective and regulated use was associated with more constructive engagement with AI-assisted learning (Wang, 2026; Liu & Zhang, 2025; Shen & Tao, 2025; Zhou & Wang, 2026).

The second trajectory was unregulated automation and dependence. Here, learners relied more extensively on generated suggestions, completed outputs, or automated evaluation, sometimes alongside reduced confidence in completing tasks independently. Co-reported responses included dependency, overreliance, anxiety, stress, self-doubt, reduced confidence, fear of judgment, and authenticity concerns (Adekoya et al., 2026; Jiang & Xu, 2026; Kalimira & Jazayeri, 2026; Ma et al., 2025; Wang & Xu, 2026; Zhang et al., 2024). These patterns were especially salient when learners questioned whether successful performance reflected their own competence, compared their abilities with AI-generated output, or accepted AI assistance with limited independent evaluation.

The distinction between these trajectories was not equivalent to a simple positive-versus-negative classification. The same technology could support constructive or problematic responses depending on how learners engaged with it. Generative AI, for example, was associated with stronger confidence and self-efficacy when used for feedback and revision, but also with dependency, anxiety, or uncertainty about competence when learners relied heavily on generated outputs. The relevant empirical contrast therefore concerned the degree of learner regulation, evaluation, and independent engagement rather than the technological tool alone.

No included study directly measured the impostor phenomenon using a validated impostor instrument. Although impostor-related terms formed part of the original search strategy, the final corpus primarily examined adjacent constructs such as self-doubt, anxiety, perceived competence, AI guilt, authenticity concerns, and uncertainty about personal ability. Accordingly, the results do not support treating the impostor phenomenon as an established psychological effect of AI-assisted learning. Its possible relevance is developed later as a theoretical question concerning competence attribution.

Table 2 summarizes the two empirical trajectories and their relevance to the four research questions. The table distinguishes observed psychological patterns from their subsequent conceptual interpretation; the latter is developed in the Discussion rather than treated as an empirical finding.

Table 2. *Empirical trajectories across the critical scoping corpus*

Empirical trajectory	Mode of learner engagement	Main psychological patterns	Illustrative studies	Relevance to epistemic analysis
Active and regulated AI use	Learners used AI for feedback, idea generation, revision, clarification, or task support while retaining active evaluation, metacognitive monitoring, and decision-making.	Higher self-efficacy, confidence, perceived competence, feedback engagement, and more constructive AI use.	Lee et al. (2025); Maeng (2025); Song et al. (2026); Wang (2026); Liu & Zhang (2025); Shen & Tao (2025); Yang et al. (2025); Zhou & Wang (2026)	Provides the empirical basis for examining AI as epistemic scaffolding, where technological assistance supports but does not replace learner judgment.
Unregulated automation and dependence	Learners relied extensively on generated suggestions, completed outputs, or automated evaluation, with reduced independent engagement or uncertainty about personal competence.	Dependency, overreliance, anxiety, stress, self-doubt, reduced confidence, fear of judgment, and authenticity concerns.	Adekoya et al. (2026); Jiang & Xu (2026); Kalimira & Jazayeri (2026); Ma et al. (2025); Wang & Xu (2026); Zhang et al. (2024)	Provides the empirical basis for examining epistemic substitution, particularly when successful performance becomes less clearly attributable to the learner's own competence.

Note. The categories represent recurrent patterns across the bounded scoping corpus and should not be interpreted as causal classifications. Additional psychological responses were included only when reported within studies that had already satisfied the predefined eligibility criteria. No included study directly measured the impostor phenomenon using a validated impostor instrument; its relevance is therefore treated as a conceptual hypothesis rather than an empirical trajectory.

Discussion

The scoping corpus revealed two recurring trajectories: active, regulated AI use was associated with higher self-efficacy, confidence, perceived competence, and feedback engagement, whereas unregulated automation was associated with dependency, overreliance, anxiety, self-doubt, and uncertainty about competence (Lee et al., 2025; Maeng, 2025; Song et al., 2026; Yang et al., 2025; Jiang & Xu, 2026; Kalimira & Jazayeri, 2026; Zhang et al., 2024). This contrast is consistent with evidence beyond the corpus showing that generative AI may improve immediate performance while weakening later unaided performance when assistance replaces rather than supports reasoning (Bastani et al., 2025), and that AI dependency can coexist with lower critical-thinking effort or weaker independent achievement (H.-P. H. Lee et al., 2025; Lintner et al., 2026; Tian & Zhang, 2026). The philosophical issue is therefore not whether AI helps, but what kind of human epistemic participation remains when it does.

Epistemic Dependence: Instrumental Reliance versus Testimonial Trust

Dependence is not inherently epistemically defective. Hardwig (1985) showed that modern knowledge practices necessarily depend on other knowers whose expertise cannot be independently reconstructed by every epistemic agent. Yet reliance on a large language model differs from ordinary testimonial dependence. Human testimony involves a speaker who can believe, intend, answer challenges, and bear social or professional responsibility. Conversational AI does not stand in that normative relation to the recipient. Freiman (2024) therefore argues that AI-mediated belief acquisition cannot simply be assimilated to ordinary testimony, while Magnus (2025) shows that familiar heuristics for trusting human informants transfer poorly to chatbots. Ferrario et al. (2024) likewise caution against inferring genuine epistemic authority from predictive or generative success alone.

This distinction sharpens the empirical pattern of dependency identified in the corpus. Heavy reliance becomes epistemically problematic when fluent output is treated as authoritative without independent evaluation, not merely when an external tool is used. Coeckelbergh (2026) similarly argues that AI can reshape belief revision and epistemic control. Accordingly, AI dependence is better understood as calibrated instrumental reliance: learners may rationally use AI as a resource, but they remain responsible for assessing relevance, credibility, and justification. Indonesian counseling scholarship documents the expansion of cybercounseling as a professional practice domain (Prabawa & Antika, 2023), while research on counselor mind

processes highlights reflective assessment and regulation in online counseling ([Ramli et al., 2023](#)).

Virtue Epistemology: Formalizing Scaffolding and Substitution through Sosa's AAA Framework

Sosa's virtue epistemology provides a precise boundary between epistemic scaffolding and epistemic substitution. A performance can be evaluated through Accuracy, Adroitness, and Aptness (Sosa, 2007, 2015). Accuracy (A1) concerns whether the performance reaches its target; Adroitness (A2) concerns whether it manifests the agent's relevant competence; and Aptness (A3) requires success because of that competence; successful performance must therefore remain causally attributable to the agent's exercised adroitness rather than merely coincide with it. An AI-assisted essay, solution, or explanation may therefore be accurate without being apt as a learner performance.

Epistemic scaffolding occurs when AI contributes to accuracy while the learner's own intellectual competence remains meaningfully involved in producing and evaluating the successful outcome. In this mode, the learner frames the problem, interrogates outputs, detects errors, compares reasons, revises claims, and determines the final judgment. The resulting performance is therefore not merely accurate but apt because its success remains causally attributable to the learner's exercised adroitness. By contrast, epistemic substitution occurs when AI supplies the decisive reasoning, synthesis, or judgment and the learner primarily accepts or stylistically modifies the output. The artifact may still be correct, but the learner's performance remains epistemically inapt because its success is no longer meaningfully attributable to the learner's own competence.

This distinction explains why performance gains and epistemic gains need not coincide. It aligns with arguments that AI extension remains epistemically responsible only when human cognitive control remains substantive ([Naeem & Hauser, 2024](#)) and with the distinction between complementary and substitutive uses of generative AI in learning ([Rivera-Novoa & Duarte Arias, 2026](#)). Related educational evidence also emphasizes the importance of evidence-based reasoning, critical evaluation, and collaborative responsibility ([Lingga et al., 2026](#)). Counseling scholarship likewise treats critical thinking and reflective mind skills as competencies that must be exercised by the agent rather than externally supplied ([Hidayah et al., 2020](#); [Hidayah et al., 2022](#)). Epistemic scaffolding is therefore defined not by minimal AI use, but by the preservation of human adroitness.

Cognitive Offloading and the Extended Mind

Cognitive offloading provides a mechanism through which scaffolding may become substitution. [Risko and Gilbert \(2016\)](#) define cognitive offloading as using external action or resources to reduce internal processing demands and show that decisions to offload are partly shaped by metacognitive judgments. Offloading is often rational. The extended-mind thesis

similarly suggests that external resources can become functionally integrated into cognition (Clark & Chalmers, 1998). AI assistance is therefore not epistemically problematic merely because cognition becomes distributed. However, the classic extended-mind case depends on an external resource that is stably available, reliably integrated, and routinely incorporated into the agent's cognitive practice. Generative LLMs complicate this condition because their outputs are probabilistic, variable, and require recurrent verification. Automatic endorsement of such outputs would therefore weaken rather than extend epistemic agency.

The tipping point occurs when learners offload not only search, storage, calculation, or routine processing but also the evaluative operations through which competence is manifested. Proust (2014) argues that epistemic agency in extended cognition depends on metacognitive monitoring and responsiveness to epistemic norms. This distinction is especially important for generative LLMs, which can generate arguments, explanations, and complete texts end-to-end; it should not automatically be generalized to more constrained intelligent tutoring or automated feedback systems.

The present corpus supports this interpretation. AI literacy, self-regulation, metacognitive strategies, and feedback literacy accompanied more constructive forms of AI engagement (Wang, 2026; Liu & Zhang, 2025; Shen & Tao, 2025; Zhou & Wang, 2026). Research on online counseling similarly shows that reflective metacognition supports assessment, prediction, and self-regulation under digitally mediated conditions (Ramli et al., 2023), while mind-skills training links metacognitive regulation with improved professional performance (Hidayah et al., 2022). Thus, the distinction is qualitative rather than quantitative. Extensive AI use may remain scaffolded when learners continue to evaluate and justify, whereas brief use may already be substitutive when a decisive inference is accepted without understanding. This also explains why frequency of AI use alone is a weak indicator of educational quality (Lintner et al., 2026).

Competence Attribution Ambiguity Hypothesis

The findings also reveal a calibration problem between perceived competence and actual epistemic participation. AI-assisted learning may increase self-efficacy and confidence, but these gains are educationally valuable only when they correspond to developing competence. Bandura (1997) conceptualizes self-efficacy as a judgment of capability rather than capability itself, while cognitive load theory cautions against equating supported task success with the internal acquisition of cognitive schemas (Sweller, 1988). Bastani et al. (2025) provide a contemporary demonstration of this distinction: AI-supported performance gains coexisted with poorer subsequent unaided performance when assistance was insufficiently constrained. When confidence increases without a corresponding increase in unaided competence, AI assistance may therefore produce an illusion of competence rather than genuine epistemic development.

The reverse mismatch is also possible. Learners may contribute meaningfully to an AI-assisted task but attribute excessive epistemic credit to the system. The corpus identified anxiety, competence uncertainty, self-doubt, and authenticity concerns consistent with such

attributional tension (Jiang & Xu, 2026; Ma et al., 2025; Wang & Xu, 2026). Broader student research also shows that self-efficacy is consequential for academic functioning and resilience, reinforcing the importance of accurate self-appraisal rather than confidence alone (Mufidah et al., 2025; Probowati et al., 2026). Among counselor students, self-awareness and self-efficacy similarly contribute to adaptive professional self-management (Setiyowati et al., 2025).

This is the appropriate conceptual location of the impostor phenomenon. No included study directly measured the impostor phenomenon using a validated impostor instrument; AI use should therefore not be claimed to cause or intensify the phenomenon. Instead, we propose a Competence Attribution Ambiguity Hypothesis: when learners succeed with substantial AI assistance, uncertainty may arise over whether the achievement reflects their own adroitness or algorithmic contribution. Digital environments can also reshape patterns of self-talk and self-evaluation, making this attributional question increasingly relevant (Mulawarman et al., 2026). Future research should test the hypothesis directly using validated impostor measures together with independent assessments of unaided competence and AI contribution.

Pedagogical and Institutional Safeguards

The framework implies that responsible AI education should protect the causal contribution of learner competence. Assessment should therefore move beyond terminal artifacts toward process-attributable evidence. Oral defense, reasoning logs, version histories, source-verification tasks, and exercises requiring students to detect and correct deliberately flawed AI outputs can make understanding, evaluation, and justification observable. Guardrailed educational AI should likewise function more as a Socratic interlocutor than an answer engine, offering hints, counterexamples, challenges, and requests for justification rather than routinely generating complete solutions. This approach is consistent with evidence that critical-thinking-centered instructional designs strengthen accountable reasoning (Lingga et al., 2026).

AI literacy should consequently be treated as epistemic literacy, not merely operational proficiency. Learners need to recognize uncertainty, verify claims, compare evidence, identify the limits of their own evaluative competence, and know when human expertise is required. Discipline-specific approaches to AI literacy reinforce this position (Stolpe et al., 2026), while Wu et al. (2025) argue that productive human–AI partnerships should preserve rather than marginalize human epistemic agency. Counselor-education research emphasizes professional competence, self-awareness, and reflective control (Setiyowati et al., 2025; Indreswari et al., 2024), while digital counseling training illustrates the need to develop these competencies for technology-mediated practice (Simon et al., 2025). These findings are relevant because the central safeguard is not technological prohibition but maintaining a human agent capable of evaluating and taking responsibility for technologically mediated decisions.

Digital counseling research in Indonesia further illustrates that technological transformation requires corresponding development of professional practices and competencies (Prabawa & Antika, 2023), while recent evidence suggests that digital environments can reshape students'

self-talk and emotional self-regulation (Mulawarman et al., 2026). These considerations support a human-guided rather than autonomous model of educational technology.

Finally, safeguards must operate institutionally as well as individually. Tanchuk (2026) warns that AI-personalized education may generate epistemic consolidation when a small number of systems become default knowledge intermediaries. Universities should therefore preserve plural sources of expertise, require transparent AI-use policies, enable human contestation and review, and avoid making a single generative architecture the de facto authority for learning. The aim is not to minimize AI assistance but to keep it scaffolded. AI-assisted accuracy should count as human epistemic achievement only when that accuracy remains meaningfully attributable to the learner's exercised competence.

Limitations and Future Research

Several limitations should be acknowledged. First, the review was based on a bounded scoping corpus rather than an exhaustive evidence base. Of 106 reports sought for retrieval, 38 (35.8%) were inaccessible, creating potential retrieval bias. The search was also limited to Scopus and ERIC, so studies indexed only in PsycINFO, Web of Science, or other databases may have been missed.

Second, the corpus was concentrated in higher education, particularly writing and language-learning contexts, which limits generalizability to other educational, counseling, clinical, and cultural settings. The included technologies were also heterogeneous, ranging from generative large language models to intelligent tutoring, automated writing evaluation, and detection systems.

Third, many studies used cross-sectional designs, self-report measures, or short interventions, limiting causal inference. Future research should use longitudinal and experimental designs, compare AI-assisted with unaided performance, and distinguish perceived from demonstrated competence.

No included study directly measured the impostor phenomenon using a validated impostor instrument; therefore, the proposed Competence Attribution Ambiguity Hypothesis requires direct testing with validated measures. Finally, epistemic scaffolding and epistemic substitution remain conceptual distinctions rather than validated empirical categories. Future studies should test whether metacognitive monitoring, verification, oral defense, and guardrailed AI preserve learner adroitness, aptness, and epistemic agency.

Conclusion

This critical scoping review and conceptual synthesis shows that AI-assisted learning can support both constructive and problematic psychological responses, depending on how learners engage with the technology. The central philosophical implication is that successful AI-assisted performance should not be equated with human epistemic achievement. Within Sosa's virtue-epistemological framework, accuracy is insufficient unless successful performance remains

causally attributable to the learner's exercised adroitness. When AI supports reasoning while learners retain understanding, evaluation, justification, and final judgment, it functions as epistemic scaffolding and can preserve apt performance. When these epistemic activities are delegated to AI, performance may remain accurate but become epistemically inapt, constituting epistemic substitution.

Cognitive offloading therefore becomes educationally significant when it displaces rather than supports human judgment. Responsible AI-assisted learning requires calibrated epistemic dependence, metacognitive monitoring, and assessment practices that make learner competence visible. Because no included study directly measured the impostor phenomenon using a validated impostor instrument, its relevance is better framed as a Competence Attribution Ambiguity Hypothesis for future empirical testing. Overall, AI should extend human epistemic agency without replacing the competence and responsibility through which learners genuinely earn epistemic credit.

Conflict of Interest

On behalf of all authors, the corresponding author states that there is no conflict of interest.

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