

Review

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Review

# Generative AI, Cognitive Offloading, and Learner Agency in Higher Education: A Scoping Review

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## Abstract

Generative artificial intelligence (GenAI) is increasingly integrated into higher education, where it supports writing, feedback, problem solving, and research-related tasks while also raising concerns about cognitive offloading and learner dependence. This scoping review mapped the literature on the relationships among GenAI, cognitive offloading, and learner agency in higher education. Peer-reviewed English-language studies were reviewed to examine how learner agency has been conceptualized, how GenAI may both enhance and erode agency, which mechanisms link GenAI use to educational outcomes, and which pedagogical conditions shape these effects. The review shows that learner agency is conceptualized as a multidimensional construct involving self-regulation, reflective judgement, intentionality, and responsible action. Across the literature, GenAI operates through a dual-pathway structure: one pathway may enhance learner agency by strengthening self-regulated learning, self-efficacy, feedback literacy, and reflective engagement, whereas the other may erode learner agency through cognitive offloading, overreliance, dependence, uncritical uptake, and weakened judgement. Overall, the findings suggest that the educational value of GenAI depends less on the technology itself than on how it is pedagogically embedded, with augmentation-oriented and scaffolded use being more supportive of learner agency than replacement-oriented use.

**Keywords:** generative artificial intelligence; learner agency; cognitive offloading; overreliance; self-regulated learning; higher education; scoping review

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## 1. Introduction

Generative artificial intelligence (GenAI) is rapidly reshaping learning practices in higher education. Across a wide range of academic tasks, including writing, reading, feedback uptake, problem solving, and research support, GenAI has increasingly become part of students' everyday learning environments. Existing studies suggest that GenAI can provide immediate feedback, personalized assistance, adaptive dialogue, and content generation, thereby extending traditional forms of academic support and creating new possibilities for learner-centered education (Zhan and Yan, 2025; Zhou et al., 2025; Zhu and Yang, 2026).

At the same time, the educational implications of GenAI are increasingly described in contradictory terms. On the one hand, a growing body of research reports that GenAI can strengthen engagement, improve perceived competence, enhance self-efficacy, and support writing, feedback, and research performance (Q. Zhang et al., 2025; Zhou and Wang, 2026; Zhu and Yang, 2026). On the other hand, scholars have also raised serious concerns about technological dependence, uncritical acceptance of AI-generated output, diminished originality, and the erosion of independent judgement. Some studies now describe this pattern as paradoxical: GenAI may simultaneously

increase learners' confidence and efficiency while also intensifying their dependence on technology (Zhang and Xu, 2025; Zheng and Wang, 2026).

These tensions suggest that it is no longer sufficient to evaluate GenAI merely in terms of learning outcomes, performance gains, or technology acceptance. A more analytically useful lens is learner agency. Recent studies have begun to conceptualize learner agency in GenAI-supported contexts as a multidimensional construct rather than a vague ideal. For example, Xia et al. (2025) defined student learning agency in GenAI-supported contexts in terms of key abilities, active actions, and essential mental characteristics. Similarly, Yang et al. (2024) proposed that student agency in GenAI-mediated higher education can be understood through different modes of engagement, including receptive, resistive, resourceful, and reflective learning activities. Together, these studies suggest that the key issue is not whether students use GenAI, but whether they remain able to direct, monitor, evaluate, and take responsibility for that use as active learners (Xia et al., 2025, 2026; Yang et al., 2024).

From this perspective, the impact of GenAI on learner agency appears to be mediated by a set of central cognitive and motivational mechanisms. Among these, self-regulation and metacognition have emerged as especially important. Research increasingly shows that when learners engage in goal setting, monitoring, evaluation, verification, and strategic revision, GenAI is more likely to function as a scaffold for learning rather than as a substitute for thinking. By contrast, when such regulatory capacities are weak, learners are more likely to slide into superficial engagement, passive uptake, and cognitive offloading (Xu et al., 2025; Zheng and Wang, 2026; Zhou and Wang, 2026). Related studies also point to the important roles of trust, self-efficacy, anxiety, and feedback literacy in shaping how learners interpret and use GenAI support (Zhan and Yan, 2025; Q. Zhang et al., 2025; Zhou and Wang, 2026).

Despite this growing body of work, the field remains fragmented in several ways. First, many studies still focus on isolated variables such as intention to use, satisfaction, writing performance, or self-efficacy, without systematically examining learner agency as the broader organizing construct. Second, although overreliance, dependence, and cognitive offloading are repeatedly mentioned in the literature, they are rarely integrated into a unified account of how GenAI may undermine learner agency. Third, the literature is methodologically and contextually heterogeneous, spanning writing, reading, speaking, feedback, problem solving, and research tasks, and employing surveys, experiments, qualitative methods, mixed-methods designs, and scale development studies. This heterogeneity makes a scoping review especially appropriate for mapping the field and clarifying its conceptual and empirical structure (Xia et al., 2025, 2026; Zhu and Yang, 2026).

Accordingly, this review argues that the educational significance of GenAI in higher education should be understood through a dual-pathway perspective. One pathway points toward the enhancement of learner agency through stronger self-regulation, greater confidence, more active feedback engagement, and deeper participation in learning. The other points toward its erosion through cognitive offloading, overreliance, technological dependence, and weakened independent judgement. Crucially, these pathways do not arise automatically from the technology itself; rather, they depend on how GenAI is used, how learners regulate that use, and whether pedagogical designs preserve reflection, evaluation, and responsibility (Wang and Zhang, 2026; Zhang and Xu, 2025; Zheng and Wang, 2026).

Against this background, the present study conducts a scoping review of research on GenAI, cognitive offloading, and learner agency in higher education. Specifically, this review aims to examine how learner agency has been conceptualized in GenAI-supported learning, how GenAI may both enhance and undermine learner agency, which central mechanisms connect GenAI use to educational outcomes, and which pedagogical conditions help ensure that GenAI functions as augmentation rather than replacement. By doing so, the review seeks to provide an integrated, mechanism-oriented framework for understanding more reflective, responsible, and agentic uses of GenAI in higher education (Xia et al., 2026; Zhou and Wang, 2026; Zhu and Yang, 2026).

## 2. Conceptual Background

### 2.1. Learner Agency in GenAI-Supported Higher Education

Learner agency has become an increasingly important concept for understanding how students act within GenAI-supported learning environments. In the present review, learner agency is not treated as a vague synonym for autonomy or participation. Rather, it is understood as learners' capacity to purposefully direct, monitor, evaluate, and take responsibility for their own learning while interacting with GenAI tools. This means that agency involves more than simply using AI; it concerns whether learners remain the ones who set goals, make judgements, select strategies, and regulate the learning process. In this sense, learner agency provides a more powerful analytical lens than outcome indicators alone, because it captures how students position themselves in relation to AI-supported learning rather than only what they achieve after using it (Xia et al., 2025, 2026).

Recent studies have begun to operationalize learner agency in more explicit and measurable ways. Xia et al. (2025), for example, developed a student learning agency scale specifically for GenAI-supported contexts and proposed that learner agency consists of three interrelated dimensions: **key abilities**, **active actions**, and **essential mental characteristics**. Within this structure, self-regulation and self-reflection are treated as foundational abilities; motivation, self-efficacy, and volition are treated as central psychological characteristics; and participation, selectivity, and responsibility are treated as core expressions of agentic action. This multidimensional account is important because it shows that agency in AI-supported learning is simultaneously cognitive, motivational, and behavioral. It is therefore insufficient to infer agency from tool use alone or from positive attitudes toward AI. Instead, agency must be examined through the ways learners interpret, control, and act upon AI support in the course of learning (Xia et al., 2025).

A complementary perspective is offered by Yang et al. (2024), who framed student agency in GenAI-supported higher education as a movement from surface to deep learning. Their analytical framework distinguishes among **receptive**, **resistive**, **resourceful**, and **reflective** forms of student activity. This distinction is especially useful for the present review because it makes clear that students may engage with GenAI in qualitatively different ways. Some may simply receive or reproduce AI output, whereas others may challenge, adapt, extend, or reflect upon it. Thus, GenAI use does not automatically imply either passivity or empowerment; what matters is the form of engagement through which learners exercise judgement and control. In this respect, learner agency is best seen as a continuum of increasingly active and reflective participation rather than as a binary attribute that learners either possess or lack (Jiang et al., 2026; Lai et al., 2026; Yang et al., 2024).

Taken together, these studies suggest that learner agency should serve as the organizing construct for interpreting GenAI use in higher education. It allows the field to move beyond narrow questions of acceptance, frequency of use, or task completion, and toward a more meaningful question: whether learners remain capable of directing their own learning in AI-mediated contexts. This is particularly important because the same technology may support agentic engagement in one context while fostering passive dependence in another. A conceptually robust account of learner agency is therefore necessary for distinguishing between these divergent possibilities (Xia et al., 2025; Yang et al., 2024).

### 2.2. Cognitive Offloading, Overreliance, and Dependence

If learner agency captures the possibility of purposeful and reflective AI-supported learning, then cognitive offloading represents its critical counterpoint. Broadly speaking, cognitive offloading refers to the delegation of cognitive work to external tools or systems. In the context of GenAI, this may include outsourcing idea generation, drafting, summarizing, revising, decision-making, or evaluative judgement to the AI system. Importantly, the literature suggests that offloading is not inherently maladaptive. Some forms of strategic offloading may reduce unnecessary load, free up cognitive resources, and support higher-order thinking. However, the same process may also become

problematic when learners rely on GenAI without verification, without reflection, or without maintaining ownership of the task (Chase and Galvin, 2026; Wang and Zhang, 2026).

This distinction between adaptive and maladaptive offloading is increasingly explicit in recent research. Wang & Zhang (2026) proposed that pedagogical partnerships with GenAI may activate two cognitive pathways simultaneously: **vigilance** and **offloading**. Their account is especially valuable because it avoids assuming that all offloading is negative. Instead, they argue that strategic offloading may, under appropriate conditions, support transformative learning by reallocating effort toward more advanced reflection. Yet they also show that such benefits depend on whether learners preserve critical oversight. In contrast, Chase and Galvin (2026) emphasized the risk of “outsourcing to GenAI” in ways that undermine learning validity and weaken cognitive ownership. Together, these studies indicate that the central issue is not whether learners offload at all, but whether they offload in ways that remain subordinate to reflection, judgement, and educational purpose.

Empirical studies further show that overreliance is not a single undifferentiated phenomenon. Hou et al. (2025), for instance, distinguished among **reflective**, **cautious**, **thoughtless**, and **collaborative** reliance behaviours when undergraduates used GenAI for problem solving. Their findings suggest that reliance becomes problematic when trust is not balanced by critical thinking, and when learners shift from reflective or cautious use toward thoughtless use. Similarly, Zheng & Wang (2026) identified different patterns of cognitive dissonance in GenAI-supported learning, including **efficiency–capacity dissonance** and **trust–reliance dissonance**, showing that learners often experience productivity gains and dependency concerns at the same time. These studies reinforce the idea that overreliance is better understood as a patterned behavioral and psychological response than as mere frequency of use (Hou et al., 2025; Zheng & Wang, 2026).

The paradox becomes even clearer in studies that examine dependence and self-belief together. Zhang & Xu (2025) found that more frequent GenAI use could simultaneously enhance students’ confidence and efficiency while intensifying technological dependence. Likewise, Jia et al. (2025) showed that GenAI dependency may distort academic self-evaluation, creating a form of false self-efficacy associated with cognitive outsourcing. These findings are particularly important for the present review because they show why agency cannot be inferred from confidence alone. Higher self-efficacy in AI-mediated learning may sometimes reflect genuine competence, but it may also coexist with reduced independent capability when learners come to rely on AI as an indispensable substitute rather than a supportive tool (Zhang & Xu, 2025; Jia et al., 2025).

For this reason, cognitive offloading, overreliance, and dependence are treated in this review not as peripheral risks but as central negative pathways through which learner agency may be weakened. They represent the possibility that GenAI use, rather than enhancing learners’ capacity to direct their own thinking, may gradually transfer control over judgement, strategy, and evaluation from the learner to the system. Understanding this negative pathway is essential if GenAI is to be conceptualized not simply as a helpful educational tool, but as a technology whose effects depend on how responsibility for thinking is distributed between human learners and AI systems (Wang and Zhang, 2026; Zhang and Xu, 2025; Zheng and Wang, 2026).

### 2.3. *Self-Regulation as the Central Linking Mechanism*

Across the literature reviewed in this study, self-regulation emerges as the central mechanism linking GenAI use to agency-related outcomes. The importance of this mechanism lies in the fact that GenAI does not act on learners in a direct, deterministic way. Instead, its educational effects are filtered through the extent to which learners can set goals, monitor progress, evaluate outputs, revise strategies, and regulate their own motivation and attention while using the technology. In other words, self-regulation helps explain why the same GenAI affordances may produce deeper learning for some students but superficial completion or dependence for others (Xia, 2025; Xu et al., 2025).

This central role of self-regulation is strongly supported by recent studies on metacognitive support. Xu et al. (2025) found that when learners worked in GenAI environments without explicit metacognitive support, their self-regulated learning could decline; by contrast, when such support

was introduced, learners showed stronger task strategy use, self-evaluation, and overall learning experience. Related studies similarly demonstrate that effective GenAI use depends heavily on metacognitive awareness. Teng (Teng, 2025) showed that students with stronger metacognitive awareness were more likely to use ChatGPT as a feedback and revision resource, whereas weaker metacognitive awareness was associated with direct copying or shallow uptake. These findings indicate that self-regulation is not merely an additional benefit of AI use; it is one of the conditions under which GenAI becomes educationally valuable in the first place (Xu et al., 2025; Teng, 2025).

At the same time, self-regulation rarely operates alone. It is closely intertwined with trust, self-efficacy, anxiety, and feedback literacy. For example, Zhou & Wang (2026) found that generative AI acceptance positively predicted writing feedback literacy, both directly and indirectly through higher writing self-efficacy and lower writing anxiety. Zhang et al. (2025) similarly showed that technological features such as responsiveness and personalization enhanced learning engagement through the mediating roles of AI trust and AI learning self-efficacy. These studies suggest that self-regulation in GenAI-supported learning is embedded in a broader psychological system: learners regulate more effectively when they trust the tool appropriately, feel capable of using it, and are less emotionally overwhelmed by the task.

The literature also indicates that self-regulation is deeply tied to evaluative judgement and critical thinking. Urban et al. (2025) demonstrated that epistemic beliefs and metacognitive accuracy influenced whether students integrated correct or incorrect ChatGPT content into their writing. Zhu & Yang (2026), in turn, showed that the relationship between GenAI use and graduate students' research competence was mediated by critical thinking and moderated by research self-efficacy. These findings are especially important because they show that self-regulation in GenAI environments is not limited to effort management or planning; it also includes epistemic monitoring, verification, and the ability to resist the automatic acceptance of plausible AI output.

For the purposes of this review, self-regulation is therefore treated as the central linking mechanism between GenAI use and learner agency. When supported by metacognitive awareness, critical thinking, calibrated trust, and self-efficacy, self-regulation enables learners to use GenAI as a scaffold for reflective and purposeful learning. When these regulatory resources are weak, the same technology is more likely to encourage dependence, passive uptake, and the erosion of learner agency. This conceptual position provides the basis for the analytical framework adopted in the review that follows.

### 3. Methods

#### 3.1. Review Design

This study adopted a **scoping review** design to map the emerging literature on generative artificial intelligence (GenAI), cognitive offloading, and learner agency in higher education. A scoping review was considered appropriate because the field is conceptually diverse and methodologically heterogeneous, spanning qualitative, quantitative, mixed-methods, experimental, and scale-development studies across multiple educational contexts. Rather than estimating a single pooled effect, the purpose of the review was to identify how learner agency has been conceptualized, how GenAI has been linked to both agentic and non-agentic learning pathways, and which mechanisms and pedagogical conditions have been proposed in the literature. This approach is consistent with the foundational rationale of scoping reviews as a method for mapping key concepts, research trends, and knowledge gaps in developing fields (Arksey and O'Malley, 2005; Levac et al., 2010; Munn et al., 2018).

The review process was further informed by the **PRISMA-ScR** reporting framework to ensure transparency in searching, screening, data charting, and synthesis (2026) (Tricco et al., 2018).

### 3.2. Search Strategy

The literature search was conducted in the **Web of Science Core Collection** on March 31, 2026. Web of Science was selected because it indexes a large body of peer-reviewed international literature and allows structured topic-based and field-specific searches suitable for interdisciplinary review work. The search strategy was designed to capture studies at the intersection of three domains: **GenAI use, higher education, and agency-related or offloading-related learning processes.**

To identify relevant studies, search terms were organized into three clusters. The first cluster captured GenAI-related concepts, including *ChatGPT, generative AI, generative artificial intelligence, GenAI, large language model, LLM, GPT-3, and GPT-4*. The second cluster captured the higher education context, including *higher education, university, college, tertiary education, undergraduate, and postgraduate*. The third cluster captured constructs relevant to the conceptual focus of the review, including *learner agency, student agency, learner autonomy, student autonomy, self-directed learning, cognitive offloading, overreliance, AI reliance, automation bias, self-efficacy, self-regulation, self-regulated learning, metacognition, and critical thinking*.

To improve conceptual precision, the search emphasized GenAI terms in titles and learning-process terms in abstracts. Studies focusing primarily on primary or secondary education, clinical populations, or non-educational uses of AI were excluded during the search and screening process. The full search string is reported in **Appendix A**.

### 3.3. Eligibility Criteria

Studies were included if they met all of the following criteria:

1. They were peer-reviewed journal articles.
2. They focused on GenAI tools, such as ChatGPT or other large language model-based systems.
3. They were situated in higher education contexts, including undergraduate, postgraduate, or other tertiary-level learning settings.
4. They addressed at least one construct related to learner agency, autonomy, self-regulation, metacognition, critical thinking, feedback literacy, self-efficacy, or to the negative pathway of cognitive offloading, overreliance, dependence, or related constructs.
5. They were published in English.

Studies were excluded if they were editorials, commentaries, opinion essays, conference abstracts, or non-peer-reviewed reports. Studies were also excluded when they focused primarily on **teachers, faculty, or institutional adoption** without providing direct evidence about student learning processes. In addition, studies centered exclusively on technical system performance, AI model benchmarking, or general technology acceptance without meaningful connection to learning processes or agency-related outcomes were not retained for the main synthesis.

Because the widespread educational use of GenAI emerged only recently, the review focused on literature published from **2022 onward**.

### 3.4. Study Selection

All retrieved records were exported and screened in multiple stages. First, duplicate records were removed. Second, titles and abstracts were screened to eliminate clearly irrelevant studies. Third, full texts were examined to assess final eligibility based on the inclusion and exclusion criteria described above. The screening process was iterative rather than purely mechanical, because many studies did not explicitly use the term *learner agency* even though they examined adjacent constructs such as autonomy, self-directed learning, self-regulation, or reflective engagement. Accordingly, eligibility decisions were made not only on the basis of keywords, but also on the substantive relevance of each study to the review's conceptual framework.

The final number of records identified, screened, excluded, and included will be reported in a **PRISMA-style flow diagram** in the final manuscript. At this stage, the flow diagram should contain the following items: records identified, duplicates removed, records screened, full texts assessed, full

texts excluded with reasons, and studies included in the final synthesis. Figure 1 presents the study selection process, including identification, screening, full-text eligibility assessment, and final inclusion.

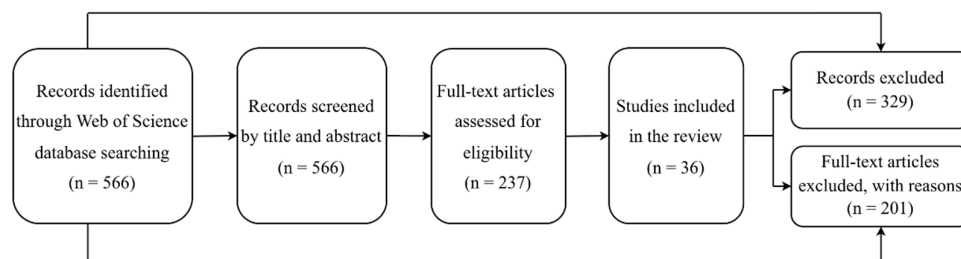


Figure 1. PRISMA flow diagram of study selection.

### 3.5. Data Charting

A structured data-charting form was developed to extract and organize relevant information from the included studies. For each article, the following information was recorded:

- author(s) and year of publication;
- country or region of study;
- educational context and disciplinary setting;
- participant characteristics;
- GenAI tool or platform examined;
- research design and method;
- focal constructs and outcome variables;
- how learner agency was conceptualized or operationalized;
- evidence of positive pathways, such as enhanced self-regulation, self-efficacy, engagement, or feedback literacy;
- evidence of negative pathways, such as cognitive offloading, overreliance, dependence, or uncritical uptake;
- mediators, moderators, or boundary conditions;
- pedagogical implications proposed by the authors.

This charting strategy was designed to support both descriptive mapping and conceptual synthesis. In particular, it allowed the review to compare studies that explicitly measured learner agency with studies that approached the construct indirectly through related dimensions such as autonomy, reflective use, strategic prompting, self-directed learning, or responsible feedback uptake.

### 3.6. Data Synthesis

The included studies were synthesized through **descriptive mapping** and **thematic analysis**. First, the literature was descriptively mapped in terms of publication year, context, study design, disciplinary distribution, and focal variables. Second, findings were coded and grouped into higher-order conceptual categories aligned with the aims of the review.

The synthesis proceeded through a combined **deductive-inductive** approach. Deductively, the review was guided by the conceptual distinction between **learner agency enhancement** and **agency erosion through cognitive offloading**. Inductively, recurrent patterns across the literature were identified and refined during repeated reading of the included studies. This process resulted in five overarching thematic domains:

1. how learner agency is conceptualized in GenAI-supported higher education;
2. positive pathways through which GenAI may enhance learner agency;
3. negative pathways involving cognitive offloading, overreliance, and dependence;

4. central mechanisms linking GenAI use to agency-related outcomes, especially self-regulation, metacognition, critical thinking, self-efficacy, trust, and feedback literacy;
5. boundary conditions and pedagogical responses that shape whether GenAI functions as augmentation or replacement.

This synthesis strategy was chosen because the field contains substantial conceptual variation and does not yet support a narrow effect-size aggregation. A scoping and thematic approach therefore provides a more appropriate basis for identifying how the field has developed, where its main tensions lie, and how future research and practice may be better guided. The PRISMA-ScR checklist is provided in Appendix A, and the full Web of Science search strategy is reported in Appendix B.

#### 4. Results

To provide an overview of the evidence base, Table 1 summarizes the 30 core studies that most directly informed the present review's analysis of learner agency, cognitive offloading, and related mechanisms in GenAI-supported higher education

**Table 1.** Characteristics of the 30 core studies included in the review.

Sources	Context / participants	Design	Key constructs	Main findings
(Xia et al., 2025)	Higher education; university students	Scale development / validation	Learning agency; key abilities; active actions; essential mental characteristics	Core measurement study defining learner agency in GenAI-supported contexts
(Xia et al., 2026)	Higher education; university students	Mixed-methods	Learning agency; self-regulated learning propensities	Shows the dual effect of GenAI: enhanced agency alongside excessive reliance and uncritical reproduction
(Yang et al., 2024)	Higher education	Conceptual / analytical framework	Receptive, resistive, resourceful, and reflective agency	Key theoretical framework linking agency to movement from surface to deep learning
(Lai et al., 2026)	Informal higher education language learning; university learners	Qualitative / taxonomy-building	Proxy agency; collective agency; shared agency; self-directed learning	Expands agency into relational and postdigital dimensions while acknowledging cognitive offloading risks
(Kim et al., 2025)	Collaborative writing; students in higher education	Design-based / experimental	Learner agency; intentionality; self-monitoring	Shows how interface design can support agency and reduce overreliance in co-writing
(Jiang et al., 2026)	Academic writing; students revising GenAI-generated texts	Qualitative / process-oriented	Learner agency in revision; evaluative choice; authorship	Demonstrates different forms of agency from compliance-oriented acceptance to content-oriented innovation
(Lukešová and Jennings, 2025)	Language learning; beginner-level students	Intervention / qualitative-quantitative	Learner autonomy; metacognitive autonomy	Shows how structured interaction with ChatGPT can support autonomy beyond surface task completion

(Lukešová and Jennings, 2026)	Language learning	Intervention	Autonomy; reflection; strategic learning	Important evidence that hint-based support is more agency-preserving than direct correction
(Chase and Galvin, 2026)	Higher education learning	Conceptual / theoretical	Cognitive ownership; learning validity	Core negative-pathway paper on outsourcing thinking to GenAI
(Hou et al., 2025)	Problem solving; undergraduates	Quantitative	Reflective, cautious, collaborative use	Distinguishes reflective from thoughtless reliance and links critical thinking to better AI use
(Jia et al., 2025)	Higher education; university students	Quantitative	Self-efficacy; academic achievement	Key Behavioral Sciences paper on dependency, cognitive outsourcing, and false self-efficacy
(Zhang and Xu, 2025)	University students; task completion	Survey / quantitative	Self-efficacy; learning efficiency	Classic paradox study showing simultaneous gains in confidence and technological dependence
(Zheng and Wang, 2026)	EFL higher education; tertiary learners	Q-methodology & interviews	Self-regulation strategies	Identifies trust–reliance and efficiency–capacity dissonance patterns in GenAI use
(Tao et al., 2026)	College students	Predictive quantitative study	Not primary focus on agency	Important for identifying predictors of GenAI reliance and dependence
(Fan et al., 2025)	Higher education learning	Experimental / quantitative	Metacognitive regulation	Introduces the important concept of metacognitive laziness as a risk of GenAI use
(Wang and Zhang, 2026)	Higher education	Conceptual / theoretical	Vigilance; reflective partnership	Key theoretical paper proposing dual pathways of vigilance and offloading
(Tekir, 2026)	EFL writing; higher education	Quantitative / correlational	Metacognitive engagement; authorial control	Shows that selective use preserves originality better than frequent AI dependence
(Tian and Xiang, 2026)	EFL writing; students	Quantitative	Effective GenAI use; self-regulation; critical thinking	One of the clearest studies showing self-regulation and critical thinking as strongest predictors of effective use
(Xu et al., 2025)	GenAI-supported learning	Experimental / quantitative	Self-regulated learning; metacognitive support	Shows that metacognitive support is essential for preventing SRL decline in AI environments
(Teng, 2025)	EFL writing	Quantitative / qualitative	Metacognitive awareness	Demonstrates that students with stronger metacognitive awareness use ChatGPT more reflectively
(Urban et al., 2025)	Academic writing	Experimental / quantitative	Epistemic beliefs; metacognitive accuracy	Key study on how learners integrate correct and incorrect AI-generated information
(Zhan and Yan, 2025)	Feedback use; higher education	Mixed-methods	Feedback literacy; engagement	Core feedback literacy study showing that students' behavioral engagement with AI feedback is often shallow

(Zhou and Wang, 2026)	EMI writing; university students	Quantitative	Writing feedback literacy; self-efficacy	Demonstrates how AI acceptance affects feedback literacy via self-efficacy and anxiety
(Zhu and Yang, 2026)	Graduate research	Quantitative	Critical thinking; research self-efficacy	Core Behavioral Sciences paper showing mechanism-based linkage from AI use to research competence
(Qi et al., 2025)	Higher education students	Quantitative	Critical thinking; self-directed learning ability; AI literacy	Key capability-based framework for explaining when students benefit from GenAI
(Lee et al., 2024)	Blended learning; college students	Experimental	Self-regulated learning; higher-order thinking	Strong evidence that guidance-based AI use is more agentic than conventional direct-answer use
(Joo et al., 2026)	Online self-regulated learning	Experimental	Metacognitive prompting; self-efficacy	Shows how prompt design can reduce cognitive load and improve regulated learning
(Sun et al., 2026)	Programming learning	Comparative / mixed-methods	Reflective debugging; persistence	Demonstrates that Socratic scaffolding is more agency-preserving than direct-answer support
(Yilmaz et al., 2026)	Online learning	Comparative quantitative study	Regulation skills; goal setting	Shows that GenAI feedback particularly benefits lower-SRL learners
(Zhou et al., 2025)	Mathematical problem solving; undergraduates	Mixed-methods	Interpretive and evaluative problem-solving activity	Key scaffolding study showing that AI support can improve performance without removing reflective activity

As shown in Table 1, the core literature is concentrated in higher education writing, feedback, problem-solving, and research-related contexts. Across these studies, learner agency is most commonly conceptualized through self-regulation, reflective engagement, evaluative judgement, and self-efficacy, whereas the negative pathway is most often described in terms of cognitive offloading, overreliance, and technological dependence.

#### 4.1. Conceptualizations of Learner Agency in GenAI-Supported Higher Education

The literature reviewed in this study shows that **learner agency** in GenAI-supported higher education is conceptualized in multiple, partially overlapping ways rather than as a single, universally agreed construct. At the broadest level, learner agency is commonly understood as students' capacity to act intentionally, regulate their goals and strategies, evaluate AI-supported outputs, and influence the direction of their own learning rather than merely responding passively to external support. In this sense, agency is closely related to self-regulation, reflective judgement, and the ability to remain the active organizer of learning in AI-mediated environments (Xia et al., 2025; Xia et al., 2026).

A particularly important conceptualization is offered by Xia et al. (2025), who developed a student learning agency scale for GenAI-supported contexts and proposed a **three-dimensional framework** consisting of **key abilities**, **active actions**, and **essential mental characteristics**. Within this structure, agency includes foundational abilities such as self-regulation and self-reflection, motivational and volitional characteristics such as self-efficacy and persistence, and action-oriented expressions such as participative, selective, and responsible engagement. This framework is significant because it moves the field beyond loosely defined notions of autonomy and provides a more systematic way to understand agency as simultaneously cognitive, motivational, and behavioral (Xia et al., 2025).

A complementary perspective is provided by Yang et al. (2024), who conceptualized learner agency through the distinction between **receptive**, **resistive**, **resourceful**, and **reflective** forms of engagement with GenAI. This framework is especially useful because it captures variation in how students interact with AI support. Some learners receive and reproduce GenAI outputs with limited reflection, whereas others question, adapt, extend, or critically evaluate them. In this sense, learner agency is not simply a trait that students possess, but a mode of engagement that becomes visible through their interactional patterns with GenAI-supported tasks (Yang et al., 2024).

Other studies conceptualize learner agency more specifically through revision, self-directed learning, or co-writing control. For example, Jiang et al. (2026) framed agency in revising GenAI-generated statements of purpose as the learner's ability to evaluate, reshape, and take ownership of AI-generated text, identifying patterns ranging from compliance-oriented acceptance to content-oriented innovation. Similarly, Kim et al. (2025) conceptualized agency in collaborative writing as intentionality and self-monitoring, and demonstrated that interface features can be explicitly designed to help learners remain "in the loop" rather than deferring uncritically to AI suggestions. Lai et al. (2026), from a more relational perspective, extended the concept further by proposing dimensions such as proxy, collective, and shared agency, suggesting that agency may also emerge through how students coordinate human and technological resources across learning environments (Jiang et al., 2026; Kim et al., 2025; Lai et al., 2026).

Taken together, these studies indicate that learner agency in GenAI-supported higher education should be understood as a **multidimensional and context-sensitive construct**. It involves learners' ability to maintain intentionality, evaluative judgement, and responsibility while interacting with GenAI. This conceptualization is central to the present review because it provides a framework for understanding why GenAI may sometimes enhance students' learning capacity while, in other cases, contributing to dependency, passivity, or reduced ownership over learning.

#### 4.2. Positive Pathways: How GenAI May Enhance Learner Agency

A substantial portion of the literature portrays GenAI as a resource that can strengthen learner agency under appropriate conditions. Across writing, reading, problem-solving, research, and feedback contexts, studies repeatedly report that GenAI may support learners' autonomy, self-direction, engagement, and confidence by making academic assistance more immediate, personalized, and interactive. In many studies, these positive effects are not interpreted as simple technological gains, but as evidence that students can become more active and capable learners when AI support is embedded in ways that preserve decision-making and reflection (Xia et al., 2026; Zhang et al., 2025; Zhou et al., 2025).

One major positive pathway concerns the development of **self-regulated learning**. Multiple studies suggest that GenAI can facilitate goal setting, planning, monitoring, and self-evaluation when learners use it as a learning scaffold rather than as a substitute for task completion. Yilmaz et al. (2026), for instance, found that GenAI-supported feedback helped improve online learners' regulation skills, especially among students with initially lower levels of self-regulated learning. Similarly, studies on writing and feedback suggest that when learners interact actively with AI-generated prompts or dialogic feedback, they become more likely to engage in revision, reflection, and strategic uptake of feedback (Yilmaz et al., 2026; Zhou & Wang, 2026; Zhan & Yan, 2025).

A second positive pathway concerns **self-efficacy**. A wide range of studies report that GenAI use may increase learners' confidence in their ability to complete academic tasks, especially when AI support reduces uncertainty, offers immediate responses, or helps learners structure complex tasks. For example, Zhang et al. (2025) found that responsiveness and personalization enhanced engagement partly by increasing AI learning self-efficacy, while Zhu and Yang (2026) showed that GenAI use was positively associated with graduate students' research competence, with research self-efficacy functioning as an important moderator. In these studies, self-efficacy operates as a psychological bridge through which students perceive themselves as more capable participants in

AI-supported learning, rather than as passive users of automated tools (Zhang et al., 2025; Zhu & Yang, 2026).

A third positive pathway involves **feedback literacy and evaluative participation**. In GenAI-supported writing environments, several studies show that students can use AI-generated feedback to become more active readers, interpreters, and users of feedback. Zhou and Wang (2026) found that generative AI acceptance positively predicted writing feedback literacy both directly and indirectly through higher writing self-efficacy and lower writing anxiety. Related work also shows that structured reflection, strategic prompting, and dialogic feedback can help students better understand feedback, judge its value, and apply it more selectively. From an agency perspective, these findings are important because they suggest that GenAI can support not only task performance but also students' capacity to engage with feedback more deliberately and productively (Zhou & Wang, 2026; Zhan & Yan, 2025).

Finally, positive pathways are also visible in studies of **research competence, reading support, and problem solving**. Zhu and Yang (2026) reported that different levels of GenAI use were positively associated with graduate students' research competence, especially when higher-order use was accompanied by critical thinking. Zhou et al. (2025) showed that ChatGPT-facilitated scaffolding improved undergraduates' mathematical problem-solving performance and encouraged more interpretive and evaluative activity among higher-performing students. In these cases, GenAI appears to enhance learner agency when it functions as a resource for reflection, knowledge structuring, and strategic support rather than direct answer delivery (Zhu & Yang, 2026; Zhou et al., 2025).

Overall, the literature suggests that GenAI may enhance learner agency when it supports learners in becoming more self-regulating, confident, evaluative, and strategically engaged. These benefits, however, are rarely automatic; they typically emerge when students remain cognitively and metacognitively involved in the task. This point becomes even clearer in the next theme, which addresses the negative pathways through which GenAI may weaken agency.

#### 4.3. Negative Pathways: Cognitive Offloading, Overreliance, and Dependence

Alongside the positive pathways described above, the literature also presents a strong and increasingly explicit account of the ways GenAI may undermine learner agency. These negative pathways are typically discussed in terms of **cognitive offloading, overreliance, technological dependence, uncritical uptake**, and the weakening of independent judgement. Rather than treating these as isolated risks, many recent studies suggest that they form a coherent pattern in which responsibility for thinking, evaluating, and deciding gradually shifts from the learner to the AI system (Chase & Galvin, 2026; Zhang & Xu, 2025; Zheng & Wang, 2026).

One recurring concern is that GenAI may encourage students to outsource cognitive work that would otherwise contribute to learning. Chase and Galvin (2026) described this as the risk of "outsourcing to GenAI," warning that when AI takes over substantive thinking processes, learning validity and cognitive ownership may be compromised. Similar concerns appear in problem-solving and writing studies, where students may move from reflective use toward shortcut-oriented completion strategies. In such cases, the issue is not merely that students use assistance, but that they no longer remain the primary agents of analysis, interpretation, or decision making (Chase & Galvin, 2026; Hou et al., 2025).

Several studies show that overreliance is not a uniform phenomenon but a differentiated one. Hou et al. (2025), for example, distinguished among **reflective, cautious, collaborative, and thoughtless** reliance behaviours. Their findings suggest that reliance becomes problematic when trust in AI is not moderated by critical thinking, and when learners shift toward thoughtless use. Zheng and Wang (2026) similarly identified different patterns of cognitive dissonance in GenAI-supported EFL learning, including **efficiency-capacity dissonance, instrumental-traditional dissonance, and trust-reliance dissonance**. These categories show that learners often experience tension between productivity gains and fears of losing competence, authenticity, or evaluative

control. Such findings suggest that dependence is not simply a matter of how often students use GenAI, but of how they resolve or fail to resolve these tensions in practice (Hou et al., 2025; Zheng & Wang, 2026).

The paradox is especially clear in studies linking GenAI use to both **self-efficacy gains and dependence risks**. Zhang and Xu (2025) found that more frequent GenAI use simultaneously enhanced students' confidence and learning efficiency while intensifying technological dependence. Jia et al. (2025) similarly reported that GenAI dependency was associated with academic achievement through self-efficacy, but also warned that such self-efficacy could become inflated or distorted in ways resembling false competence. These studies are important because they complicate any simple positive interpretation of self-efficacy: learners may feel more capable while becoming less independently capable. From the perspective of learner agency, this means that confidence alone cannot be taken as evidence of empowerment (Zhang & Xu, 2025; Jia et al., 2025).

Negative pathways are also visible in studies of writing and authorship. Tekir (2026) found that frequent reliance on GenAI in EFL writing was associated with reduced originality, weaker critical reasoning, and lower authorial control, while more selective use preserved stronger personal voice and metacognitive engagement. Likewise, mixed-method studies of learning agency report that although students may experience improved self-regulated learning propensities, they may also reproduce AI-generated content uncritically or rely on AI-generated responses without sufficient evaluation. These findings indicate that agency erosion often occurs not through overt misuse alone, but through subtle shifts in who is generating ideas, making judgements, and owning the resulting work (Tekir, 2026; Xia et al., 2026).

In sum, the negative pathway in the literature can be understood as a movement from supported learning toward displaced learning. GenAI may become problematic when it reduces the learner's need to plan, monitor, verify, and decide. This risk does not cancel out the technology's educational potential, but it does show that cognitive offloading, overreliance, and dependence are central to understanding how learner agency may be weakened in AI-supported higher education.

#### 4.4. Central Mechanisms Linking GenAI Use to Agency Outcomes

Across the reviewed studies, the most consistent finding is that the effects of GenAI on learner agency are rarely direct. Instead, they are mediated by a set of interrelated psychological and behavioral mechanisms. Among these, **self-regulation, metacognition, critical thinking, self-efficacy, trust, and feedback literacy** appear most central. Together, these mechanisms help explain why GenAI may serve as a scaffold for some learners and as a source of dependence for others (Xu et al., 2025; Zhu & Yang, 2026; Zhou & Wang, 2026).

Among these variables, **self-regulation** emerges as the most important overarching mechanism. Studies repeatedly show that when learners use GenAI in ways that involve goal setting, monitoring, evaluation, and strategy revision, they are more likely to benefit from AI support without losing ownership of learning. Xu et al. (2025) showed that metacognitive support was crucial in maintaining and improving self-regulated learning in GenAI environments. Xia (2025) further demonstrated that self-regulated learning is dynamically linked to deeper approaches to learning over time. These findings suggest that self-regulation is not merely one positive outcome among others; it is the process through which learner agency is enacted in AI-supported learning (Xu et al., 2025; Xia, 2025).

**Metacognition and metacognitive awareness** form a closely related mechanism cluster. Teng (2025) found that learners' metacognitive awareness strongly shaped whether they copied from ChatGPT or used it as a resource for reflection and improvement. Urban et al. (2025) showed that metacognitive accuracy and epistemic beliefs influenced whether students correctly integrated or incorrectly adopted ChatGPT-generated information in academic writing. Yao et al. (2025) similarly identified planning, monitoring, evaluating, information management, and debugging as central metacognitive strategies used by postgraduate students when employing ChatGPT for academic writing. Together, these studies indicate that metacognition determines whether AI outputs are

treated as raw material for thinking or as authoritative content to be adopted with minimal scrutiny (Teng, 2025; Urban et al., 2025; Yao et al., 2025).

Another major mechanism is **critical thinking**. In several studies, critical thinking functions as either a mediator, a moderator, or a protective capacity against uncritical AI uptake. Hou et al. (2025) showed that critical thinking promoted reflective and cautious reliance while buffering the effect of trust on thoughtless use. Zhu and Yang (2026) found that critical thinking mediated the relationship between GenAI use and graduate students' research competence. Tian and Xiang (2026) further reported that critical thinking, together with self-regulation, was among the strongest predictors of effective GenAI use. These findings collectively suggest that critical thinking is not simply an educational outcome threatened by AI, but an active mechanism that determines how AI is used in the first place (Hou et al., 2025; Tian & Xiang, 2026; Zhu & Yang, 2026).

**Self-efficacy** also emerges as a recurring bridge mechanism, although the literature suggests that its role is ambivalent. On the positive side, self-efficacy often enables stronger engagement, more active use of feedback, and greater persistence in AI-supported tasks. On the negative side, self-efficacy may coexist with technological dependence or become inflated when learners mistake AI-assisted success for independent competence. This dual role is clear across studies of engagement, research competence, and dependence, suggesting that self-efficacy should be interpreted cautiously in GenAI environments: it can support agentic learning, but only when accompanied by reflection and evaluative judgement (Zhang et al., 2025; Zhang & Xu, 2025; Jia et al., 2025).

Finally, **trust** and **feedback literacy** function as important connecting mechanisms between technological affordances and learner response. Zhang et al. (2025) showed that responsiveness and personalization did not influence engagement directly in the same way; instead, trust and AI learning self-efficacy played mediating roles. Zhou and Wang (2026) showed that generative AI acceptance improved writing feedback literacy by increasing self-efficacy and reducing anxiety. Zhan and Yan (2025) also found that students' engagement with ChatGPT feedback was often limited by shallow behavioral participation, which points to the need for stronger prompt-based, evaluative, and metacognitive feedback literacy. Taken together, these studies show that learners' agency in AI-supported contexts depends not only on access to AI support, but also on whether they trust it appropriately, can use it competently, and can evaluate and apply its feedback selectively (Zhang et al., 2025; Zhou & Wang, 2026; Zhan & Yan, 2025).

Overall, the reviewed literature suggests that self-regulation and metacognition form the core regulatory mechanism, while critical thinking, self-efficacy, trust, and feedback literacy operate as enabling or constraining bridges between GenAI use and learner agency outcomes. This integrated mechanism view helps explain why the same GenAI tool can produce different educational consequences across learners and settings.

#### 4.5. Boundary Conditions and Pedagogical Responses

A final major theme in the literature concerns the conditions under which GenAI is more likely to enhance rather than erode learner agency. The reviewed studies strongly suggest that GenAI does not operate in isolation; its effects depend on how it is pedagogically embedded, how learners are guided to use it, and whether the learning design preserves reflection, evaluation, and responsibility. In other words, the field increasingly treats GenAI not as a self-sufficient instructional solution, but as a technology whose educational value depends on surrounding supports and constraints (Lee et al., 2024; Sun et al., 2026; Zhou et al., 2025).

One of the clearest findings is that **scaffolded use is consistently more beneficial than direct-answer use**. Lee et al. (2024) showed that a guidance-based ChatGPT-assisted learning design, in which learners first thought independently and then received hints rather than final answers, was more effective in promoting self-regulated learning, higher-order thinking, and knowledge construction than conventional use. Sun et al. (2026) similarly found that a Socratic, scaffolded GenAI approach supported reflective debugging and persistence, whereas direct-answer use was more likely to foster trial-and-error behavior and overreliance. Zhou et al. (2025) likewise showed that

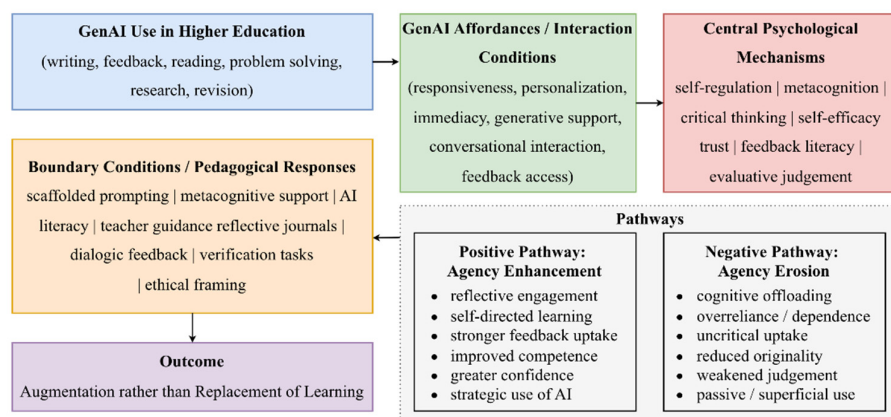
ChatGPT-facilitated scaffolding improved problem-solving performance and promoted more interpretive and evaluative behaviors in mathematics. Together, these studies indicate that GenAI is most educationally productive when it is embedded in structures that require learners to remain active interpreters rather than passive recipients (Lee et al., 2024; Sun et al., 2026; Zhou et al., 2025).

A second boundary condition concerns **metacognitive prompting and reflective support**. Joo et al. (2026) found that metacognitive prompts in GenAI-supported online self-regulated learning reduced cognitive load and improved performance and self-efficacy. Reflection journals have also been shown to function as useful scaffolds in GenAI-assisted writing. Zhang et al. (2025) reported that structured and semi-structured reflection journals improved postgraduate students' GenAI literacy, especially in relation to critical evaluation, ethics, and autonomy. These findings suggest that reflection should not be treated as an optional add-on to AI use; rather, it is one of the pedagogical mechanisms through which learner agency is preserved (Joo et al., 2026; Zhang et al., 2025).

A third boundary condition is **AI literacy and feedback literacy development**. Several studies show that learners require more than technical familiarity to use GenAI well. They must also develop the capacity to judge output quality, recognize risk, formulate productive prompts, and use feedback selectively. Studies of writing feedback literacy, engagement with ChatGPT feedback, and GenAI literacy all point to the same conclusion: students are more likely to use GenAI agentially when they understand not only how to operate the tool, but how to question it, verify it, and position themselves in relation to it. In this sense, AI literacy is less about technological comfort than about preserving human judgement within AI-supported learning (Zhan & Yan, 2025; Zhou & Wang, 2026; Zhang et al., 2025).

Finally, several studies suggest that **teacher guidance and human mediation remain important**, even in highly AI-supported environments. Research on academic help-seeking, feedback use, and collaborative tasks suggests that students may be drawn to GenAI because of fluency, immediacy, and convenience, but these same qualities may increase the risk of shallow trust or premature closure unless pedagogical structures require verification and reflection. Consequently, the strongest practical implication across the literature is not that educators should reject GenAI, but that they should design for **augmentation rather than replacement**. This means keeping learners in roles that require interpretation, evaluation, decision making, and accountability, even when AI support is available (Zhang & Yang, 2025; Wang & Zhang, 2026; Zhu & Yang, 2026).

Taken together, these studies show that the difference between agency-enhancing GenAI use and agency-eroding GenAI use often lies in the surrounding design. Guidance-based interaction, reflective prompts, scaffolded feedback, AI literacy development, and continued human mediation all function as boundary conditions that shape whether GenAI becomes a cognitive scaffold or a cognitive substitute. This conclusion sets the stage for the Discussion section, which integrates these themes into a dual-pathway account of GenAI, cognitive offloading, and learner agency in higher education.



**Figure 2.** A dual-pathway framework of GenAI, cognitive offloading, and learner agency in higher education.

The framework illustrates how GenAI use in higher education activates a set of central psychological mechanisms, including self-regulation, metacognition, critical thinking, self-efficacy, trust, and feedback literacy. These mechanisms may channel learners toward either an agency-enhancing pathway or an agency-eroding pathway. Pedagogical conditions such as scaffolding, metacognitive prompting, AI literacy, and teacher guidance shape whether GenAI functions as augmentation rather than replacement.

Table 2 summarizes the five major themes identified in the review, along with their central mechanisms, representative studies, and pedagogical implications. As shown, the literature consistently portrays GenAI as operating through a dual-pathway structure: one pathway may enhance learner agency through self-regulation, feedback engagement, and confidence, whereas the other may erode agency through cognitive offloading, overreliance, and dependence.

**Table 2.** Summary of major themes, mechanisms, and pedagogical implications.

Theme	Core interpretation	Key mechanisms / constructs	Main pedagogical implications	Representative studies
1. Conceptualizations of learner agency in GenAI-supported higher education	Learner agency is conceptualized as a multidimensional construct rather than a simple synonym for autonomy or participation. It includes learners' ability to regulate, evaluate, choose, and act responsibly in AI-mediated learning.	Learning agency; key abilities; active actions; essential mental characteristics; reflective, resourceful, resistive, and receptive engagement	Agency should be treated as a core evaluative construct in GenAI research and pedagogy, not inferred indirectly from tool use or performance alone.	Xia et al. (2025); Xia et al. (2026); Yang et al. (2024); Lai et al. (2026); Kim et al. (2025); Jiang et al. (2026)
2. Positive pathways: how GenAI may enhance learner agency	Under supportive conditions, GenAI can enhance agency by strengthening learners' self-direction, confidence, feedback engagement, and strategic participation in learning tasks.	Self-regulated learning; self-efficacy; feedback literacy; engagement; self-directed learning; reflective participation	GenAI should be used to support reflection, revision, and strategic feedback uptake rather than merely accelerate task completion.	Xia et al. (2026); Zhang et al. (2025); Zhou & Wang (2026); Zhu & Yang (2026); Zhou et al. (2025)
3. Negative pathways: cognitive offloading, overreliance, and dependence	GenAI may weaken learner agency when students outsource judgement, idea generation, revision, or evaluation to AI without sufficient reflection or verification.	Cognitive offloading; outsourcing; overreliance; technological dependence; uncritical reproduction; reduced originality;	AI-supported learning designs should explicitly guard against shortcut use, passive uptake, and the transfer of cognitive responsibility from learner to system.	Chase & Galvin (2026); Hou et al. (2025); Jia et al. (2025); Zhang & Xu (2025); Zheng & Wang (2026); Tekir (2026)

		diminished authorial control		
4. Central mechanisms linking GenAI use to agency outcomes	The effects of GenAI on learner agency are rarely direct; they are mediated by a cluster of cognitive, motivational, and evaluative mechanisms.	Self-regulation; metacognition; metacognitive awareness; critical thinking; self-efficacy; trust; anxiety; feedback literacy; epistemic beliefs	Educational interventions should target self-regulation and metacognition as central conditions for productive GenAI use, while also strengthening critical thinking and trust calibration.	Xu et al. (2025); Teng (2025); Urban et al. (2025); Zhou & Wang (2026); Zhu & Yang (2026); Zhang et al. (2025)
5. Boundary conditions and pedagogical responses	Whether GenAI enhances or erodes agency depends heavily on how it is pedagogically embedded. Structured support is consistently more beneficial than unrestricted or direct-answer use.	Scaffolding; guidance-based design; metacognitive prompts; reflection journals; AI literacy; teacher guidance; dialogic feedback; verification tasks	The most effective AI-integrated teaching designs are those that preserve learner judgement through scaffolding, prompting, reflection, and human mediation.	Lee et al. (2024); Joo et al. (2026); Sun et al. (2026); Zhan & Yan (2025); Zhang et al. (2025); Zhou et al. (2025)

## 5. Discussion

The findings of this review suggest that the educational significance of GenAI in higher education is best understood not through a simple benefits-versus-risks framing, but through a **dual-pathway account**. Across the reviewed literature, GenAI consistently appears as a technology that can both strengthen and weaken learner agency. On the positive side, it can support self-regulation, confidence, feedback engagement, and task performance. On the negative side, it can also encourage cognitive offloading, technological dependence, uncritical reproduction, and the gradual displacement of learners' own judgement. Importantly, these pathways are not mutually exclusive. Several studies indicate that they may coexist within the same learning process, producing gains in perceived capability at the same time as losses in independent cognitive ownership.

A central contribution of the present review is therefore to clarify why the literature often appears contradictory. Much of the inconsistency across studies does not arise because some researchers are "right" and others are "wrong," but because they examine different layers of the same phenomenon. Studies focusing on engagement, confidence, or performance often capture the **immediate functional affordances** of GenAI, such as responsiveness, personalization, and real-time support. By contrast, studies emphasizing dependence, overreliance, or erosion of originality often capture the **longer-term redistribution of cognitive responsibility** between learner and system. When these layers are considered together, a more coherent picture emerges: GenAI may improve the efficiency and subjective ease of learning while simultaneously altering the conditions under which learners develop autonomy, evaluative judgement, and sustained independent capability.

From this perspective, the most important theoretical implication of the review is that **learner agency should be treated as the organizing construct** for future GenAI research in higher education. Existing work on learning agency already provides a strong basis for this move. The literature reviewed here shows that agency can be understood through key abilities, active actions, and essential mental characteristics, and also through concrete forms of engagement such as receptive, resistive, resourceful, and reflective activity. Taken together, these perspectives suggest that agency is not simply a downstream outcome of AI use. Rather, it is the most meaningful way to judge whether AI-supported learning remains genuinely educational. If learners still set goals, monitor progress, evaluate outputs, revise strategically, and act responsibly, GenAI may be said to support agency. If these functions are increasingly ceded to the system, then even apparently successful AI use may mask the weakening of agency.

A second major implication concerns the role of **self-regulation and metacognition**. Across the reviewed studies, self-regulation appears not merely as one positive learning outcome among others, but as the central mechanism through which GenAI becomes either a scaffold or a substitute. When students engage in planning, monitoring, self-evaluation, verification, and strategic revision, GenAI is more likely to support deeper participation and reflective learning. When these regulatory capacities are weak, the technology is more likely to become a shortcut that narrows rather than expands learners' role in the learning process. This pattern is particularly important because it suggests that the key issue is not AI access itself, but whether learners possess and enact the metacognitive resources needed to govern that access. Put differently, the central question is not "Do students use GenAI?" but "Can they still regulate what that use means for their learning?"

The review also suggests that **self-efficacy is a more ambivalent construct in AI-supported learning than has often been assumed**. In traditional educational psychology, higher self-efficacy is usually interpreted as an unambiguously positive indicator of learner capacity. However, the GenAI literature complicates this assumption. Several studies indicate that AI-supported success can enhance students' confidence and efficiency while simultaneously strengthening dependence on AI systems. In such cases, self-efficacy may reflect not only the learner's own strengthened competence, but also the ease of completing tasks with external cognitive support. This distinction is crucial. If self-efficacy grows alongside reduced independent problem-solving capability, then it may represent a form of **supported confidence rather than autonomous competence**. The literature on dependence and false self-efficacy therefore suggests that future research should be more cautious in interpreting positive self-efficacy effects in AI-supported contexts.

Another important conclusion is that **cognitive offloading should not be conceptualized as uniformly harmful**. One of the most theoretically interesting developments in the recent literature is the argument that strategic offloading may, under certain conditions, enhance rather than undermine deep learning. In particular, work on pedagogical partnerships with GenAI suggests that offloading routine or lower-order operations can free cognitive resources for higher-order reflection, provided that learners remain vigilant, evaluative, and responsible for the broader task. This is an important refinement of earlier offloading theory. Rather than treating all delegation as evidence of passivity, the emerging literature suggests that the educational value of offloading depends on *what* is delegated, *why* it is delegated, and *whether* the learner remains the final arbiter of meaning, quality, and direction. Strategic delegation may support transformation; uncritical delegation may erode agency.

This distinction between **strategic** and **maladaptive** offloading helps explain why some studies report positive outcomes from AI support while others warn of dependence and reduced originality. Strategic offloading seems most likely when AI is embedded within pedagogical structures that require students to question, verify, revise, and make explicit decisions. Maladaptive offloading, by contrast, becomes more likely when AI is used primarily for speed, answer generation, or frictionless completion. This suggests that learner agency is shaped not only by the availability of AI, but by the *task ecology* surrounding its use. When GenAI is aligned with reflective demands, it may augment agency; when aligned primarily with efficiency demands, it may encourage displacement of agency.

A further implication of the review is that **trust must be understood as a calibrated rather than uniformly desirable state**. The literature consistently shows that trust can facilitate engagement, acceptance, and willingness to use AI-supported learning tools. Yet high trust without critical oversight can also contribute to overreliance and shallow uptake. This tension is especially clear in studies where trust and self-efficacy mediate the effects of technological features on engagement, while risk perception weakens the trust–acceptance link. The broader lesson is that educationally productive trust is not blind trust, but trust that remains coupled with verification, scepticism, and epistemic accountability. In other words, what students need is not simply more trust in GenAI, but more **appropriately calibrated trust**.

These findings carry direct pedagogical implications. Most importantly, the review suggests that **GenAI should be designed and used as augmentation rather than replacement**. This principle appears consistently across studies of scaffolding, dialogic feedback, metacognitive prompts, reflection journals, and guidance-based learning. The strongest learning benefits tend to occur when GenAI is used to provide hints, alternative perspectives, feedback for revision, or support for evaluative reflection, rather than to bypass student thinking altogether. In practice, this means that higher education instructors should avoid designing tasks in which AI can simply produce final answers with minimal human judgement. Instead, tasks should require students to justify prompt choices, compare AI outputs with other sources, reflect on why they accepted or rejected suggestions, and revise on the basis of explicit reasoning. When AI use is embedded within these kinds of reflective loops, the literature suggests that learner agency is more likely to be preserved.

The review also highlights the importance of **AI literacy and feedback literacy** as pedagogical priorities. Students need more than operational familiarity with GenAI tools. They need to develop evaluative judgement, risk awareness, metacognitive awareness, and the ability to interpret AI-generated feedback selectively. This is especially important in writing and research contexts, where the boundary between assistance and substitution can become blurred. Educational responses should therefore focus not only on whether students are “allowed” to use AI, but on whether they are being taught to use it in ways that preserve authorship, critical reasoning, and responsibility.

At the level of future research, several directions follow from this review. First, the field would benefit from more studies that directly measure learner agency rather than relying only on adjacent variables such as acceptance, intention, or satisfaction. Second, more longitudinal and mixed-methods work is needed to understand how agency-enhancing and agency-eroding processes unfold over time. Third, future studies should more clearly distinguish strategic offloading from overreliance, and should not assume that all AI delegation has the same educational meaning. Finally, more research is needed across disciplinary and cultural contexts, since recent evidence suggests that the same dual-pathway structure may be broadly robust while still being shaped by local educational traditions and task demands.

Overall, the discussion of this review leads to a clear conclusion: GenAI does not simply support or undermine higher education learning. Rather, it redistributes the conditions under which learner agency is enacted. Whether that redistribution becomes empowering or corrosive depends on the learner’s regulatory capacities, the calibration of trust and confidence, and the pedagogical structures surrounding AI use. The most productive future for GenAI in higher education will therefore not come from maximizing automation, but from designing environments in which learners continue to think, judge, revise, and take responsibility while working with AI.

## 6. Implications

### 6.1. Pedagogical Implications

The findings of this review suggest that the central pedagogical challenge is no longer whether GenAI should be present in higher education, but **how it should be pedagogically positioned**. The literature consistently indicates that GenAI is most beneficial when it is used as a form of **augmentation** rather than **replacement**. In practical terms, this means that GenAI should not simply be treated as an answer-generating tool that removes difficulty from learning tasks. Instead, it should

be integrated in ways that preserve learners' responsibility for interpretation, evaluation, revision, and decision making. Studies on pedagogical partnerships, research competence, and writing support repeatedly show that the educational value of GenAI depends on whether students remain the active agents of meaning making rather than outsourcing that role to the system (Wang & Zhang, 2026; Zhu & Yang, 2026).

A first implication, therefore, is that instructors should prioritize **scaffolded AI use over direct-answer use**. The strongest positive outcomes in the reviewed literature were associated with learning designs in which GenAI provided hints, prompts, feedback, or intermediate support rather than fully formed solutions. Guidance-based designs, Socratic questioning, metacognitive prompting, and AI-facilitated scaffolding all appear more conducive to agency-preserving learning than unrestricted answer delivery. These approaches keep students cognitively engaged and make it more difficult for them to drift into passive acceptance or superficial completion (Lee et al., 2024; Joo et al., 2026; Sun et al., 2026; Zhou et al., 2025).

A second implication concerns the explicit teaching of **self-regulation, metacognition, and critical evaluation**. The reviewed studies repeatedly show that these are not secondary skills in AI-supported learning; they are the conditions under which GenAI becomes educationally productive. Students need structured opportunities to set goals, monitor their own use of AI, compare alternative outputs, verify accuracy, justify acceptance or rejection of AI suggestions, and reflect on how AI support affects their own thinking. Reflection journals, dialogic feedback routines, and tasks that require explanation of revision choices are especially promising because they turn AI use into an object of reflection rather than a hidden background process (Zhan & Yan, 2025; Zhang et al., 2025; Zhou & Wang, 2026).

A third pedagogical implication is the need to cultivate **AI literacy as evaluative literacy**, not merely technical familiarity. The literature suggests that students benefit most from GenAI when they understand not only how to use the tool, but also how to question it. This includes recognizing limitations, detecting risk, calibrating trust, and distinguishing support from substitution. Instructors should therefore design learning activities that require students to evaluate AI-generated content against disciplinary standards, prior knowledge, human feedback, and alternative sources. In writing and research contexts in particular, AI literacy should be closely linked to authorship, evidence use, and responsible academic practice (Qi et al., 2025; Zhu and Yang, 2026).

A fourth implication is that **feedback literacy** deserves particular attention in the AI era. Several studies show that students may interact with AI-generated feedback at a shallow level unless they are taught how to request, interpret, evaluate, and act on that feedback. This means that higher education institutions should not assume that AI feedback automatically leads to revision or learning improvement. Rather, students need explicit support in developing evaluative judgement, emotional reflexivity, and selective uptake. Feedback literacy should therefore be treated as a core educational outcome in AI-supported learning, especially in writing-intensive and research-intensive programs (Zhan & Yan, 2025; Zhou & Wang, 2026).

Finally, the review indicates that **human mediation remains essential**. Even when GenAI provides highly responsive and personalized support, teachers still play a crucial role in shaping the conditions under which students use AI reflectively and responsibly. The most productive pedagogical environments are not those in which teachers withdraw in favor of automation, but those in which instructors guide students in using GenAI as a reflective partner, a source of challenge, and a scaffold for deeper learning. In this sense, the goal is not to minimize the teacher's role, but to reconfigure it toward designing tasks, prompting reflection, and preserving learner agency in AI-mediated education (Smirnova, 2025; Wang and Zhang, 2026).

## 6.2. Implications for Future Research

The review also has several implications for future research. First, the field would benefit from more studies that **directly conceptualize and measure learner agency** rather than relying only on adjacent constructs such as intention to use, acceptance, satisfaction, or performance. Recent work

has begun to offer scale-based and framework-based approaches to learner agency, but the concept is still unevenly operationalized across studies. More explicit use of agency as a central construct would allow stronger comparison across contexts and improve the theoretical coherence of the field (Xia et al., 2025; Yang et al., 2024).

Second, future studies should more clearly distinguish between **strategic cognitive offloading** and **maladaptive overreliance**. A major contribution of the recent literature is the suggestion that not all delegation to AI is harmful. However, many studies still treat dependence, offloading, and AI assistance as if they were conceptually interchangeable. More fine-grained work is needed to identify what kinds of delegation are compatible with learner agency and what kinds undermine it. This distinction is essential if the field is to move beyond generalized anxiety about AI and toward more precise explanations of learning processes (Wang & Zhang, 2026; Hou et al., 2025).

Third, the field would benefit from more **longitudinal, mixed-methods, and behavior-trace research**. Much of the existing literature remains cross-sectional and self-report based. While such studies have established important patterns, they provide limited insight into how agency-enhancing and agency-eroding effects evolve over time. Longitudinal and mixed-methods studies would make it possible to examine how students' trust, self-regulation, feedback use, and dependence develop across sustained interaction with GenAI, and whether short-term gains in confidence translate into long-term gains in autonomous competence (Xia, 2025; Xia et al., 2026).

Fourth, more comparative research is needed across **disciplines, learner populations, and cultural contexts**. The reviewed literature spans writing, language learning, research training, problem solving, and other domains, but some areas remain much more heavily represented than others. There is also strong concentration in certain regional contexts, especially Chinese and EFL-related higher education settings. Although this concentration has generated valuable insights, broader disciplinary and contextual diversity would improve the generalizability of future findings and reveal whether the same dual-pathway structure holds across different educational traditions and epistemic practices (Zhang, Rice, & Wang, 2024; Zheng & Wang, 2026).

## 7. Limitations

This review should be interpreted in light of several limitations. First, the review focused on **peer-reviewed journal articles published in English**, which means that relevant work published in other languages or in non-journal formats may not have been captured. As a result, the present synthesis should be understood as a structured mapping of a substantial segment of the literature rather than an exhaustive representation of all available knowledge on the topic.

Second, the review concentrated specifically on **higher education contexts** and excluded studies focused primarily on teachers, faculty adoption, or institutional implementation unless they offered direct relevance to student learning processes. This decision strengthened conceptual focus, but it also means that broader ecosystem-level factors shaping GenAI use in universities may be underrepresented in the synthesis.

Third, the literature included in the review is **methodologically heterogeneous**, covering surveys, experiments, qualitative studies, mixed-methods designs, behavioral analyses, and scale-development studies. This diversity is one of the reasons a scoping review was appropriate, but it also means that the conclusions of the review are conceptual and interpretive rather than causal in a narrow statistical sense. The review maps patterns, mechanisms, and tensions in the literature; it does not provide a meta-analytic estimate of the average effect of GenAI on any single educational outcome.

Fourth, a large proportion of the studies reviewed were concentrated in **language-learning, writing, and Chinese/EFL higher education settings**. This concentration reflects the current state of the field, but it may limit the transferability of some conclusions to other disciplines or regions. Although the review identified recurring themes across diverse contexts, the relative weight of those themes may vary in less represented areas such as laboratory-based disciplines, design education, or professional education outside language-focused domains.

Fifth, the search strategy restricted GenAI-related terms to the title field, which improved precision but may have reduced recall for relevant studies that discussed GenAI extensively in abstracts or keywords without explicitly naming it in the title.

Finally, many of the included studies were based on **cross-sectional self-report data**, which limits the ability of the underlying literature to capture how learner agency, dependence, and offloading develop over time. Accordingly, although this review proposes a dual-pathway interpretation, the temporal dynamics of that interpretation remain to be tested more rigorously through longitudinal and multimodal research.

## 8. Conclusions

This scoping review examined how the literature has conceptualized the relationships among generative AI, cognitive offloading, and learner agency in higher education. The review shows that GenAI cannot be adequately understood through a simple positive-or-negative lens. Instead, the literature consistently points to a **dual-pathway structure**. One pathway suggests that GenAI may strengthen learner agency by supporting self-regulation, confidence, feedback engagement, and strategic participation in learning. The other suggests that GenAI may weaken learner agency by encouraging cognitive offloading, overreliance, technological dependence, and uncritical uptake of AI-generated output.

A key conclusion of the review is that **learner agency offers the most meaningful framework for interpreting these tensions**. The crucial question is not whether students use GenAI, but whether they retain the capacity to direct, monitor, evaluate, and take responsibility for that use. In this sense, learner agency serves as both an analytic construct and a normative educational criterion: it helps explain variation in outcomes, and it identifies what should be preserved in AI-mediated learning.

The review also indicates that **self-regulation and metacognition are the central mechanisms** through which GenAI becomes either a scaffold or a substitute. When learners continue to set goals, verify outputs, reflect on feedback, and exercise evaluative judgement, GenAI is more likely to function as augmentation. When these processes weaken, the same technology may begin to displace rather than support thinking. Trust, self-efficacy, anxiety, and feedback literacy further shape this process by influencing how students interpret and act on AI-supported learning opportunities.

Overall, the findings suggest that the future educational value of GenAI in higher education will depend less on how powerful the technology becomes and more on how effectively learning environments preserve human judgement, reflective participation, and responsibility. The most productive path forward is therefore not to maximize automation for its own sake, but to design GenAI-supported education in ways that keep learners actively involved in thinking, evaluating, revising, and deciding. In that sense, the fundamental challenge of the AI era is not simply teaching students to use GenAI, but ensuring that they remain **agentic learners while doing so**.

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## Appendix A. PRISMA-ScR Checklist

This review was reported with reference to the PRISMA extension for Scoping Reviews (PRISMA-ScR). Table A1 indicates where each checklist item is addressed in the manuscript.

**Table A1.** PRISMA-ScR checklist and location of reported items in the manuscript.

Section	Item No.	PRISMA-ScR Item	Reported in Manuscript
Title	1	Identify the report as a scoping review.	Title
Abstract	2	Provide a structured summary that includes background, objectives, eligibility criteria, sources of evidence, charting methods, results, and conclusions.	Abstract
Introduction	3	Describe the rationale for the review in the context of what is already known and explain why the review questions are suitable for a scoping review approach.	Section 1. Introduction
Introduction	4	State the objectives or questions of the review with reference to key elements such as population, concepts, and context.	Section 1. Introduction
Methods	5	Indicate whether a review protocol exists and, if applicable, where it can be accessed.	Not applicable; no formal protocol was registered
Methods	6	Specify the eligibility criteria for sources of evidence, including years considered, language, publication status, and rationale.	Section 3.3. Eligibility Criteria
Methods	7	Describe all information sources used in the search and the date of the most recent search.	Section 3.2. Search Strategy; Appendix B
Methods	8	Present the full electronic search strategy for at least one database, including any limits used.	Appendix B
Methods	9	Describe the process for selecting sources of evidence, including screening and eligibility assessment.	Section 3.4. Study Selection
Methods	10	Describe the methods used to chart data from the included studies.	Section 3.5. Data Charting
Methods	11	List and define all variables for which data were sought and any assumptions or simplifications made.	Section 3.5. Data Charting
Methods	12	If done, describe any critical appraisal of included sources and how this information was used.	Not applicable; formal critical appraisal was not conducted
Methods	13	Describe the methods used to summarize and synthesize the charted data.	Section 3.6. Data Synthesis
Results	14	Report the numbers of sources screened, assessed for eligibility, and included, with reasons for	Section 3.4. Study Selection; Figure 1

		exclusions at each stage, ideally using a flow diagram.	
<b>Results</b>	15	Describe the characteristics of the included sources of evidence.	Table 1; Section 4
<b>Results</b>	16	If done, present results of any critical appraisal of included sources.	Not applicable
<b>Results</b>	17	Present the relevant data that were charted from each included source of evidence.	Table 1
<b>Results</b>	18	Summarize and present the charting results in relation to the review questions and objectives.	Sections 4.1–4.5; Table 2
<b>Discussion</b>	19	Summarize the main results, including an overview of concepts, themes, and types of evidence available, and link these to the review questions.	Section 5. Discussion
<b>Discussion</b>	20	Discuss the limitations of the scoping review process.	Section 7. Limitations
<b>Discussion / Conclusion</b>	21	Provide a general interpretation of the results with respect to the review questions and possible implications.	Sections 5. Discussion; 6. Implications; 8. Conclusion
<b>Funding</b>	22	Describe sources of funding for the included sources of evidence, where available, and describe the role of funders for the scoping review.	Funding Statement

## Appendix B. Full Search Strategy

### Appendix B.1. Database and Search Scope

The literature search was conducted in the **Web of Science Core Collection** on [insert exact search date]. The search focused on **English-language, peer-reviewed journal articles**.

The search strategy was developed to identify studies at the intersection of three conceptual domains:

- (1) **generative AI technologies** (e.g., ChatGPT, generative AI, and large language models);
- (2) **higher education contexts** (e.g., higher education, university, college, tertiary education, undergraduate, and postgraduate); and
- (3) **agency-, offloading-, and mechanism-related constructs**.

To improve conceptual coverage, the search strategy included three groups of topic combinations. The first group focused on **learner agency, learner autonomy, and self-directed learning**; the second focused on **cognitive offloading, overreliance, and AI reliance**; and the third focused on related **mechanism-oriented constructs**, including **self-efficacy, self-regulation, metacognition, and critical thinking**. The third search block was included to capture studies that did not explicitly use the terms *learner agency* or *cognitive offloading* but were conceptually relevant to the review focus.

No publication year filter was applied during the database search. Studies published before **2022** were excluded during screening because they predated the widespread educational uptake of generative AI in higher education. Studies on primary or secondary education, child or adolescent populations, and clinical or patient contexts were also excluded.

### Appendix B.2. Full Web of Science Search String

((TI=(ChatGPT OR "generative AI" OR "generative artificial intelligence" OR GenAI OR "large language model\*" OR LLM\* OR GPT-3 OR GPT-4) AND AB=((("higher education" OR universit\* OR college\* OR "tertiary education" OR undergraduate\* OR postgraduate\*) AND ("learner agency" OR

“student agency” OR “learner autonomy” OR “student autonomy” OR “self-directed learning”)) NOT AB=(“primary school\*” OR “secondary school\*” OR “high school\*” OR K-12 OR child\* OR adolescen\* OR patient\* OR clinical)))

OR

((TI=(ChatGPT OR “generative AI” OR “generative artificial intelligence” OR GenAI OR “large language model\*” OR LLM\* OR GPT-3 OR GPT-4) AND AB=(“higher education” OR universit\* OR college\* OR “tertiary education” OR undergraduate\* OR postgraduate\*) AND (“cognitive offload\*” OR overreliance OR “over-reliance” OR “AI reliance” OR “reliance on ChatGPT” OR “automation bias” OR “cognitive outsourcing”)) NOT AB=(“primary school\*” OR “secondary school\*” OR “high school\*” OR K-12 OR child\* OR adolescen\* OR patient\* OR clinical)))

OR

((TI=(ChatGPT OR “generative AI” OR “generative artificial intelligence” OR GenAI OR “large language model\*” OR LLM\* OR GPT-3 OR GPT-4) AND AB=(“higher education” OR universit\* OR college\* OR “tertiary education” OR undergraduate\* OR postgraduate\*) AND (“self-efficacy” OR “self efficacy” OR “self-regulation” OR “self regulation” OR “self-regulated learning” OR metacognit\* OR “critical thinking”)) NOT AB=(“primary school\*” OR “secondary school\*” OR “high school\*” OR K-12 OR child\* OR adolescen\* OR patient\* OR clinical)))

### Appendix B.3. Additional Screening Notes

Following retrieval, records were exported for duplicate removal and screening. Title and abstract screening was then conducted according to the eligibility criteria described in Section 3.3. In particular, studies were retained if they were situated in **higher education**, focused on **GenAI or large language model-based tools**, and addressed either (a) **learner agency/autonomy/self-directed learning**, (b) **cognitive offloading/overreliance/dependence**, or (c) closely related **mechanism-oriented constructs** such as self-regulation, metacognition, self-efficacy, critical thinking, or feedback-related engagement.

### Appendix B.4. Note on Search Precision

Because GenAI-related terms were restricted to the **title field**, the search strategy prioritized topical precision. However, this decision may have reduced recall for potentially relevant studies that referred to GenAI primarily in abstracts or keywords without explicitly naming it in the title.

## References

- Arksey, H. and O’Malley, L. (2005). ‘Scoping studies: towards a methodological framework’. *International Journal of Social Research Methodology*, **8**, 19–32.
- Chase, A.-M. and Galvin, K. (2026). ‘Thinking to learn: managing the risks of outsourcing to GenAI’. *Assessment & Evaluation in Higher Education*, 1–20.
- Fan, Y., Tang, L., Le, H., Shen, K., Tan, S., Zhao, Y., et al. (2025). ‘Beware of metacognitive laziness: Effects of generative artificial intelligence on learning motivation, processes, and performance’. *British Journal of Educational Technology*, **56**, 489–530.
- Hou, C., Zhu, G., and Sudarshan, V. (2025). ‘The role of critical thinking on undergraduates’ reliance behaviours on generative AI in problem-solving’. *British Journal of Educational Technology*, **56**, 1919–1941.
- Jia, W., Pan, L., and Neary, S. (2025). ‘Effect of GenAI Dependency on University Students’ Academic Achievement: The Mediating Role of Self-Efficacy and Moderating Role of Perceived Teacher Caring’. *Behavioral Sciences*, **15**, 1348.
- Jiang, Y., Wu, Q., Yang, Y., Jian, C., and Zhao, J. (2026). ‘Learner agency in revising GenAI-generated statements of purpose’. *British Journal of Educational Technology*. Available At <https://bera-journals.onlinelibrary.wiley.com/doi/10.1111/bjet.70041>.
- Joo, S., Han, I., and Park, I. (2026). ‘The effect of metacognitive prompts using generative AI on cognitive load, task performance, and self-efficacy in online self-regulated learning’. *Educational Psychology*, 1–24.

- Kim, S., So, H., and Park, K. (2025). 'Supporting learner agency in collaborative writing with generative <sc>AI</sc>'. *British Journal of Educational Technology*. Available At <https://bera-journals.onlinelibrary.wiley.com/doi/10.1111/bjet.70015>.
- Lai, C., Pan, M., Pi, R., Shen, K., and Liu, Y. (2026). 'Learner agency in self-directed use of GenAI for informal language learning'. *Innovation in Language Learning and Teaching*, 1–23.
- Lee, H.-Y., Chen, P.-H., Wang, W.-S., Huang, Y.-M., and Wu, T.-T. (2024). 'Empowering ChatGPT with guidance mechanism in blended learning: effect of self-regulated learning, higher-order thinking skills, and knowledge construction'. *International Journal of Educational Technology in Higher Education*. Available At <https://educationaltechnologyjournal.springeropen.com/articles/10.1186/s41239-024-00447-4>, 21.
- Levac, D., Colquhoun, H., and O'Brien, K. K. (2010). 'Scoping studies: advancing the methodology'. *Implementation Science*, 5, 69.
- Lukešová, A. and Jennings, P. J. (2025). 'Beyond the interface: Supporting beginner-level CEFR mediation and learner autonomy with ChatGPT'. *Language Teaching Research*. Available At <https://journals.sagepub.com/doi/10.1177/13621688251393481>.
- Lukešová, A. and Jennings, P. J. (2026). 'Clue before correction: ChatGPT-enhanced strategy for promoting autonomous and reflective language learning'. *Innovation in Language Learning and Teaching*, 1–29.
- Munn, Z., Peters, M. D. J., Stern, C., Tufanaru, C., McArthur, A., and Aromataris, E. (2018). 'Systematic review or scoping review? Guidance for authors when choosing between a systematic or scoping review approach'. *BMC Medical Research Methodology*, 18, 143.
- Qi, J., Liu, J., and Xu, Y. (2025). 'The Role of Individual Capabilities in Maximizing the Benefits for Students Using GenAI Tools in Higher Education'. *Behavioral Sciences*, 15, 328.
- Smirnova, L. (2025). 'Developing students' agency and voice by using generative AI in an online EAP module'. *Innovation in Language Learning and Teaching*, 1–11.
- Sun, D., Zheng, Y., Xu, J., and Yang, Z. (2026). 'When Generative AI Meets Socratic Method: Investigating Programming Learning Dynamics Through Behaviours, Interaction Qualities and Perceptions'. *Journal of Computer Assisted Learning*. Available At <https://onlinelibrary.wiley.com/doi/10.1002/jcal.70210>, 42.
- Tao, S., Zhang, H., and Ding, L. (2026). 'Explainable machine learning for sustainable education: Predicting college students' reliance on generative artificial intelligence'. *Acta Psychologica*, 265, 106622.
- Tekir, S. (2026). 'Generative AI use in EFL writing: associations with originality, critical reasoning, and metacognitive engagement in a Turkish higher education context'. *Computer Assisted Language Learning*, 1–22.
- Teng, M. F. (2025). 'Understanding EFL student writers' metacognitive awareness in utilizing ChatGPT'. *System*, 135, 103848.
- Tian, S. and Xiang, H. (2026). 'Exploring EFL students' effective use of GenAI in writing: Interplay of self-regulation, critical thinking, growth mindset, general writing competence, and GenAI literacy'. *Education and Information Technologies*, 31, 1351–1383.
- Urban, M., Brom, C., Lukavský, J., Děchtěrenko, F., Hein, V., Svacha, F., et al. (2025). "'ChatGPT can make mistakes. Check important info.'" Epistemic beliefs and metacognitive accuracy in students' integration of ChatGPT content into academic writing'. *British Journal of Educational Technology*, 56, 1897–1918.
- Wang, S. and Zhang, H. (2026). 'Pedagogical partnerships with generative AI in higher education: how dual cognitive pathways paradoxically enable transformative learning'. *International Journal of Educational Technology in Higher Education*, 23, 11.
- Xia, L., Shen, K., Sun, H., An, X., and Dong, Y. (2025). 'Developing and validating the student learning agency scale in generative artificial intelligence (AI)-supported contexts'. *Education and Information Technologies*, 30, 13999–14021.
- Xia, L., Zhang, L., Shen, K., and Dong, Y. (2026). 'The impact of generative artificial intelligence (GenAI) on university students' learning agency: A mixed-methods study'. *Teaching in Higher Education*, 1–18.
- Xia, Q. (2025). 'Time tells the tale: tracing the interplay between self-regulated learning and deep approaches to learning with GenAI through individual differences'. *Interactive Learning Environments*, 1–19.

- Xu, X., Qiao, L., Cheng, N., Liu, H., and Zhao, W. (2025). 'Enhancing self-regulated learning and learning experience in generative AI environments: The critical role of metacognitive support'. *British Journal of Educational Technology*, **56**, 1842–1863.
- Yang, Y., Luo, J., Yang, M., Yang, R., and Chen, J. (2024). 'From surface to deep learning approaches with Generative AI in higher education: an analytical framework of student agency'. *Studies in Higher Education*, **49**, 817–830.
- Yao, Y., Sun, Y., Zhu, S., and Zhu, X. (2025). 'A Qualitative Inquiry Into Metacognitive Strategies of Postgraduate Students in Employing ChatGPT for English Academic Writing'. *European Journal of Education*. Available At <https://onlinelibrary.wiley.com/doi/10.1111/ejed.12824>, **60**.
- Yilmaz, M., Gauthier, A., and Cukurova, M. (2026). 'Supporting online learners' regulation skills with the help of learning analytics and generative artificial intelligence'. *Educational technology research and development*. Available At <https://link.springer.com/10.1007/s11423-026-10595-1>.
- Zhan, Y. and Yan, Z. (2025). 'Students' engagement with ChatGPT feedback: implications for student feedback literacy in the context of generative artificial intelligence'. *Assessment & Evaluation in Higher Education*, 1–14.
- Zhang, D., Wen, L., and Wu, J. G. (2025). 'Structured or Semi-Structured? The Use of Reflection Journals in Postgraduates' Generative Artificial Intelligence Literacy Development in an L2 Academic Writing Context'. *European Journal of Education*, **60**, e70189.
- Zhang, L. and Xu, J. (2025). 'The paradox of self-efficacy and technological dependence: Unraveling generative AI's impact on university students' task completion'. *The Internet and Higher Education*, **65**, 100978.
- Zhang, Q., Pan, X., and Fan, J. (2025). 'Uncovering the Mediating Effects of AI Trust and Self-Efficacy on Engagement in Human-GenAI Communication for EFL Learning'. *European Journal of Education*, **60**, e70336.
- Zheng, C. and Wang, Y. (2026). 'Generative AI in EFL contexts: Q-methodological analysis of cognitive dissonance patterns and self-regulation strategies among Chinese tertiary learners'. *Acta Psychologica*, **264**, 106531.
- Zhou, C. and Wang, Y. (2026). 'University Students' Writing Feedback Literacy in the AI Era: The Interplay of Generative AI Acceptance, Writing Anxiety and Writing Self-Efficacy in Chinese EMI Educational Contexts'. *European Journal of Education*. Available At <https://onlinelibrary.wiley.com/doi/10.1111/ejed.70478>, **61**.
- Zhou, R., He, X., Fan, Q., Li, Yangyang, Li, Yue, Xiao, X., et al. (2025). 'Exploring <scp>ChatGPT</scp>-Facilitated Scaffolding in Undergraduates' Mathematical Problem Solving'. *Journal of Computer Assisted Learning*. Available At <https://onlinelibrary.wiley.com/doi/10.1111/jcal.70077>, **41**.
- Zhu, H. and Yang, S. (2026). 'The Impact of Generative AI Use on Graduate Students' Research Competence: The Mediating Role of Critical Thinking and the Moderating Role of Research Self-Efficacy'. *Behavioral Sciences*, **16**, 304.

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