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Artificial Intelligence and Human Cognitive Development: A Thematic Analysis

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Abstract

There is still uncertainty surrounding whether generative artificial intelligence (GenAI) enhances or decreases human cognition as the proof is scattered all around. This thematic analysis synthesises 46 core peer-reviewed articles (2011–2026), selected from 165 Scopus records after an assessment, to conclude how AI applications affect the development of human cognition in learning. The six-phase process proposed by Braun and Clarke (2006) yielded six themes: (1) AI-assisted performance does not equal productive learning; (2) cognitive offloading is mixed in quality and dependent and autonomous vary in approach; (3) critical and higher-order thinking depend on usage of AI rather than simply on AI existence; (4) metacognition, self-regulation and calibration play the main role; (5) either strengths of creativity and cognitive agency depend on process of engagement; and (6) pedagogical design has implications for all listed above. The proof of a long-lasting, self-sufficient gain is scarce and varies, whereas the data largely comprise cross-sectional opinions of university undergraduates. The final evaluation shows that the cognitive influence of artificial intelligence is variable. It's dependent on the governing behaviour and the teaching method. The research gives rise to a human-centred agenda, which aims to maintain productive effort, use artificial intelligence indirectly, and assess the process besides the result.

Keywords: artificial intelligence; generative AI; cognitive development; cognitive offloading; critical thinking; metacognition; thematic analysis

1. INTRODUCTION

Generative artificial intelligence (GenAI) has changed from being new to being moderately accepted in higher education in a few years. For instance, some tools such as ChatGPT can now explain ideas, write and rewrite texts, make arguments and give solutions just when needed instead of students having to do that themselves (Zhu et al., 2026). This all leads to a long-standing question being raised in a sharper way: if a powerful external system is doing some part of the thinking, what happens to the thinker in this case? The matter is important not just from a classroom perspective, as critical thinking, reasoning, creativity, and self-regulation are considered the main aspects of human cognitive process development (Si et al., 2026; Yavich, 2025).

The literature has revealed two contrasting responses to this inquiry: the optimistic perspective considers AI as a cognitive aid or collaborator that lowers barriers to entry, offers instant feedback, and releases cognitive task capacity for higher-order jobs. Experimental and survey research shows evidence of improvement in knowledge acquisition, problem-solving, creativity, and critical thinking associated with using AI appropriately (Essel et al., 2024; Nathaniel et al., 2025; Urban et al., 2024; Zhao et al., 2025). Additionally, the analysis of logs in tutoring systems suggests that experience with AI contributes to

improved monitoring, control, and engagement (Li, 2026). According to the pessimistic perspective, students who use ChatGPT improve the produced outcome but may not gain new knowledge, which institutions sometimes refer to as "metacognitive laziness" (Fan et al., 2025). More significant use of AI decreases critical thinking ability (Tian & Zhang, 2025), and systems depending on AI can harm the critical reasoning ability of individuals who use them (Liu et al., 2026).

Some new findings imply that these positions are not as contradictory as they seem. Most of the disagreement is caused by the confusion between non-durable learning and performance augmented by artificial intelligence (Rowe, 2026). Lin and Al-Hada (2026) introduce a phenomenon called the critical thinking paradox of GenAI-based learning, which implies that while the quality of the learners' output improves, their cognitive involvement decreases. Wang and Shan (2026) write about the safety gap between the quality of the students' output with AI and their ability to verify the result independently. In all the considered cases, it is not access to AI, but the way it is used that acts as a key factor, including whether the user produces the content on their own, evaluates it critically, and takes responsibility for the results (Liu et al., 2026; Su et al., 2026; Zhu et al., 2026).

Although there is a certain degree of convergence in the findings, the evidence available is fragmented. The studies discussed differed in terms of outcomes under investigation (e.g. critical thinking, creativity, metacognition, knowledge transfer), theoretical frameworks used (e.g. cognitive offloading, cognitive load, self-regulated learning, distributed cognition), and methodology employed (single-session experiments, cross-sectional surveys, purely conceptual models). There were only a few synthesis reviews incorporating most of these strands into one coherent narrative focusing on the broader issue of human cognitive development, and the majority of relevant studies were published in the last two years. Hence, a systematic thematic synthesis is due.

This paper fills that void in the literature by examining 46 main publications out of the 165 Scopus records screened. The article identifies the themes that frequently recur in the selected articles, establishes the processes that underlie the positive and negative impact of AI on academic performance in education, and describes its implications for teaching and designing educational tools, as well as recommends further research on this topic. The Introduction presents the goals and objectives; Methodology explains the approach adopted in the study; the Results describe the identified common themes of the articles; Implications analyse these themes; and Limitations and Conclusion summarise the main findings of the research.

2. RESEARCH OBJECTIVES AND QUESTIONS

The study aims to develop a human-centred, evidence-based understanding of how artificial intelligence relates to human cognitive development in educational contexts. Four objectives follow from the gaps identified above:

1. To investigate the relationship between AI technology usage, especially GenAI technology usage, and learners' cognitive outcomes, especially regarding critical and higher-order thinking, creativity, and long-lasting learning.
2. To determine the psychological mechanisms such as cognitive offloading, metacognition and self-regulation that clarify why the same technology produces different cognitive outcomes.
3. To investigate the individual and contextual conditions influencing these outcomes, including AI literacy, reflective thinking, motivation and prior knowledge.

4. To provide an overview of the relevant pedagogical and design solutions recommended or studied to mitigate cognitive load and learner agency.

The objectives translate into four research questions:

RQ1. What cognitive outcomes are linked to AI use in the selected studies, and how consistent is the evidence?

RQ2. Which mechanisms explain when AI supports and when it undermines cognitive development?

RQ3. Which learner characteristics and contextual conditions change the direction or size of these effects?

RQ4. Which instructional and design approaches preserve cognitive effort and agency while still using AI?

3. METHODLOGY

3.1 DESIGN

This research is of a qualitative thematic analysis type based on previously published studies. The research follows the six steps of thematic analysis as suggested by Braun and Clarke (2006). These include becoming familiar with the data, creating the initial codes, searching for themes, reviewing the themes, defining and naming the themes, and finally producing the report. This thematic approach can be utilised for this research because the body of literature includes experiments, surveys, and qualitative studies that cannot be statistically aggregated, but can be interpreted through thematic analysis.

3.2 SEARCH AND SELECTION

Records were retrieved from the Scopus database using the following Boolean search string: ("artificial intelligence" OR "generative AI" OR "ChatGPT" OR "large language model" OR "AI tool") AND ("cognitive development" OR "critical thinking" OR "cognitive offloading" OR "metacognition" OR "cognitive skill" OR "cognitive function"). In the original search, 9,798 documents were found. However, the publication date period was limited to 2011–2026, resulting in 9,445 documents being procured. Further filtering was done by limiting the field of study to Psychology and Social Sciences (4,910), the type of document to Articles (2,867), and the language used to English (2,735). After that, keyword searching using the following terms, “Critical Thinking” and “Metacognition,” left us with 816 documents. Lastly, the publishing type was narrowed down to journals and left with 814 documents in total with 219 source titles (Table 1). A total of 14 studies that were selected were screened and classified further into four types based on their relevance to AI and human cognition development: Core (46), Supporting (63), Peripheral (41), and Excluded (15). This classification helped us narrow our literature review down to the studies that had a direct relationship to our research area (Table 2).

Step	Screening filter applied	Records remaining	Records removed
1	Initial Scopus search string	9,798	–
2	Publication year: 2011–2026	9,445	353
3	Subject area: psychology and social sciences	4,910	4,535
4	Document type: article	2,867	2,043
5	Language: English	2,735	132
6	Keywords: critical thinking, metacognition	816	1,919
7	Source type: journal	814	2

8	Source title: 15 selected journals	219	595
9	Publication stage: final	203	16
10	Access: open access	165	38
11		46	119

Table 1: Search and screening procedure

Tier	Label	Records	Meaning
A	Core	46	AI use is studied directly for its effect on human cognition (critical thinking, metacognition, offloading, creativity, autonomy)
B	Supporting	63	AI plus a cognitive construct, but cognition is a mediator, a side outcome, or the paper is a scale or framework
C	Peripheral	41	AI in education, but the focus is writing scores, perceptions or niche domains
D	Exclude	15	Off-topic, or AI is incidental

Table 2 Relevance classification of the 165 screened records

3.3 CHARACTERISTICS OF THE CORPUS

The corpus is recent: 3 articles were published in 2024, 9 in 2025 and 34 in 2026. Most studies sampled university students, with exceptions that include primary-school learners (Zhao et al., 2025), pre-service teachers (Su et al., 2026), doctoral students (Gao & Zhang, 2026) and mixed student and early-career samples (Zhu et al., 2026). Several studies drew on Chinese undergraduates (for example, Chen, 2026; Li et al., 2026; Si et al., 2026; Tian & Zhang, 2025; Yan et al., 2026), while others sampled students in Ghana (Davor et al., 2026; Essel et al., 2024), Jordan (Alkam et al., 2026) and Colombia (Bolaños-Cristancho et al., 2026). Table 3 classifies the articles by their primary design, based on how each article describes itself.

Primary design	Articles (n)	Illustrative examples
Survey-based, cross-sectional or time-lagged	14	Alkam et al. (2026); Tian & Zhang (2025); Zhu et al. (2026)
Experimental, quasi-experimental or intervention	16	Fan et al. (2025); Liu et al. (2026); Ren (2026)
Qualitative, mixed-methods, log-based or psychometric	7	Gao & Zhang (2026); Li & Liu (2026); Varghese & Sharma (2026)
Conceptual, theoretical or review	9	Lin & Al-Hada (2026); Rowe (2026); Sternberg (2026)

Table 3. Primary design of the 46 core articles

3.4 ANALYSIS PROCEDURE

Details of the articles in terms of their bibliographic outlines, nature of research study design, characteristics of the sample, constructs used in the study, results, and limitations were noted. The segments regarding cognitive outcomes, processes, moderators and pedagogy were then analysed. The themes were checked for the coded fragments and complete text, combined if any overlaps, and labelled

as per their central connecting idea. The analysis resulted in six key themes that were set for validation. To increase the reliability of the results, it was ensured that themes correspond to particular articles, counter and null findings were presented, and experimental findings were separated from cross-sectional findings in terms of self-reports. As only published studies were used in the analysis, no ethical approvals were needed.

4. FINDINGS: THEMATIC ANALYSIS

The analysis produced six themes. Table 4 summarises each theme's central claim and the articles that carry it, and the sections that follow develop each theme in turn.

Theme	Central claim	Key articles
4.1 Performance is not durable learning	AI reliably improves supported output, but gains in unaided competence and transfer are less certain	Chen (2026); Fan et al. (2025); Liu et al. (2026); Melanou et al. (2026)
4.2 Heterogeneous cognitive offloading	Dependent and autonomous offloading have different downstream correlates	Si et al. (2026); Tian & Zhang (2025); Zhu et al. (2026)
4.3 Critical and higher-order thinking	Effects depend on how AI is used and on learners' dispositions	Alkam et al. (2026); Hou et al. (2025); Yan et al. (2026); Zhao et al. (2025)
4.4 Metacognition and calibration	Regulation and accurate self-monitoring are the hinge between AI use and outcomes	Davor et al. (2026); Gao & Zhang (2026); Ren (2026); Urban et al. (2025)
4.5 Creativity and cognitive agency	Creative gains and ownership of thinking depend on the manner of engagement	Su et al. (2026); Urban et al. (2024); Yuan et al. (2026)
4.6 Pedagogical design conditions	Bounded, staged and reflective use preserves effort and agency	Liubertaitė (2026); Rowe (2026); Wang et al. (2026)

Table 4. Themes and their central claims

4.1 AI-SUPPORTED PERFORMANCE IS NOT DURABLE LEARNING

The most common conclusion in the reviewed materials is that AI boosts the learners' performance while it is used, and the indications of its impact on the learners' capability of applying knowledge or skills in further education are less strong. In a randomized research, students who used ChatGPT wrote better essays than students who turned for help to human expert and students who did not use any means, while the study showed that students didn't increase their knowledge and transfer it and the authors cautioned about addiction and "metacognitive laziness" (Fan et al., 2025). Chen (2026) proves the same conclusions in an eight-week classroom study, maintaining that the highest scores were achieved with the help of OpenAI. However, when trying to conduct an assessment without an AI tool in Week 8, the students' performance was better when using bounded support than in the previous situation. The authors state that the gaps are very small since the values of the wild cluster p from .050 to .063 appear and six classes remain unchanged. Urban et al. (2024) similarly reported that ChatGPT improved the quality, elaboration and originality of creative solutions and raised self-efficacy, while participants perceived the task as easier and less effortful.

The most compelling proof that there is a cost once support is withdrawn comes from Liu et al. (2026). In a three-phase experiment, those using a direct-adoption process performed worse on an unaided essay than individuals who had never employed AI (adjusted difference = −0.38 on a 7-point scale, d = −0.28), while individuals who formulated their position first before querying the AI did not deviate from the norm. The authors take caution to indicate that this is an immediate near-transfer cost and does not show any enduring loss of skills, pointing out the differences in the two modes aside from the autonomy aspect. The longitudinal findings are sobering but not disconcerting: A semester-long study indicates that students in all groups were able to increase their knowledge, as adding AI did not make any difference (Melanou et al., 2026), while a shorter study shows that the degree of improvement is independent of how much scaffolding is used (Melanou & Beege, 2026).

Evidence of the cost following the support is illustrated through the work of Liu et al. (2026). In their study, they conducted a three-way experiment in which it was shown that the participants using a direct adoption-based workflow got worse results on their unofficial essay when asked to complete it without assistance. The difference was achieved through comparison with those who had never used AI before the task (diff=−0.38, d=−0.28), and note that those who used their own thinking before deep diving into the material gained positive results. Different workflows produced different outcomes because the authors clarify that the evidence represents a simple temporary decline at the very moment. However, the study by Melanou et al. (2026) presents the participants from all cohorts receiving great knowledge, along with the endpoint that the use of AI did not bring any additional benefits in the process of studies.

Theoretical terms have been given to this empirical phenomenon by means of a range of conceptual papers. For example, Lan and Niu (2026) differentiate strategic uptake from "cognitive bypass", wherein an operation of learning is assigned to AI without participation, analysis or reworking. They argue that better drafts produced with the support of AI do not necessarily imply better effective learning. The theory of "cognitive debt", which is a cumulative decrease in metacognitive regulation and unaided higher-order results, is proposed by Lin and Al-Hada (2026), and the authors suggest product-process separation in the deep processing type of activity. Rowe (2026), Wang and Shan (2026), and Wang et al. (2026) provide a similar position emphasising the gap between performance and learning, the "safety gap" between a piece of assistance and a capability to evaluate it, and "performance without learning".

There is evidence that indicates that the data does not support any connection between performance and learning. For example, an examination of the log data of the use of an AI tutoring platform showed that the use of AI made students more aware of monitoring and controlling their activities. Moreover, this exposure to AI influenced engagement and near transfer, and some delayed benefit in performance was observed after seven days (Li, 2026). However, it is worth mentioning that this study deals with structured tutoring systems rather than open-ended chatting sessions. This fact leads to the idea that the AI design is a distinctive factor that influences the relationship between performance and learning.

4.2 COGNITIVE OFFLOADING IS HETEROGENEOUS

There are multiple definitions of cognitive offloading, which is defined as using external assistance in thinking processes. This phenomenon is presented in all the selected samples of papers, but they emphasise that it is not one unified process. The authors Zhu and co-authors believe in a distinction between dependent and autonomous cognitive offloading, where the process is managed by the AI entity but not by an individual in the former case. The study holds relevance of 589 university students and early workers and examines their types of cognitive offloading. Dependent cognitive offloading is believed to go along with enhanced dependency on AI technology and negative outcomes, while autonomous cognitive

offloading – higher level of intrinsic motivation and positive outcomes of cognitive offload. It should also be noted that both dependent and autonomous types of cognitive offloading provide immediate benefits. Various studies have arrived at similar conclusions through different methodologies. One study analysed 353 university students through cluster analysis and singled out four profiles: "simple question and answer users" included 25.2% of participants; the "critical thinkers" accounted for 15.6%. According to this study, motivation for learning played a key role in obtaining critical thinking skills (Si et al., 2026). This study produced an interesting finding: while cognitive offloading positively predicted cognitive autonomy loss, it did not imply 100% efficiency of cognitive techniques. Marín DJaz (2025) discovered three profiles of automation users (from automation-dependent to autonomous users) in the study of 1,273 participants. The researchers explained how students and PhD candidates moved from task-oriented structures to the so-called calibration crisis when misunderstanding was confused with comprehension and critical thinking was built again through verification and self-explanation.

The offloading concept experienced both positive and negative effects within the model. For example, Fan et al. (2026) found that in-class AI-facilitated cognitive relief functioned as a favourable mediator for positive attitudes, while cognitive offloading played an unfavourable mediatory role, pulling in opposite directions. Li et al. (2026) also discovered such competing relationships: the intensity of GenAI use was positively related to perceived academic creativity, while negatively mediated through cognitive dependence, which resulted in a minimal overall association ($\beta \approx .040$). Tian and Zhang (2025) showed that AI dependence was negatively related to critical thinking, partly because cognitive fatigue was involved; yet, information literacy decreased the negative effect of the relationship while simultaneously aggravating fatigue from high dependence. Regular cognitive offloading, different from general AI use, was shown to be related to cognitive ownership loss experienced by pre-service teachers (Su et al., 2026). The findings in the two studies reveal that offloading does not carry any negative connotation. People offloaded their attention-requiring tracking tasks to a social robot and improved their outcome; however, they considered it an algorithm rather than a partner in the task (Wahn et al., 2026). In writing, the issue of the distribution of labour proved to be significant: whereas in some arrangements where students assessed AI-generated texts produced better results than those when AI evaluated students' writing, students with a tendency to rely on others outsourced the activities they were supposed to perform in the first place (Fan & Chang, 2026). According to the authors, the division of labour determines assignment instead of cognition. Lin and Al-Hada (2026) differentiate between episodic offloading, which is intentional and task-specific, and habitual offloading, which is established and weakly regulated.

4.3 CRITICAL AND HIGHER-ORDER THINKING DEPEND ON HOW AI IS USED

Critical thinking is the most analysed and researched amongst the outcomes, and the results seem to be conditional. Some works show that there are positive results. For example, among 480 medical students, utilisation of AI depends on critical thinking and self-directed learning through cognitive load, which partly mediates the relationship (Arshad et al., 2026). In another study among 421 Chinese students, GenAI was found to predict self-reported critical thinking ($\beta = .257$), and almost all of the association was mediated through GenAI feedback literacy (Yan et al., 2026). Zhou et al. (2024) discovered that perceived ease of use promotes self-regulation, which consequently predicts critical thinking, while perceived usefulness and educational value did not show such results. Moreover, in an experiment with sixth-graders, GenAI was utilised as a cognitive tool or a thinking tool; the use of GenAI still improved deep learning, and critical thinking multiplied its impact on the values of utilisation (Zhao et al., 2025).

Other studies demonstrate where the benefits cease. In an AI usage study involving 555 postgraduate learners in Jordan, lower-order skills (which include remembering, understanding, and applying) saw support from the AI for everybody, while the much weaker gains in higher-order skills of analysing, evaluating, and creating depended on the students' academic integrity (Alkam et al., 2026). In a programming course, scaffolded GenAI showed gains in problem-solving, conditional reasoning, and creativity while indicating not-so-great levels of gain in code optimisation and solution evaluation (Nathaniel et al., 2025). A multi-actor research study conducted in Colombia found that, on the stand of creative thinking issues, which formed 31% of the whole, general cognitive skills and critical thinking occupied the second and third positions at 25% and 24%, respectively, with differential concerns for different actors, including students, faculty, and administrators, which were fully raised by Bolaños-Cristancho et al. (2026). The negative edge is represented by Tian and Zhang (2025) and the very cautionary analysis by Yavich (2025) that advises against excessive reliance on the latter, for all fear it would lead to diminished self-directed analysis and cognitive efforts among students.

The research that delineates these discrepancies converges upon one idea—that critical thinking constitutes both the results of Artificial Intelligence (AI) utilisation and the factor influencing AI application. The research conducted on 808 undergraduate students shows that high critical thinking tends to correlate with reflective, cautious and collaborative AI utilisation, while the level of trust in AI predicts the reckless use of AI, and the critical thinking ability neutralises the impact of trust (Hou et al., 2025). Positive results were achieved through follow-up intervention with 226 students aimed at improving self-reported critical thinking, even though this was not successful in achieving the goal because the intervention was short (Hou et al., 2026). According to Davor et al. (2026), AI task scaffolding helps achieve better results in critical thinking than offloading. Vendrelle and Johnston (2026) provide practical application of the theoretical considerations above and summarise them in six processes of critical engagement: conceptual interpretation, inferential reasoning, evaluative judgment, metacognitive regulation, intellectual curiosity and epistemic integrity.

There is a particular methodology to remark on here. A positive correlation between utilisation of AI and cognitive skills comes from the results of the same-method, self-assessed evaluation, which the authors themselves label as a positive correlation but not established causation (Yan et al., 2026). The more careful results are, on the contrary, based on the testing of the same results with the stimulus (Chen, 2026; Liu et al., 2026). The two bodies of evidence do not conflict as they deal with different things, and thus they cannot be interpreted as a common estimation.

4.4 METACOGNITION, SELF-REGULATION AND CALIBRATION ARE THE HINGE

Metacognition is often referred to as the mechanism that connects AI utilisation to cognitive outcomes. The relationship between the use of GenAI and critical thinking and problem-solving abilities was mediated by self-regulation (Zhou et al., 2024), while metacognitive self-regulation was responsible for the indirect effect of AI verification literacy on higher-level outcomes (Davor et al., 2026) and self-regulated learning moderated the effect of cognitive load on medical students (Arshad et al., 2026). Among the 820 students, perceived interactivity with AI predicted interdisciplinary learning self-efficacy via AI metacognition, with cognitive flexibility moderating this route. Also, females benefitted from interactive AI more than males (Wu et al., 2026). Fan et al. (2025) showed the opposite pole, in which ChatGPT support altered the number and order of self-regulated learning processes, leading to "metacognitive laziness".

A second theme is related to calibration, which refers to learners' ability to properly evaluate both the AI and their own understanding. In one study of 342 college undergraduate students, using ChatGPT caused a rise in learners' confidence but also increased instances of accepting incorrect AI decisions up to 63% of the time, whereas the use of a short metacognitive prompt dramatically lowered the percentage of wrong AI decisions accepted and caused the correct rejection of the AI in 39.7% of the cases (OR = 0.40) (Ren, 2026). Urban et al. (2025) found that less pronounced metacognitive bias led to more correct information being included, while more bias combined with certain beliefs provided more wrong answers from ChatGPT. Urban et al. (2024) established that students who used ChatGPT failed to calibrate their self-assessments properly and had their judgments influenced by the perceived usefulness of the tool, resulting in even more inaccurate assessments. Gao and Zhang (2026) described this situation as mistaking recognition for understanding, fluency for mastery, and coherence for rationale.

The research indicates that metacognition is now being applied in novel ways. For instance, Li and Liu (2026) examined the interaction logs and think-alouds of 79 undergraduate students and discovered that although regulation was the most prevalent instance of metacognition when expressed in either form, verbal monitoring and control systems were detected by different sources. Another example can be considered the validation of a new framework addressing metacognition involving the use of AI. The researchers Varghese and Sharma (2026) published a study detailing their innovative approach to measuring GPT-enabled metacognition. Li (2026) used behavioural indicators to prove the effectiveness of AI-assisted teaching in increasing the level of metacognitive awareness for students. At the same time, the analysis is not always able to demonstrate the metacognitive path.

4.5 CREATIVITY AND COGNITIVE AGENCY DEPEND ON THE MANNER OF ENGAGEMENT

Evidence on creativity is mixed and once again depends on the way in which AI is applied. Experimental studies show that ChatGPT led to higher quality, elaboration, and originality in solutions to poorly framed problems (Urban et al., 2024), had an influence on the creativity, critical, and reflective thinking of college students (Essel et al., 2024), while a critical thinking intervention resulted in more creative group ideas (Hou et al., 2026). On the other hand, Yuan et al. (2026) used one survey and two experiments to demonstrate that dependence on AI was related to less creative output, with critical thinking as a mediator of this relationship. A process-oriented thinking style lessened the impact of this effect, whereas an outcome-oriented thinking style had no effect (index of moderated mediation = 0.22). Li et al. (2026) suggested that gains and losses fully cancelled each other out. In the case of third-language speakers, self-efficacy in AI promotes creativity through AI literacy and critical thinking habits (Yang et al., 2026).

The problem of creativity is also a perceived one. Students in Colombia were most afraid of the loss of their creative skills because of dependence on AI, which accounted for half of their coded worries; teachers, on the other hand, were more prepared to apply GenAI as a means of enhancing creativity (Bolaños-Cristancho et al., 2026). According to Katsenou et al. (2025), it is possible to speak of a dialectic interpretation of the problem of individual agency versus collaborative co-agency.

At the core of the problem relating to creativity lies the issue of agency or believing that one's thoughts are by oneself. According to Su et al. (2026), it is habitual offloading instead of using AI-based techniques that leads to the sense of losing cognitive ownership. As stated by Zhu et al. (2026), the use of the method of dependent offloading transfers one's cognitive agency to AI; although metacognitive monitoring can mitigate the effects of the process, it cannot get rid of the issue completely. At the theoretical level, Chick and Morella (2026) practice Human-AI Symbiotic Theory and the Agency-Preserving Scaffolding feature,

which aim to allow students to maintain control while relying on AI in their learning. Sternberg (2026) states that the problem of giftedness and intelligence in general is whether the use of AI will entail the growth of human cognitive abilities worldwide or not, since the outcome highly depends on the decision of every member of society.

4.6 PEDAGOGICAL DESIGN CONDITIONS SHAPE OUTCOMES

At the core of the problem relating to creativity lies the issue of agency or believing that one's thoughts are by oneself. According to Su et al. (2026), it is habitual offloading instead of using AI-based techniques that leads to the sense of losing cognitive ownership. As stated by Zhu et al. (2026), the use of the method of dependent offloading transfers one's cognitive agency to AI, whereas although metacognitive monitoring can mitigate the effects of the process, it cannot get rid of the issue completely. At the theoretical level, Chick and Morella (2026) practice Human-AI Symbiotic Theory and Agency-Preserving Scaffolding features, which aim to allow students control while relying on AI in their learning. Sternberg (2026) states that the problem of giftedness and intelligence in general is whether the use of AI will entail the growth of human cognitive abilities worldwide or not, since the outcome highly depends on the decision of every member of society.

The second principle here is the idea of providing prompting and evaluation of the process through the use of technology. It has been reported in a seven-week program that included scaffolding and an advanced version of the prompting process that positive effects were achieved in problem-solving skills and other areas (Nathaniel and others, 2025). The authors also relied on the implementation of the IDEA framework, where students learn how to define the purpose of their actions, break down tasks, formulate instructions, and refine the end product. It was observed that the combination of methods resulted in better prompts and products in a pilot project with 42 students as the effectiveness of the prompts was noticed during the unaided tasks completed five days later (Wang and others, 2026). At the same time, it was indicated that there is no correlation between the intensity of the scaffolding method and the results achieved, as Melanou and Beege (2026) demonstrated improvement in all situations without difference in the level of scaffolding. Researchers have established that outcomes were related to the educational approach and students' ability to self-regulate their thinking, and they have found no evidence that the use of AI makes performance differences between students with different levels of knowledge larger.

The third principle is staged implementation of AI usage based on learner readiness. Rowe (2026) developed the Gradual Release of AI Technology model consisting of three modes: independent cognition, shared cognition with teacher's guidance, and offloaded cognition with strategic delegation and maintenance of evaluative judgment. The advancement relies on the degree of knowledge achieved, skills acquired, epistemic comprehension, and the level of AI knowledge. Vendrell and Johnston (2026) advocate sequencing the stages of AI and non-AI participant modes.

The fourth principle is keeping productive friction intact. As argued by Wang and Shan (2016), "Oracle-type" systems whose function is to give a definite answer take away productive struggle, which is a key part of constructing schemas. Wendrell and Johnston (2016) explain that one of the design principles they differentiate is keeping cognitive friction, as well as making PLM work as a provisional thinking partner. Hou et al. (2016) show that the use of structured dialogue and peer mentoring, with the help of AI-made peers, reduces the use of AI-possessed ideas. In all of these articles, good design here does not mean restricting AI, but rather means knowing when AI should appear in the learning process and what the learner still needs to do.

5. DISCUSSION

The six topics provide one central conclusion: the impact of AI upon cognitive processes is not governed by the technology itself but by the interaction of the instrument, the learner, and the educational design. For example, the same system can assist in producing a new draft, and yet disable the author from thinking independently while creating another paper (Liu et al., 2026; Zhu et al., 2026). Therefore, the focus of research and practice changes from whether AI is beneficial or harmful to identifying the circumstances in which this technology is advantageous or disadvantageous.

5.1 CONDITIONS THAT SEPARATE SUPPORT FROM EROSION

Table 3 consolidates the conditions that recur across the corpus. Most of them concern the order and manner of engagement, which learners and teachers can change, rather than fixed traits.

Dimension	Tends to support cognition	Tends to erode cognition	Illustrative evidence
Sequence	Learner generates first, then consults AI	Direct adoption of AI output	Liu et al. (2026); Chen (2026)
Offloading type	Autonomous, episodic, scaffolding	Dependent, habitual, substitutive	Zhu et al. (2026); Lin & Al-Hada (2026)
Evaluation	Student judges and revises AI output	Evaluation re-outsourced to AI	Fan & Chang (2026); Ren (2026)
Metacognition	Accurate calibration and monitoring	Fluency mistaken for understanding	Gao & Zhang (2026); Urban et al. (2025)
Learner dispositions	Critical thinking, reflective thinking, AI and feedback literacy	Trust without evaluation, outcome orientation	Hou et al. (2025); Yan et al. (2026); Yuan et al. (2026)
Task design	Bounded, staged, reflective, with AI-free phases	Open-ended use, answer-delivery tools	Rowe (2026); Wang & Shan (2026)

Table 3. Conditions associated with supportive and eroding patterns of AI use

5.2 PERFORMANCE, LEARNING AND THE PROBLEM OF DETECTION

One practically significant implication is that learners may not become aware of occasions when the use of AI is undermining them. Autonomous and dependent offloading confer, with similar immediate benefits, information transfer rates that seldom contribute to satisfaction to error detection; open ChatGPT assistance induces an increase in assurance and a higher acceptance of erroneous guidance; and perceived ease of use informs self-assessment in a way that can reduce accuracy. If experience itself may not be a good guide, then safeguards cannot depend on the learner's own sense of how well the AI does its task. Instead, they must be embedded in the structure of tasks, assessments and tool designs, as in unaided checkpoints or process-based assessments.

5.3 IMPLICATIONS

For educators. Focus on teaching and evaluating independent performance and the use of AI at the readiness stage of learners, while including AI-free periods in the learning process and requiring learners to produce, justify and confirm the outcome (Rowe, 2026; Vendrell & Johnston, 2026).

For tool designers. Incorporate preservation of effort in technology design. Evidence suggests that tools that prevent giving direct answers, encourage students to think about the task, and allow for easier verification are more effective than tools that simply provide answers (Liubertaitė, 2026; Wang & Shan, 2026).

For institutions and policy. Invest in developing AI literacy, feedback literacy and academic integrity to ensure the beneficial application of AI because these characteristics lead to better results in several studies (Alkam et al., 2026; Li et al., 2026; Yan et al., 2026). It is also important to consider that students, teachers and staff have different issues regarding the same problem (Bolaños-Cristancho et al., 2026).

For learners. Apply AI only after grasping the initial meaning, double-check the results by referring to the sources and see the difference between knowing and understanding the facts (Gao & Zhang, 2026; Liu et al., 2026).

5.4 TOWARD A HUMAN-CENTRED CONCEPTUAL UNDERSTANDING

Combining the themes contributes to a concise explanation. AI alters the cognitive labour distribution between the individual and the device. The answer to the question of whether this redistribution improves or undermines human ability depends on several aspects: whether the learner is in control of the generative and evaluative aspects of the process; whether the learner can keep track and adjust properly (metacognition); whether the task is created in a way to maintain effort level and involve unaided practice (design); and whether the learner has the skills to analyse AI-generated information. When these points are respected, offloading acts as a support mechanism. When not, it becomes substitution, and effectiveness can increase at the same time the capability stops developing. This explanation is in line with human-based and symbiotic approaches described in the referenced books (Chick & Morello, 2026; Katsenou et al., 2025) and Sternberg's (2026) argument that the result depends on the choice made.

6. LIMITATIONS AND FUTURE RESEARCH

This synthesis has several limitations. Foremost of all, it relies on records from one database, Scopus, and 46 core articles chosen out of 165; thus, relevant work that is either indexed elsewhere or excluded at screening may have been missed. Second, 34 out of 46 articles are recent, with publication dates in 2026 or later, and many of these have yet to be cited and replicated. Third, the evidence base is uneven: 14 articles are survey-based, with some relying on self-reported cognition, which limits causal inference (Si et al., 2026; Yan et al., 2026), while nine are conceptual pieces proposing testable hypotheses and not testing them (Lin & Al-Hada, 2026; Lan & Niu, 2026). Fourth, most samples comprise university students, invariably drawn, often from one institution; hence the findings may not transfer down to younger learners, workers, or other cultural contexts. Fifth, constructs such as critical thinking, cognitive offloading, and dependence are inconsistently measured. This renders any comparison thematic rather than additive. Finally, thematic analysis embodies researcher judgment, and the themes only reflect one reading of the corpus.

These limitations point to five directions for future research.

1. **Measure unaided, delayed outcomes.** Studies should test performance after AI is removed and after a delay, rather than only supported output (Chen, 2026; Liu et al., 2026; Lin & Al-Hada, 2026).
2. **Test mechanisms directly.** Metacognitive, motivational and agency pathways are often proposed but not isolated, and one experiment could not detect a metacognitive pathway (Liu et al., 2026).
3. **Use process data.** Interaction logs and think-aloud protocols capture different aspects of regulation and should be combined (Li & Liu, 2026), using validated instruments such as the GPT-assisted metacognition scale (Varghese & Sharma, 2026).
4. **Broaden populations and time horizons.** Longitudinal studies of younger learners, doctoral students and workers are needed, alongside tests of whether developmental stage and prior knowledge moderate effects (Lin & Al-Hada, 2026; Melanou et al., 2026).

5. **Evaluate designs for preserving effort.** Staged and Socratic frameworks such as GRAIT, IDEA and EFFORT-AI need empirical testing across disciplines (Liubertaitė, 2026; Rowe, 2026; Wang et al., 2026).

7. CONCLUSION

This study of 46 basic articles suggests that there is no definite influence of artificial intelligence on human cognitive development. AI increases task performance, but the impact of any activity must be evaluated according to specific criteria: whether that activity supports the learner or is used as a substitute for his or her own cognitive processes. The use of AI may facilitate weak reasoning, creativity and independence of thinking when dependence on the technology is high. As a result, the question is not whether students use AI or not, but rather how they use it and in what cases. A learner-centred approach to the use of AI is necessary in order to help students acquire the knowledge and skills required for productive use of the technology.

8. REFERENCES

1. Alkam, R. S., Alsawalqa, R. O., & Alreesi, R. (2026). The moderating role of academic integrity in the relationship between artificial intelligence and critical thinking among graduate students in Jordan. *Frontiers in Education*, *11*, Article 1776308. https://doi.org/10.3389/feduc.2026.1776308
2. Arshad, A., Lone, A., Arickswamy, L., Hassan, K., Alnaim, A. A., & AlFarhan, M. F. (2026). From AI use to critical thinking among medical students: A moderated mediation perspective on cognitive load and self-regulated learning. *Frontiers in Psychology*, *17*, Article 1883053. https://doi.org/10.3389/fpsyg.2026.1883053
3. Bolaños-Cristancho, N., Montaña, D., Cantor, H., Cocomá Arciniegas, G., Santiago Franco, D., Hernández, C., Jiménez-Leal, W., Mariño, O., & Fernández Pinto, M. (2026). Impact of generative AI on higher-order thinking skills (HOTS) in higher education: A multi-actor analysis. *Thinking Skills and Creativity*, *62*, Article 102337. https://doi.org/10.1016/j.tsc.2026.102337
4. Chen, X. (2026). Layer-sensitive cognitive offloading in generative AI-assisted writing: Supported performance and independent no-AI outcomes. *Frontiers in Psychology*, *17*, Article 1906199. https://doi.org/10.3389/fpsyg.2026.1906199
5. Chick, J. C., & Morello, L. T. (2026). Developing talent with artificial intelligence: Human–AI symbiotic theory (HAIST) as a framework for AI-mediated learning and talent development. *Journal of Intelligence*, *14*(5), Article 86. https://doi.org/10.3390/jintelligence14050086
6. Davor, I., Larbi, E., & Boateng, F. O. (2026). Artificial intelligence-supported learning and higher-order cognitive outcomes: The mediating role of metacognitive self-regulation. *Frontiers in Education*, *11*, Article 1855869. https://doi.org/10.3389/feduc.2026.1855869
7. Essel, H. B., Vlachopoulos, D., Essuman, A. B., & Amankwa, J. O. (2024). ChatGPT effects on cognitive skills of undergraduate students: Receiving instant responses from AI-based conversational large language models (LLMs). *Computers and Education: Artificial Intelligence*, *6*, Article 100198. https://doi.org/10.1016/j.caeai.2023.100198
8. Fan, M., & Chang, P. (2026). Telling students to evaluate does not make it happen: Task stage, offloading tendency, and error detection in AI-assisted student writing. *Behavioural Sciences*, *16*(9), Article 1671. https://doi.org/10.3390/bs16091671

9. Fan, W., Cheng, L., Wang, Y., Zhao, Q., & Li, Y. (2026). In-class AI use and attitudes among university students: The different mediating roles of cognitive relief and cognitive offloading. *Behavioural Sciences*, *16*(6), Article 1014. https://doi.org/10.3390/bs16061014
10. Fan, Y., Tang, L., Le, H., Shen, K., Tan, S., Zhao, Y., Shen, Y., Li, X., & Gašević, D. (2025). Beware of metacognitive laziness: Effects of generative artificial intelligence on learning motivation, processes, and performance. *British Journal of Educational Technology*, *56*(2), 489–530. https://doi.org/10.1111/bjet.13544
11. Gao, L., & Zhang, F. (2026). Cognitive offloading and metacognitive calibration in generative AI-mediated doctoral learning: A grounded theory study of accountable reconstruction. *Frontiers in Psychology*, *17*, Article 1920947. https://doi.org/10.3389/fpsyg.2026.1920947
12. Hou, C., Zhu, G., Liu, Y., Sudarshan, V., Chong, J. L. L., Zhang, F. Y., Tan, M. Y. H., & Ong, Y. S. (2026). The effects of critical thinking intervention on reliance behaviours, problem-solving quality, and creativity during human-generative AI collaborative learning. *Computers & Education*, *247*, Article 105576. https://doi.org/10.1016/j.compedu.2026.105576
13. Hou, C., Zhu, G., & Sudarshan, V. (2025). The role of critical thinking on undergraduates' reliance behaviours on generative AI in problem-solving. *British Journal of Educational Technology*, *56*(5), 1919–1941. https://doi.org/10.1111/bjet.13613
14. Katsenou, R., Kotsidis, K., Papadopoulou, A., Anastasiadis, P., & Deliyannis, I. (2025). Beyond assistance: Embracing AI as a collaborative co-agent in education. *Education Sciences*, *15*(8), Article 1006. https://doi.org/10.3390/educsci15081006
15. Lan, Z., & Niu, C. (2026). AI-mediated writing and durable learning: A psychological theory of calibration, bypassing and uptake. *Frontiers in Psychology*, *17*, Article 1866062. https://doi.org/10.3389/fpsyg.2026.1866062
16. Li, J. (2026). The causal effects of artificial intelligence use on metacognition, engagement, and knowledge transfer in educational contexts. *Frontiers in Psychology*, *17*, Article 1811065. https://doi.org/10.3389/fpsyg.2026.1811065
17. Li, S., & Liu, J. (2026). Mapping the distribution and depth of metacognitive processes in generative AI-assisted learning: Evidence from interaction logs and concurrent think-aloud protocols. *Behavioural Sciences*, *16*(8), Article 1365. https://doi.org/10.3390/bs16081365
18. Li, W., Zhang, W., Li, M., & Zhang, Y. (2026). Generative AI as an external cognitive tool: Cognitive dependence, AI literacy, and perceived academic creativity. *Journal of Intelligence*, *14*(8), Article 185. https://doi.org/10.3390/jintelligence14080185
19. Lin, J., & Al-Hada, N. M. (2026). The critical-thinking paradox in generative AI-integrated learning: Distinguishing efficiency from cognitive depth—a differentiated framework and testable propositions. *Frontiers in Psychology*, *17*, Article 1906070. https://doi.org/10.3389/fpsyg.2026.1906070
20. Liu, C., Guo, J., Gao, R., Chen, X., Zhu, Q., & Chang, P. (2026). Borrowed or kept? How self-generation-first and direct-adoption AI workflows shape immediate unaided reasoning. *Frontiers in Psychology*, *17*, Article 1910545. https://doi.org/10.3389/fpsyg.2026.1910545
21. Liubertaitė, A. D. (2026). EFFORT-AI: An effort-preserving module for cognitively aligned human-AI learning. *Frontiers in Education*, *11*, Article 1849821. https://doi.org/10.3389/feduc.2026.1849821
22. Marín Díaz, G. (2025). Supporting reflective AI use in education: A fuzzy-explainable model for identifying cognitive risk profiles. *Education Sciences*, *15*(7), Article 923. https://doi.org/10.3390/educsci15070923

23. Melanou, C., & Beege, M. (2026). Scaffolding generative AI as a tutor: A quasi-experimental study of learning outcomes and motivational, cognitive and metacognitive processes. *Education Sciences*, *16*(4), Article 651. https://doi.org/10.3390/educsci16040651
24. Melanou, C., Beege, M., & Kimmig, M. (2026). Generative AI and learning dynamics in higher education: A longitudinal empirical study. *Journal of Computer Assisted Learning*, *42*(5), Article e70322. https://doi.org/10.1002/jcal.70322
25. Nathaniel, J., Oyelere, S. S., Suhonen, J., & Tedre, M. (2025). Investigating the impact of generative AI integration on the sustenance of higher-order thinking skills and understanding of programming logic. *Computers and Education: Artificial Intelligence*, *9*, Article 100460. https://doi.org/10.1016/j.caeai.2025.100460
26. Ren, S. (2026). College students' metacognitive awareness of generative-AI reliance: An experimental study of decision confidence and attribution bias. *Frontiers in Psychology*, *17*, Article 1926110. https://doi.org/10.3389/fpsyg.2026.1926110
27. Rowe, L. (2026). From gradual release of responsibility to gradual release of technology: A case for the staged use of AI in formal education. *Education Sciences*, *16*(8), Article 1291. https://doi.org/10.3390/educsci16081291
28. Si, S., Qi, Y., Xu, J., & Qi, X. (2026). When thinking is outsourced: Cognitive offloading and the heterogeneity of critical thinking among Chinese university students using generative artificial intelligence. *Journal of Intelligence*, *14*(7), Article 116. https://doi.org/10.3390/jintelligence14070116
29. Sternberg, R. J. (2026). Does AI increase cognitive abilities, decrease them, or a little bit of each? And what are its implications for identification and development of the gifted? *Frontiers in Education*, *11*, Article 1759062. https://doi.org/10.3389/feduc.2026.1759062
30. Su, J., Wang, Z., Qiang, Z., & Wang, Z. (2026). Is it mine or not mine? Cognitive offloading to generative AI and concern over the erosion of cognitive ownership. *Journal of Intelligence*, *14*(8), Article 182. https://doi.org/10.3390/jintelligence14080182
31. Tian, J., & Zhang, R. (2025). Learners' AI dependence and critical thinking: The psychological mechanism of fatigue and the social buffering role of AI literacy. *Acta Psychologica*, *260*, Article 105725. https://doi.org/10.1016/j.actpsy.2025.105725
32. Urban, M., Brom, C., Lukavský, J., Děchtěrenko, F., Hein, V., Svacha, F., Kmoníčková, P., & Urban, K. (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*(5), 1897–1918. https://doi.org/10.1111/bjet.13591
33. Urban, M., Děchtěrenko, F., Lukavský, J., Hrabalová, V., Svacha, F., Brom, C., & Urban, K. (2024). ChatGPT improves creative problem-solving performance in university students: An experimental study. *Computers & Education*, *215*, Article 105031. https://doi.org/10.1016/j.compedu.2024.105031
34. Varghese, M. A., & Sharma, P. (2026). Measuring human metacognition in GPT-assisted cognition: Development and psychometric validation of a novel scale. *Frontiers in Psychology*, *17*, Article 1823525. https://doi.org/10.3389/fpsyg.2026.1823525
35. Vendrell, M., & Johnston, S.-K. (2026). Scaffolding critical thinking with generative AI: Design principles for integrating large language models in higher education. *Computers and Education: Artificial Intelligence*, *10*, Article 100572. https://doi.org/10.1016/j.caeai.2026.100572

36. Wahn, B., Bawari, K., & Wiese, E. (2026). Humans do not "play fair" with social robots: Unequal task sharing in an attentional task. *Acta Psychologica*, *267*, Article 107139. https://doi.org/10.1016/j.actpsy.2026.107139
37. Wang, H., & Shan, W. (2026). The safety gap: Restoring productive struggle through pedagogically aligned generative AI. *Frontiers in Education*, *11*, Article 1757622. https://doi.org/10.3389/feduc.2026.1757622
38. Wang, X., Zheng, Z., Zhang, J., Hou, X., & Zhu, Z. (2026). The IDEA framework for metacognitively regulated GenAI use in higher education: Development and exploratory pilot evidence. *Computers and Education: Artificial Intelligence*, *11*, Article 100657. https://doi.org/10.1016/j.caeai.2026.100657
39. Wu, H., Wang, Z., & Wen, X. (2026). Examining interactive AI-supported learning environments: The mediating role of AI metacognition and the moderating role of cognitive flexibility. *Acta Psychologica*, *266*, Article 106874. https://doi.org/10.1016/j.actpsy.2026.106874
40. Yan, Z., Fang, Z., & Zou, W. (2026). The association between generative AI use and university students' critical thinking: A moderated mediation model of GenAI feedback literacy and reflective thinking. *Frontiers in Psychology*, *17*, Article 1939286. https://doi.org/10.3389/fpsyg.2026.1939286
41. Yang, Y., Zhang, S., & Li, Y. (2026). The influence of AI on critical thinking and creativity in L2 learning contexts: A social cognitive perspective. *Journal of Intelligence*, *14*(5), Article 78. https://doi.org/10.3390/jintelligence14050078
42. Yavich, R. (2025). Will the use of AI undermine students independent thinking? *Education Sciences*, *15*(6), Article 669. https://doi.org/10.3390/educsci15060669
43. Yuan, F., Liu, C., & Yang, J. (2026). The impact of generative AI dependence on university students' creativity: The mediating role of critical thinking and the moderating role of thinking orientation. *Journal of Intelligence*, *14*(8), Article 168. https://doi.org/10.3390/jintelligence14080168
44. Zhao, G., Sheng, H., Wang, Y., Cai, X., & Long, T. (2025). Generative artificial intelligence amplifies the role of critical thinking skills and reduces reliance on prior knowledge while promoting in-depth learning. *Education Sciences*, *15*(5), Article 554. https://doi.org/10.3390/educsci15050554
45. Zhou, X., Teng, D., & Al-Samarraie, H. (2024). The mediating role of generative AI self-regulation on students' critical thinking and problem-solving. *Education Sciences*, *14*(12), Article 1302. https://doi.org/10.3390/educsci14121302
46. Zhu, Q., Li, X., Dong, Y., Chang, P., & Fan, M. (2026). Not all cognitive offloading is equal: Distinguishing dependent and autonomous offloading to generative AI. *Frontiers in Psychology*, *17*, Article 1878629. https://doi.org/10.3389/fpsyg.2026.1878629