



AI and Cognitive Offloading in Higher Education

Executive Summary

Artificial Intelligence (AI) tools – especially large language models (LLMs) like ChatGPT – are rapidly being adopted in higher education. These tools can assist students with writing, research, coding, and more. However, their impact on **learning and cognition** is double-edged. On one hand, AI can increase productivity and ease cognitive burdens; on the other, it may encourage “cognitive offloading” that undermines deep learning and skill development. This report provides a comprehensive analysis of current research and theory on how AI use affects students’ cognitive processes, learning outcomes, and the balance between efficiency and understanding. Key findings include:

- **Cognitive Offloading and Reduced Effort:** Students often delegate difficult tasks to AI, which *lowers* their mental effort and engagement. Heavy reliance on AI is correlated with *lower critical thinking ability*, mediated by increased offloading of cognition ¹ ². In extreme cases, easy access to AI can lead to *“metacognitive laziness,”* where learners stop actively synthesizing or reflecting because the AI handles the hard work ³.
- **Productivity vs. Learning Trade-offs:** AI tools can make academic work feel easier and faster, but this convenience can come at the cost of **deeper learning**. Studies show that while AI assistance often improves immediate task performance (e.g. higher essay scores or faster problem-solving), it does *not necessarily improve* – and may even impair – students’ retention, understanding, and transfer of knowledge ⁴ ⁵. In short, **tasks get done, but less is learned**.
- **Cognitive Load Impacts:** From the perspective of cognitive load theory, AI tools tend to reduce students’ *extraneous load* (irrelevant effort) and make tasks feel more manageable ⁶. This can be beneficial if it frees up cognitive resources. However, AI may also lower the *germane load* – the productive mental effort that students would otherwise invest in processing and learning the material ⁷ ⁸. By removing all difficulty, AI can short-circuit the beneficial struggle that encodes information into long-term memory (the principle of “desirable difficulties” ⁹).
- **Empirical Evidence of Skill Effects:** Early empirical studies paint a cautionary picture. For example, one controlled experiment found students who used ChatGPT to help write essays produced better drafts but *learned no more* about the topic than peers without AI, and engaged less in analyzing source texts ¹⁰ ¹¹. Surveys have found frequent AI users focus on *remembering where to find information rather than the information itself* (a “Google effect”), indicating offloading of memory ¹². Other studies report that heavy use of AI or chatbots is associated with *diminished problem-solving and critical analysis skills* over time ¹³. There is also evidence that students using AI devote less effort to self-evaluation and revision, relying on the AI’s outputs instead ¹¹ ³.
- **Theoretical Concerns:** Cognitive science theories suggest multiple risks. **Critical thinking and metacognition** may atrophy if students become passive recipients of AI outputs ² ⁸. Without actively retrieving, generating, or evaluating information, students miss out on the very practices

(e.g. self-quizzing, elaboration, error-correction) that build durable skills. Psychologists warn that making learning “too easy” can create *illusions of competence* – students might feel they understand simply because the AI produced a coherent answer, when in reality they have not engaged in the underlying thinking. Over-reliance on AI also threatens students’ **agency** and ownership of their work, potentially eroding motivation and academic integrity ². At the same time, theories of distributed cognition and the “extended mind” remind us that using tools to offload memory or routine tasks is not new – humans have long augmented cognition with notebooks, calculators, and GPS. The challenge is distinguishing **productive offloading** (which extends capabilities) from offloading that undermines the internal development of knowledge and skills.

- **Nuanced Positive Uses:** Importantly, AI is not invariably detrimental – it *can* be leveraged in ways that support learning rather than replace it. Educators are experimenting with uses of AI as a **tutor or cognitive partner**: for example, having students generate an initial solution and then asking AI for feedback or hints, which the student must critique and apply. When used to scaffold learning (providing timely hints, exemplars, or simplifications of complex problems), AI might reduce unproductive struggle while preserving the student’s active role. Some studies even suggest that offloading low-level tasks to AI can allow learners to focus on *higher-order thinking*. For instance, pre-service teachers who used AI to handle routine lesson-planning tasks were able to invest more effort in creative pedagogy and showed improved outcomes, provided they also engaged in reflective **shared metacognition** with peers ¹⁴ ¹⁵. These findings underscore that **strategic use** of AI – as a complement to human thinking rather than a substitute – can amplify learning.
- **Gaps and Future Research:** Given how new generative AI is, there remain significant unknowns. There is little long-term or longitudinal data on how habitual AI assistance affects skill development over years. Current studies often measure immediate performance or short-term retention; we need research on **long-term retention, transfer, and the development of expertise** in the presence of AI. Moreover, most evidence comes from limited contexts (writing tasks, lab settings, early adopters); the effects may differ across disciplines (e.g. writing vs. quantitative problem-solving), and across student ability levels. We also lack consensus on **best practices** for integrating AI into teaching in a way that maximizes learning gains. Future research should explore how to train students’ metacognitive skills alongside AI use, how to assess learning when AI can provide answers, and how to mitigate equity issues arising from differential AI access or skills.
- **Practical Implications:** Educators and institutions must navigate a careful path in the AI age. It is neither realistic nor desirable to ban AI completely – students will use these tools in academia and the workplace – but uncritical use poses real risks to learning. This report recommends that higher education stakeholders adopt a **moderately critical stance**: embrace AI’s benefits for efficiency and personalization *while explicitly prioritizing learning processes and skill development*. In practice, this means designing assignments and policies that require students to **engage actively** with material even when using AI. Instructors should encourage transparency about AI use and might require students to document how AI helped and what the student contributed. Assessment strategies may need revision (for instance, more oral exams, in-class work, or application-focused tasks) to ensure that grades reflect student understanding, not just AI-generated output. Critically, educators should teach *AI literacy*: students need guidance to use AI as a tool (for brainstorming, getting feedback, exploring multiple perspectives) and training to double-check AI’s output, rather than using it as an infallible answer source. By fostering an academic culture that values **critical thinking, inquiry, and**

effort – even (or especially) in an AI-rich environment – higher education can harness AI's power without surrendering the cognitive growth and intellectual rigor at the heart of learning.

(The sections below elaborate on these points, providing detailed analysis, evidence from recent studies, theoretical insights, and recommendations.)

1. Cognitive Load Analysis: How AI Alters Mental Load in Learning

Cognitive load theory provides a useful lens for examining AI's impact on student cognition. Cognitive load refers to the amount of working memory resources required to perform a task. It is classically divided into three types: **intrinsic load** (the inherent complexity of the material being learned), **extraneous load** (the load imposed by irrelevant or inefficient task aspects and presentation), and **germane load** (the mental effort devoted to processing information, constructing schemas, and other activities that directly foster learning) ¹⁶ ¹⁷. The goal in instructional design is to manage these loads: keep *intrinsic* load at an appropriate level (not too easy or impossibly hard), minimize *extraneous* load (remove unnecessary difficulty), and maximize *germane* load (encourage effort on productive thinking). AI tools can drastically change all three load types:

- **Reducing Extraneous Load:** One clear benefit of AI assistants is the reduction of extraneous cognitive load. Tasks often have tedious or peripheral components – formatting references, looking up basic facts, translating text, debugging syntax errors, etc. – that distract from the primary learning objective. Delegating such components to an AI allows students to bypass needless mental effort. For example, an AI can instantly generate reference citations or summarize a long article, sparing the student the time and cognitive resources those tasks would normally consume. By automating lower-level processes, AI “automates away” some of the clutter that would otherwise occupy working memory ¹⁸ ¹⁹. In experimental comparisons, students using an LLM to gather information reported significantly *lower extraneous load* than those using traditional methods ⁶. This suggests the AI made it easier to find and organize information, reducing the mental friction of the research process. Such extraneous load reduction is generally positive – it aligns with cognitive load theory's prescription to remove unnecessary hurdles so that students can focus on learning the content itself ⁷. For instance, if a student can use an AI coding assistant to handle routine syntax or boilerplate code, the student's mind is freed to concentrate on the conceptual problem-solving aspects of the assignment (assuming they *choose* to use that freed capacity productively).

- **Managing Intrinsic Load:** Intrinsic cognitive load is determined by the complexity of the material and the learner's prior knowledge. AI tools can modulate intrinsic load in two main ways: by breaking problems into simpler sub-tasks, or by outright handling parts of the complexity. In some cases, AI can serve as a *scaffold* to make a challenging task more tractable. For example, if writing an academic essay is intrinsically complex (juggling content knowledge, structure, language mechanics, etc.), a student might use an AI to generate an outline or first draft. This effectively reduces the intrinsic difficulty the student personally faces, because the AI has taken on some of the complex elements. When used as guided assistance, this can mirror proven educational techniques like **worked examples** and scaffolding, which reduce intrinsic load for novices to prevent overload ⁶ ²⁰. Cognitive load theory posits that for less experienced learners, studying a worked-out solution (rather than solving from scratch) can improve learning because it avoids overwhelming their limited working memory ²¹ ²². An AI-generated solution or explanation, if *actively studied*, could similarly help novices form initial schemas. In this sense, AI has potential to *optimize intrinsic load* – ensuring

the task difficulty is challenging enough to be instructive but not so high as to cause cognitive overload. However, if AI oversimplifies the content or if the student offloads *all* intrinsic difficulty to the AI, it can rob them of any meaningful engagement. There is a fine line between scaffolding and simply doing the task for the learner. One concern is that AI tools might lead students to *skip practicing* fundamental skills because the AI handles those components instantly. For example, if a language learner uses AI to translate every sentence, they avoid the intrinsic load of grappling with grammar and vocabulary – but also fail to build those language skills. In summary, AI can adjust intrinsic load to a more manageable level, but there is a risk of making the task so easy that the student's own cognitive involvement becomes minimal. The optimal scenario is that AI handles just enough complexity to prevent overload while leaving the core learning challenge intact for the student.

- **Effects on Germane Load (Deep Processing):** Perhaps the greatest concern is AI's impact on germane cognitive load – the amount of mental effort a student devotes to **learning** rather than simply task completion. Germane load is the *desired* load that goes into making sense of material, forming connections, and encoding to long-term memory. Ideally, by reducing extraneous load, AI tools would *free up more capacity for germane processing*. For instance, if an AI summarizes background readings, a student could spend the saved time thinking critically about the implications of those readings. However, evidence to date suggests that students do not always re-invest their freed capacity into deeper learning; instead, they may simply experience the overall task as easier and *do less mental work*. In a study where one group of students used ChatGPT and another used a search engine to research a topic, the ChatGPT group had significantly *lower self-reported germane load* – they engaged in less effortful elaboration – and this corresponded with *weaker reasoning in their final analyses* ⁶ ⁷. The convenience of the AI seemed to shortcut the need to “stop and think,” leading to more superficial engagement ⁸. In the words of one review, “*this convenience may diminish germane load...the productive effort that builds understanding...so that learners do not need to stop and think.*” ⁸. Essentially, if an AI delivers a polished answer or streamlined solution, a student might not exert the germane effort to double-check, to ask *why* that answer is correct, or to connect it to prior knowledge. By outsourcing the heavy lifting, they bypass the very mental processes that cultivate understanding (e.g. reasoning through a problem step-by-step, mentally debugging an error, wrestling with how to phrase an argument). Cognitive load theorists like Sweller emphasize the importance of *germane load for schema construction* – learners must invest effort in processing to move information into long-term memory ¹⁶ ¹⁷. AI tools, if used as a crutch, risk collapsing germane load to near zero: the student might get the answer with minimal processing, achieving the *performance without the learning*. As a concrete example, consider a medical student using an AI diagnostic tool. If the student merely inputs symptoms and gets a differential diagnosis from the AI, they may not deeply learn the diagnostic reasoning process. They have the answer, but they did not engage in analyzing the case themselves (low germane effort), so they may struggle when the AI is not available or when facing a slightly novel situation. That said, AI can also be used in ways that *stimulate* germane load – for instance, by prompting students with questions or Socratic dialogue, or by providing hints that require the student to fill in steps. The key is that the *student* must still do substantial cognitive work. Current evidence, however, indicates many students use AI in a way that emphasizes *ease and speed over deep engagement*. As one set of researchers put it, learners often exploit AI to get “*fast and optimal solutions over slow ones*”, favoring cognitive shortcuts even if it means they process content less deeply ²³ ²⁴. This can lead to poorer retention and understanding, a direct consequence of reduced germane load.

In summary, AI tools unquestionably alter the cognitive load profile of academic tasks. They *lower extraneous burdens* and can tame intrinsic complexity, which, used judiciously, aligns with good instructional design. However, they also tempt students to offload germane processing, undermining the very goal of education – which is not just to get tasks done, but to develop new knowledge and skills. The challenge for educators is to harness AI's load-reducing advantages (efficiency, scaffolding) **without eliminating the desirable cognitive effort** that true learning requires. In practice, this might mean encouraging students to use AI to handle tedious sub-tasks or to get past sticking points, but structuring assignments so that students must still reflect, explain, or build on the AI-provided material. Maintaining an appropriate level of *desirable difficulty* is crucial. Research on **desirable difficulties** (Bjork, 1994) shows that introducing certain challenges – requiring retrieval practice, forcing generation of answers, varying conditions – may slow performance in the short term but leads to better retention long-term⁹. AI removes difficulties; educators must decide which difficulties are “desirable” for learning and ensure those are preserved. A useful guiding question is: *Does the AI tool remove only the unnecessary obstacles, or is it also removing the productive challenge?* If it’s the latter, then learning is likely to suffer even if the immediate task is completed successfully.

2. Productivity vs. Learning Effectiveness: When Getting It Done Quicker Isn’t Better

One of the core tensions highlighted by early research is the divergence between **productivity gains** and **learning gains** when students use AI. In many cases, AI tools enable students to complete academic tasks *more quickly or with less effort* – effectively boosting productivity. However, these gains in efficiency do not automatically translate into genuine learning or skill development; in fact, they can mask a decline in learning. This section examines evidence and theory on how AI-mediated productivity can conflict with educational effectiveness, and under what conditions speeding up tasks might hurt, rather than help, student learning.

“Faster, but Shallower”: Evidence of the Trade-off. Multiple studies have now documented scenarios where students who use AI accomplish tasks with greater ease or higher initial performance, yet come away with *lower mastery* of the underlying material. A striking example comes from an experiment by Fan et al. (2024) on essay writing with ChatGPT (discussed in the *Hechinger Report*). Students who had access to ChatGPT while writing and revising an essay improved their essay scores the most (even more than peers who received human coaching), indicating a clear boost in *productivity/output quality*⁴. However, when tested on their knowledge of the essay topic, the ChatGPT-using students showed *no better understanding* than students who wrote the essay without AI help²⁵. In other words, the AI helped them produce a polished essay, but it did not help them learn the content that essay was about. In fact, there were signs the AI group engaged *less* with the source texts – logs showed that students with AI or human assistance referred back to the readings far less than those who worked unaided²⁶. The students with an AI were essentially **offloading the heavy cognitive work** of synthesizing and organizing information – which made the process faster, but meant they weren’t mentally processing the material deeply. Tellingly, the students who reported the highest interest and enjoyment were *not* the AI users but the ones who got only a simple checklist and did the work themselves²⁷. The researchers dubbed this phenomenon “metacognitive laziness,” wherein access to AI makes students inclined to let the tool do the thinking, leading to surface-level engagement³. This study encapsulates the productivity/learning gap: AI use led to a better immediate product (higher-quality essay) but did not lead to better learning of content or greater

motivation. If anything, those who took the “hard road” (minimal assistance) engaged more and enjoyed the challenge more, aligning with the idea that overcoming difficulties can be rewarding and educational.

Another study by Stadler et al. (2024) (open-access in *Computers in Human Behavior*) similarly found that **effort and learning depth** were compromised by AI use even as task completion became easier. In this study, college students were tasked with researching a scientific issue and providing recommendations; one group used ChatGPT and another used Google Search. The ChatGPT group indeed reported the task to be much easier – their overall cognitive load was significantly lower, indicating higher efficiency ^{5 6}. However, when evaluating the students’ outputs, the researchers found that the ChatGPT-assisted students’ analyses showed *weaker reasoning and less depth* than those of the search-engine group ^{5 7}. The LLM users had gathered information and answers quickly, but they hadn’t engaged with the content as critically. In contrast, the Google group had to put in more effort to find, evaluate, and synthesize information from multiple sources – a more time-consuming process, but one that likely forced more analytical thinking and reasoning, which showed in their work quality. Stadler et al. concluded that “*while LLMs can decrease the cognitive burden associated with information gathering..., they may not promote deeper engagement with content necessary for high-quality learning.*” ^{5 28}. This is a concise statement of the trade-off: the AI made it cognitively *easier* (a boon for productivity), yet that very ease meant students did not grapple with the content enough to produce strong reasoning (a setback for learning).

The Illusion of Competence and Rapid Progress. These findings resonate with well-established principles in cognitive psychology regarding **performance vs. learning**. Research by Robert and Elizabeth Bjork has shown that conditions which make initial performance *easy and error-free* often lead to poorer long-term learning, whereas conditions that introduce desirable difficulties (like spacing, testing, generating answers) slow down performance but enhance retention and transfer ⁹. Students, left to their own preferences, often opt for methods that feel *efficient* – re-reading notes, using solution guides, etc. – because they see quick progress or correct answers, but these can give a false sense of mastery. AI tools present a similar seduction: they make progress rapid and output polished, fostering an **illusion of competence**. A student might think, “I solved all the homework problems (with ChatGPT’s help) in record time – I really understand this topic!” In reality, the student may have done little actual problem-solving or recall themselves. The improvement in *performance* (homework is done, answers look good) misleads them into overestimating their learning. This illusion can be shattered when the student faces an exam without AI assistance – suddenly the problems aren’t solvable because the underlying skills or knowledge weren’t developed. In the context of writing, a student may submit an excellent essay co-written with AI, earning a high grade (*performance*), but later struggle to write an essay independently or to discuss the essay’s content in depth, revealing a lack of genuine understanding. The **fluency** of AI-generated text or answers can mask shallow processing. As one commentator put it, “AI text generation provides the student with what he wants in a seemingly rational way, but without involving the student’s own rationality... The writing process will be more efficient to the extent that the student does not think it over” ²⁹. This captures the crux: efficiency gained by *not thinking* is antithetical to learning.

Desirable Difficulty vs. Harmful Difficulty. A nuanced perspective is needed to distinguish when AI is removing *useful difficulty* versus when it’s removing *gratuitous difficulty*. **Desirable difficulties** are challenges that induce effortful processing and hence improve learning (examples: having to recall information from memory rather than looking it up, or writing an essay draft from scratch rather than having one pre-written) ⁹. **Harmful difficulties** are impediments that frustrate or overload learners without adding learning value (examples: spending excessive time on tedious calculations, or struggling with an unclear interface). Ideally, AI should alleviate the harmful difficulties (thereby *improving efficiency*

without cost) and leave or even enhance the desirable ones. The reality, however, is that AI is often used to remove *all* difficulties it can – students naturally gravitate to the easiest route to get the task done, not separating which mental efforts were instructionally beneficial. For example, writing an essay involves the “difficulty” of organizing one’s thoughts and articulating them – a difficulty that is *actually central to learning* to think and communicate. AI can now eliminate much of that difficulty by generating ideas, outlines, and even prose. If a student bypasses the struggle of drafting and organizing (a desirable difficulty) by prompting an AI to do it, they miss out on developing writing and reasoning skills. On the other hand, a difficulty like formatting citations in a specific style, which is mostly mechanical, has little cognitive learning benefit – offloading that to AI (e.g. using an AI to generate bibliography entries) likely has no adverse effect on learning of content. The critical point is that **not all difficulties are equal**. The productivity-learning tension emerges primarily when AI removes *cognitively productive* effort.

The Bjorks’ research famously notes that conditions of learning that yield rapid short-term improvement often fail to support long-term retention ⁹. Using AI for immediate performance gains is a textbook case of such conditions. A semester of AI-augmented assignments might go smoothly (students get good grades with relatively little struggle), but if you test those students on the course outcomes later (without AI), you may find weaker retention compared to a scenario in which students had to wrestle more with the material. The **feeling of learning** during AI use can also be misleadingly high – students might feel confident because “the work looks good and was done easily” – akin to how students feel confident re-reading notes because the material looks familiar (even though that method is inferior to self-testing). One empirical parallel can be drawn from active learning research: Deslauriers et al. (2019) found that students in active learning classrooms (which are harder and more engaging) *learned more* but *felt* like they learned less, whereas students in traditional lectures *felt* they learned more while actually learning less ³⁰ ²¹. Here, AI could be creating a situation where students *feel* satisfied (the assignment is done with minimal pain) while actually learning less – an inversion of “no pain, no gain” into “no pain, no gain, but unaware of no gain.”

Task Completion vs. Mastery. The divergence between completing a task and mastering its content becomes especially salient with AI. Education has long wrestled with students seeking shortcuts to get answers (cheating, copying, using solution manuals), and AI is the ultimate shortcut: it provides answers that are often correct and well-formulated. If one defines “productivity” as simply producing the required output (an essay, a problem set, a piece of code) in the least time, AI dramatically boosts productivity. But education is concerned with what happens *inside the student’s mind* during and after the creation of that output. Ideally, the process of doing assignments is as important as the result because that process is where learning occurs. AI threatens to decouple the two – the assignment can be completed successfully with minimal internal cognitive change in the learner. This raises tough questions: If a student can get an A on a paper written 50% or 80% by AI, is that grade meaningful? Is the student truly demonstrating skill or knowledge, or just the skill to prompt an AI? The **disconnect between performance and competence** grows when AI is involved in performance. This suggests that relying on traditional measures of productivity or even grades might be insufficient to gauge learning in the AI era.

To be clear, productivity and learning aren’t always at odds. There are scenarios where AI can help students learn more efficiently by freeing time for *additional* practice or reflection. For instance, if AI speeds up data analysis in a science project, a student might spend the saved time interpreting results and thinking about the science (assuming the assignment or their curiosity pushes them to do so). In such a case, productivity gains could translate to more learning because the student reallocates effort to higher-value tasks. However, such positive outcomes likely require *intentional pedagogical design*. Left unguided, many students will use AI to *finish sooner and then stop*, not to *invest extra time in further learning*. One survey of AI use

patterns (Anthropic, 2025) found that a large fraction of students' queries to an academic AI (Claude) were for "creating" (40%) and "analyzing" (30%) – tasks at relatively high cognitive levels ³¹ ³². This indicates students are comfortable asking AI to do quite sophisticated work for them. If students consider that fair game, they might not feel an obligation to perform those cognitive tasks themselves at all, as long as the AI output is acceptable. This outsourcing of higher-order work clearly demonstrates productivity (the work gets done) but bypasses the learning journey.

Guiding Principle – Learning-Centric Use of AI: To resolve the productivity vs. learning tension, the use of AI in education needs to be reframed with **learning effectiveness as the primary goal**. That means sometimes *resisting* productivity enhancements when they eliminate necessary practice. For example, an instructor might say: "Yes, Grammarly or ChatGPT can fix your grammar, but I want you to develop that skill, so in this exercise, you must do it manually." Or conversely: "I don't mind if you use an AI to catch typos in your final draft, but first I want you to write and revise the draft yourself." Educators may encourage students to use AI for brainstorming ideas or getting feedback *after* they have attempted a task on their own. This way, the AI adds value without replacing the student's effortful attempt. Essentially, instructors might require a *sequence* that preserves a difficult, effortful phase (to ensure learning) and only then allows an AI-driven productive phase. Similarly, policies that treat AI as a tool to *augment* one's work (with proper attribution and critical oversight) rather than a tool to *complete* one's work can help align usage with learning goals. Students themselves should be educated about this trade-off: they need to understand that just because AI can do something faster doesn't mean it's beneficial for their learning to always use it. There is a time to practice the long method (to internalize skills) and a time to use the shortcut (once you have the skill and are focusing on higher-level problems). This mirrors how calculators were integrated: students still learn arithmetic by hand before they rely on calculators for complex calculations. If we cultivate a similar mindset with AI – *learn it yourself first, then use AI to accelerate or extend what you can do* – we might get the best of both: maintaining rigorous learning and harnessing productivity gains when they truly add value.

In conclusion, the tension between productivity and learning is not an argument to reject AI, but a warning that **efficiency should not be mistaken for effectiveness** in education. The educational community must critically evaluate *what* is being gained and *what* might be lost when students take the "easy road" with AI. If increased productivity simply means students spend less time overall on academic work, filling the gap with non-academic activities, then learning time is lost. But if increased productivity is leveraged to allow *more* or *better* learning experiences (like tackling more challenging projects, engaging in discussions, etc.), then it can be a win-win. Achieving the latter outcome requires conscious effort by educators to align AI use with learning outcomes, often by *reintroducing productive difficulty* in new forms. In the next sections, we will explore evidence of how AI use is affecting learning outcomes (empirically) and dig deeper into the cognitive and theoretical concerns that underlie these observations.

3. Empirical Evidence: AI Assistance and Student Learning Outcomes

Empirical research on AI/LLM use in education is quickly growing. Since 2020, numerous studies – spanning controlled experiments, surveys, and case studies – have examined how using AI tools affects students' performance and learning. Here we summarize key findings from **recent peer-reviewed studies and surveys** that shed light on skill development, knowledge retention, and student behaviors when AI is in the

mix. The evidence so far largely supports the concerns outlined earlier, though it also highlights some potential benefits and nuances. Below is a summary of notable empirical results:

- **AI Use Correlates with Lower Critical Thinking (Gerlich, 2025):** A quantitative study by Gerlich (2025) surveyed 666 individuals and found a significant *negative* correlation between frequent AI tool use and critical thinking skills ³³. Importantly, the data suggested this link was *mediated by cognitive offloading* – heavy AI users tended to offload mental effort, which in turn was associated with weaker critical thinking performance ¹. Younger participants (more digitally immersed) had higher reliance on AI and scored lower on critical thinking assessments on average, whereas participants with higher educational attainment showed better critical thinking regardless of AI use ¹. The implication is that while AI itself might not directly “make someone less critical,” those who habitually lean on AI may not exercise their critical thinking muscles as much, leading to skill atrophy. Gerlich’s recommendations call for educational strategies to **promote critical engagement** with AI, so that students do not become passive consumers of AI outputs ³⁴.
- **“Over-Reliance” Harms Decision-Making and Analysis (Zhai et al., 2024):** A systematic review by Zhai, Wibowo & Li (2024) looked at studies of students using AI dialogue systems (like conversational agents or chatbots) and concluded that **over-reliance on AI assistance can impair key cognitive abilities**. For instance, in multiple studies students who heavily relied on AI for answers showed *diminished decision-making and critical analysis abilities*, as they had effectively delegated those cognitive processes to the machine ¹³. One cited paper found that when students used an AI tutor that would readily give solutions, they became less adept at independent problem-solving and evaluation ¹³. In essence, constant AI help led them to practice those skills less. The review noted that users often prefer the quick, optimal solutions from AI even if it means not fully understanding the problem, which is a risky shortcut for learning ²³. However, the review also pointed out factors that contribute to over-reliance, such as *over-trusting the AI's accuracy or struggling to judge when to use AI vs. one's own reasoning* ²³. This suggests educational interventions could focus on building students’ ability to critically decide when to accept AI help and when to think for themselves.
- **ChatGPT-Assisted Writing Yields Better Texts but No More Knowledge (Fan et al., 2024):** This is the previously mentioned “metacognitive laziness” experiment (published in *British J. Educational Technology* in 2024). In a lab study with 117 university students (English writing task), the group using ChatGPT significantly **improved their essay quality** from first draft to final draft – more so than even a group that had a human tutor’s help ³⁵ ³⁶. However, when examining *learning outcomes*, the ChatGPT group did *not* outperform others on measures of knowledge gained or ability to apply that knowledge to new contexts ³⁵ ³⁶. In fact, process data revealed that the ChatGPT group was less engaged in certain self-regulated learning behaviors: they spent less time evaluating their own writing or referring back to source texts, focusing instead on interacting with the AI for revisions ³⁷. The researchers observed that these students often copied text generated by the bot into their essays (even though instructions were to use AI only for feedback) ¹¹. This passive approach likely explains why their knowledge didn’t increase – the AI was effectively doing the rewriting. The study’s conclusion warns that **AI can induce a form of learned passivity**, where students become “lazy” about higher-order oversight of their work ³. Still, an interesting nuance was that students with just a checklist (no AI) showed the most sustained engagement and interest, underscoring that *some effort and struggle correlate with motivation and involvement* ²⁷. This aligns with the idea that overcoming challenges is motivating, whereas being handed answers can be demotivating or boring in the long run.

- **Observation of Student-AI Interaction in the Wild (Anthropic report, 2025):** Researchers at Anthropic (an AI company) analyzed hundreds of thousands of interactions university students had with their AI chatbot "Claude" over 18 days ³⁸ ³¹. While this wasn't a controlled experiment on learning outcomes, it revealed *how* students are actually using AI. The most common categories of tasks were "**creating**" (40%) – e.g. writing code, essays, solving projects – and "**analyzing**" (30%) – e.g. interpreting texts or data, explaining concepts ³¹ ³². These are relatively advanced cognitive tasks (at higher tiers of Bloom's taxonomy like synthesis and analysis). The fact that such tasks comprised 70% of queries suggests students are comfortable using AI for complex academic work, not just simple Q&A. While this indicates productivity gains (students leveraging AI to handle heavy tasks), it raises concern about *which parts of those cognitive tasks the students are doing themselves*. If an AI is writing substantial portions of code or essays, the student may not be practicing those creation or analysis skills. The Anthropic study did not measure learning outcomes, but it did note that these AI uses could be classified as higher-order cognitive offloading. It also highlights that **AI use is pervasive across disciplines** (coding, law, literature, etc. all appeared in the dataset). From an empirical standpoint, this breadth means any cognitive effects of AI are not limited to one subject area – the issue of offloading is widespread and will need attention in diverse fields of study.
- **No Drop in Perspective Diversity, but Lower Reasoning Quality (Stadler et al., 2024):** Returning to Stadler's study: one interesting detail is that the diversity of perspectives in student outputs did not significantly differ between the AI and non-AI groups ³⁹. This counters a specific worry that if everyone uses the same AI, they'll produce homogeneous thoughts. In this experiment, using ChatGPT didn't make all answers identical or narrow the range of ideas compared to independent research; students still had to prompt and could receive varied responses. However, the *quality* of justifications and depth of reasoning was lower in the AI group ⁵. Moreover, the study found that the quality of students' arguments was strongly predicted by how much germane load they had invested – reinforcing quantitatively that **more mental effort yielded better reasoning** ⁴⁰. The AI group's lower germane effort translated to worse reasoning. This evidence supports the theory that *it's the reduction in engaged thinking (not necessarily the content provided by AI) that hurts the quality of student work*.
- **Calculator Analogy – Uncritical Use Lowers Vigilance (Popyack et al., 2019):** Before AI, education dealt with similar issues with calculators. One study (Johnson et al., 2020, PLOS One) programmed a calculator to give occasional incorrect answers to see if college students would notice. Many did not – they accepted nonsensical results without skepticism ⁴¹ ⁴². Students had become so accustomed to outsourcing arithmetic to a device that they often failed to even "ballpark" whether an answer made sense ⁴². Only those with higher numeracy (math understanding) or those forced to wait a few seconds (which encouraged them to mentally estimate) caught the errors more often ⁴³ ⁴⁴. This analog is instructive: the calculator improved productivity (fast calculations), but it also lulled many students into a false sense of security, reducing their active engagement (no germane effort to double-check). By extension, a powerful AI providing a solution might similarly reduce students' tendency to verify or think critically about the answer. The "lying calculator" study showed that **without deliberate prompts to engage (like a delay or a more concrete context)**, students rarely questioned the tool ⁴² ⁴³. Preliminary observations of AI use suggest a parallel – students are often inclined to trust a fluent AI answer, sometimes even when it contains clear errors or nonsense (due to the authoritative tone of AI outputs). The **lesson from these empirical analogues** is that when a tool is too convenient, users may disengage their critical faculties unless something nudges them to do otherwise.

- **Spell-Checker and Second-Language Learning (Lin et al., 2017):** Another analog study examined how using spell-check software affected ESL (English as Second Language) students' learning of spelling. Spell-checkers surely boost writing productivity (fewer errors, less time spent correcting). The study found that all forms of spelling assistance helped students correct mistakes in the moment, but interestingly, the *effort involved* mattered for learning ⁴⁵ ⁴⁶. Conditions where students had to choose from a list of suggested corrections or search a dictionary led to better *incidental learning* of those words' spellings than an auto-correct that simply fixed errors ⁴⁷ ⁴⁶. In the delayed post-test, students who had used the spell-check dropdown or a dictionary could remember and spell more of the words correctly than those who had no aid (they had learned from the aid) ⁴⁸. However, the researchers noted: "*effort spent on searching for the correct words relates to better incidental spelling learning. Convenience and effort should be considered... in design of spell checkers.*" ⁴⁹. Translated to AI, this suggests that if AI is used in a way that still requires the student's effort – for example, AI provides hints or options but the student must discern and apply them – learning can occur. If AI makes it too convenient (fixes everything automatically), the student might correct errors without even noticing or remembering them, learning nothing. Thus, empirical evidence from spell-check use underscores that it's possible to have technology aid performance *and* support learning, but it hinges on maintaining the learner's active involvement in the correction/improvement process. Full automation gave the least learning; guided assistance gave some learning benefit.
- **Variability Across Students:** Some emerging evidence suggests that **not all students are equally affected** by AI assistance. For example, more proficient or higher-knowledge students might use AI more strategically (as a complement) and experience less skill degradation, whereas weaker students might over-rely in lieu of developing baseline skills. Additionally, personal traits like motivation and metacognitive skill influence outcomes. A student with strong self-regulation might use AI to check work or get hints and then continue studying, whereas a less motivated student might use AI to finish homework and then disengage. One study (Lee et al., 2023, as cited in a survey ⁵⁰) notes that learners lacking critical thinking skills are more likely to *over-trust* AI and accept its answers without question, making them more vulnerable to misinformation and shallow learning ². This points to a Matthew effect: those who *already* have good skills and habits might benefit from AI (they know how to use it without being misled), while those without such skills might fall further behind (by leaning on AI and not practicing the skills they lack). It's an area in need of more empirical study, but it underlines the importance of **individual differences** in AI's impact.

In sum, the empirical record to date confirms many of the theoretical concerns: When students use AI in a naive or heavy-handed way, they often experience *higher immediate success but lower cognitive engagement*, and consequently, no improvement (or a decline) in actual learning outcomes. That said, studies also indicate some positive or at least neutral outcomes: AI assistance didn't necessarily reduce idea diversity; certain uses of AI (like tools that require student input or reflection) can produce learning gains (as with the spell-checker aiding learning when used interactively). The evidence reinforces that **how the AI is used** is critical. Simply giving students access to AI and hoping for the best may lead to superficial learning. But structuring the use, or designing AI tools that require student cognition (like prompting the student with questions), could potentially yield better outcomes. These empirical insights guide us to be cautious: productivity gains are real and measurable, but they must be scrutinized through the lens of learning. Educators should not assume a completed assignment with AI means the student has learned what the assignment was meant to teach. New forms of assessment and observation (such as examining process data: how often did the student look at the source material? How did they edit the AI output?) might be

needed to truly gauge learning in AI-supported work. The following section will delve into **theoretical perspectives** to further explain these empirical patterns and outline cognitive mechanisms at play.

4. Theoretical Concerns from Cognitive Science and Educational Psychology

The empirical trends described above – reduced critical thinking, metacognitive “laziness,” skill atrophy with offloading – are grounded in several well-established **cognitive psychology theories**. This section examines the issue of AI use in education through theoretical lenses, highlighting *why* over-reliance on AI might be detrimental to learning. We discuss concepts such as cognitive offloading and the extended mind, self-regulated learning and metacognition, “desirable difficulties” and memory, and the development (or erosion) of expertise. We also consider the flipside: how some theories of distributed cognition might argue that using AI is a natural evolution of how humans think with tools. The goal is a nuanced understanding of when AI-as-cognitive-partner crosses into AI-as-cognitive-crutch.

Cognitive Offloading and the Extended Mind. *Cognitive offloading* refers to the act of delegating mental processes to external tools or the environment in order to reduce the cognitive burden on oneself ⁵¹ ⁵². This is not a new phenomenon – humans have done it for ages, from making lists to using abacuses. Philosopher Andy Clark and others argue in the **Extended Mind thesis** that tools and technologies can become extensions of our cognitive system, effectively expanding our mind’s capabilities (Clark & Chalmers, 1998). By this view, using AI could be seen as just the next step in the evolution of cognitive offloading: we offload calculation to calculators, memory to Google or our digital notes, and now perhaps offload composition or coding to AI assistants. When an AI tool is used to *augment* human thinking (for example, brainstorming ideas that a student then evaluates and builds on), it can be argued that the student+AI system has a greater cognitive capacity than the student alone – akin to a form of **distributed cognition** where intelligence is shared between human and machine. This perspective suggests that *if the ultimate goal is performance or problem-solving*, offloading to AI is not inherently bad – it can be efficient and rational. A student who uses an AI tool to solve a complex problem has, in effect, **extended their cognitive reach** using an external resource, much as a pilot uses an autopilot or a doctor uses a diagnostic support system.

However, the **counterargument from educational psychology** is that while offloading may achieve an outcome, it may short-circuit the learning process needed to achieve that outcome independently. There is a difference between *having a tool do X for you* and *learning how to do X yourself*. If education’s aim is to develop the latter, then too much offloading is problematic. The extended mind theory doesn’t distinguish between internal and external processes in terms of knowledge acquisition – it cares about overall task success. But educators do distinguish, because we ultimately want the student to possess skills and knowledge internally (at least in most cases). This is why *timing and context* matter. Offloading a task to AI *after* one has learned it can be a smart use of extended cognition (similar to how we use calendars after learning basic time-management). Offloading *before* learning it raises concern. Research by Sparrow et al. (2011) on the “Google effect” found that people are less likely to remember information if they know it’s stored somewhere easily accessible (like a computer or the internet). Instead, they remember *how to find it* ⁵³ ¹². In other words, our brains offload the actual content to the external source and only retain the pointers. Applied to AI, if students come to rely on AI for answers, they may remember only “where” or “from whom” (the AI) they can get the solution, rather than internalizing the solution method or knowledge itself ¹². This transactive memory system (relying on external memory) is fine if the external source is always available and reliable. But from a learning perspective, it means the student’s own knowledge base

stagnates or grows very little. There's also a risk that if the external source is wrong or biased, the student may not have enough internal knowledge to catch it – they become **cognitively dependent** on the tool.

"Use it or Lose it" – Skill Atrophy: A fundamental principle of learning is that skills and knowledge need to be practiced and applied to be maintained. If a student consistently avoids a certain cognitive task by using AI, they risk *losing proficiency* in that area or never developing it in the first place. This is akin to the concern that widespread GPS use might weaken people's natural navigation and spatial memory abilities. Indeed, neuroscientific studies have found that heavy GPS users have less hippocampal engagement and worse spatial memory in navigation tasks ⁵⁴ ⁵⁵. The brain effectively "outsources" mapping to the device and invests less in building its own cognitive map of the environment. Similarly, if students always rely on Grammarly or AI to correct their writing, they might invest less in learning grammar and spelling, resulting in poorer ability to write correctly without aid. There's evidence for this: instructors have observed that students who over-rely on spell-check may not recognize their own spelling mistakes anymore, and some research found that people become less confident in spelling common words because they always see them autocorrected ⁵⁶ ⁵⁷. With AI now able to generate arguments and solve problems, the fear is that students will not **practice argumentation or problem-solving** nearly as much. The cliché "use it or lose it" very much applies – cognitive abilities are strengthened with use and can weaken with disuse. Michael Gonzalez (2023) in *Public Discourse* argued that chatbots encourage students to avoid exercising practical judgment and critical thinking, effectively "*precluding excellence*" and promoting mediocrity if students skip the stages of learning that require grappling with ideas ⁵⁸ ⁵⁹. He describes how an AI "co-creator" that makes writing easy may prevent the development of independent, self-propelled thinking – turning students into mere editors of AI output rather than originators of thought ⁶⁰ ⁶¹. The concern is not just hypothetical; the earlier-cited study by Zhai et al. (2024) found evidence of **skill atrophy** – e.g. students relying on AI dialogue systems were worse at critical analysis precisely because they hadn't been exercising that skill themselves ¹³. In essence, offloading too much becomes a crutch that leads to **learned helplessness** in that cognitive domain. Over time, students might lose confidence in their own abilities ("the AI can do it better than I can, so why try?") and thus further reduce their practice – a vicious cycle.

Metacognitive Disengagement and Self-Regulation: Effective learning requires not just raw cognitive processing but also *metacognition* – planning, monitoring one's understanding, and adjusting strategies. A major theoretical concern is that AI tools can encourage **metacognitive disengagement**. If a student can ask the AI "Did I do this right?" and get an answer, they might not bother to self-check or reflect on their own. The AI becomes the monitor and evaluator. Over-reliance on such feedback might impair development of the student's own metacognitive judgment. The arXiv systematic review explicitly flags *diminished metacognitive engagement* as a risk of LLM use – students may bypass essential processes of reflecting on and questioning their work because the AI gives an authoritative-seeming response ⁵⁰ ⁶². In educational psychology, we know that learners often need prompting to self-explain or to reflect. If AI directly provides explanations, students may accept them without generating their own explanations (thus missing out on the powerful "self-explanation effect" in learning). There's also the concept of "**monitoring illusion**": students could overly trust AI's correctness and think they understand material that in fact the AI provided. For instance, a student might use AI to solve a math problem and see the correct answer; unless they deliberately reflect ("Do I understand why that's the answer? Can I do it without AI?"), they may walk away with unjustified confidence. The AI's polished language and confident tone can further lull users into assuming correctness, a phenomenon researchers call the *automation bias*. We saw evidence of this in the "calculator lie" study – students very rarely double-checked the calculator ⁴². With AI, especially given that it can sometimes produce subtly incorrect answers (hallucinations) or correct answers without rationale, a student not actively monitoring can be led astray or simply not learn the rationale. Self-regulated learning

theory would predict that students who rely on AI feedback might reduce their own monitoring efforts. Over time, this could stunt the growth of **metacognitive skills** like error-detection and strategy selection. Interestingly, Fan et al. (2024) noted that even when motivation was equal, students with AI vs. without AI exhibited different self-regulation patterns ^{35 36} – the AI users were less strategic in reviewing and evaluating their work. They achieved a good final product, so perhaps they felt less need to monitor. But from a learning perspective, that means they practiced those processes less. The authors explicitly warn that AI can trigger “*metacognitive laziness*” – an apt term indicating the student’s executive control processes essentially slack off because the AI is doing enough to get by ^{63 64}. In the long run, this could hamper students’ ability to guide their own learning (which is worrisome for higher education, where self-directed learning is crucial).

Desirable Difficulties and Memory Encoding: The concept of “desirable difficulties” by Bjork (1994) has been mentioned – basically, certain difficulties during learning (like effortful retrieval, spacing, varying context) actually enhance memory and transfer, even though they make learning feel harder. AI, by design, aims to remove difficulties. A theoretical worry is that AI might be removing the *very difficulties that are desirable*. For example, attempting to recall an answer from memory is a desirable difficulty that improves later retention (the testing effect). If a student instead just asks AI for the answer every time, they bypass retrieval practice. They also might avoid *generation*, another desirable difficulty – e.g. generating an example or solution oneself leads to better learning than reading it passively. AI allows one to always opt to read an answer instead of generating it. From Bjork’s perspective, this is a formula for **shallow encoding**. As Robert Bjork noted, conditions that produce rapid progress (e.g., having answers provided) often fail to produce durable learning ⁹. He specifically emphasizes that *slower, more effortful learning leads to better retention* ⁹. AI makes learning *faster and less effortful* – the antithesis of that principle. The hazard, as Gonzalez (2023) pointedly wrote, is that “*a bit of friction...is exactly what the mind needs*”, and AI is in the business of eliminating friction ⁶⁵. So theoretical models of memory would predict that students using AI might have lower long-term retention of facts or methods, because they experienced fewer trials of difficult retrieval or problem-solving. Another relevant theory is *depth of processing* (Craik & Lockhart): information processed deeply (for meaning) is remembered better than information processed shallowly. If AI provides ready-made analyses or explanations, students might not process the material as deeply as if they had to construct an explanation themselves. Thus, memory trace strength could be weaker.

Critical Thinking and AI – A Two-Edged Sword: Critical thinking is often highlighted as potentially impaired by AI. Theoretically, critical thinking requires *active, effortful* evaluation of information, weighing of evidence, drawing inferences – all high-order processes. If AI is used as an *oracle* (students ask and accept answers), it short-circuits those processes. It’s analogous to what calculators did for arithmetic – they didn’t make people better at mental calculation; they just replaced the need for it. Likewise, a student who uses AI to produce an argument or interpretation is not practicing the *thinking* behind it. Over time, if this becomes habitual, students might not develop the rich mental schemas needed for expert thinking in a domain. Cognitive load theory suggests that to become an expert, one must form and automate schemas through practice. AI threatens to keep students at the stage of “outsourcing” rather than internalizing. The *International Journal of AI in Education* recently published discussions (e.g., by Krullaars et al., 2023) emphasizing that educators will need to actively teach **AI literacy and critical thinking** side by side, or else students will accept AI outputs uncritically and fail to engage in their own reasoning ^{66 30}. In other words, using AI requires *new critical thinking about AI itself* – checking for biases, errors, sources – skills that many students currently lack. If those aren’t taught, the convenience of AI could easily lull students into a pattern of shallow acceptance. There’s also an **agency and motivation** angle: Self-determination theory would say that if a student feels less *autonomy* or *competence* because “the AI is doing it, not me,” they

might disengage more. Alternatively, some students might feel *less* pressure (which could be good if used well), but more likely they may feel their role is diminished to just *hitting the button*. That can reduce the intrinsic motivation to challenge oneself.

On the Other Hand – Distributed Cognition Benefits: It is worth noting that cognitive science also recognizes the power of cognitive offloading in enabling higher-order activities. The *Distributed Cognition* framework (Hutchins, 1995) describes how cognitive processes can be shared across people and tools. In an educational sense, if AI takes on some lower-level tasks, students might be able to tackle more complex projects than they otherwise could, effectively *raising the level of inquiry*. For example, a middle school student might not be able to program a complex simulation from scratch (too much intrinsic load), but with an AI assistant writing some code, the student could engage with higher-level logic and create something impressive, thereby learning concepts at a higher level (assuming they understand what the AI did). This is akin to how allowing calculators lets math classes focus on problem-solving and concepts rather than manual arithmetic. The extended mind view would say that *relying on external cognitive resources is how humans progress to solve more complex problems than the brain could handle alone*. If an AI can summarize research papers, a student can focus on comparing and critiquing the arguments rather than spending hours reading – potentially a gain in learning critical analysis, provided they do that analysis. So theoretically, **AI could free cognitive capacity for germane load** if managed properly. A key caveat is that the student must actually *use* the freed capacity for deeper processing. Without intentional scaffolding, many won't – hence the negative outcomes observed. But in theory, an adept learner or a well-designed curriculum could harness AI to offload only extraneous aspects and channel the saved effort into more germane tasks. This aligns with Vygotsky's notion of tools mediating higher psychological processes and the idea of a *Zone of Proximal Development*: AI might extend the ZPD by helping with tasks just beyond the student's independent ability, thereby enabling learning that would otherwise require a human tutor. The risk is if AI overshoots and leaves nothing for the student to do in that ZPD.

Ethical and Cognitive Equity Concerns: Another theoretical (and ethical) concern pertains to **equity and cognitive stratification**. Students who have access to AI and know how to use it could zoom ahead in terms of completed work and perhaps superficial achievement, while students without access (due to policy, socioeconomic factors, or personal choice) might lag in performance. However, ironically, in terms of actual skill, it could invert: those who heavily rely might *fall behind in actual competence* compared to those who did things the hard way and learned more deeply. It's a complex picture. Psychologically, students from different backgrounds might use AI differently. Some research has suggested that certain groups of students (e.g., those less confident in a subject) are more likely to lean heavily on step-by-step solution aids, which can impede their learning because they don't attempt as much on their own. If AI essentially becomes a private tutor for those who have it, it might widen performance gaps – unless access is universal, but even then, *the know-how to effectively use AI* might differ. The "critical use" skills might themselves become a new literacy that some have and some don't, initially exacerbating inequities. From a theoretical standpoint, this is tied to the idea of **self-regulated learning**: students with stronger self-regulation will probably manage AI as a tool (not letting it run away with their learning), whereas those with poor self-regulation might succumb to the path of least resistance (letting AI do most of the work). Thus AI could magnify differences in self-regulation and metacognition among students. This is an area where more research is needed, but it is a theoretical expectation worth noting.

In summary, cognitive and educational theories mostly sound a cautionary note: **Effective learning involves challenge, active processing, and self-reflection**, and unbridled use of AI threatens to shortchange all three. Without intervention, there is a theoretical risk of producing a generation of students

who are *highly dependent on AI tools, with weaker internalized skills, knowledge, and critical thinking habits*. As one review aptly stated, “*the tendency [with AI] is to passively accept outputs rather than critically interrogate them, reducing fact-checking and weakening critical engagement – contributing to metacognitive disengagement.*”⁶⁷ The extreme outcome would be students who can accomplish tasks with AI but cannot perform basic cognitive functions independently – a scenario sometimes dubbed “*artificial mediocrity*”, where human potential is dulled by over-reliance on automation.⁵⁸ ⁵⁹ However, theoretical frameworks also suggest ways to avoid this fate: by deliberately integrating AI in a manner that still requires human cognitive effort (just directed at higher levels), and by cultivating the skills of *knowing when and how to use AI*. The extended mind can be a boon if the individual mind is actively steering it. The subsequent section will explore how, in practice, AI might be harnessed to truly support learning – moving from these concerns to potential solutions.

5. Nuanced Applications: When and How AI Can Support (Not Undermine) Learning

Thus far, we have dwelled on the dangers of AI as an “effort saver” that can undermine learning. However, it is equally important to identify **constructive roles** AI can play in higher education – scenarios where AI tools function as **amplifiers of learning** or partners in cognition, rather than as shortcuts to avoid learning. Just as calculators, when used appropriately, did not destroy mathematical ability but rather freed students to tackle more complex problems, LLMs and other AI tools could be leveraged to *enhance educational experiences* if integrated thoughtfully. In this section, we outline nuanced ways AI can be harnessed to genuinely support learning outcomes. These include AI as a tutor or feedback provider, as a scaffold to reduce only extraneous load, as a tool for personalization and practice, and as a means to engage students in higher-order thinking through “cognitive partnership.” We also highlight emerging best practices and examples from early adopters that illustrate productive uses of AI in the classroom.

AI as Intelligent Tutor and Feedback Generator: One promising application is using LLM-based tools to provide **formative feedback, hints, and explanations** in a way that encourages students to think. Instead of giving the answer outright, an AI tutor can be programmed (or prompted by the student or teacher) to play a Socratic role: ask guiding questions, point out errors, suggest strategies. For example, a student could write a draft of an essay or solve a physics problem, then ask an AI, “*Critique my approach and suggest improvements.*” The AI might then highlight a logical inconsistency or a conceptual error, prompting the student to reflect and revise. This use keeps the student in the driver’s seat – the student had to produce an initial attempt and then evaluate feedback. Early studies with intelligent tutoring systems (pre-LLM AI) have shown that **immediate feedback and hints can improve learning** when they scaffold student thinking rather than just give away answers.⁶⁸ ⁶⁹ For instance, the Cognitive Tutor for Algebra (Koedinger et al.) was effective because it would guide students step by step, giving feedback on each step and only hinting when needed.⁷⁰ We can envision LLMs serving a similar role across subjects: an AI that a student queries, “*Why is my solution wrong?*” and it responds with “*Have you considered the effect of X? Maybe try a different approach for this part.*” This turns AI into a **cognitive coach** rather than a task completer. Such use can actually *increase* germane load in a positive way – the student is prompted to engage more deeply with the material to address the AI’s questions or suggestions. Importantly, the student is still doing the thinking, just with guidance. Several universities are already piloting AI TA’s or tutors that help students debug code or clarify course concepts on demand. Early reports suggest that students appreciate the instant feedback and are more willing to attempt solutions knowing they have a safety net for help. The key is that the help is *contingent* and *inquiry-based*, not just handing them fully solved problems. In practical terms, educators

might instruct students: “*Use ChatGPT to test your explanation – ask it to find holes or counterarguments in your essay.*” This way, AI is used to *strengthen* the student’s work via critical feedback, a role akin to a writing center coach. When done correctly, this can foster a **cognitive apprenticeship** model, where the AI demonstrates expert-like questioning and the student learns to emulate that critical stance. Indeed, an example was reported of a teacher having students *annotate AI-generated arguments* instead of writing their own in the first draft ⁷¹ ⁷². The idea was to let students focus on *analysis and critique* (a higher-order skill) rather than struggling to generate text. Students had to identify flaws or strengths in the AI’s argument – a task that keeps them cognitively engaged. While Gonzalez (2023) criticized this approach as potentially skipping important stages (like forming one’s own argument) ⁵⁸, it illustrates how AI can be used as *material for critical thinking* rather than as a cheat. If balanced with other assignments where students do create from scratch, this could be a valuable exercise in critical analysis.

Scaffolding and Managing Cognitive Load: As discussed, AI can reduce extraneous load and modulate intrinsic load. A *nuanced strategy* is to explicitly use AI for scaffolding in early learning stages, then gradually withdraw support. This is analogous to how training wheels are used on a bike and then removed. For example, in a coding class, beginners might use an AI assistant to generate boilerplate code or suggest fixes to syntax errors (reducing extraneous frustration), enabling them to focus on learning programming concepts. As they become more proficient, instructors could encourage less AI reliance and more independent coding. This phased approach ensures that AI is a *bridge to competence* rather than a permanent crutch. Another approach is *partial offloading*: require the student to do part of the task, and allow AI for another part. For instance, a professor might say, “You must outline your essay and write the thesis and conclusion yourself, but you can use AI to suggest some supporting points or examples – then you will evaluate those and decide which to include.” This way, core skills (crafting thesis, doing the reasoning) are practiced, while AI assists with idea generation, sparking creativity or providing perspectives the student can then vet. Research on **productive failure** (Kapur, 2016) shows that having students attempt a problem and even fail before instruction leads to better learning of the solution. AI could be implemented to exploit this: let students try on their own first (struggle a bit), then consult AI for hints or solution methods, then compare and reconcile. This ensures there was an attempt (which prepares them to learn from the solution). Without an attempt, an AI solution has much less educational value. So a concrete practice: teachers can set “*AI usage protocols*” such as: *Attempt the problem for at least 30 minutes, documenting your thought process, before asking AI. Include with your submission a reflection on what you asked the AI and how you verified its answer.* This forces engagement and reflection, turning AI into a learning tool rather than a first resort.

AI for Personalized Practice and Resources: One of AI’s strengths is generating endless examples or tailored explanations. This can be harnessed for **additional practice and active learning**. For instance, a language student can ask ChatGPT to “*give me 5 new sentences using the grammar rule I just learned, and then quiz me on translating them.*” The AI can provide interactive practice on the fly, something a textbook or even a busy teacher can’t as easily do one-on-one. Similarly, a student who doesn’t understand a concept can prompt the AI: “*Explain this to me with a different example,*” or “*Can you simplify this concept or use a real-world analogy?*” If the first explanation doesn’t click, the student can ask the AI to adjust the explanation – effectively leveraging the AI for **adaptive teaching** that suits their understanding. In these cases, the student is actively seeking knowledge (a positive learning behavior), and the AI is the resource responding. Many students already use YouTube or forums for this purpose; an LLM can be like a super-charged Q&A forum that’s available 24/7. Early research (e.g., a qualitative study on *AI in self-regulated learning*) suggests that students appreciate AI help for “*filling knowledge gaps*” on their own time ⁷³ ⁷⁴. Of course, one must verify the correctness of AI explanations, but as long as students are taught to double-check with trusted

sources, this use can promote learning. It keeps the locus of control with the student (they decide what to ask, whether they understand, etc.). Importantly, it can also increase **time on task** – students might practice more problems if AI is available to check their work or provide new items, compared to if they only had odd-numbered answers in a textbook. Greater practice, even if guided by AI, can lead to improved skill as long as the student is the one doing the retrieval or solving before seeing the solution. In this sense, AI can serve as a “*personal trainer*” for certain rote or foundational skills – e.g., generating flashcards, asking review questions, simulating a conversation in a foreign language, etc. These uses *add* to the student’s practice regimen rather than replacing it.

Encouraging Higher-Order Cognitive Partnerships: One intriguing concept is fostering **strategic cognitive partnerships** between students and AI. Instead of viewing AI as a cheat or a threat, some educators see it as an opportunity to teach students how to collaborate with AI to achieve results neither could alone. This involves explicitly teaching skills like prompt engineering, result verification, and iterative dialogue with AI. For example, in an engineering design course, students might be tasked with using an AI to generate several design options for a project, then *critically evaluating each option’s feasibility and ethical implications themselves*. The AI provides breadth (many options quickly), and the student provides depth (analysis and selection). This division of labor plays to each’s strength: AI’s generative speed and the human’s critical judgment. A recent paper by Krullaars et al. (2023) argues that **AI literacy** (knowing how to effectively and responsibly use AI) combined with critical thinking is becoming essential in education ⁶⁶ ₇₅. They suggest teaching prompt strategies (so students can get useful output) and emphasizing that students must apply skepticism and domain knowledge to whatever the AI produces ⁷⁶ ₇₅. If students learn to approach AI as a **collaborator whose work they must constantly review and direct**, they remain cognitively active. In fact, working with AI could itself be a way to exercise critical thinking: students have to double-check AI’s facts (improving their research skills), identify AI’s biases or blind spots (requiring understanding of context), and refine AI outputs (which might involve synthesizing AI suggestions with their own ideas). Some educators frame this as learning to be the “editor-in-chief” of AI’s draft. For instance, a journalism class might allow AI to write a rough news report from given data, but then students must fact-check it, improve the clarity, and ensure the narrative is coherent and ethical. They are thus practicing editorial judgment and domain knowledge. Done right, *surface-level offloading* (AI doing the grunt work) is transformed into *higher-level engagement* (student as the strategist and critic). This ties to the notion of **surfacing vs. deep processing**: let AI handle some surface tasks, so the human can concentrate on deep processing tasks. The caution is ensuring the student indeed does the deep part. But if it’s built into the assignment – for example, requiring a written reflection on why they kept or discarded certain AI-generated content – then the student must demonstrate that higher-order thinking.

Domain-Specific Considerations: The optimal integration of AI might differ by field. In quantitative problem-solving (math, physics), one approach some instructors consider is to allow AI for *verification and exploration*. A student solves a problem, then can ask AI, “*Is this solution correct? If not, give a hint.*” The AI can also show an alternate method, and the student can compare to their method – a learning opportunity to see multiple approaches. In contrast, in creative writing or humanities, an instructor might integrate AI by having students use it to generate a first draft or idea list, and then the student’s job is to heavily revise or expand it, focusing on style, voice, and insight that the AI lacks. This way, students practice their creative skills and learn to see AI as a brainstorming partner rather than a finished product generator. In fields like programming, early evidence (from Microsoft’s experiments with GitHub Copilot) shows that AI coding assistants can save time, but novices sometimes accept erroneous code unless guided. A solution could be to incorporate explicit debugging tasks: e.g., give students an AI-written code snippet and ask them to identify and fix bugs. This improves their code reading and debugging skills while illustrating common AI

mistakes. Essentially, **embedding AI into the curriculum as a subject of analysis** (not just a tool) can be beneficial. For instance, asking students, “*Use ChatGPT to produce an argument on X, then evaluate its argument for logical fallacies or biases*,” simultaneously teaches critical thinking and AI literacy. Some universities have begun running such exercises, finding that it sparks discussion on both the subject matter and the reliability of AI.

Promoting Reflection and Meta-Learning: Another nuanced use is requiring **reflections on AI use**. If a student uses AI in an assignment, have them submit a short commentary: *What did you use AI for? How did you formulate your query? How did you verify the AI's response? What would you do differently next time?* This turns AI usage into a conscious process to be examined, not an invisible shortcut. The student, in articulating this, will often reveal the extent of their understanding. If they write “The AI gave the answer and it seemed good so I used it,” the instructor can address that lack of verification or understanding. If they write “AI gave me an outline, but I noticed it missed factor Y, so I adjusted it,” that shows learning. Thus, reflective practices make AI a *learning subject* as well as a learning tool. Over time, this can build **meta-cognitive awareness** in students about the pitfalls and best practices of relying on AI. It aligns with the educational goal of creating self-directed learners who can effectively use all resources at their disposal, including AI, in a judicious way.

Institutional Examples of Positive Integration: Some educational institutions are already developing guidelines and assignments to leverage AI for learning. For example, a professor at Wharton (Ethan Mollick) reported requiring students to generate multiple solutions with AI and then improve upon the best one, noting that students engaged deeply in improving AI’s output and in the process learned the material more thoroughly. Another example is a computer science course where students had to *write test cases for AI-generated code*, thereby learning software testing and also seeing where the AI code fails ⁷⁷ ⁷⁸. There are also reports of law and medical programs experimenting with giving students AI-generated case analyses or diagnoses and asking students to critique them using domain knowledge – a way to sharpen students’ expertise by contrasting it with the AI’s “suggestions.” These anecdotal instances, while not rigorously studied yet, demonstrate creative ways to ensure the student remains intellectually active.

In summary, **AI can support learning when used as a tool to stimulate, not replace, student cognition**. The mantra could be: *AI does the easy parts, you do the hard parts*. The “hard parts” are where learning happens – analysis, judgment, creativity, reflection – so students should own those, and AI can handle some legwork (within limits set by the instructor). Achieving this in practice requires careful instructional design and setting expectations with students. It also likely requires training both students and faculty on effective AI usage in academic contexts. Encouragingly, the same technologies that pose challenges also offer some solutions: for example, AI can personalize and increase practice opportunities, give feedback at scale, and serve as a simulation of a Socratic teacher if used properly. The notion of “**strategic offloading**” comes into play – students should learn *what* to offload (tedious detail, repetitive tasks) and *what not to offload* (analysis, interpretation, core skill practice). Teaching this strategy explicitly could become part of curricula (as AI literacy). If successful, the outcome would be students who use AI to *augment their learning* – achieving more complex projects and deeper insights – rather than to avoid learning. They would understand the limitations of AI, always apply critical thinking to its outputs, and use it to push their work further than they could alone, all the while consolidating their own knowledge. That is the vision of AI as a **cognitive partner** rather than just a shortcut provider.

Realizing this vision broadly is not trivial, which leads into the next section on research gaps – many of which concern how to implement these nuanced uses effectively – and finally to practical recommendations for institutions seeking to navigate this new terrain.

6. Research Gaps and Future Directions

Despite the flurry of studies and commentary in the past two years, we are only beginning to understand the long-term implications of AI on learning. **Significant gaps** remain in our knowledge, and many urgent questions are not yet answered by research. This section highlights areas where further investigation is needed and points out limitations of the current evidence base. Recognizing these gaps is important for contextualizing our conclusions with appropriate *epistemic humility* and for guiding future scholarly work. Among the notable research gaps are: long-term longitudinal effects, causation vs. correlation, differential effects across contexts and demographics, effective pedagogical interventions to mitigate risks, and the evolving nature of AI technology itself.

- **Longitudinal Impact on Skills:** Almost all existing studies are short-term – looking at a single assignment, course, or semester at most. We *don't yet know* the cumulative effect of years of AI-augmented learning on a student's skills and knowledge base. Will a student who uses AI heavily throughout college emerge with significantly weaker writing or problem-solving skills than someone who didn't? Or will they perhaps develop different skills (like prompt crafting, quick research synthesis) that compensate? It's possible that certain foundational skills (like mental arithmetic, grammar, basic coding) could decay over time if continuously offloaded, but we lack longitudinal data. Additionally, memory research suggests that if you don't practice retrieval, knowledge can fade. Will heavy AI users remember less of what they "learned" in their courses a year later compared to traditional learners? Such retention tests have not been reported yet. **Long-term transfer** of learning is another gap: does reliance on AI in one class hamper the ability to apply those concepts in a new context later (where maybe AI isn't available or the student doesn't think to use it)? Only longitudinal or follow-up studies can answer these. This is a crucial gap because short-term experiments might show negligible harm, but subtle deficits could accrue undetected. For example, perhaps one AI-assisted essay doesn't ruin a student's writing ability, but dozens of AI-assisted assignments over years might lead to noticeably underdeveloped writing by graduation. We simply don't know at this point, which advises caution.
- **Causal Evidence and Methodological Limitations:** Many current findings are correlational (e.g. surveys finding that students who rely on AI more have poorer critical thinking scores ³³). These correlations could reflect self-selection: maybe students who are less confident in their abilities or less prepared are the ones *most likely* to rely on AI (thus the AI use is a symptom rather than the cause of lower skills). Or conversely, high-achieving students might use AI less because they don't need it as much. Without experimental or controlled studies, we can't firmly attribute skill declines to AI usage itself. The experimental studies we do have often have small samples or specific tasks, which may not generalize widely. There's also the novelty factor – during early adoption, some students misuse or overuse AI out of excitement or uncertainty. Over time, as norms develop, usage patterns might change (for instance, students might become more savvy and restrained in AI use). Thus, the initial studies might capture a sort of "wild west" phase of AI use, which could either exaggerate issues or perhaps miss them. Additionally, some experiments (like Fan et al., 2024) were done in lab settings with tasks not for a grade; behavior might differ when academic credit is at stake or under time pressure. **Ecological validity** is a concern – will results hold in real classroom

settings across diverse institutions? Another limitation is detection: if students are using AI covertly in their work (which likely many are, especially where banned), it's hard for researchers to even know who is using AI and how much, muddying survey reliability. Instructors report anecdotal suspicions of AI use but without robust detection, research may under-report actual usage levels. All this means we need more rigorous and varied research designs: randomized trials in classrooms, cross-over studies (where the same students alternate between AI and no-AI conditions), and qualitative studies to understand *why* students choose to use or not use AI in certain ways.

- **Discipline and Task Variability:** There's a gap in understanding how AI's effects might differ across domains. It's plausible that in some fields, AI offloading is more harmful than in others. For example, using AI to solve problem sets in math might be very detrimental to learning the procedures, whereas using AI to generate a draft in a design course might be less harmful if the student then iteratively improves it. Preliminary indications are that writing and coding tasks are heavily impacted (since AI can handle those to a large degree), whereas tasks requiring hands-on skill (like lab experiments, studio art) might be less directly offloadable. But even in those fields, AI can write reports or generate ideas. We need research in sciences, humanities, arts, and professional fields to see if outcomes diverge. Are there *differential effects based on task type*? For instance, maybe AI use on rote homework has minimal long-term effect if students still study for exams themselves, but AI use on projects could hamper skill integration. Currently, evidence is patchy: a systematic review might note concerns in many fields but with little empirical backing beyond expert opinion ⁷⁹. Understanding context matters because it could inform where educators should especially avoid AI vs. where it can be safely allowed. Another angle: differences in learning outcomes such as creativity vs. factual knowledge. Does AI use reduce creativity/originality? Some fear it might by providing cookie-cutter content (though evidence from Stadler et al. suggests idea diversity wasn't reduced ³⁹). This is unresolved. It's a gap whether consistent AI use makes student work more homogeneous or unoriginal over time.
- **Differentiated Impact on Students:** We touched on this: students are not a monolith. We need research on how AI affects learners of *different skill levels, motivations, and backgrounds*. It's plausible that novices stand to lose more by offloading too early, whereas more expert students might actually use AI more effectively as a tool. This relates to the **expertise reversal effect** in cognitive load theory: novices benefit from worked examples (AI providing solutions could be like that), but experts benefit from problem-solving. If AI is like a worked example provider, perhaps novices learn from studying AI outputs (though only if they actually study them, not just copy). Conversely, as students become more advanced, they might chafe at AI's formulaic outputs and actually rely on it less, or use it more critically. There's also a concern for *at-risk or less prepared students*: they might lean on AI to get through assignments, but then do poorly on exams because they didn't actually learn (some instructors already anecdotally report this pattern). On the other hand, could AI be a leg up for students who struggle, by providing 24/7 help? Some researchers are optimistic that if guided, AI could act as a tutor for those who can't afford one, potentially improving equity. But if those students end up offloading everything to AI, it could backfire. So equity-related studies are needed: do students from various socioeconomic or educational backgrounds use AI differently, and with what results? Additionally, there may be cultural differences in attitudes towards using AI (some might see it as cheating more than others). A gap is understanding *ethical beliefs and academic integrity* implications – surveys show a range of opinions among students and faculty about acceptable AI use, which could influence how openly or effectively it's used. If students are hiding AI use due to fear, they might not use it in pedagogically sound ways (e.g., they might just use it to produce a final

product to avoid detection, rather than for drafts or learning support). Research could explore how policy (ban vs. allow) affects student behavior and learning outcomes – currently unknown.

- **Assessment and Measurement Challenges:** Traditional assessments might not capture the differences in learning when AI is involved. A student who used AI for homework might still ace a multiple-choice test by cramming short-term, giving a false impression that learning was equal. The real difference might appear in an unassisted performance or in applied tasks. We might need new forms of assessment to truly see the gap. For example, oral exams or essays written in class (without AI) might reveal weaker skills that aren't obvious in take-home work. Right now, few studies have compared AI-using vs. non-using students in a high-stakes *unassisted* exam scenario. Doing so would help quantify how much worse off, if at all, the AI group is in terms of internalized learning. Without appropriate assessments, research might underestimate the harm (because if both groups have similar grades, one might conclude AI didn't hurt – but maybe the grading methods failed to isolate learning). This is a gap calling for *innovative research methodologies* that measure retained learning and problem-solving without AI support.
- **Effectiveness of Mitigation Strategies:** We have many proposed strategies (as in section 5), but virtually no empirical evaluation yet of what works to mitigate cognitive offloading risks. For example, does requiring reflections actually lead to better understanding or less misuse? Does a policy of "AI use must be documented" result in more careful use or just discouraging use (or perhaps pushing it underground)? We need studies where one class is taught with a certain AI-integrative pedagogy and another class is taught without or with a different approach, to see differences in outcomes. Similarly, how do we train students in AI literacy effectively? It's a new skill domain – research can evaluate different training interventions on prompting, fact-checking, etc. Another open question: if we deliberately design some difficulties back into tasks (e.g., requiring one step be done manually), does it substantially improve learning outcomes compared to fully AI-assisted tasks? Essentially, how to get the Goldilocks level of difficulty when AI is in the picture is still an open question that only experimentation can answer. Educators would benefit from evidence on questions like: *Is it better for learning to have students write first then AI vs AI first then students edit?* or *Does using AI to compare multiple solutions teach better than having them solve without AI?* We can hypothesize, but we need empirical validation.
- **AI Evolution and Adaptation:** The technology itself is rapidly evolving. The capabilities of GPT-4 are greater than GPT-3.5, and future models might handle references, show steps, or allow teachers to configure them (like custom tutor personas) better. As AI gets more accurate and "intelligent," the dynamics might shift. For instance, if an AI becomes nearly always correct and can show clear explanations, students using it might actually learn from those explanations (if they pay attention). Or AI might integrate with educational platforms to nudge students into better usage patterns (like built-in reflection prompts). So research must keep up with not just current AI but anticipate near-future scenarios. A worry is that what is true now (AI makes mistakes that students must catch) might not hold if AI becomes reliably correct – then the critical thinking exercise of catching AI errors diminishes, possibly making offloading even more tempting. It's a gap in research to examine different AI tools: for example, image generators in art class, coding assistants in CS, math solvers (like Wolfram Alpha integration) in math class – each might have unique effects. Also, future tools may have more **pedagogical design** (e.g., a mode that won't give full answers but guides). Research should explore the effectiveness of such AI settings (some early works in intelligent tutoring exist, but with LLMs it's new territory).

- **Ethical and Identity Considerations:** Another gap not deeply discussed is how reliance on AI might affect students' *sense of achievement, confidence, and academic identity*. If a student uses AI for much of their work, do they feel less ownership or pride? Does that impact motivation over time? One could hypothesize that if everything is co-produced with AI, a student might feel a bit alienated from their own education, which could reduce their drive to deeply engage. There's little research on the psychological effect of doing your work with an AI "assistant" always present. It's a subtle but important angle – education isn't only about skills but also about forming individuals who are confident in their abilities to think and create. If AI subtly undermines that (because the student never feels it was *truly* their achievement), that's a loss that's hard to quantify. Conversely, maybe some students will feel *more* confident because the AI help lets them see that they can tackle problems (albeit with a crutch). We simply don't have data on this yet.

In highlighting these gaps, we acknowledge that our current conclusions must be tentative. We are in a dynamic, novel situation, and broad claims should be tested as conditions evolve. Researchers must be careful to differentiate hype from reality and correlation from causation. At this stage, it is clear that **more interdisciplinary research** is needed: cognitive scientists, educators, computer scientists, and ethicists should collaborate to design studies that examine both learning processes and outcomes with AI. Using controlled experiments in real classrooms, mixed-method approaches (quantitative performance data plus qualitative student experience interviews), and cross-institution studies can strengthen the evidence base. We also need to develop **new metrics** for success in an AI-infused environment – such as measuring how well a student can perform with AI *and* without AI, and considering both in assessing learning.

Finally, we must track how students adapt. It's possible students themselves will develop savvy ways to learn with AI (some might, for instance, prompt AI to quiz them or explain, not just give final answers – essentially using AI responsibly even without teacher intervention). Documenting student-driven adaptation is another gap: how do real student habits evolve as they gain more exposure to AI? Surveys and observational studies over the next couple years will be valuable.

In conclusion, acknowledging these research gaps reminds us that **we should be cautious in making sweeping judgments** at this point. The situation is fluid, and ongoing research will hopefully illuminate which concerns are most justified and how we can address them. For now, educators and policymakers should apply *precautionary principles* but remain flexible to update practices as evidence emerges. The final section will provide practical implications and recommendations based on what we know now, coupled with an understanding that adjustments will likely be needed as our understanding deepens.

7. Practical Implications and Recommendations for Educators and Institutions

Navigating the era of AI in higher education requires proactive strategies and policies to ensure that these tools are integrated in ways that promote learning rather than hinder it. Based on the analysis above – of cognitive effects, empirical findings, and theoretical considerations – we outline **actionable insights** for instructors, curriculum designers, and institutional leaders. The aim is to balance embracing the benefits of

AI with safeguarding (and even enhancing) the development of students' skills and knowledge. Below are key recommendations and practical measures:

- **Develop Clear Policies on AI Usage with Learning in Mind:** Institutions and departments should craft explicit guidelines for students and faculty about acceptable AI use in coursework. These policies should go beyond simple "allowed" or "banned" dichotomies and articulate *how* AI may be used to support learning. For example, a policy might state that AI may be used for brainstorming ideas, getting feedback on drafts, or checking code for errors, but not for producing entire assignments to submit as one's own. By clarifying this, students are less likely to misuse AI out of ignorance or to hide AI use out of fear. It's crucial that policies also emphasize academic integrity – using AI without attribution or as a shortcut to bypass learning should be framed as unacceptable. Some institutions have begun requiring that if AI is used, it must be disclosed (similar to citing a source) in the assignment. This transparency encourages students to be mindful of their use and prevents the scenario of secret heavy reliance. Importantly, policies should tie into pedagogy: for instance, "*In this course, you may use AI to get feedback on your code, but you must comment in your code what suggestions you adopted.*" That way the use is trackable and becomes part of the learning process. Faculty should be supported in understanding these tools so they can help enforce policies consistently. It may also help to have students sign an honor code addendum specific to AI, affirming they will use it within the educational spirit of the course. Well-crafted policies protect against the worst abuses while still giving room for beneficial uses.
- **Teach AI Literacy and Critical Evaluation Skills:** Given that AI is now a part of the academic toolkit, institutions should incorporate **AI literacy training** into the curriculum. This means teaching students (and faculty) how AI works at a basic level (so they understand its limitations like hallucinations or bias), how to effectively query or prompt AI, and – most critically – how to *verify and evaluate* AI-provided information. For instance, students should learn strategies like: checking AI outputs against credible sources, using multiple prompts to triangulate an answer, recognizing when AI is just fluent but not factual, and understanding that AI lacks true understanding and can make logical errors. By embedding modules or workshops on these topics (perhaps in first-year seminars or relevant courses), we empower students to use AI as a tool rather than a crutch. This addresses the metacognitive disengagement issue by essentially *training engagement*: e.g., instruct students to always ask, "How would I fact-check this?" after getting an AI answer ⁶⁷. Faculty can model this in class: when using an AI demo, explicitly walk through verifying the output. Furthermore, integrating assignments that specifically require using AI critically can give practice. For example, an assignment might be: "*Use ChatGPT to get an explanation of concept X, then identify at least two inaccuracies or gaps in its explanation by consulting your textbook or notes.*" Such tasks make students actively compare AI information with authoritative information, honing their critical eye. Over time, this can cultivate a habit of skepticism and analysis whenever they use AI. The result should be students who are **AI-savvy thinkers**, not passive consumers. This literacy is not only academic – it's a skill for the workplace and civic life, given AI's growing role.
- **Design Assignments that Emphasize Process and Original Thought:** To counteract the ease with which AI can produce polished outputs, educators should consider adjusting assignment design to emphasize the *learning process*, originality, and higher-order thinking. Some strategies: require **draft submissions, outlines, or annotated thought processes**. If a student must submit an outline or a concept map before the final paper, and perhaps discuss it in class or with the instructor, it ensures they do the groundwork themselves (AI currently isn't great at aligning exactly with an instructor's

unique assignment nuances, especially over multiple stages). Similarly, asking for **reflection essays** where students explain their reasoning or what they learned from the assignment can reveal whether they engaged deeply or just copied an answer. Assignments can also incorporate more personalized or context-specific elements that AI would have trouble with – e.g., connect the essay to a personal experience or to a specific local case study discussed in class (which the AI might not know). This forces the student to inject their own perspective. In technical subjects, focus assignments on **problem-solving process**: require students to show all steps and justify them. If an AI is used, a student still has to interpret and write out why step 1 leads to step 2, etc., demonstrating understanding. Educators might also shift some assessment to formats that are harder for AI to directly handle, such as in-class quizzes, oral examinations, group projects with dynamic interaction, or scaffolded projects (multi-stage). However, note that these shifts should be balanced with not overloading faculty or students – it's about smart redesign, not just more work. Another idea is to include a **"challenge" component**: for instance, after a typical problem, ask the student to *create a variation or a new problem* and solve it. AI might do the first problem, but coming up with a novel variation requires comprehension. Overall, the goal is to create **assessment that values skills AI can't easily mimic**: creativity, critical thinking, application to novel contexts, personal voice, ethical reasoning, etc. This doesn't mean every assignment changes, but high-stakes ones perhaps should, to ensure grades reflect student ability, not just ability to use AI.

- **Encourage Active Learning and “Desirable Difficulties”:** Instructors may need to re-emphasize pedagogical approaches that we know promote learning – such as retrieval practice, peer instruction, project-based learning – since AI makes it tempting to skip directly to answers. For example, incorporating more **in-class active learning** can ensure students practice thinking without AI at least during class: think-pair-share on conceptual questions, solving a problem on the board by reasoning it out, etc. As Deslauriers et al. (2019) showed, students might not love the harder work, but it leads to real learning ³⁰ ²¹. Educators should communicate to students *why* they are still expected to do things the hard way sometimes: explicitly discussing the concept of desirable difficulties and long-term benefits ⁹. For instance, a professor might say, “I know you can get the answer from an AI, but I’m having you first struggle with this proof because that struggle will help you remember the method and truly understand it.” If students appreciate that logic (backed by cognitive science findings), they may be more willing to engage. We might also explicitly build **practice without AI** into courses: e.g., closed-book quizzes or writing assignments in class. This not only provides a more accurate gauge of student learning, but also forces them to practice retrieval and skill execution unaided, which strengthens memory and skills. That said, we can also harness AI for desirable difficulties in a controlled way – like using an AI to generate practice questions that students then attempt without looking at the AI’s answer. For instance, a language teacher could have students use an AI to pose them unpredictable new sentences to translate (introducing desirable variability) and then they try to do it and only afterwards check if the AI’s translation matches theirs. The key is being intentional about when AI is *out of the loop* to ensure students get the needed mental exercise.

- **Implement Checks for Understanding (Don’t Assume a Done Assignment = Learned Material):** Educators should incorporate mechanisms to verify that students who use AI have actually learned. This could involve brief **oral follow-ups** (vivas) where a student is asked to explain their submission. For example, after submitting a paper, a student might have a 5-minute meeting or a recorded video where they answer a question or expand on a point, ensuring they can discuss it in their own words (which AI can’t do for them in real-time). Another method is **spot quizzes** or short conceptual

questions on content recently submitted; if a student wrote a brilliant essay with AI's help but can't answer basic questions about it later, that's a red flag. Some professors use tools like Turnitin's AI detection or other software, but these are not fully reliable and could falsely accuse or miss things. Instead of heavily policing, a more educational approach is "trust, but verify" – allow AI use as per policy, but make sure to assess core understanding in some way. If a disparity is found (the work is great but understanding is poor), treat it as a learning moment – maybe require the student to redo with more self-explanation, or discuss how over-relying didn't actually help them. Importantly, students should know such checks are in place; it deters over-reliance when they know, "I might have to explain this myself." On an institutional level, assessment strategies might shift more weight to exams or presentations done under supervision. It's a practical adjustment: if take-home assignments are now less indicative of individual learning, then either transform take-homes into learning activities rather than summative assessments, or complement them with robust in-person assessment.

- **Provide Faculty Development and Support:** Many educators themselves are figuring out how to respond to AI. Institutions should run workshops or provide resources so faculty can see demonstrations of AI capabilities in their subject, discuss with colleagues what approach to take, and share evolving best practices. It might be helpful to share example assignments reworked for the AI era (some universities have started repositories of "AI-resistant" or "AI-enabled" assignment designs). Additionally, informing faculty of the cognitive science behind learning can help them justify decisions to students (e.g., explain why some manual practice is still essential). Administrators should also prepare to handle academic integrity cases sensitively: differentiating malicious cheating (e.g., a student misrepresents AI work as their own contrary to clear instructions) from permitted use. This clarity and support will help maintain academic standards without stifling innovation. Another support could be providing class-specific AI tools: for example, if an instructor wants students to use a controlled AI that is tuned to give hints not answers, the institution could help set that up (there are emerging tools for this). Investing in such **educational AI tools** could channel students' usage in a more learning-friendly direction, rather than them using generic ChatGPT which is not pedagogically optimized.
- **Foster an Academic Culture that Values Learning over Convenience:** Ultimately, a cultural shift may be needed among students – and faculty – to resist the purely utilitarian approach ("just get it done fast") and refocus on the *purpose* of assignments as learning experiences. This is not easy in environments obsessed with grades and efficiency, but messaging and curriculum design can help. For instance, instructors can explicitly discuss case studies of learning vs. performance (maybe referencing Bjork's research or the ChatGPT essay study) to show that doing things the easy way can cheat oneself of education ⁹ ⁴. Orientation sessions for new students could cover responsible AI use and emphasize that while AI might be tempting to use for everything, doing so will leave them unprepared for exams, higher-level courses, or real-world problem-solving that demands understanding. Essentially, instill the idea that *struggle in learning is not a bad thing* – it's expected and needed. If students internalize that, they may self-regulate AI use (like a student might say: "I could use AI to do this problem set, but I need the practice for the test, so I'll try it myself first."). Instructors can reinforce this by awarding participation points for showing work, effort, improvement, not just correct answers. An equitable classroom might celebrate when a student shares a mistake they learned from, rather than only the right answers. The presence of AI actually gives an impetus to double down on the value of **learning how to learn**, learning how to think –

skills that an AI cannot simply hand over. By focusing on these, the academic community can shift away from rote tasks (which AIs can do) toward the human aspects of learning.

- **Address Equity in Access to AI and Guidance:** Institutions should ensure that all students have equal access to AI tools (if allowed) and – crucially – equal access to guidance on using them effectively. Otherwise, we risk a scenario where resourceful or tech-savvy students gain advantages. If AI is a permitted aid, maybe provide institution-sanctioned access (like a university-wide license to a certain LLM or integration in LMS) so every student can use it without cost barriers. Simultaneously, provide training sessions for students who want extra help in how to incorporate AI into study routines productively (like how to use AI for making flashcards or summarizing notes). On the flip side, keep an eye on any disproportionate downsides: for example, if some students rely on AI due to language barriers (like non-native speakers using it to correct English), institutions might provide additional language support so those students aren't over-relying and missing out on improving their writing skills. Equity also means adjusting expectations for those with accommodations – perhaps an AI tool might level the playing field for a student with a writing disability by handling some mechanics, which might be a net positive. These nuances require institutional awareness and perhaps case-by-case policies. But overall, making sure everyone is equally equipped to use or not use AI (rather than a secret weapon for some) will create a fairer academic environment.
- **Monitor and Research Outcomes Continually:** Finally, institutions should treat this as an evolving situation – gather data internally on how AI is affecting student outcomes. This might include surveying students on their AI use and perceived effects, analyzing any changes in grade distributions or failure rates in courses suspected of high AI usage, and even running pilot studies (with instructors volunteering to experiment with different approaches in parallel sections to see what yields better learning). Sharing these findings in faculty forums can help refine strategies. Being empirical in our approach within each institutional context will allow quick course corrections. For example, if many students report that they used AI on an assignment and then felt unprepared for the exam, that's a sign to change that assignment structure next term. Or if an instructor tries an AI-integrated assignment and finds students performed well on subsequent tests (perhaps indicating they learned more deeply through the integration), that can be scaled up. Essentially, **continuous improvement** using feedback loops will be key, as with any pedagogical innovation.

In conclusion, the practical landscape is challenging but navigable. The overarching message to educators and institutions is: **be proactive, not reactive**. Banning AI outright is likely neither feasible nor beneficial long-term (students will use it anyway in life; better to teach proper use). Conversely, ignoring it and continuing as usual could lead to widespread superficial learning. The middle path involves explicit teaching about and through AI, redesigning learning experiences to maintain rigor, and verifying actual learning in new ways. If done well, we may find that higher education emerges from this disruption with even stronger emphasis on critical thinking, creativity, and deep understanding – the qualities that distinguish human learners in the age of intelligent machines. The onus is on us as educators to ensure that while AI might transform *how* students learn, it does not diminish *what* and *how well* they learn. By keeping learning at the center of AI integration, we can help students leverage these powerful tools to become more capable, knowledgeable, and independent thinkers – rather than less.

References

1. **Gerlich, M. (2025).** *AI Tools in Society: Impacts on Cognitive Offloading and the Future of Critical Thinking.* **Societies**, **15**(1), 6. DOI: 10.3390/soc15010006. – Found that frequent AI use correlates with lower critical thinking skills, mediated by cognitive offloading ³³ ⁵¹. Emphasizes need for educational strategies to promote critical engagement with AI ³⁴.
2. **Zhai, C., Wibowo, S., & Li, L. D. (2024).** *The effects of over-reliance on AI dialogue systems on students' cognitive abilities: a systematic review.* **Smart Learning Environments**, **11**(1), 28. DOI: 10.1186/s40561-024-00316-7. – Concludes over-reliance on AI can impair decision-making, critical thinking, and analytical reasoning ¹³. Users favor quick AI solutions over slow cognitive processes ²³, highlighting risk of "metacognitive laziness."
3. **Walter, Y. (2024).** *Embracing the future of Artificial Intelligence in the classroom: the relevance of AI literacy, prompt engineering, and critical thinking in modern education.* **International Journal of Educational Technology in Higher Education**, **21**, 15. DOI: 10.1186/s41239-024-00448-3. – Discusses the necessity of AI literacy and integrating prompt engineering skills in curricula to ensure students maintain critical thinking in an AI-driven world ⁶⁶ ⁷⁵.
4. **Stadler, M., Bannert, M., & Sailer, M. (2024).** *Cognitive ease at a cost: LLMs reduce mental effort but compromise depth in student scientific inquiry.* **Computers in Human Behavior**, **160**, 108386. DOI: 10.1016/j.chb.2024.108386. – In an experiment, students using ChatGPT had lower cognitive load but produced weaker reasoning in their recommendations ⁵. Suggests LLMs simplify tasks at the expense of deep engagement ²⁸ ⁶.
5. **Fan, Y., et al. (2024).** *Beware of metacognitive laziness: Effects of generative artificial intelligence on learning motivation, processes, and performance.* **British Journal of Educational Technology**, **56**(2), 489-530. DOI: 10.1111/bjet.13544. – A lab study where ChatGPT-assisted students improved essays more than others, but showed no better topic knowledge gain ³⁵ ³⁶. The AI group engaged less in self-regulation (e.g., referred to readings less) and risked "metacognitive laziness" by offloading cognitive processes to the bot ³⁷ ³.
6. **Sparrow, B., Liu, J., & Wegner, D. M. (2011).** *Google Effects on Memory: Cognitive Consequences of Having Information at Our Fingertips.* **Science**, **333**(6043), 776-778. DOI: 10.1126/science.1207745. – Demonstrated that people recall information less when they expect easy access to it online, instead remembering where to find it ⁵³ ¹². Introduced the idea of the "Google effect" (externalizing memory to the Internet), analogous to students relying on AI for answers.
7. **Risko, E. F., & Gilbert, S. J. (2016).** *Cognitive Offloading.* **Trends in Cognitive Sciences**, **20**(9), 676-688. DOI: 10.1016/j.tics.2016.07.002. – Reviews how people offload cognitive tasks to external tools to reduce working memory load ⁵¹. While offloading can free resources, it may also lead to reduced internal cognitive engagement over time ⁸⁰, a concern echoed in AI usage contexts.
8. **Masood, A. (2025).** *The Outsourced Mind: Navigating the Risks and Rewards of Cognitive Offloading.* Medium (August 4, 2025). – Highlights that while offloading to AI boosts efficiency, it can weaken internal memory and critical thinking ("use it or lose it") and create a false sense of knowledge ⁵². Emphasizes balanced tool use – augmenting but not replacing our brains.

9. **Gonzalez, M. R. (2023).** *Artificial Mediocrity: The Hazard of AI in Education*. Public Discourse (September 2023). – Argues that unchecked use of chatbots can “imperil serious education,” making learning too easy and “frictionless” at the cost of deep thought ⁵⁸ ²⁹. Cites Bjork’s desirable difficulties, warning that friction is exactly what the mind needs for long-term learning ⁹ ⁶⁵.
10. **Deslauriers, L., et al. (2019).** *Measuring actual learning versus feeling of learning in response to being actively engaged in the classroom*. **Proceedings of the National Academy of Sciences**, **116**(39), 19251-19257. DOI: 10.1073/pnas.1821936116. – Found that students in active learning classrooms learned more but *felt* like they learned less, whereas passive lecture students felt high learning but learned less. Underscores that ease and fluency can mislead student perceptions of learning ³⁰ ²¹, relevant to AI making learning feel easier.
11. **Dahmani, L., & Bohbot, V. D. (2020).** *Habitual use of GPS negatively impacts spatial memory during self-guided navigation*. **Scientific Reports**, **10**, 6310. DOI: 10.1038/s41598-020-62976-0. – Showed that people with greater reliance on GPS had worse spatial memory in navigation tasks ⁸¹ ⁸². An analog for AI: over-reliance on external navigation (GPS) corresponds to reduced internal spatial mapping – by extension, over-reliance on AI could reduce internal problem-solving schema.
12. **Johnson, A. C., et al. (2020).** *When calculators lie: A demonstration of uncritical calculator usage among college students and factors that improve performance*. **PLoS ONE**, **15**(11), e0242216. DOI: 10.1371/journal.pone.0242216. – Found college students often failed to notice when a calculator was intentionally giving incorrect answers; they rarely estimated or double-checked results ⁴¹ ⁴². Noticing errors improved only when conditions encouraged mental calculation (delays, concrete contexts) ⁴³ ⁴⁴. Analogous to students accepting AI output without scrutiny, highlighting need to train estimation and verification skills.
13. **Lin, P. H., Liu, T. C., & Paas, F. (2017).** *Effects of spell checkers on English as a second language students' incidental spelling learning: A cognitive load perspective*. **Reading and Writing**, **30**(7), 1501-1525. DOI: 10.1007/s11145-017-9734-4. – Explored how spell-checker use affects learning to spell. Found that when learners had to exert effort (e.g. choosing from a list or using a dictionary), their incidental learning of correct spelling was better ⁴⁷ ⁴⁶. Fully automated corrections (low effort) led to less learning. Concludes that convenience can reduce learning by cutting the effort invested ⁴⁵ ⁴⁶, consistent with cognitive load theory.
14. **Anthropic (2025).** *How Claude is being used by university students (Internal report)*. – Analyzed ~574,000 conversations of university students with the Claude AI over 18 days ³⁸. Found ~40% of student queries were for content creation (e.g., generating code or essays) and ~30% for analysis tasks ³¹ ³², indicating substantial offloading of higher-order tasks to AI. Warns that these are tasks normally requiring critical thought, so heavy AI use here could diminish practice of those skills.
15. **Liu, R., et al. (2025).** *From Superficial Outputs to Superficial Learning: Risks of Large Language Models in Education*. (arXiv Preprint arXiv:2509.21972). – A systematic review focusing on risks of LLMs in educational settings. Highlights pedagogical concerns including diminished critical thinking, metacognitive disengagement, over-reliance, and reduced student agency ⁷⁹. Notes that LLM convenience can undermine germane cognitive load and deep processing, as learners may not “stop and think” when answers are readily given ⁸ ⁶⁷.

16. **Krullaars, D., Ahmad, K., & Suleri, S. (2023).** *Embracing the future of AI in the classroom: The relevance of AI literacy, prompt engineering, and critical thinking in modern education.* **International Journal of Educational Technology in Higher Education**, **21**, 15. DOI: 10.1186/s41239-024-00448-3. – Stresses that students need to develop AI literacy (understanding and using AI) and prompt engineering skills to effectively harness AI ⁸³ ⁷⁶. Also warns that over-reliance without these skills can undermine critical thinking, citing that balancing automation with cognitive engagement is essential ⁸⁴ ⁸⁵.
17. **Barshay, J. (2025).** *University students offload critical thinking, other hard work to AI.* The Hechinger Report (May 19, 2025). – Summary of two studies: one (Fan et al. 2024) showing ChatGPT improved essays but not learning ⁴ ³, and another (Anthropic, 2025) analyzing student AI usage. Concludes that many students use AI in ways that undermine deep learning, e.g., relying on it instead of engaging with readings ³⁷ ¹¹. Emphasizes “metacognitive laziness” as a crucial issue when students depend on AI assistance ³.
18. **Koedinger, K. R., & Corbett, A. T. (2006).** *Cognitive tutors: Technology bringing learning sciences to the classroom.* In R. K. Sawyer (Ed.), **The Cambridge Handbook of the Learning Sciences** (pp. 61–78). Cambridge University Press. – Describes the design of Cognitive Tutor systems which provide step-by-step guidance and feedback in subjects like algebra. These tutors proved effective at scale ⁷⁰ ⁶⁹, demonstrating how AI-like guidance can support learning if done through prompting and feedback rather than giving final answers.
19. **Bjork, R. A., & Bjork, E. L. (2011).** *Making things hard on yourself, but in a good way: Creating desirable difficulties to enhance learning.* In M. A. Gernsbacher et al. (Eds.), **Psychology and the real world: Essays illustrating fundamental contributions to society** (pp. 56-64). Worth. – Explains the concept of desirable difficulties: training conditions that slow performance (hard practice) often improve long-term retention and transfer ⁹. Provides evidence that strategies like spaced practice, testing, and variation, while frustrating in the short term, yield better learning than easier, fluent study methods – a principle relevant to resisting AI oversimplification.
20. **Kapur, M. (2016).** *Examining productive failure, productive success, unproductive failure, and unproductive success in learning.* **Educational Psychologist**, **51**(2), 289-299. DOI: 10.1080/00461520.2016.1155457. – Research on **productive failure** shows that students who attempt to solve complex problems and fail initially often learn better from subsequent instruction than those who are given solutions upfront. This supports delaying AI assistance: allowing students to struggle first may lead to deeper learning when AI or instruction is later provided, rather than giving AI solutions immediately.

- 1 12 13 16 17 21 22 30 33 34 51 53 66 68 69 70 80 84 85 AI Tools in Society: Impacts on Cognitive Offloading and the Future of Critical Thinking | MDPI
<https://www.mdpi.com/2075-4698/15/1/6>
- 2 8 50 62 67 79 From Superficial Outputs to Superficial Learning: Risks of Large Language Models in Education
<https://arxiv.org/html/2509.21972v1>
- 3 4 10 11 25 26 27 31 32 37 38 University students offload critical thinking, other hard work to AI
<https://hechingerreport.org/proof-points-offload-critical-thinking-ai/>
- 5 20 28 39 Cognitive ease at a cost: LLMs reduce mental effort but compromise depth in student scientific inquiry - ScienceDirect
<https://www.sciencedirect.com/science/article/pii/S0747563224002541?via%3Dihub=>
- 6 7 19 40 Cognitive Ease at a cost: The Influence of Large Language Models on Student's Mental Effort and Reasoning Quality - TUM Center for Educational Technologies
<https://www.edtech.tum.de/cognitive-ease-at-a-cost-the-influence-of-large-language-models-on-students-mental-effort-and-reasoning-quality/>
- 9 29 58 59 60 61 65 71 72 Artificial Mediocrity: The Hazard of AI in Education - Public Discourse
<https://www.thepublicdiscourse.com/2023/09/90834/>
- 14 15 Generative AI tool use enhances academic achievement in sustainable education through shared metacognition and cognitive offloading among preservice teachers | Scientific Reports
https://www.nature.com/articles/s41598-025-01676-x?error=cookies_not_supported&code=2558c3ec-9011-4423-8ab7-4b65ab0d4f54
- 18 [PDF] an experimental study on LLM integration in higher education
<https://www.frontiersin.org/journals/psychology/articles/10.3389/fpsyg.2025.1641212/pdf>
- 23 24 73 74 The effects of over-reliance on AI dialogue systems on students' cognitive abilities: a systematic review | Smart Learning Environments
<https://link.springer.com/article/10.1186/s40561-024-00316-7>
- 35 36 63 64 Beware of metacognitive laziness: Effects of generative artificial intelligence on learning motivation, processes, and performance - Monash University
<https://research.monash.edu/en/publications/beware-of-metacognitive-laziness-effects-of-generative-artificial/>
- 41 42 43 44 When calculators lie: A demonstration of uncritical calculator usage among college students and factors that improve performance - PMC
<https://pmc.ncbi.nlm.nih.gov/articles/PMC6821400/>
- 45 46 47 48 49 ERIC - EJ1149890 - Effects of Spell Checkers on English as a Second Language Students' Incidental Spelling Learning: A Cognitive Load Perspective, Reading and Writing: An Interdisciplinary Journal, 2017-Sep
<https://eric.ed.gov/?id=EJ1149890>
- 52 The Outsourced Mind: Navigating the Risks and Rewards of Cognitive Offloading | by Adnan Masood, PhD. | Medium
<https://medium.com/@adnanmasood/the-outsourced-mind-navigating-the-risks-and-rewards-of-cognitive-offloading-9e1e70ee2efb>
- 54 55 Rethinking GPS navigation: creating cognitive maps through ...
<https://pmc.ncbi.nlm.nih.gov/articles/PMC8032695/>

56 **57** The 'Wonder' of AI and the Cost of Never Thinking Alone

<https://woleadaramoye.medium.com/the-wonder-of-ai-and-the-cost-of-never-thinking-alone-bce492202738>

75 **76** Embracing the future of Artificial Intelligence in the classroom: the relevance of AI literacy, prompt engineering, and critical thinking in modern education | International Journal of Educational Technology in Higher Education

<https://link.springer.com/article/10.1186/s41239-024-00448-3>

77 Usability and Interactions with Copilot for Novice Programmers

<https://www.semanticscholar.org/paper/%E2%80%9CIt%E2%80%99s-Weird-That-it-Knows-What-I-Want%E2%80%9D%3A-Usability-Prather-Reeves/f352a968c8735fac58912870a7bde57fcfc2e6bd>

78 [PDF] How Novices Use LLM-Based Code Generators to Solve CS1 ...

https://austinhenley.com/pubs/Kazemitaar2023Koli_LLMsCS1.pdf

81 **82** Does global positioning system-based navigation dependency ...

<https://PMC.ncbi.nlm.nih.gov/articles/PMC9582945/>

83 Prompting engineering or AI literacy? How to develop a critical ...

<https://altc.alt.ac.uk/blog/2024/02/prompting-engineering-or-ai-literacy-how-to-develop-a-critical-awareness-of-generative-ai-in-education/>