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Cognitive Offloading to Artificial Intelligence and Perceived Self-Efficacy

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Abstract

Artificial intelligence has become an increasingly accessible external cognitive resource for information retrieval, idea generation, summarization, problem solving, drafting, planning, and decision support. Its growing role in everyday knowledge work raises a significant psychological question: when individuals delegate cognitive operations to artificial intelligence, does the resulting reduction in mental effort strengthen their perceived capability or gradually weaken confidence in their ability to perform independently? This study examines the relationship between cognitive offloading to artificial intelligence and perceived self-efficacy through a simulation-based analytical design grounded in cognitive offloading theory and social cognitive theory. Rather than presenting synthetic observations as real participant data, the study constructs a reproducible hypothetical dataset of 360 cases to test a theoretically informed nonlinear model. AI cognitive offloading was modeled on a five-point continuum, while perceived self-efficacy represented confidence in independently understanding, evaluating, solving, and completing cognitively demanding tasks. The simulation also incorporated AI literacy as a control variable. Results produced a curvilinear pattern. Mean perceived self-efficacy increased from 3.44 among low-offloading cases to 3.76 under moderate offloading, before declining to 3.53 among high-offloading cases. Quadratic regression supported the simulated inverted-U relationship, with the negative squared offloading coefficient indicating that increasing delegation became progressively less beneficial after a moderate level.

The findings support a distinction between supportive offloading, in which AI reduces peripheral cognitive burden while preserving human judgment, and substitutive offloading, in which AI begins to replace cognitively consequential processes required for mastery and confidence formation. The study therefore argues that the central psychological issue is not whether people use AI, but which cognitive operations they delegate, how frequently they verify AI outputs, and whether they retain opportunities for independent mastery. Implications are developed for higher education, professional learning, human–AI interface design, and future longitudinal research.

Keywords: artificial intelligence, cognitive offloading, perceived self-efficacy, generative AI, cognitive dependence, human–AI collaboration, metacognition, cognitive agency

1. Introduction

Artificial intelligence is changing the practical boundaries between internal cognition and external cognitive support. Individuals can now ask generative AI systems to retrieve and reorganize information, formulate explanations, compare alternatives, create outlines, summarize complex material, generate code, diagnose errors, propose decisions, and produce substantial portions of written work. Cognitive science has long recognized that people reduce internal cognitive demands by restructuring their environments or assigning memory and processing functions to external artifacts. Risko and Gilbert describe cognitive offloading as the use of external actions or resources to modify the information-processing demands of a task, showing that offloading is not unique to contemporary AI but belongs to a broader family of adaptive cognitive strategies. The distinctive feature of generative AI is its capacity to accept delegation of operations that extend beyond storage and retrieval into explanation, inference, synthesis, and content generation. Consequently, the question has shifted from whether technology supports cognition to how extensively cognition itself should be distributed between the individual and an intelligent system.

The psychological consequences of this distribution cannot be understood exclusively through measures of speed or task accuracy. A person may complete an assignment more efficiently with AI while developing either greater or weaker confidence in independent performance. Self-efficacy provides an important theoretical construct for examining this distinction. Bandura conceptualized self-efficacy as an individual's belief in the capability to organize and execute actions necessary for successful performance, emphasizing that efficacy expectations influence effort, persistence, behavioral initiation, and responses to difficulty. Applied to AI-supported cognition, perceived self-efficacy concerns more than confidence in operating an AI interface. It concerns whether individuals continue to believe that they themselves can understand a problem, evaluate evidence, generate alternatives, correct errors, and complete important cognitive work when automated assistance is limited or unavailable. AI can potentially strengthen such beliefs when it functions as scaffolding, but it may weaken them when successful performance is attributed principally to the external system.

Recent evidence makes this distinction particularly important. Lee and colleagues, in their study of generative AI and critical thinking among knowledge workers, found that higher confidence in generative AI was associated with lower reported critical-thinking engagement, whereas higher self-confidence was associated with greater critical-thinking activity. Research in higher education similarly shows that AI-based cognitive offloading is not a unitary practice. Jiang and Chen distinguish different forms of AI-based cognitive offloading among university students, drawing attention to the importance of what kind of cognitive activity is delegated rather than treating all AI use as equivalent. These findings suggest that a learner who asks AI to organize routine information while retaining interpretation and judgment may experience a different psychological trajectory from a learner who routinely delegates reasoning, explanation, and final decision formation.

At the same time, evidence does not justify a simple conclusion that offloading necessarily undermines learning or confidence. Iqbal and colleagues describe generative AI as capable of reducing demands associated with simpler cognitive tasks so that learners can direct resources toward more complex academic activity. Wang's 2026 study is especially relevant because cognitive offloading through digital tools was positively associated with cognitive self-efficacy, and cognitive self-efficacy subsequently predicted critical thinking, task persistence, and learning depth. Wang found significant indirect pathways from offloading through self-efficacy to these learning outcomes, indicating that externally supported cognition can remain psychologically productive when it reinforces rather than displaces perceived competence. Hashmi and colleagues likewise reported positive relationships among generative AI use, technological self-efficacy, cognitive offloading, and self-regulated learning, while participants also identified risks involving over-reliance, cognitive overload, metacognitive passivity, and erosion of academic skills.

2. Objectives of the Study

2.1 To Examine the Relationship Between AI Cognitive Offloading and Perceived Self-Efficacy

The first objective is to evaluate how increasing reliance on artificial intelligence for cognitive assistance may correspond with changes in perceived personal capability. The study distinguishes the use of AI as an external resource from psychological dependence on AI. The analytical emphasis is therefore placed on the degree to which cognitive work is delegated and on whether such delegation remains compatible with an individual's perception that they can understand and perform the underlying task independently.

2.2 To Test Whether the Relationship Is Nonlinear

The second objective is to assess a theoretically informed curvilinear hypothesis. Moderate cognitive offloading may conserve limited working resources, reduce avoidable overload, and create successful task experiences, whereas very high levels of delegation may diminish direct practice and independent mastery. The study consequently tests whether self-efficacy initially rises with offloading but begins to decline when reliance becomes sufficiently intensive.

2.3 To Identify Implications for Responsible Human–AI Collaboration

The third objective is to translate the proposed relationship into practical implications for educational institutions, professional organizations, AI developers, and individual users. Particular attention is given to maintaining cognitive agency, preserving opportunities for mastery, encouraging verification, and designing AI interactions that enhance human competence rather than merely accelerating task completion.

3. Review of Literature

3.1 Cognitive Offloading From External Memory to Generative AI

Cognitive offloading predates digital technology. Notes, calendars, written calculations, maps, reminders, diagrams, and other environmental structures allow individuals to shift selected cognitive demands outside biological memory. Risko and Gilbert's influential synthesis established cognitive offloading as a meaningful component of human cognition rather than an exceptional response to technological environments. Externalization can be rational because human working memory, attention, and prospective memory are limited. When an external resource performs a reliable peripheral operation, internal resources can be redirected to other components of the task.

Empirical research also demonstrates that offloading can improve immediate performance while changing what is retained internally. Grinschgl, Papenmeier, and Meyerhoff reported that cognitive offloading can improve task performance while reducing memory for information that has been externalized. This trade-off is central to the AI debate. Performance during assisted activity does not necessarily demonstrate equivalent internal learning. A person may produce a stronger output because the external system carries some cognitive workload, yet the individual may not acquire the knowledge or procedural fluency that would have emerged through unaided practice.

Generative AI expands this problem because the externalized activity may include processes traditionally considered central to knowledge construction. AI can generate not only reminders or stored information but arguments, interpretations, comparisons, examples, explanations, summaries, and proposed judgments. Lee and colleagues' CHI 2020 study showed that generative AI reduced perceived critical-thinking effort in knowledge work and that confidence relationships influenced how users allocated cognitive effort. The practical convenience of an AI response can therefore create a delegation decision before the user has fully attempted the task independently.

Delegation quality depends partly on metaknowledge. Fügener and colleagues demonstrated in human–AI collaboration research that people may perform poorly when they lack accurate knowledge about the comparative capabilities of themselves and AI, leading to ineffective delegation decisions. This principle is highly relevant to generative AI. Strategic offloading requires a user to recognize which operations are appropriate for automation and which require personal reasoning, domain expertise, contextual understanding, or accountability. Cognitive offloading becomes potentially problematic when delegation is determined primarily by convenience rather than by calibrated knowledge of task demands.

3.2 Perceived Self-Efficacy in AI-Supported Cognition

Self-efficacy theory provides a framework for understanding why identical AI assistance may produce different psychological outcomes. Bandura's theory proposes that efficacy beliefs influence whether people approach challenging tasks, how much effort they invest, and how persistently they continue when difficulties emerge. Mastery experiences are especially consequential because successful performance can become evidence that the individual possesses the relevant capability. In AI-assisted work, however, attribution becomes more complicated because successful performance is jointly produced.

When individuals use AI to remove peripheral barriers while retaining ownership of core reasoning, successful task completion may still be experienced as personal mastery. AI can reduce unnecessary search effort, provide examples, check grammar, restructure routine information, or offer formative feedback while leaving the learner responsible for evaluating evidence and constructing the final judgment. Under these circumstances, offloading may increase the probability of successful engagement with difficult tasks and thereby reinforce perceived efficacy.

Wang's empirical study offers direct support for this interpretation. Cognitive offloading through digital tools was positively associated with cognitive self-efficacy, and self-efficacy significantly mediated relationships with critical thinking, persistence, and learning depth. The reported standardized path from cognitive offloading to cognitive self-efficacy was positive, while bootstrap mediation estimates supported indirect effects on multiple outcomes. This indicates that offloading is not psychologically equivalent to surrendering competence. External support can become part of an effective cognitive strategy when individuals remain active agents in interpretation and decision making.

The opposite pathway is also plausible. If important elements of the task are repeatedly completed by AI before users attempt them, successful outputs may provide limited evidence of independent capability. In such circumstances, people may become increasingly confident in achieving outcomes with AI while becoming less certain that they can achieve equivalent outcomes without AI. Lee and colleagues' finding that tool confidence and self-confidence are differently associated with critical-thinking effort reinforces the need to separate confidence in automation from confidence in oneself. A psychologically mature model of AI-supported learning must therefore measure both assisted performance and perceived independent capability.

3.3 Strategic Assistance, Dependency, and the Emerging Research Gap

Recent educational research increasingly rejects an all-or-nothing view of AI use. Iqbal and colleagues describe cognitive offloading as one mechanism through which generative AI can reduce routine demands and permit greater attention to complex academic activities. Hashmi and colleagues similarly found that technological self-efficacy and cognitive offloading can operate within a productive pathway connecting generative AI use with perceived self-regulated learning. Their multi-country study nevertheless records concerns about over-reliance and deterioration of important academic capabilities, emphasizing that beneficial outcomes are conditional rather than automatic.

Jiang and Chen's 2020 work is particularly valuable because it treats AI-based cognitive offloading as multidimensional and distinguishes lower- and higher-order forms of delegation among students in higher education. This distinction helps explain why aggregate measures such as "frequency of AI use" may be theoretically inadequate. Delegating retrieval of a definition, reformatting citations, or checking surface errors is cognitively different from delegating interpretation, argument construction, diagnosis, or evaluative judgment. Frequency alone does not identify what is being surrendered.

The available literature therefore supports both an augmentation pathway and a dependency pathway. One explanation for apparently conflicting results is that researchers often assume linear effects. If moderate offloading is helpful while intensive offloading becomes counterproductive, studies focused on different user populations or different ranges of AI dependence may produce different conclusions without genuinely contradicting one another. A nonlinear formulation offers a plausible means of integrating these findings.

The present study addresses this gap by modeling perceived self-efficacy as a curvilinear function of AI cognitive offloading. The proposed theoretical sequence is that low-to-moderate offloading can remove peripheral burden and facilitate mastery, while high offloading may reduce independent practice, weaken internal attribution of successful outcomes, and increase uncertainty about unaided capability. The model does not claim that a universal numerical threshold exists. Instead, it treats the transition from supportive to substitutive offloading as a research hypothesis whose exact location is likely to vary across domains, task complexity, expertise levels, and AI systems.

4. Research Methodology

4.1 Research Design and Simulation Logic

The study uses a quantitative simulation-based research design. This choice is methodologically important because no genuine participant observations were supplied for the paper. Presenting invented survey responses as completed empirical research would create false evidence. Instead, synthetic observations are generated transparently to determine whether the proposed theoretical pattern produces identifiable statistical signatures and to provide a reproducible analytical model for later empirical validation.

A synthetic sample of 360 cases was generated using a fixed random seed of 42. AI cognitive offloading was represented on a continuous five-point scale. Values were generated from a symmetrical beta distribution mapped onto the interval from 1 to 5 so that most hypothetical cases occupied moderate positions while fewer occupied the extremes. AI literacy was modeled as a control variable with values constrained to the same five-point range.

4.2 Constructs, Operationalization, and Proposed Measurement

Table 1: Operational Framework for the Simulation-Based Study

Construct	Operational Meaning	Simulated Scale/Specification	Analytical Role
AI Cognitive Offloading	Degree to which an individual delegates information processing, generation, organization, reasoning, or problem-solving activity to AI	Continuous score, 1–5	Primary predictor
Perceived Self-Efficacy	Confidence in one's capability to understand, evaluate, solve, and complete cognitively demanding tasks	Continuous score, 1–5	Outcome variable
AI Literacy	Ability to understand AI capabilities, limitations, uncertainty, and appropriate verification requirements	Continuous score, 1–5	Control variable
Offloading Squared	Nonlinear transformation of AI cognitive offloading	Offloading × Offloading	Curvilinear predictor
Offloading Category	Relative intensity of simulated AI delegation	Low = 1.00–2.33; Moderate = 2.34–3.67; High = 3.68–5.00	Descriptive comparison

4.3 Statistical Procedure, Reproducibility, and Ethical Status

The analysis was conducted in three stages. First, descriptive statistics were calculated for the simulated constructs. Second, the offloading measure was divided into low, moderate, and high categories to permit an intuitive comparison of mean self-efficacy. Third, ordinary least squares regression estimated the linear offloading coefficient, quadratic offloading coefficient, and AI-literacy control coefficient. Evidence of an inverted-U relationship requires a positive first-order offloading coefficient together with a statistically meaningful negative quadratic coefficient.

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Because this paper uses synthetic observations, inferential statistics must be interpreted differently from statistics estimated from probability samples of real people. P-values demonstrate whether the programmed theoretical signal can be recovered from simulated variation; they do not establish the prevalence, magnitude, or causality of the relationship in any human population. The statistical output should therefore be read as model validation within a simulated environment, not as empirical proof.

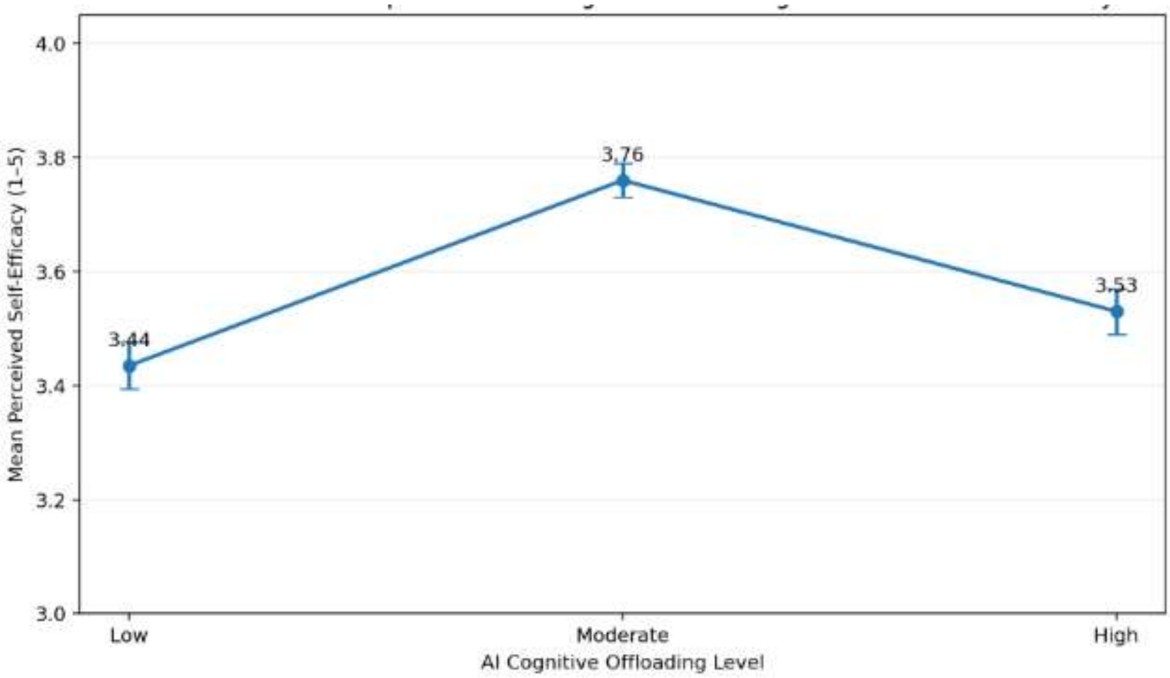
The use of synthetic data also determines the study's ethical status. No identifiable information was collected, no participants were recruited, no intervention was conducted, and no personal or sensitive data were processed. Human-subject ethics approval was therefore not applicable to the simulation itself. Any future study administering the proposed questionnaire or experimentally manipulating AI access should obtain appropriate institutional ethical review, informed consent, and data-protection safeguards before collecting participant information.

5. Analysis

5.1 Pattern of Perceived Self-Efficacy Across Offloading Levels

This pattern is theoretically important because it is inconsistent with both a simple "AI always strengthens confidence" proposition and a simple "AI always destroys confidence" proposition. Within the simulation, modest delegation appears insufficient to maximize perceived capability, while intensive delegation also fails to produce the strongest efficacy beliefs. The highest level occurs when external assistance is substantial enough to reduce unnecessary burden but not extensive enough to replace the user's central cognitive role.

Graph 1: Simulated Relationship between AI Cognitive Offloading and Perceived Self-Efficacy



Interpretation: The line rises between low and moderate cognitive offloading and subsequently falls under high offloading. Moderate offloading is associated with the strongest simulated self-efficacy. The visual pattern therefore illustrates an inverted-U relationship in which some delegation can support perceived capability while extensive delegation produces diminishing and eventually negative psychological returns.

Key Finding: The central simulated result is not that offloading should be minimized, but that the psychological value of AI assistance may depend on maintaining a balance between external cognitive support and opportunities for independent mastery.

5.2 Quadratic Regression Results

The nonlinear pattern was formally evaluated through quadratic regression. The estimated first-order coefficient for AI cognitive offloading was positive at $B = 1.502$, whereas the quadratic coefficient was negative at $B = -0.243$. Both terms were strongly recoverable within the synthetic dataset. The estimated turning point of the fitted relationship occurred at an offloading score of approximately 3.09 on the five-point continuum.

5.3 Analytical Interpretation: From Cognitive Support to Cognitive Substitution

The pattern can be interpreted through the distinction between supportive offloading and substitutive offloading. Supportive offloading occurs when AI performs peripheral, repetitive, memory-intensive, or organizational components while the human user retains problem representation, evidence evaluation, interpretation, final judgment, and responsibility. Such a configuration can decrease avoidable cognitive friction without eliminating the cognitive activities through which mastery develops.

Substitutive offloading emerges when AI increasingly performs the cognitively consequential components that users would otherwise need to practice. Under that condition, task success may cease to provide a strong mastery signal. A user can observe that a good answer was produced without being equally certain that the answer reflects their own competence. As repeated successful outcomes become attributed to the AI system, perceived dependence may grow even if externally measured task productivity remains high.

6. Discussion

6.1 Why Moderate Cognitive Offloading May Strengthen Self-Efficacy

The simulated results support the proposition that AI assistance can strengthen self-efficacy when it reduces unnecessary cognitive burden without removing the user's responsibility for understanding. This mechanism is consistent with social cognitive theory because efficacy develops partly through experiences interpreted as successful personal performance. When AI removes peripheral obstacles—such as reorganizing notes, generating alternative examples, locating terminology, checking routine errors, or creating a preliminary structure—the individual may be better positioned to engage successfully with the substantive intellectual challenge. Successful completion can then reinforce a sense of competence rather than dependence.

The argument is not that mental effort itself should always be maximized. Human cognitive resources are limited, and poorly allocated effort can obstruct learning rather than improve it. Risko and Gilbert's cognitive-offloading framework provides a strong theoretical basis for treating strategic externalization as an adaptive component of cognition. Likewise, Iqbal and colleagues describe AIenabled offloading of simpler tasks as a means of redirecting resources toward more demanding academic processes. The educational challenge is therefore to determine which cognitive demands are extraneous to the learning objective and which constitute the learning objective itself.

6.2 Why Intensive Offloading May Produce an Efficacy Paradox

The decline in simulated self-efficacy under high offloading illustrates what may be termed an efficacy paradox. AI can make a person more capable of producing a successful external output while simultaneously making them less certain of their ability to produce that output independently. This distinction becomes increasingly important as AI systems move from assisting isolated operations to generating integrated solutions.

High-quality AI output can conceal the amount of human competence that remains unused. If a student repeatedly asks AI to generate an interpretation before reading the source carefully, or if a professional requests a recommended decision before independently defining the problem, the user receives fewer opportunities to observe their own problem-solving capacity. The reduction in mastery opportunities can matter even when immediate output quality improves. In Bandura's framework, efficacy beliefs do not arise merely because a favorable outcome exists; they are shaped by how individuals interpret the causes of successful and unsuccessful performance.

Lee and colleagues provide an important empirical parallel. Their findings indicate that confidence in generative AI is associated with reduced critical-thinking effort, while greater self-confidence is associated with more critical-thinking engagement. This suggests that increasing confidence in the tool does not necessarily translate into confidence in one's own cognitive capacity. If AI is routinely positioned as the first and final cognitive authority, users may increasingly experience themselves as supervisors of machine output rather than originators of reasoning.

6.3 Implications for Education, Professional Work, and AI Design

Educational institutions should therefore move beyond policies framed only around whether AI is permitted. A more educationally meaningful policy asks what may be offloaded, at what stage, and with what evidence of human understanding. Students can be encouraged to formulate an initial position before consulting AI, compare their reasoning with AI-generated alternatives, identify errors or unsupported assumptions in machine outputs, and submit short explanations of how the final judgment was reached. Such practices preserve opportunities for mastery while still benefiting from external cognitive support.

Assessment design also requires reconsideration. If an educational task can be completed entirely through AI-generated text without requiring the learner to demonstrate understanding, the assessment may measure access to assistance rather than individual competence. Conversely, banning AI from every stage of learning may remove useful scaffolding and fail to prepare students for realistic human–AI collaboration. A more defensible approach separates practice for internal competence from performance with external augmentation and evaluates both.

Professional organizations face a similar challenge. AI can enhance productivity in legal analysis, administration, software development, healthcare support, financial analysis, research, communication, and other knowledge-intensive environments. Yet organizational efficiency metrics may overlook whether employees retain the ability to recognize errors, challenge recommendations, and act effectively during system failure. Fügener and colleagues' work on productive delegation demonstrates why metaknowledge is essential: users need accurate beliefs about both their own abilities and those of AI to make effective delegation decisions.

AI interface design can also influence cognitive agency. Systems optimized exclusively for frictionless completion may encourage premature delegation. Interfaces could instead incorporate productive mechanisms such as asking the user for an initial hypothesis, requesting a justification before revealing a recommendation, presenting uncertainty, inviting comparison among alternatives, or prompting users to identify which parts of an output they independently verified. These interventions should not be designed merely to make AI less convenient. Their purpose would be to ensure that efficiency does not systematically displace the cognitive activity required for long-term competence.

7. Conclusion

Cognitive offloading to artificial intelligence should not be understood as an inherently beneficial or inherently harmful behavior. Human cognition has always relied on external supports, and AI represents a powerful extension of that tradition. The psychological consequences of AI use depend on the cognitive function delegated, the intensity of delegation, the user's expertise, the degree of verification, and whether successful task completion continues to provide evidence of personal mastery. The literature increasingly supports this more differentiated perspective, with studies demonstrating both productive self-efficacy pathways and risks associated with over-reliance.

The simulation developed in this paper provides a theoretical demonstration of an inverted-U relationship between AI cognitive offloading and perceived self-efficacy. Low offloading produced a simulated mean self-efficacy score of 3.44, moderate offloading produced the highest mean of 3.76, and high offloading was associated with a decline to 3.53. Quadratic regression reproduced this pattern, with a positive initial offloading coefficient and a negative squared coefficient. Because the data are synthetic, these numerical results must not be interpreted as empirical estimates of a human population.

The conceptual distinction between supportive and substitutive offloading is the paper's principal contribution. Supportive offloading uses AI to reduce peripheral burden while preserving human interpretation, evaluation, and judgment. Substitutive offloading transfers cognitively central activities to AI and may consequently reduce opportunities for mastery, independent practice, and accurate self-assessment. This distinction helps reconcile findings suggesting that AI can both enhance learning and contribute to cognitive dependency.

Responsible AI integration should therefore aim neither for maximum automation nor minimum use. The more defensible goal is calibrated cognitive delegation. Individuals should use AI where external assistance expands their capacity to reason, but retain sufficient independent activity to know what they understand, what they can perform unaided, when the system may be wrong, and why a final conclusion should be trusted. Future empirical research should determine how this balance varies across disciplines, age groups, levels of expertise, task types, and AI systems. The long-term success of human–AI collaboration will depend not only on what artificial intelligence can do for people, but also on whether repeated collaboration leaves people more capable of thinking, judging, and acting for themselves.

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