# Memory in the Age of Artificial Intelligence: Cognitive Offloading, Hybrid Minds, and the Reshaping of Recall

## 1. Introduction

Artificial intelligence, commonly referred to as AI, has rapidly expanded from specialized research environments into everyday life. Once confined to laboratories and technical domains, AI systems now mediate routine cognitive activities through search engines, digital assistants, recommendation algorithms, and generative tools. These technologies support information retrieval, organization, and decision-making across fields such as education, medicine, communication, and finance. While their efficiency and accessibility have transformed how individuals interact with information, they also raise important questions about how sustained reliance on intelligent systems may influence fundamental cognitive processes.

Memory is a central component of human cognition, supporting learning, reasoning, identity formation, and critical thinking. It depends on active encoding, sustained attention, emotional engagement, and repeated retrieval to form durable representations. As AI systems increasingly store, retrieve, and summarize information, individuals may shift cognitive effort away from internal memory processes toward external technological supports. This phenomenon, often described as cognitive offloading, has prompted debate over whether AI weakens memory by reducing cognitive engagement or enhances cognition by freeing mental resources for higher-order thinking. Addressing this debate requires examining not only whether memory changes in the presence of AI, but also how and why those changes occur

Cognitive offloading is not unique to artificial intelligence. Humans have long relied on external supports such as writing systems, books, maps, calendars, calculators, catalogs, and search engines to reduce the demands placed on internal memory. This pattern is consistent with theories of extended cognition, transactive memory, distributed cognition, and cognitive offloading, which show that human cognition has often been supported by tools, other people, and environmental systems (1-5). In this sense, offloading is a long-standing human strategy, and AI represents a newer and more generative medium through which that strategy is carried out. The central question, therefore, is not whether AI created cognitive offloading, but whether AI changes the nature of offloading by moving beyond storage and lookup toward generation, summarization, inference, and reframing. Compared with traditional tools, generative AI may shift offloading from remembering information to outsourcing parts of interpretation and reasoning.

Table 1. Conceptual differences between static cognitive offloading and generative AI-mediated offloading

| Dimension | Static cognitive offloading | Generative AI-mediated offloading | Cognitive implication |
|---|---|---|---|
| Primary memory operation | Stores or displays information for later lookup | Generates, summarizes, infers, and reframes information | AI may alter not only access to information, but also how information is reconstructed |
| User action required | User must initiate search, locate the source, and interpret the content | User can receive synthesized output through a prompt-response interaction | AI lowers the effort required for retrieval and synthesis |

| | | | |
|---|---|---|---|
| Interpretation layer | Interpretation is mostly performed by the user | Interpretation may be partly performed by the system | AI may offload parts of thinking, not only memory |
| Cognitive substitution risk | Usually limited because the tool preserves information without reasoning over it | Potentially higher because the system may produce explanations, comparisons, and judgments | Users may bypass retrieval practice and evaluative reasoning |
| Error pattern | Often source-bound, stable, or easier to trace | Probabilistic, variable, and sometimes difficult to detect | Users must verify fluently presented outputs rather than merely retrieve stored information |
| Predicted effect on retrieval practice | Limited unless the user stops attempting recall | Possibly reduced when users consult AI before attempting recall | The timing of AI use may determine whether offloading weakens or supports memory |

Note. This table develops the comparison between traditional tools and AI systems into a conceptual distinction between static cognitive offloading and generative AI-mediated offloading. It draws on prior work on cognitive offloading, extended cognition, transactive memory, distributed cognition, and AI-associated cognitive offloading (1-6).

This framework clarifies that the key difference is not the existence of offloading itself, but the shift from static storage-based support to generative and interpretive support. Traditional tools are usually static and user-initiated: they store or display information, but the user must still search, interpret, and synthesize the material. AI systems add an interpretation layer because they can summarize, infer, and reframe information in response to user prompts. As a result, AI-mediated offloading may move beyond offloading memory alone and toward offloading parts of thinking. The relevant question therefore diverges from whether AI created cognitive offloading, and is instead whether AI changes the nature of offloading by transforming storage-based support into generative and interpretive support.

Recent research suggests that the relationship between AI and memory is neither uniform nor inherently detrimental. Experimental studies demonstrate that memory retention depends on retrieval structure, attention, and engagement, while behavioral evidence indicates that individuals selectively offload certain types of information while retaining others internally. Emotional relevance and intrinsic motivation further shape what is consolidated into long-term memory. At the same time, correlational findings link increased AI tool use with greater cognitive offloading and changes in critical thinking performance, suggesting that shifts in memory practice may have broader cognitive consequences. Together, these findings point toward a reorganization of memory rather than its disappearance.

This paper examines how artificial intelligence is reshaping memory by integrating evidence from cognitive neuroscience, psychology, and behavioral research. Section 1 explores the cognitive and neural mechanisms underlying memory formation and retrieval in AI-supported environments. Section 2 examines the biological, emotional, and motivational factors that influence selective cognitive offloading across different types of information. Section 3 synthesizes these findings to analyze how AI-mediated memory practices are associated with broader changes in cognitive engagement, critical thinking, and effort allocation. Section 4 extends this analysis beyond the individual to examine how AI systems operate as collective memory agents while also clarifying how

this paper builds on, but differs from, prior frameworks of extended cognition, transactive memory, and distributed cognition. Through this multi-level approach, the paper aims to clarify whether AI functions primarily as a cognitive support, a substitute for internal memory, or a force that redefines the role of memory within human cognition. Each section builds on the previous one by moving from mechanism to selectivity to consequence, progressively refining the claim that AI reshapes memory by altering the conditions under which cognitive effort is allocated.

### 1.1. Assumptions and Scope

This manuscript is a conceptual synthesis rather than an empirical investigation. The proposed mechanisms and experimental framework assume that 1) AI-mediated cognitive offloading influences memory primarily by altering attention, encoding, and retrieval processes rather than directly changing neural structure; 2) the relationships described between AI use, cognitive offloading, and critical thinking are correlational unless supported by experimental evidence; and 3) the proposed Passive Substitution-Active Scaffolding model represents a theoretical framework intended to generate testable hypotheses rather than established causal effects. These assumptions are based on the current literature on cognitive offloading, memory, and AI-supported cognition. Consequently, the conclusions should be interpreted as theoretically grounded predictions that require future experimental validation

## 2. Cognitive and Neural Mechanisms of Memory in AI-Supported Environments

This section addresses the question of whether reliance on AI alters memory by reducing internal encoding processes or by redistributing cognitive effort across neural systems. The central hypothesis is that AI does not directly impair memory capacity, but instead changes the conditions under which memory is formed by reducing attentional engagement during encoding and increasing reliance on external retrieval.

Cognitive offloading refers to the use of external systems to store, organize, or retrieve information that might otherwise be maintained internally. This strategy long predates AI, appearing in tools such as written notes, books, maps, calculators, catalogs, and search engines (1-5). However, AI-mediated offloading differs from many earlier forms because it can generate, summarize, infer, and reframe information rather than merely preserve or retrieve it. This makes AI closer to a system for offloading parts of thinking, not only memory. Empirical evidence supports concern about this shift. A large-scale survey shows that frequent AI use for information retrieval and problem-solving is associated with greater cognitive offloading and lower critical thinking performance, suggesting that habitual reliance on AI may reduce opportunities for effortful reasoning (6).

From a cognitive standpoint, this pattern reflects a redistribution of mental effort rather than a simple loss of memory ability. Strong memory formation requires sustained attention, elaboration, and repeated retrieval, processes that reinforce neural representations over time. When people expect information to remain easily accessible through external systems, they often invest less effort during encoding, resulting in weaker consolidation. Research on digital amnesia and the Google effect supports this idea, showing that individuals increasingly remember where information is stored rather than the information itself (7, 8). While this strategy improves efficiency, it raises concerns about the depth and durability of internally stored knowledge.

Neuroscientific findings help explain why reduced engagement during encoding may matter. Memory formation and consolidation depend on neural systems including the hippocampus, which plays an important role in declarative and episodic memory (9). Recognition memory also involves distinguishable processes of recollection and familiarity; neuroimaging evidence has associated hippocampal activity more strongly with recollection than with familiarity-based recognition (10). These findings do not demonstrate that AI itself reduces hippocampal activity, but they provide a neural framework for examining how changes in attention, encoding, and retrieval practice may affect the depth of later memory.

Subjective experience further complicates this shift. The speed and fluency of AI-generated outputs can create an inflated sense of understanding, where users feel knowledgeable despite having weak internal representations (11). Familiarity can feel similar to true recall, even when it lacks the depth required for long-term retention. In environments where AI frequently summarizes or generates content, repeated exposure may strengthen familiarity without reinforcing the neural processes needed for durable memory.

Experimental evidence further clarifies these mechanisms by demonstrating that memory decline depends on how information is encoded and later retrieved. A study examined how retrieval cues and intrinsic interest affect memory retention for gist-based versus detail-based information over time (12). Participants learned material designed to emphasize either conceptual understanding or specific details and were later tested using retrieval cues that were either aligned or misaligned with the original encoding.

**Figure 1.** Effect of retrieval cue type on forgetting rates from 10 minutes to 1 week across memory type and interest level.

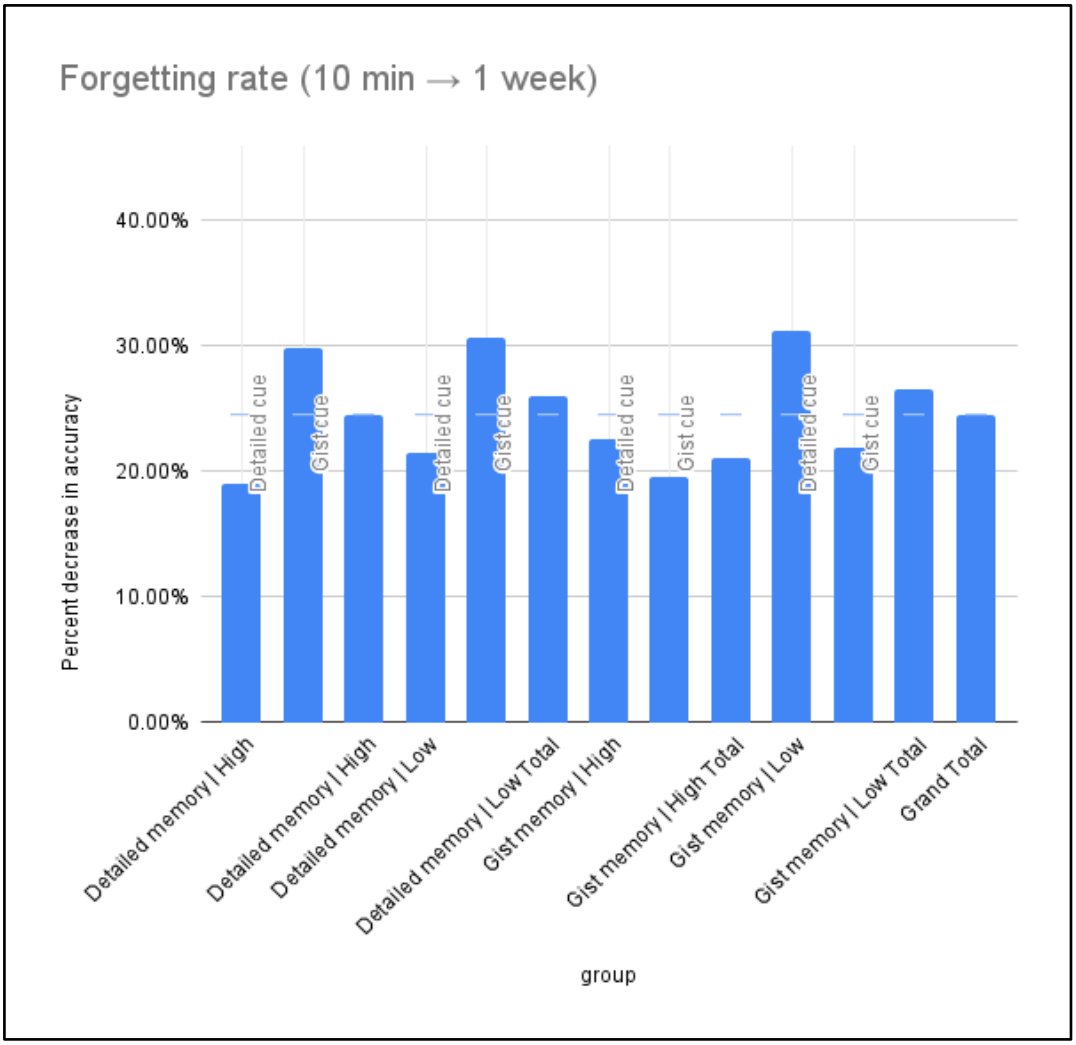


Figure 1. Effect of retrieval cue type (gist vs detailed) on forgetting rates from 10 minutes to 1 week across memory type and interest level. For detailed memories, forgetting is greater when retrieval relies on gist cues, whereas for gist memories, forgetting is greater when retrieval relies on detailed cues, indicating an effect of cue-memory mismatch. Higher interest reduces overall forgetting across both memory types but does not eliminate differences driven by retrieval cues.

The percent decrease in recall accuracy from 10 minutes to one week across experimental conditions makes it clear that memory decline is steepest when retrieval cues are misaligned with the type of memory encoded and when engagement during learning is low. In contrast, aligned retrieval cues and higher engagement substantially reduce forgetting over time. This pattern directly supports the section's hypothesis that AI-related memory changes arise from altered encoding and retrieval conditions rather than from an inherent degradation of memory capacity. As AI systems increasingly mediate how information is summarized, prompted, and revisited, they may bias memory toward superficial familiarity unless retrieval structures actively reinforce deeper encoding.

Beyond individual cognition, memory is also shaped by repeated exposure within broader information environments. AI has been described as a collective memory agent that reinforces certain representations through algorithmic curation (13). Since repetition strongly predicts retention, AI-driven prioritization of specific topics indirectly shapes individual memory by increasing the salience of some information while allowing other content to fade. A review of digital media and brain development further supports this pattern, showing that technology-rich environments can alter attentional allocation and working memory load, conditions that directly influence the depth of encoding (14). Together, these findings show that AI reshapes memory by altering attention, encoding, and

retrieval conditions. Cognitive offloading may improve efficiency, but when engagement becomes passive, it can weaken the processes required for lasting learning.

Taken together, the evidence reviewed in this section supports the hypothesis that AI does not directly impair memory capacity, but instead reshapes memory by altering the conditions under which encoding and retrieval occur. Reduced attentional engagement during encoding, combined with expectations of external accessibility, weakens consolidation within hippocampal networks and shifts cognition toward familiarity-based recognition rather than detailed recollection. These changes reflect a redistribution of cognitive effort rather than a loss of memory function. AI-mediated environments therefore modify how memory is formed and accessed, favoring efficiency and external retrieval over internally consolidated representations.

**3. Biological and Emotional Mechanisms of Memory in the Digital Age**

Memory in the digital age is not only changing in how it operates, but also in how it is distributed between internal cognition and external technologies, raising the question of whether this redistribution occurs uniformly or is shaped by biological, emotional, and motivational factors. While Section 1 established that AI reshapes memory by altering encoding and retrieval conditions, this alone does not explain whether these changes occur uniformly across all types of information. This section advances the hypothesis that cognitive offloading is selective rather than uniform, with information low in emotional salience or personal relevance more likely to be externalized, while meaningful and emotionally significant knowledge is retained internally.

Classic experiments on the Google effect showed that when people expected information to remain available, they were more likely to remember where it could be found than to remember the information itself (8). This finding supports the idea that digital tools have become integrated into human memory systems. This form of transactive memory reflects a shift in which technology acts as a cognitive partner rather than a passive storage device (3,8).

Importantly, cognitive offloading does not occur uniformly across all types of information. Behavioral evidence shows that people selectively externalize certain kinds of memory while preserving others internally. Procedural and frequently updated information, such as phone numbers, schedules, and directions, is more likely to be offloaded, whereas general knowledge and semantic information are more likely to be retained internally. This pattern suggests that offloading is an adaptive strategy rather than a general decline in memory capacity.

**Figure 2.** Redistribution of memory reliance between internal and external systems.

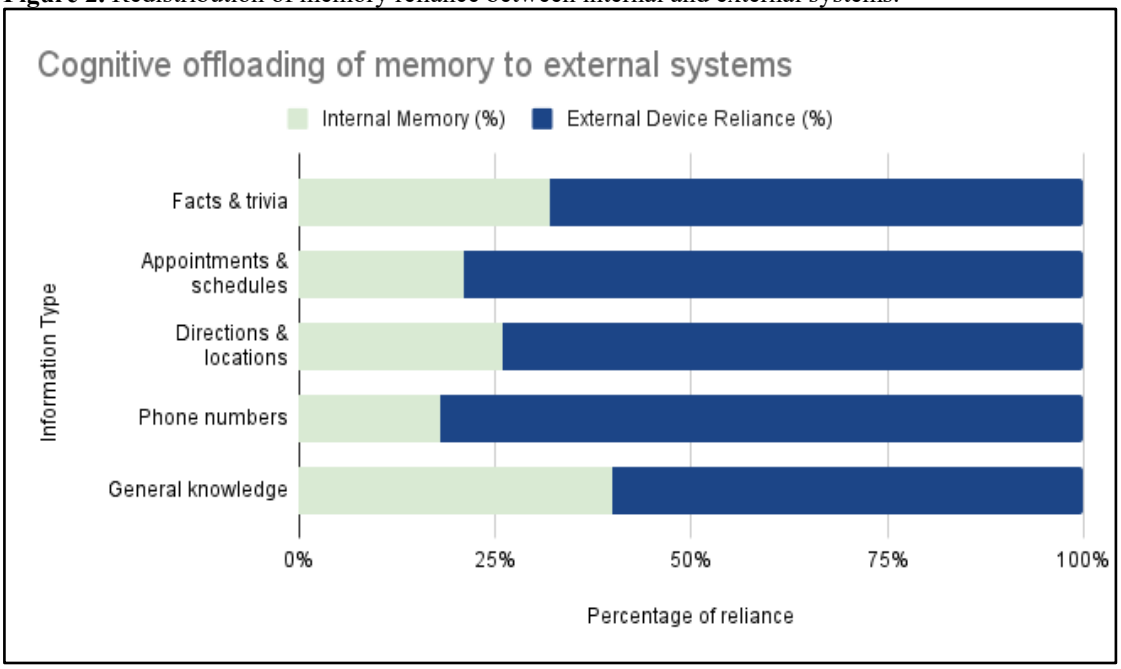


Figure 2. Redistribution of memory reliance between internal and external systems. Across categories, external devices are relied on more than internal memory, especially for phone numbers, appointments, and directions. In contrast, general knowledge and facts show relatively greater reliance on internal memory, indicating selective cognitive offloading based on information type.

Figure 2 shows that reliance on external systems is highest for information that is procedural, frequently updated, or low in emotional and semantic significance, such as phone numbers, schedules, and navigation. In contrast, general knowledge and factual information are more often retained internally. This contrast clarifies the central claim of this section: cognitive offloading reflects an adaptive strategy shaped by emotional relevance and biological memory systems rather than a generalized decline in memory. By visually distinguishing which types of information are externalized versus retained, the figure reinforces the hypothesis that emotionally and semantically meaningful knowledge resists offloading because it supports comprehension, identity, and long-term cognitive integration.

Motivation and personal relevance further influence what is retained internally. Research on retrieval cues and interest found that both explicit instructions to remember and intrinsic interest significantly improve recall (12). Participants who were genuinely interested in the material retained more information over time, even without external prompts. These findings suggest that memory is reinforced when information carries personal meaning or cognitive value.

Neuroscientific research supports this distinction. Recollection relies on hippocampal networks responsible for contextual detail, while familiarity depends more on the perirhinal cortex (10). Selective offloading may therefore bias externally stored information toward familiarity-based recognition, while internally retained knowledge supports deeper recollection. Emotion also plays a key role. Emotionally charged information is more likely to be consolidated into long-term memory through coordinated amygdala-hippocampal activity (9). In digital environments that emphasize emotionally salient content, this mechanism may strengthen retention of meaningful experiences while allowing emotionally neutral information to be externalized more readily.

The findings presented in this section confirm that cognitive offloading is selective rather than uniform, consistent with the proposed hypothesis. Information that is procedural, frequently updated, or low in emotional salience is more likely to be externalized, while semantically meaningful and emotionally relevant knowledge is retained internally. Biological distinctions between recollection and familiarity, along with the influence of motivation and emotional engagement, explain why certain memories resist offloading. Rather than indicating cognitive decline, this pattern reflects an adaptive reorganization of memory that balances efficiency with the preservation of personally and cognitively significant information. However, demonstrating that offloading is selective raises a further question: how do these individual-level allocation patterns scale to influence broader cognitive processes such as reasoning and critical thinking?

**4. How AI Is Reshaping What and How We Remember**

Evidence from neuroscience, psychology, and behavioral research shows that AI reshapes memory through interconnected mechanisms rather than a single pathway, creating downstream consequences for cognitive engagement and critical thinking. Building on the mechanisms described in Section 1 and the selectivity established in Section 2, this section examines how these combined shifts in encoding, retrieval, and allocation of effort produce downstream cognitive effects. This section is guided by the hypothesis that as AI-mediated memory practices increase cognitive offloading, they also reduce opportunities for retrieval practice and evaluative reasoning, thereby altering how memory supports higher-order cognition.

Sections 1 and 2 showed that AI alters memory formation and selectively redistributes what is retained internally; this section extends that argument by examining how those shifts change the role memory plays in supporting higher-order cognition. These changes affect not only what is remembered, but also how people reason, evaluate information, and think independently. Neurobiological research suggests that sustained reliance on intelligent technologies can change attentional patterns and depth of processing. Reduced engagement in effortful cognitive processing aligns with earlier findings on decreased hippocampal involvement when information is accessed externally. Over time, reliance on recognition and verification may replace internally generated recall.

Behavioral evidence reinforces this interpretation. Gerlich found that increased AI tool use correlates with greater cognitive offloading and lower critical thinking performance (6). While these findings do not prove causation, they suggest that delegating cognitive tasks to AI reduces opportunities for retrieval practice and reflective reasoning. These relationships are captured empirically in the correlations reported by Gerlich, summarized in Figure 3.

**Figure 3.** Correlations among AI tool use, cognitive offloading, and critical thinking.

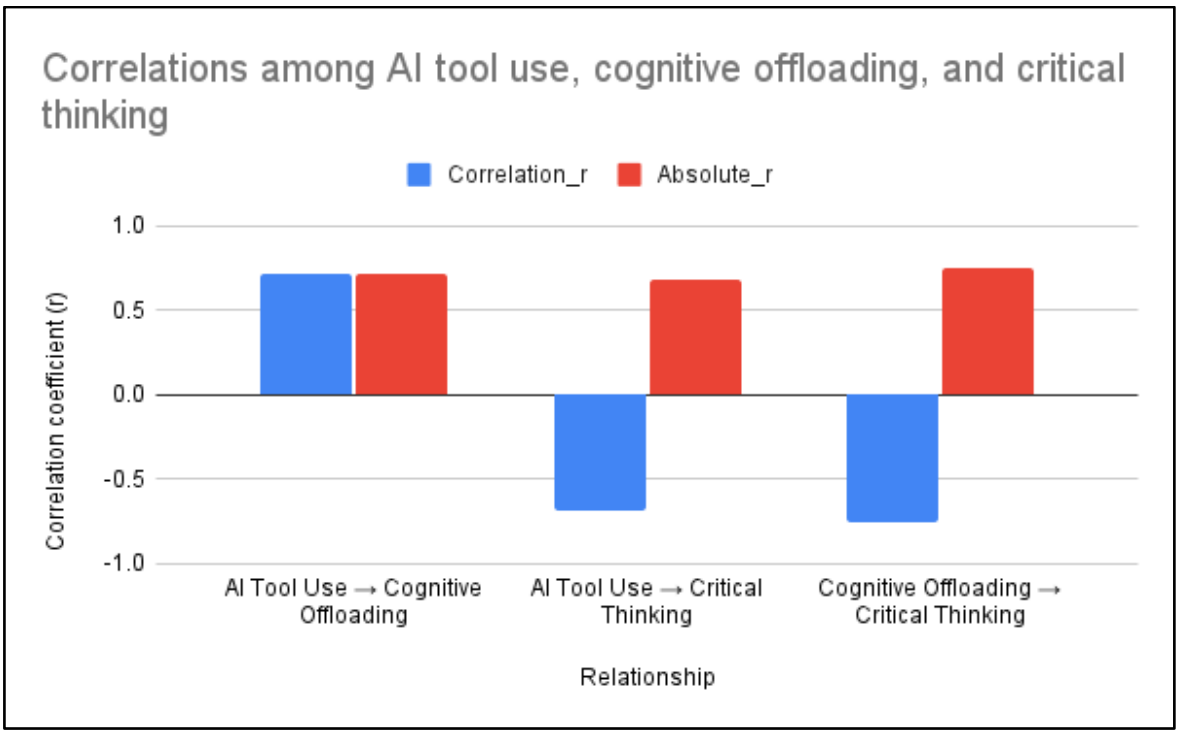


Figure 3. Correlations among AI tool use, cognitive offloading, and critical thinking. Bars show reported Pearson correlations (r) and their magnitudes (|r|) from Gerlich (2025), illustrating positive association with cognitive offloading and negative associations with critical thinking.

This figure illustrates three key associations. First, AI tool use shows a strong positive correlation with cognitive offloading, indicating that increased reliance on AI corresponds with greater delegation of memory and reasoning tasks to external systems. Second, AI tool use demonstrates a strong negative correlation with critical thinking performance; however, this relationship is correlational and does not establish a direct causal effect. One plausible interpretation is that frequent reliance on AI may reduce opportunities for retrieval practice, sustained attention, or reflective evaluation, which are known to support analytic reasoning. Similarly, cognitive offloading itself is negatively correlated with critical thinking, suggesting that the habitual delegation of memory and reasoning tasks may coincide with reduced engagement in evaluative processing over time, rather than directly causing its decline. While these correlations do not establish causation, their consistency supports a coherent pattern in which AI-mediated cognition alters how individuals allocate mental effort.

Recent work reports that adolescents with greater executive-functioning challenges perceived generative AI as more useful for schoolwork, suggesting that AI may function as a cognitive scaffold for some users rather than affecting all users uniformly (15). Together, these patterns suggest that AI shifts cognition toward external processing. Memory may increasingly function as a pointer to information rather than solely as a repository for conceptual understanding. This shift does not eliminate memory, but it alters its role.

To make this claim more precise, it is necessary to define what memory is being used for in AI-mediated contexts. Memory does not serve a single function. It can support storage, unaided retrieval, indexing, evaluation, and integration. AI may affect each of these functions differently, which means that the effect of AI on memory should not be described only as improvement or decline.

**Table 2.** Proposed operationalization of memory functions in AI-mediated cognition

| Function | Description | Possible measure | AI effect (hypothesized) |
|---|---|---|---|

| | | | |
|---|---|---|---|
| Storage | Retaining facts internally | Delayed recall accuracy without AI or notes | ↓ May decrease when users rely on AI for facts |
| Retrieval | Recalling without cues | Percentage of correct unaided responses before lookup | ↓ May decrease if users consult AI before attempting recall |
| Indexing | Knowing where information is | Lookup reliance, source-location accuracy, prompt success | ↑ Likely increases because users remember access pathways |
| Evaluation | Judging correctness | Error-detection accuracy, justification quality, source checking | ↑ with active evaluation; ↓ with passive acceptance |
| Integration | Linking concepts | Transfer tasks, abstraction tasks, problem-solving performance | Unclear/context-dependent; may improve with engagement or weaken with substitution |

Note. This table proposes one operational framework for measuring how AI may shift memory from internal storage and unaided retrieval toward indexing, evaluation, and context-dependent integration. The possible-measure column is included to show how changes could be quantified across recall, lookup reliance, error detection, transfer, abstraction, and problem-solving. The table is a conceptual synthesis based on transactive memory, cognitive offloading, the Google effect, and AI-use findings (1, 3, 6, 8).

These functional categories complicate a common assumption about Bloom's taxonomy. It may be tempting to assume that if AI reduces the burden of remembering and basic understanding, users will naturally move toward higher-order cognition such as analysis, evaluation, and creation. The evidence reviewed here suggests that this movement is possible, but not automatic. Bloom's revised taxonomy distinguishes lower-order cognitive processes such as remembering and understanding from higher-order processes such as analyzing, evaluating, and creating (16,17). AI changes the cost structure of cognition by making storage, retrieval, and summarization easier, but lower retrieval cost does not by itself increase cognitive depth. If AI-mediated offloading shifts users away from retention and recall and toward indexing and evaluation, then higher-order thinking depends on whether users actively verify, compare, and integrate AI-generated information. Passive acceptance may partially shift portions of evaluative processing to AI and may be associated with lower engagement in critical thinking.. In this sense, AI can create conditions for movement upward in Bloom's taxonomy, but only when users maintain deliberate cognitive engagement. Without such engagement, AI may flatten cognitive effort rather than elevate it.

### 4.1. Operational Definitions and the Passive Substitution–Active Scaffolding Model

To make the proposed mechanism testable, the key constructs must be operationally defined. In this paper, "AI use" refers to the frequency, timing, and depth of interaction with generative AI tools during a task, including the number of prompts submitted, the proportion of task steps assisted by AI, and whether AI is used before or after an unaided recall attempt. "Cognitive offloading" refers to the proportion of memory or reasoning work delegated to an external system rather than performed internally. "Critical thinking" refers to performance on tasks requiring justification, comparison, error detection, transfer, and evaluation of claims. These definitions allow AI-mediated memory change to be measured through outcomes such as unaided recall accuracy, lookup reliance, delayed retention, error-detection performance, and quality of reasoning.

The proposed passive substitution–active scaffolding model argues that AI's effect depends on whether users bypass or preserve unaided cognitive effort after retrieval becomes easier. When users consult AI before attempting recall,

retrieval practice may decrease, weakening unaided recall and consolidation. When users first attempt recall independently and then use AI to check, compare, or revise their thinking, AI may scaffold higher-order cognition rather than replace it. The expected effects are therefore heterogeneous and may differ by age, prior ability, expertise, task type, motivation, and baseline executive functioning. Because this paper is a conceptual synthesis rather than an empirical study, the predicted effect sizes should be treated as hypothetical and testable rather than established.

Because this paper is a conceptual synthesis, it does not report established effect sizes. However, the proposed model makes future effect sizes measurable through percentage changes in delayed recall accuracy, lookup reliance, error-detection accuracy, transfer performance, abstraction performance, and performance decline after AI removal. These effects could be reported using mean differences, percentage-point changes, correlation coefficients, or standardized effect sizes such as Cohen's d.

**Table 3.** Effort allocation model of AI-mediated cognitive offloading.

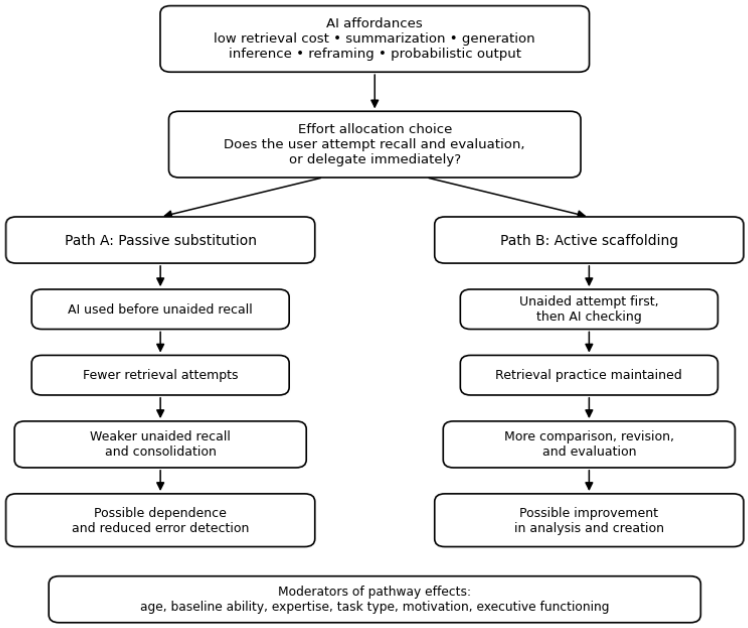


Table 3 shows the proposed distinction between passive substitution and active scaffolding. In the passive substitution pathway, users consult AI before attempting recall or reasoning, which may reduce retrieval attempts and weaken unaided recall. In the active scaffolding pathway, users first attempt recall or reasoning independently and then use AI to check, compare, revise, or extend their thinking. The model therefore predicts that AI's cognitive effect depends less on access itself and more on how effort is allocated after access becomes easier. This framework also predicts heterogeneous outcomes across user engagement, ability, expertise, motivation, task type, and executive functioning.

#### 4.1.1. Proposed Experimental Design

A future experiment could test whether AI-mediated offloading produces different outcomes depending not only on whether AI is available, but also on when and how it is used. Participants would first complete a baseline assessment of reasoning ability, domain knowledge, and unaided recall. Baseline ability would be used to compare higher- and lower-baseline participants, but the main experimental manipulation would focus on AI timing. Participants would then be randomly assigned to one of three task conditions: a no-AI control condition, an AI-first condition, and an unaided-first/AI-check condition. In the no-AI condition, participants would complete all tasks without external tools. In the AI-first condition, participants could consult AI before attempting an answer. In the unaided-first/AI-check condition, participants would first attempt recall or reasoning independently and then use AI only to check, compare, or revise their answer.

In Phase 1, participants would complete tasks aligned with Bloom's taxonomy, including remembering, understanding, applying, analyzing, evaluating, and creating within a single topic domain. In Phase 2, AI access would be removed for all participants, and they would complete a parallel task set of comparable difficulty. Outcomes would include delayed recall accuracy, lookup reliance, error-detection accuracy, explanation quality, transfer performance, and decline or stability after AI removal. This design tests whether AI functions as substitution when used before unaided effort and as scaffolding when used after initial cognitive engagement.

**Table 4.** Proposed experimental design testing AI timing, effort allocation, and post-AI performance

| Condition | Phase 1 task structure | Phase 2 condition | Primary outcomes | Predicted interpretation |
|---|---|---|---|---|
| No-AI control | Participants complete tasks without external tools | No AI | Baseline recall, reasoning, transfer, and error detection | Stable baseline performance |
| AI-first | Participants may consult AI before attempting recall or reasoning | No AI | Immediate task performance, delayed recall, performance drop after AI removal | Possible substitution or dependence if Phase 2 performance declines |
| Unaided-first/AI-check | Participants attempt answers independently before using AI to check or revise | No AI | Recall retention, quality of revisions, error detection, transfer performance | Possible scaffolding if Phase 2 performance remains stable or improves |
| Baseline ability moderator | Participants are analyzed by initial reasoning/domain-knowledge level | No AI | Differences across higher- and lower-baseline participants | Tests whether AI amplifies existing ability or increases dependence risk |

This design makes the claim falsifiable by comparing immediate AI-supported performance with later unaided performance. If AI-first users perform well only while AI is available but decline in Phase 2, AI may be operating as a substitute for retrieval and evaluation. If unaided-first/AI-check users maintain or improve performance after AI removal, AI may be functioning as a scaffold that supports higher-order cognition without replacing retrieval practice.

Importantly, these effects are not uniform. For neurodiverse individuals or those with executive functioning challenges, AI tools can act as cognitive scaffolds, supporting organization and sustained attention. When AI guides thinking while preserving engagement, it can strengthen learning. When it replaces effortful processing, cognitive skills may weaken. AI also shapes memory at the collective level by determining which information is repeatedly encountered, influencing both individual and societal recall.

Evidence reviewed in this section supports the hypothesis that increased AI-mediated cognitive offloading is associated with reduced opportunities for retrieval practice and evaluative reasoning, with downstream effects on critical thinking. However, the proposed model clarifies that this relationship is conditional rather than universal. AI may weaken memory-supported cognition when it is used as a substitute for recall, comparison, and evaluation, but it may support higher-order cognition when it is used after an initial unaided attempt and paired with active checking or revision. The proposed experimental design provides one way to test this distinction by comparing

immediate AI-supported performance with later unaided performance. As a result, memory's role in sustaining higher-order cognition may be weakened when AI substitutes for active engagement, but preserved or strengthened when AI functions as a scaffold.

## 5. Redefining Memory in the Era of Intelligent Technology

The findings across this paper converge on a central conclusion: artificial intelligence is not simply augmenting or diminishing human memory, but fundamentally reshaping how memory functions within the broader cognitive system. While the previous section focused on individual cognitive consequences, this section expands the analysis to the system level, examining how these same mechanisms operate across distributed technological and social environments. This section advances the hypothesis that these changes extend beyond individual cognition, redefining memory as a hybrid process distributed across biological systems, technological infrastructures, and collective information environments. By altering the conditions of encoding, retrieval, emotional engagement, and evaluative effort, AI influences not only what information is remembered, but how memory supports reasoning, decision-making, and critical thought. Rather than operating as an isolated cognitive faculty, memory emerges as a dynamic process increasingly distributed across biological and technological systems.

### 5.1. How This Paper Extends Prior Frameworks

This paper builds on, but does not simply repeat, earlier theories of extended cognition, transactive memory, and distributed cognition. Extended cognition argues that external tools can become part of cognitive activity when they are reliably integrated into thought (2). Transactive memory explains how individuals remember not only information itself, but also where information is stored or who has access to it (3). Distributed cognition shows how thinking can be spread across people, artifacts, and environments rather than confined to one individual mind (4, 5). These frameworks are essential because they show that memory has never been purely internal.

However, AI introduces features that earlier frameworks do not fully explain. Traditional offloading tools usually preserve, index, or display information that humans have already produced. Generative AI can transform information by summarizing, inferring, reframing, and producing new language in response to user prompts. It also introduces a probabilistic error model, where fluent outputs may be incorrect or fabricated. This means AI-mediated offloading may change not only where memory is stored, but how information is reconstructed and interpreted during retrieval.

The contribution of this paper is therefore not the claim that offloading began with AI. Instead, the paper argues that AI changes the cost structure and interpretive layer of offloading. By reducing retrieval effort and adding generative output, AI may shift memory from internal storage and recall toward indexing, verification, and evaluation. This extends prior frameworks by identifying AI as a form of transformational offloading: the external system does not merely hold information for the user, but participates in shaping what is retrieved, how it is framed, and whether users remain cognitively engaged. This argument moves beyond the linear claim that AI causes offloading and offloading changes memory; instead, it specifies the mechanism by which AI changes offloading: lower retrieval cost, generative reconstruction, probabilistic output, and user-dependent effort allocation.

To ground this broader shift, it is necessary to reconnect these system-level changes to the underlying cognitive mechanisms previously established. At the mechanistic level, the evidence reviewed in Section 1 demonstrates that memory formation depends on sustained attention, elaboration, and retrieval practice, processes that engage hippocampal networks responsible for contextual integration. When AI systems reduce the need for these processes by providing rapid access to information, users may engage less frequently in deep encoding. Experimental findings on retrieval cue mismatch further show that memory retention is shaped by how information is prompted and revisited, not simply by time. As AI systems increasingly structure retrieval through summaries, prompts, and recommendations, they may influence which aspects of information are reinforced and which decay. These mechanisms suggest that AI does not erase memory, but modifies the pathways through which memory is strengthened or weakened.

Section 2 extends this analysis by demonstrating that cognitive offloading is selective rather than uniform. Individuals strategically externalize information that is procedural, low in emotional salience, or frequently updated, while retaining semantically meaningful and emotionally relevant knowledge internally. This redistribution reflects adaptive efficiency rather than cognitive failure. Motivation and emotional engagement further determine what resists offloading, with emotionally charged and personally meaningful information more likely to be consolidated into long-term memory. From a biological perspective, this selectivity aligns with known distinctions between hippocampal-dependent recollection and familiarity-based recognition. Information routinely accessed through

external systems may rely more heavily on recognition processes, while internally retained knowledge supports deeper contextual reconstruction.

However, selective offloading does not occur in isolation. Section 3 demonstrates that increasing reliance on AI-mediated cognition is associated with broader shifts in cognitive engagement. Correlational evidence indicates that AI tool use is positively associated with cognitive offloading and negatively associated with critical thinking performance. While these relationships do not establish causation, their consistency suggests that habitual delegation of cognitive effort may reduce opportunities for evaluative reasoning, reflection, and independent problem-solving. Memory plays a central role in this process. When memory functions primarily as an access system rather than a repository for conceptual understanding, its capacity to support critical thinking may be diminished.

Taken together, these findings suggest that AI reshapes cognition by altering how mental effort is allocated. When AI systems handle increasing portions of retrieval, organization, and interpretation, internal memory systems may be engaged less frequently for integrative tasks. Over time, this redistribution may favor speed, convenience, and surface-level processing over depth and analytic rigor. Importantly, this transformation does not imply inevitable cognitive decline. Research on neurodiverse learners and individuals with executive functioning challenges demonstrates that AI can function as a cognitive scaffold, reducing working memory load and enabling engagement with complex material. The critical distinction lies in whether AI supplements internal cognition or substitutes for it.

Beyond individual cognition, AI also influences memory at the collective level. Algorithmic curation determines which information is repeatedly encountered, shaping both personal recall and shared cultural memory. Repetition and emotional salience reinforce familiarity, while less-visible information fades from awareness. As AI systems increasingly generate, summarize, and prioritize information, they participate in the construction of collective knowledge, influencing what societies remember and forget. Memory thus becomes a hybrid construct, co-produced by human cognition and technological mediation.

The implications of these findings extend beyond efficiency or convenience. Memory underlies identity, understanding, and intellectual autonomy. As AI becomes embedded in daily life, the challenge is not to resist technological integration but to guide it intentionally. Educational, technological, and ethical frameworks must encourage active engagement, critical evaluation, and reflective use of AI systems. When AI is used to support retrieval practice, organization, and conceptual integration, it can enhance learning and resilience. When relied upon passively, it risks narrowing the role of memory to mere access.

In redefining memory for the age of artificial intelligence, this research highlights a paradox. AI represents the most powerful cognitive aid yet developed, yet it also poses a challenge to the processes that sustain deep understanding. Memory is not being replaced by AI. It is being reorganized. The future of human cognition will depend on how deliberately this reorganization is shaped, ensuring that technology remains a partner in thought rather than a substitute for it.

This section resolves its hypothesis by demonstrating that AI-driven changes to memory extend beyond the individual, redefining memory as a hybrid process distributed across biological cognition, technological systems, and collective information environments. Algorithmic curation shapes repeated exposure, reinforcing certain representations while allowing others to fade, thereby influencing both personal recall and shared cultural memory. Memory thus emerges as a co-produced phenomenon, shaped by human attention and technological mediation. AI does not replace memory, but reorganizes its function across individual and societal levels, raising important implications for autonomy, identity, and knowledge formation.

## 6. Conclusion

This paper frames the relationship between artificial intelligence and memory as a process of reorganization rather than loss or enhancement. This conclusion follows directly from the progression established across the paper: mechanistic changes in encoding and retrieval in Section 1, selective offloading across information types in Section 2, consequences for higher-order cognition in Section 3, and system-level implications in Section 4. AI contributes to a hybrid memory system in which internal cognition and external technological supports operate together, reshaping the role memory plays within broader cognitive activity. The significance of this shift lies not in offloading itself, which has long been part of human cognition, but in how AI changes the cost, speed, and interpretive structure of offloading.

**Figure 4.** Conceptual distinction between AI as cognitive support and AI as cognitive substitution.

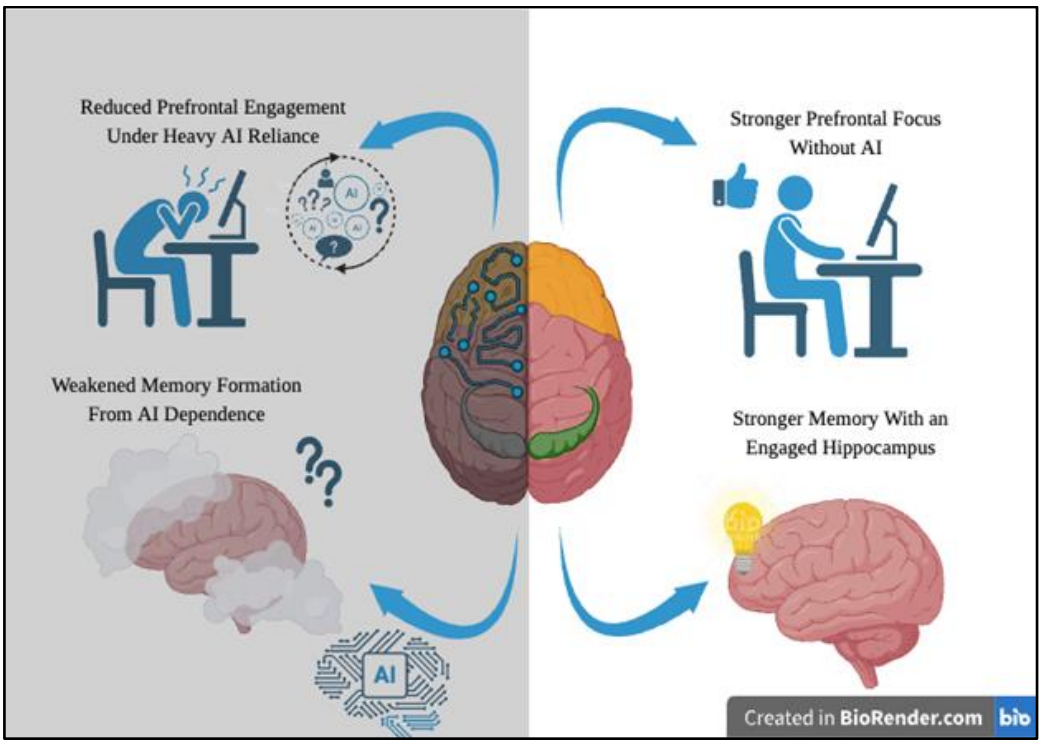


Figure 4. This figure visualizes the distinction between AI as cognitive support and AI as cognitive substitution. It illustrates two possible pathways: passive reliance on AI may reduce retrieval practice and internal engagement, whereas active, unaided effort followed by AI-supported checking may preserve cognitive engagement. The figure is conceptual and does not imply that AI directly causes reduced activity in a specific brain region. This reinforces the argument that AI reshapes memory by redistributing cognitive effort, with outcomes determined by the level of engagement rather than access to information alone. Image created using BioRender.com.

The cognitive consequences of this reorganization depend on the conditions under which AI is integrated. When AI use preserves active engagement and supports interpretation and judgment, memory continues to function as a foundation for understanding. When AI substitutes for effortful cognitive processes, memory's role narrows toward access rather than integration, as shown in Figure 4.

Memory is also reshaped beyond the individual. AI-mediated information environments influence patterns of exposure and reinforcement, positioning memory as part of a distributed system that spans personal and collective levels. Ultimately, AI does not determine cognitive outcomes on its own. How memory functions in the age of artificial intelligence depends on how deliberately this hybrid system is designed and used to support reasoning, autonomy, and critical thought.

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