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ARTICLE

Beyond Prompting: Biological Memory, Cognitive Offloading, and Human Expertise in the Age of GenAI

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Abstract

Generative artificial intelligence (GenAI) is driving unprecedented changes in higher education by enabling students to outsource complex cognitive tasks, including writing, summarisation, reasoning, and problem-solving. While these technologies offer accessibility, personalisation, and educational support, they raise concerns regarding cognitive offloading, eroding biological memory, and development of human expertise. This paper argues that prompting AI systems should not be conflated with learning because expertise depends upon durable internal cognitive structures developed through encoding, retrieval, schema formation, and critical reflective reasoning over time. Drawing upon cognitive psychology, educational neuroscience, and contemporary AI research, the paper introduces the concept of biological memory as the foundation of independent professional judgment and adaptive expertise. Excessive reliance on GenAI may without careful management contribute to cognitive debt, reduced neural engagement and cognitive decline. The paper proposes brain-aligned approaches to curriculum, assessment, AI literacy, and educational design that position AI as a scaffold for cognition rather than a substitute for it.

Keywords: Generative artificial intelligence, cognitive offloading, biological memory, higher education, human expertise, cognitive debt, cognitive decline

1. INTRODUCTION

Universities struggle to respond to the opportunities and risks associated with large language models (LLM), moving from concerns about academic integrity [1,2,3] towards broader debates about curriculum redesign [4], assessment validity [5,6], and the future of expertise [7,8]. While GenAI systems can support brainstorming, summarisation, drafting, revision, feedback, and accessibility [4,9], they also raise a deeper educational question: what happens when technologies perform the cognitive work that learners traditionally need to undertake themselves to master a discipline [10,11,12]. Students may produce polished assignments with AI assistance [13] while simultaneously engaging in less cognitive processing and critical thinking [14]. Emerging evidence suggests that excessive reliance on GenAI contributes to forms of cognitive offloading where effortful thinking, retrieval, synthesis, and reflection are delegated to external systems [10,15]. Cognitive offloading is not new, humans have long relied on calculators, books, maps, and search engines, but GenAI differs in its ability to simulate reasoning, generate persuasive prose, visual representations, programming and complete complex intellectual tasks conversationally and at scale. The educational implications of this shift are qualitatively different from earlier technological transitions.

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Central to these concerns lies the relationship between cognition, memory, and expertise. Research in cognitive psychology and educational neuroscience demonstrates that durable learning depends upon active encoding, retrieval, rehearsal, and schema formation within human memory systems [16,17]. Expertise develops through repeated effortful engagement with knowledge over time, experimental success and failures enabling the formation of interconnected cognitive structures that support pattern recognition, reasoning, transfer, and professional judgment [18]. Yet many current uses of GenAI risk bypassing precisely these processes by enabling students to obtain outputs without necessarily constructing the internal knowledge structures required to independently reproduce, understand, evaluate, or apply that knowledge later in the same or different contexts [7,8].

This paper conceptualises these durable internal knowledge structures as biological memory: the adaptive, retained, interconnected, and retrievable disciplinary knowledge encoded within human cognitive systems through sustained learning and application. Biological memory extends beyond the temporary recall of isolated facts. It encompasses the adaptive development of cognitive schemas, professional intuition, conceptual fluency, and the capacity to synthesise knowledge under conditions of uncertainty. In professional disciplines such as law, medicine, engineering, and education, biological memory underpins the ability to recognise problems, evaluate evidence, ask appropriate questions, conduct research, develop hypothesis and solutions, and exercise informed judgment in the same or different contexts. Although digital technologies may augment these capabilities, they cannot wholly substitute for them because the interpretation, verification, and contextual application of knowledge still depend on internal cognitive structures developed through experience and learning. Without these cognitive experience driven structures, incorrect prompts are entered into AI systems, and the user is incapable of critically evaluating the usefulness or otherwise of output provided.

The emergence of GenAI therefore raises concerns not merely about academic integrity or technological disruption, but about the possible erosion of the cognitive foundations of expertise itself. Recent scholarship has begun warning that AI-supported learning environments may encourage “false mastery,” where students appear competent because they can generate sophisticated outputs while lacking the underlying understanding those outputs traditionally represented [4,19]. Preliminary neuroscience research similarly suggests that extensive reliance on AI-assisted writing may reduce neural engagement associated with active composition and impair subsequent recall of material produced with AI assistance [19,20]. Although this research remains emergent, it aligns with broader concerns regarding declining attention spans, fragmented digital engagement, and reduced tolerance for effortful cognitive work in technologically saturated environments [21].

At the same time, the problem should not be framed as a simplistic opposition between humans and technology. GenAI also has genuine educational potential if managed appropriately [2,22]. AI systems may enhance accessibility, support personalised learning, provide scaffolding for struggling learners, and improve opportunities for feedback and practice [4,9,22]. The central issue is therefore not whether AI should be used in higher education, but how it should be integrated in ways that strengthen rather than weaken the cognitive processes required for long-term learning and human expertise [23]. This distinction between augmentation and substitution is increasingly recognised within recent literature on AI and education [7,15]. Higher education must move beyond viewing prompting as synonymous with learning and instead reconsider the role of biological memory in AI-augmented educational environments.

2. GENAI AND COGNITIVE OFFLOADING

2.1. Cognitive Offloading

Cognitive offloading refers to the delegation of cognitive processes to external tools or environments in ways that reduce internal mental effort [24]. Humans externalise aspects of cognition through technologies such as writing, audiovisual systems, calculators, maps, and digital search systems [25,26]. These tools enhance human capability by reducing cognitive burden and increasing efficiency [27]. GenAI differs from earlier technologies because it offloads not only information storage or retrieval, but also aspects of cognition, reasoning, synthesis, organisation, and expression [28].

Earlier cognitive technologies supported discrete functions while preserving the need for substantial biological processing. Calculators accelerated arithmetic but did not independently generate mathematical understanding [29]. Search engines facilitated information access but still required users to evaluate, interpret, and synthesise knowledge. GPS systems automated navigation while leaving broader reasoning and decision-making capacities intact. GenAI systems, by contrast, compress the cognitive distance between novice and expert performance by producing outputs that simulate sophisticated reasoning and disciplinary fluency [7,8] without developing the underpinning biological memory of professional competence.

This distinction has implications for higher education because expertise depends upon more than the production of correct outputs [30]. Professional competence requires durable biological knowledge structures enabling recognition, judgment, transfer, and adaptation under novel conditions [31]. These structures emerge through repeated effortful engagement with information over time. When AI systems perform the integrative work of summarising, organising, explaining, and drafting, learners may complete tasks while engaging in less cognitive activity themselves [32].

Recent research has conceptualised this phenomenon as cognitive debt [10], referring to the accumulation of unrealised cognitive effort resulting from repeated reliance on AI systems to perform mental tasks that would otherwise contribute to learning and schema development. Immediate efficiency gains may produce longer-term reductions in independent capability if learners bypass the effortful processes through which expertise develops.

Neuroscience evidence supports this concern. Electroencephalography (EEG) studies examining AI-assisted writing tasks suggest reduced neural connectivity associated with active composition and memory consolidation among participants extensively relying on GenAI tools [10]. While this research remains emergent and should be interpreted cautiously, it aligns with broader findings from cognitive psychology and educational neuroscience that durable learning depends heavily upon retrieval practice, elaboration, working memory engagement, and repeated schema activation over time [16,17].

GenAI may obscure reductions in cognitive engagement because fluent outputs create a mirage of competence irrespective of underlying understanding. Students experience what appears to be successful performance while developing weaker internal conceptual structures. GenAI risks producing forms of simulated expertise in which sophisticated outputs no longer reliably indicate corresponding cognitive development of the individual.

The educational problem is not simply technological dependence, but the possibility that capable AI systems reduce opportunities for productive cognitive struggle. From a neuroscience perspective, effort is not incidental to learning; it is central to the biological strengthening of neural pathways underpinning memory, transfer, and expertise. If GenAI increasingly replaces rather than scaffolds these processes, higher education may unintentionally privilege efficiency over cognition itself. The result may be graduates with limited ability, reliant on AI support systems and less suited to supporting industries demanding creativity, cognitive ability and critical thinking. The value of qualifications of institutions encouraging cognitive deficits in graduates will decline.

If academics grading students cannot distinguish between AI outputs and genuine student effort, the risk that AI dependent students receive high grades over those building biological memory heightens. All students become incentivised to outsource to AI to avoid poor outcomes. The net result will challenge graduate attributes, capabilities and employment prospects. Worse still the impact of AI on high school students may see those building biological schemas receiving lower grades and not meeting grade thresholds for university courses. The entire educational pipeline is under treat.

2.2. Why Prompting Is Not Learning

The emergence of prompt engineering has led to claims that the ability to effectively direct AI systems constitute a new form of literacy or expertise [35]. While prompting may become available professional skill, prompting alone should not be conflated with learning [34].

Prompting concerns the optimisation of external system outputs. Learning, by contrast, involves durable biological changes in knowledge, understanding, reasoning, critical thinking and cognitive capability. The distinction is fundamental. A learner may generate sophisticated responses through carefully structured prompts without independently possessing the conceptual understanding represented within those outputs. The learner may in fact not understand the outputs of the process nor be capable of critical thinking. If performance is linked to iterative AI prompting the learner may not be capable of undertaking this task as they have not developed the biological memory needed to modify the prompts.

This reflects a divergence between performance and competence. GenAI enables users to produce outputs that resemble expert reasoning while bypassing many of the processes traditionally required to develop expertise itself. Higher education has historically relied upon activities such as writing, notetaking, problem-solving, explanation, retrieval, critical thinking, and synthesis not merely to assess learning, but to create it. These activities strengthen memory pathways, reinforce conceptual relationships, and contribute to schema formation through repeated cognitive effort [16,33].

LLMs complicate this relationship because they generate highly fluent language that can create an illusion of understanding. Contemporary AI systems operate primarily through statistical pattern prediction rather than grounded comprehension of concepts, causality, or truth [19]. The capacity to generate persuasive responses differs fundamentally from possessing understanding in a human cognitive sense.

This distinction becomes important in educational environments because students may mistake access to generated knowledge for acquisition of biological knowledge. The ability to prompt an AI system to produce an answer does not necessarily indicate that the learner can independently reconstruct, verify, transfer, or apply that knowledge under unfamiliar conditions. Prompting risks transforming expertise from an internally developed cognitive capacity into an externally accessible performance resource.

The issue is not that AI-assisted learning lacks value. GenAI can support questioning, feedback, revision, and metacognitive reflection when integrated appropriately within pedagogy [2,5]. The educational challenge lies in determining whether AI functions primarily as a scaffold for cognition or as a substitute for it. Scaffolds support learners while preserving engagement in the cognitive processes necessary for capability development. Substitutes bypass those processes altogether.

The central danger is therefore not that students use AI, but that educational systems reward the appearance of expertise while neglecting the biological development of expertise itself. The preservation of human learning may depend upon maintaining educational structures that continue to require retrieval, effortful processing, reflection, and independent reasoning despite the availability of systems capable of simulating these capacities on demand.

3. BIOLOGICAL MEMORY AND HUMAN EXPERTISE

3.1 Defining Biological Memory

Biological memory refers to the durable, interconnected, retrievable knowledge structures encoded within human cognitive systems through sustained learning, reflection, and experience [36] extending beyond the temporary retention of isolated facts or procedural routines. It encompasses the development of conceptual schemas, disciplinary intuition, pattern recognition, and professional judgment that together enable humans to interpret, evaluate, synthesise, and apply knowledge under uncertain or novel conditions [37].

Within higher education, biological memory forms the cognitive foundation of expertise (Sweller, 2020). Professionals in disciplines such as medicine, law, engineering, teaching, and science rely not merely on access to information, but on internally developed structures of understanding enabling rapid recognition of problems, identification of relevant variables, anticipation of consequences, and adaptive decision-making. These capabilities emerge through repeated engagement with knowledge over time rather than through episodic exposure to information alone [38].

The concept differs from notions of memorisation. Memorisation often implies rote retention detached from meaning or application. Biological memory instead refers to meaningful cognitive encoding, organisation, schema formation, and retrieval. Knowledge becomes biologically embedded when learners repeatedly connect concepts, experiences, procedures, and interpretations into sophisticated cognitive schemas capable of supporting transfer and reasoning. Expertise depends not upon the accumulation of isolated information, but upon the organisation and accessibility of interconnected knowledge structures within human memory systems.

Contemporary neuroscience supports this view of cognition as an integrative process involving distributed interactions between memory, attention, prediction, emotion, and adaptive control systems [7]. Human expertise is not reducible to information retrieval alone. Experts do not merely recall knowledge; they perceive relationships, recognise patterns, filter irrelevant information, and generate judgments informed by deeply internalised disciplinary structures developed through extensive experience and practice.

Biological memory is inherently embodied and contextual. Human cognition develops through interaction with physical, social, emotional, and cultural environments rather than through abstract linguistic processing alone [8]. This distinction is significant in the context of GenAI because contemporary large language models generate statistically plausible outputs without possessing biologically grounded experiences, embodiment, or internally lived contexts comparable to human learning. Human expertise involves not only informational content but also biologically developed interpretive structures shaped by effort, uncertainty, emotion, and experience over time.

The educational significance of biological memory lies in its relationship to independent cognition. Higher education has historically functioned not simply to expose students to information, but to cultivate enduring cognitive capabilities enabling learners to think, reason, evaluate, and act without constant external assistance. The availability of GenAI systems raises a fundamental question: if sophisticated technologies perform many intellectual tasks externally, what forms of biological memory remain necessary for human expertise?

3.2. Encoding, Storage, and Retrieval

Biological memory depends upon the interaction of three interrelated cognitive processes: encoding, storage, and retrieval. These processes form the basis through which information is transformed into durable knowledge capable of supporting reasoning and expertise.

Encoding refers to the initial processing and integration of information into memory systems. Cognitive psychology consistently demonstrates that encoding is strengthened through attention, elaboration, association, and active engagement rather than passive exposure alone [16]. Information becomes more durable when learners connect new concepts to existing schemas, generate explanations, solve problems, or reorganise knowledge in personally meaningful ways. Educational activities such as writing, discussion, note-making, questioning, and retrieval practice are important not merely because they demonstrate learning, but because they actively contribute to the formation of memory itself.

The role of cognitive effort during encoding is important. Productive struggle, reflection, and repeated rehearsal strengthen neural pathways associated with long-term retention and transfer [17,33]. Neuroscientific research suggests that learning involves dynamic interactions between working memory, attentional systems, emotional regulation, and long-term consolidation processes distributed across multiple brain networks [39]. From this perspective, effortful cognition is not an obstacle to learning but a biological requirement for durable schema formation.

Storage refers to the consolidation and organisation of encoded information into long-term memory systems. Human memory is not a passive archive, but an active and adaptive process shaped by relevance, repetition, emotional salience, and contextual association [19]. Information retained in isolation is more vulnerable to forgetting, whereas interconnected knowledge structures supported by multiple associations become durable and retrievable over time. Educationally, this explains why expertise develops gradually through repeated exposure, application, and reinforcement across varied contexts rather than through short-term memorisation alone.

Retrieval completes this cycle by enabling previously encoded knowledge to be accessed and applied when required. Retrieval is central to expertise because professional reasoning depends upon the rapid activation of relevant schemas under conditions of uncertainty or complexity. Importantly, retrieval itself strengthens memory through reconsolidation processes, making repeated retrieval one of the most effective mechanisms for durable learning [40]. Educational practices such as testing, discussion, oral explanation, and applied problem-solving contribute to learning not simply through assessment, but through repeated activation of cognitive pathways underpinning biological memory.

GenAI systems intersect with each of these processes in disruptive ways. AI-generated summaries may reduce elaborative encoding by compressing information into simplified outputs requiring minimal active processing. AI-assisted writing may bypass the organisational and retrieval processes traditionally associated with composition. Conversational AI systems may externalise retrieval itself by enabling learners to access answers instantly without independently reconstructing knowledge from memory. While these tools increase efficiency, they may also reduce opportunities for the effortful cognitive engagement necessary for durable biological memory formation.

This distinction highlights an emerging educational tension between informational access and cognitive development. Technologies optimised for frictionless access may unintentionally weaken the very processes through which expertise biologically develops. The challenge for higher education is not merely incorporating AI into learning environments but ensuring they continue to preserve opportunities for encoding, retrieval, and schema consolidation despite the availability of systems capable of performing these functions externally.

3.3. Expertise as Schema Formation

Expertise develops through the gradual formation and refinement of cognitive schemas enabling efficient recognition, interpretation, and application of knowledge within domains. Schemas are organised mental structures that integrate concepts, experiences, procedures, and patterns into coherent frameworks capable of guiding perception and reasoning [17]. They reduce cognitive load by enabling individuals to process complex information as meaningful wholes rather than as disconnected fragments.

The distinction between novice and expert performance is not simply one of information quantity, but of cognitive organisation developed over time. Experts possess richly interconnected schemas allowing rapid recognition of patterns, anticipation of outcomes, and adaptive responses to novel situations [38]. Expertise depends upon biologically embedded structures enabling fluent interpretation and judgment rather than conscious step-by-step reconstruction alone. Schema formation requires repeated cognitive effort over extended periods of time. Learning involves progressively integrating new knowledge into existing frameworks through retrieval, elaboration, correction, and application. Importantly, this process cannot be fully outsourced because schemas are not external informational objects but biologically developed cognitive structures. Access to information may support expertise development, but access alone does not constitute expertise.

This distinction becomes important in AI-mediated educational environments because generative systems simulate expert-like outputs without requiring learners to develop the schemas associated with expertise itself. Students may generate sophisticated assignments, explanations, or solutions through AI assistance while possessing comparatively weak internal conceptual structures. The educational danger is not that students use AI, but that educational systems reward externally generated performance while overlooking whether learners have developed the biological memory underpinning independent reasoning. This produces a false narrative where students believe they need to use AI to remain competitive in assessment tasks. It puts added pressure on academics to try and identify true biological ability from an AI driven illusion.

Contemporary AI systems intensify this problem because they produce fluent outputs capable of masking gaps in understanding. The appearance of competence may become disconnected from actual cognitive capability. This creates the possibility of what might be termed synthetic competence: externally mediated performance that resembles expertise without reflecting equivalent schema development within the learner [41].

The distinction between synthetic competence and biological expertise has implications for higher education. Educational assessment relies upon the assumption that sophisticated outputs reflect corresponding internal cognitive development. GenAI destabilises this assumption by enabling high-quality outputs to be produced independently of substantial schema formation. In this context, preserving educational integrity increasingly requires attention not merely to output quality, but to whether learners continue engaging in the cognitive processes through which expertise biologically develops.

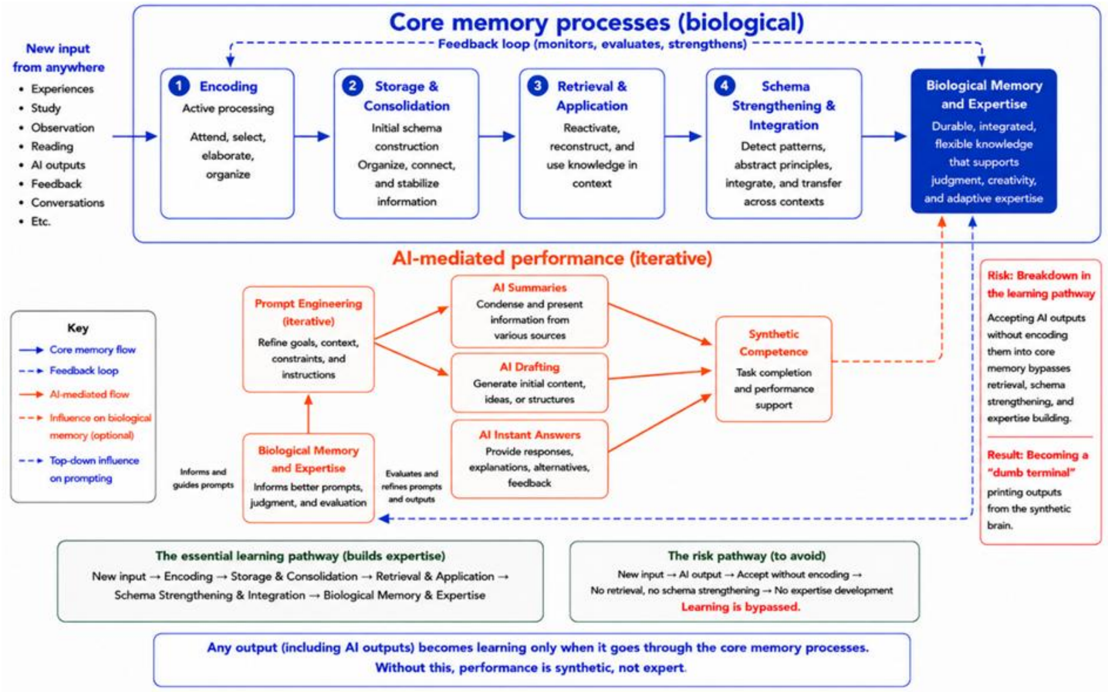

Figure1. The Cognitive Pathway to Human Expertise

Expertise develops through cumulative interactions involving encoding, schema formation, retrieval, and biological memory rather than through isolated task performance alone (Figure 1). The use of GenAI in higher education blurs the distinction between externally assisted performance and internally developed expertise. Contemporary AI systems can generate sophisticated disciplinary outputs that resemble expert reasoning, writing, and analysis despite learners possessing comparatively underdeveloped cognitive schemas. This distinction is educationally significant because expertise depends not simply on the production of correct outputs, but on biologically consolidated memory structures enabling independent reasoning, transfer, contextual interpretation, and professional judgment. Figure 2 contrasts forms of synthetic competence enabled through AI-mediated performance with the characteristics of biologically developed human expertise.

Dimension	Synthetic Competence	Biological Expertise
Nature of performance	AI-mediated performance	Internally developed cognition
Expression	Output fluency	Conceptual understanding
Optimisation focus	Prompt optimisation	Schema formation
Source of knowledge	External retrieval	Long-term memory
Type of reasoning	Assisted reasoning	Independent judgment
Primary goal	Task completion	Adaptive expertise
Time horizon	Immediate generation	Cumulative learning
Type of understanding	Simulated understanding	Biological understanding
System relationship	Dependence on AI systems	Cognitive autonomy
Output nature	Probabilistic outputs	Relational outputs
Learning depth	Shallow learning	Deep learning
Retrieval mechanism	External retrieval	Biological schematic retrieval
Coherence level	Surface-level coherence	Deep disciplinary integration
End capability	AI-supported productivity	Human professional capability

Figure 2. Synthetic Competence and Biological Expertise in AI-Mediated Learning

3.4 Why AI Cannot Replace Biological Memory

GenAI systems are capable of producing outputs that resemble human expertise. Large language models can generate essays, explain concepts, summarise research, answer professional questions, present info graphics, and simulate disciplinary discourse with remarkable fluency. AI systems however cannot replace biological memory because human expertise depends upon forms of cognition fundamentally different from statistical language generation.

Contemporary large language models primarily operate through probabilistic prediction based on patterns identified across massive textual datasets [8]. Their outputs reflect statistical relationships between linguistic tokens rather than biologically grounded understanding of concepts, causality, embodiment, or lived experience. While such systems may simulate reasoning convincingly, simulation differs fundamentally from the internally developed cognitive structures underpinning human expertise.

Biological memory enables humans not merely to retrieve information, but to interpret significance, evaluate uncertainty, recognise contextual nuance, and adapt knowledge to unfamiliar situations. Human experts operate through richly interconnected cognitive schemas shaped by emotional salience, sensory experience, social interaction, and embodied engagement with the world over time [7]. These processes involve forms of adaptive cognition extending beyond linguistic prediction alone.

Human expertise also depends upon metacognition: the capacity to evaluate one's own understanding, recognise uncertainty, identify gaps in knowledge, and regulate reasoning processes accordingly. Although GenAI systems may mimic confidence or uncertainty linguistically, they do not possess self-awareness or biologically grounded reflective cognition comparable to human metacognitive processes. This distinction is critical because professional judgment often depends less upon retrieving correct information than upon recognising ambiguity, ethical complexity, emotional context, contextual risk, or incomplete understanding.

AI systems also lack genuine ownership of knowledge. Human biological memory is inseparable from personal history, identity, responsibility, and accountability. Professionals are ethically and socially accountable for judgments arising from their expertise because those judgments emerge from internally developed cognitive capabilities shaped through education, experience, and reflection. AI-generated outputs, by contrast, are externally produced artefacts lacking personal understanding or responsibility. This distinction becomes important in professions requiring trust, ethical reasoning, interpersonal interactions, and contextual judgment under uncertain conditions.

The sophistication of GenAI creates an educational risk because it encourages the mistaken assumption that access to generated expertise is equivalent to possession of expertise. AI systems externalise expert performance while leaving underlying human cognitive capability underdeveloped. This distinction reflects a broader shift from internal cognition towards externally mediated cognition in which learners become dependent upon systems capable of simulating expertise on demand.

4. NEUROSCIENCE, AI, AND THE LIMITS OF PROMPT-BASED INTELLIGENCE

4.1. Prediction Versus Understanding

One of the central limitations of contemporary GenAI systems lies in the distinction between prediction and understanding. Large language models generate fluent outputs by predicting statistically probable token sequences derived from large-scale training data. Their apparent intelligence emerges from probabilistic pattern completion rather than biologically grounded conceptual understanding [8,19]. This distinction is significant because linguistic fluency can create the illusion of comprehension even where underlying causal, embodied, or experiential understanding is absent.

Recent debates within artificial intelligence and cognitive neuroscience question whether predictive language systems can genuinely be said to "understand" in a human cognitive sense. Research on world models argues that intelligence requires internally grounded representations of objects, causality, spatial relationships, and temporal dynamics rather than surface-level correlation alone [42]. Human cognition develops through embodied interaction with physical and social environments in which meaning is tied to action, consequence, emotion, and perception over time. By contrast, LLMs primarily learn statistical relationships between linguistic patterns detached from direct sensorimotor experience.

This distinction reflects the longstanding symbol grounding problem within cognitive science. Although LLMs can manipulate symbolic representations with extraordinary sophistication, critics argue that they lack grounded semantic understanding because their representations are derived primarily from textual correlations rather than embodied interaction with reality [43]. AI systems may generate outputs that are linguistically coherent yet conceptually unstable when confronted with unfamiliar contexts, ambiguity, or causal reasoning demands.

The educational implications of this distinction are profound. Human expertise depends not only on generating plausible responses, but on understanding why particular interpretations, judgments, or actions are appropriate under specific conditions. Professional reasoning frequently involves ambiguity, contextual sensitivity, emotive states, political positioning, ethical judgment, and adaptive transfer across novel situations. Prompt-based AI systems may increasingly simulate these capacities convincingly without genuinely possessing them. As a result, learners may mistake generated fluency for understanding itself. Without fully developed biological memory and expertise the potential for mistakes multiplies.

4.2. Emotion, Attention, and Memory

Human cognition involves emotion, attention, and memory. Emotion influences attention, attention regulates encoding, and memory formation depends heavily upon the salience, meaning, and contextual significance assigned to information during learning. This integration is important because educational technologies often prioritise efficiency while overlooking the biological conditions necessary for durable cognition. Human attention is limited, metabolically expensive, and highly sensitive to distraction. Encoding into long-term memory requires sustained attentional engagement and repeated activation of neural pathways over time [16]. Information encountered passively or processed superficially is less likely to become biologically consolidated into durable schemas.

The convenience of AI-generated cognition may weaken the sustained attentional effort required for deep learning. Generative systems reduce friction in information acquisition by compressing reading, summarisation, drafting, and retrieval into rapid conversational exchanges. While efficient, this acceleration risks fragmenting the slower cognitive processes associated with elaboration, reflection, and consolidation. Neuroscience research consistently demonstrates that durable memory formation depends not simply on exposure to information, but on repeated attentional engagement and active reconstruction over time [44].

Prompt-based AI interaction may unintentionally weaken these processes by reducing cognitive struggle. Many educationally significant learning experiences involve uncertainty, effort, revision, and emotional investment. The gradual mastery associated with expertise formation is often psychologically demanding precisely because it requires repeated confrontation with confusion, error, uncertainty and incomplete understanding. AI systems increasingly smooth these difficulties by providing immediate responses and polished outputs, potentially reducing the emotional and attentional intensity through which durable learning frequently develops.

4.3. Cognitive Debt and Neural Underdevelopment

The concept of cognitive debt provides an emerging framework for understanding the long-term neurological implications of sustained reliance on GenAI systems. Cognitive debt refers to the accumulation of unrealised cognitive effort resulting from repeated outsourcing of mental processes to external technologies [10]. Like financial debt, short-term gains in efficiency may generate longer-term reductions in independent capability if foundational cognitive processes are consistently bypassed rather than exercised.

Recent neuroscience-informed studies suggest that extensive AI-assisted cognition may alter patterns of neural engagement associated with learning and memory formation. In a widely discussed EEG study examining essay writing with and without AI assistance, participants using ChatGPT exhibited substantially weaker neural connectivity patterns than participants relying on independent cognition or conventional search tools [10]. Reduced activation was particularly evident in regions associated with active composition, attentional integration, and memory consolidation. Participants heavily reliant on AI assistance also demonstrated weaker recall of their own written work and lower subjective ownership of generated outputs.

Although these findings remain preliminary and have attracted methodological debate [45], they align with broader concerns regarding cognitive offloading and neural under-engagement in AI-mediated learning environments. Importantly, the issue is not that AI reduces intelligence, but that repeated reductions in effortful cognitive engagement may weaken the repeated neural activation necessary for schema consolidation and expertise development. Just as spaced repetition can enhance memory retention, reduction in repetition reduces memory.

This concern extends beyond individual tasks towards broader patterns of intellectual behaviour. GenAI systems increasingly encourage forms of passive cognitive consumption in which learners evaluate, edit, or approve generated outputs rather than constructing understanding independently. Over time, this may alter educational norms surrounding effort, concentration, revision, and reflective thinking. Preliminary evidence already suggests that extensive AI use may reduce cognitive engagement, originality, and deep processing during academic writing tasks [46].

5. IMPLICATIONS FOR HIGHER EDUCATION

5.1. Curriculum Design

The rise of GenAI requires higher education institutions to reconsider the fundamental purpose of curriculum design as traditionally, curricula have been structured around the progressive acquisition of disciplinary knowledge and skills through cumulative exposure, practice, and assessment. In AI-mediated educational environments, however, access to information and even simulated expertise is increasingly externalised through conversational systems capable of generating sophisticated outputs on demand. Consequently, curriculum design can no longer focus primarily on informational coverage alone. Instead, it must increasingly prioritise the development of durable biological memory, cognitive resilience, and independent reasoning capacities that remain essential despite technological augmentation.

This paradigmatic shift has significant implications for sequencing, repetition, and integration within curricula. Research in learning science consistently demonstrates that expertise develops through repeated retrieval, spaced repetition, elaboration, and transfer across contexts rather than through isolated exposure to content [47]. Yet many contemporary curricula remain organised around fragmented subject silos encouraging short-term performance optimisation rather than long-term schema consolidation. GenAI may intensify this fragmentation by enabling students to bypass integrative cognitive work through rapid summarisation, automated drafting, and outsourced synthesis.

GenAI also raises questions regarding what forms of knowledge should remain internalised within professional education. Historically, higher education assumed that significant bodies of disciplinary knowledge needed to reside within human memory because external retrieval was slow or inaccessible. AI systems challenge this assumption by providing immediate access to generated information. However, professions still depend upon internalised expertise capable of recognising risk, contextual nuance, ethical implications, and conceptual relationships that cannot reliably be delegated to probabilistic systems. Curriculum design must therefore distinguish between knowledge appropriate for technological augmentation and knowledge requiring durable biological consolidation.

5.2. Assessment Design

GenAI destabilises many of the assumptions underpinning conventional assessment practices in higher education [18]. Traditionally, assessments have functioned not only as measures of learning but also as mechanisms through which learning occurs. Activities such as essay writing, problem-solving, explanation, and applied analysis required sustained retrieval, synthesis, and cognitive organisation. In AI-mediated environments, however, students may increasingly generate high-quality outputs without engaging extensively in the intellectual processes those assessments were originally designed to cultivate [18]. This creates a disconnect between output quality and underlying competence.

AI-rich environments require a shift from product-based assessment towards process-visible assessment [48, 49]. Process-visible assessment emphasises the demonstration of reasoning, reflection, retrieval, adaptation, and judgment rather than the production of polished outputs alone [2]. Oral examinations, staged drafting, in-class problem-solving, authentic simulations, viva voce assessment, and iterative portfolio approaches may therefore become increasingly important because they reveal learners' underlying cognitive processes more effectively than static submitted products.

The sophistication of wearable AI technologies further intensifies these concerns. AI-enabled smart glasses, real-time prompting systems, and covert conversational interfaces increasingly blur the boundary between independent cognition and networked assistance [6]. In this context, escalating surveillance alone is unlikely to provide a sustainable educational response. Instead, assessment design may need to shift towards tasks that require contextual judgment, adaptive reasoning, ethical evaluation, and reflective explanation that are more difficult to outsource seamlessly to external systems.

Higher education institutions should avoid regression towards rote memorisation or excessive restriction. Closed-book examinations alone do not necessarily produce expertise and may inadequately reflect contemporary professional environments based on technology-assisted practice. The challenge is to design assessments preserving biological memory and independent reasoning while acknowledging the legitimate role of AI within modern knowledge work.

5.3. AI as Scaffold Rather Than a Substitute

The educational impact of GenAI depends less on the technology itself than on how it is pedagogically positioned. A distinction exists between AI functioning as a scaffold for cognition and AI functioning as a substitute for cognition. Scaffolds support learners while preserving engagement in the cognitive processes necessary for long-term capability development. Substitution bypasses those processes entirely.

This distinction has become important because many current educational uses of GenAI risk transforming students from active constructors of knowledge into users of machine-generated outputs. AI systems now routinely generate summaries, explanations, drafts, and solutions requiring learners primarily to select, edit, or approve content rather than independently construct understanding. While such practices may increase efficiency, they may also reduce the retrieval, elaboration, and reflective effort through which biological memory develops.

Educational scaffolding traditionally involves temporary support structures gradually removed as learners develop increasing independence [36]. Effective scaffolds therefore strengthen capability development rather than create permanent dependency. GenAI systems, however, possess the potential to become persistent cognitive prostheses if learners repeatedly outsource foundational reasoning processes rather than using AI to extend already established schemas.

Recent work in educational neuroscience suggests that learning technologies should be evaluated not only for immediate performance outcomes but also for their long-term effects on attentional regulation, retrieval practice, schema development, and cognitive resilience [50,51]. This shifts the educational question from "Does AI improve task completion?" towards "What forms of cognition does AI strengthen or weaken over time?"

This distinction also has broader societal significance. If higher education systems normalise substitutive AI use during foundational learning stages, graduates may increasingly enter professional environments possessing weaker biological memory and greater dependence upon external cognitive systems. The issue is not merely educational efficiency, but the long-term preservation of independent human expertise within AI-augmented societies.

The most productive educational future may involve what could be termed augmentation pedagogy: pedagogical approaches explicitly designed around complementarity between human cognition and AI systems. Within such models, AI enhances reflection, questioning, simulation, and adaptive support while educational structures continue requiring retrieval, uncertainty tolerance, deep reading, explanation, and independent reasoning. In this sense, the future of higher education may depend upon ensuring that AI remains a scaffold for biological expertise rather than a replacement for it.

5.4. AI Literacy and Verification

This challenge is significant because GenAI systems produce fluent and authoritative language irrespective of factual accuracy. Hallucinated references, fabricated evidence, distorted reasoning, and confident misinformation remain persistent features of contemporary LLM architectures [1,3]. Learners with limited prior knowledge are especially vulnerable because they may lack the biological memory necessary to identify inaccuracies or inconsistencies within generated outputs or how to iteratively develop prompts to overcome these issues.

AI literacy increasingly depends upon verification literacy: the capacity to critically evaluate generated information against disciplinary standards, trusted sources, and independent reasoning processes. Verification literacy requires learners to understand how generative systems operate probabilistically, why hallucinations occur, and how confidence simulation differs from epistemic reliability. In this sense, AI literacy becomes inseparable from critical thinking itself.

Verification is cognitively demanding. It requires retrieval of prior knowledge, contextual interpretation, source evaluation, and reflective judgment. Ironically, effective AI use may depend upon precisely the forms of biological expertise that excessive AI reliance risks weakening. Students lacking sufficiently developed disciplinary schemas may become dependent upon systems they are simultaneously least equipped to critically evaluate.

This creates a paradox at the centre of AI-mediated education: the more persuasive AI systems become, the more important biological memory and independent expertise become for their safe and effective use. In this sense, AI literacy should not be conceptualised merely as technological fluency, but as cognitively grounded judgment within environments saturated by machine-generated information.

Table 1. Risks and Educational Responses

AI Risk	Cognitive Impact	Educational Response
AI summarisation	Reduced encoding	Retrieval activities, synthesis and critical review of summaries
AI writing	Reduced schema formation	Oral defence, process logs
AI tutoring dependence	Cognitive dependency	Staged scaffolding, teamwork exercises
AI hallucinations	Weak verification	AI literacy training, peer review and source validation exercises

The future educational challenge is not teaching students how to use AI but preserving the biological capacities necessary to remain intellectually independent in environments increasingly shaped by generated cognition. AI literacy becomes not a substitute for expertise, but a dependent extension of it. Table 1 synthesises key cognitive and educational risks associated with AI-mediated learning alongside potential pedagogical and assessment responses designed to strengthen biological memory, independent reasoning, and long-term human expertise in higher education environments.

6. TOWARDS BIOLOGICAL MEMORY ALIGNED AI IN HIGHER EDUCATION

The concept of brain-aligned AI reflects a significant departure from prevailing technology-centred approaches to educational innovation. Much contemporary AI development implicitly treats cognition as an information-processing problem in which learning can be optimised through faster access to answers, personalised content delivery, and reduced cognitive friction. Neuroscience suggests a more complex reality. Human expertise emerges through effortful interaction between memory, emotion, attention, uncertainty, reflection, and adaptive problem-solving over extended periods of time [44]. Technologies optimised solely for efficiency may therefore conflict with the biological processes through which durable learning develops. Brain-aligned AI consequently requires a shift from replacement-oriented design towards augmentation-oriented design. Rather than automating cognition wherever possible, educational AI systems should increasingly be designed to strengthen the cognitive processes associated with biological memory formation. This may involve AI systems that deliberately promote retrieval practice, reflective questioning, elaboration, conceptual linking, uncertainty tolerance, and metacognitive monitoring rather than simply generating completed outputs [52].

Future educational AI systems may need to become cognitively diagnostic rather than merely generative. Contemporary AI primarily evaluates outputs. Brain-aligned AI would seek to identify patterns of cognitive engagement, conceptual misunderstanding, retrieval weakness, attentional fragmentation, or overdependence on external generation. Advances in neuroadaptive learning systems integrating physiological and behavioural indicators suggest the possibility of AI environments capable of responding dynamically to learner cognitive states rather than merely producing content [20]. Such systems could potentially support attentional regulation, pacing, and metacognitive reflection in ways aligned with biological learning processes.

Brain-aligned AI does not imply technologically restrictive education or nostalgia for pre-digital learning environments. The issue is not technological augmentation itself, but whether emerging technologies preserve sufficient opportunities for learners to develop independent cognitive capability. Educational systems that progressively eliminate retrieval, uncertainty, reflection, and productive struggle may inadvertently weaken the very expertise they seek to enhance. Future AI tutors may become capable of anticipating learner needs, detecting confusion, adjusting explanations dynamically, and generating highly individualised educational experiences. While potentially beneficial, such systems also risk creating forms of permanent cognitive dependency if learners become habituated to continuous external guidance rather than developing autonomous reasoning capacities. Brain-aligned educational design therefore requires maintaining what might be termed desirable cognitive resistance: sufficient intellectual effort, uncertainty, and retrieval demand to preserve biological memory formation despite increasing technological assistance.

The distinction between cognitive support and cognitive replacement will likely become one of the defining educational issues of the AI era. In this sense, future educational governance may require forms of cognitive impact assessment analogous to ethical or privacy review processes. AI systems designed for educational environments should be evaluated according to their effects on retrieval practice, attentional stability, schema formation, metacognitive development, and long-term cognitive resilience.

7. CONCLUSION, RECOMMENDATIONS AND FUTURE DIRECTIONS

Generative artificial intelligence is the most significant disruptor to higher education since the emergence of the internet, not because it merely improves access to information, but because it performs intellectual labour previously central to human learning itself. This paper has argued that the core educational challenge posed by GenAI is not academic integrity, technological adoption, or productivity enhancement, but the erosion of biological memory and the cognitive foundations of human expertise. Human expertise depends upon effortful encoding, retrieval, schema formation, reflection, and adaptive reasoning developed through sustained cognitive engagement over time. While GenAI systems can simulate elements of expertise with extraordinary fluency, they cannot replace the biologically grounded understanding, judgment, and metacognitive awareness underpinning independent human cognition. Higher education faces a critical choice between designing AI-mediated learning environments that preserve cognitive development or unintentionally normalising systems that prioritise performance efficiency over intellectual formation.

The future of higher education should not involve rejecting artificial intelligence but reorienting its use towards brain-aligned educational design. Universities should develop curricula, pedagogies, and assessment systems that position AI as a scaffold for cognition rather than a substitute for it. This includes preserving opportunities for retrieval practice, productive struggle, reflective thinking, deep reading, oral reasoning, and independent problem-solving despite the growing availability of AI-generated outputs. Future research should move beyond speculative debate towards longitudinal investigation of how sustained AI use influences memory consolidation, attentional regulation, schema development, metacognition, and professional capability over time. Neuroscience-informed educational research, cognitive impact assessment frameworks, and empirical studies examining the relationship between AI-supported learning and biological expertise development will become increasingly important as AI systems grow more adaptive and persuasive. Ultimately, the central challenge of the AI era is not whether machines become more intelligent, but whether educational systems continue cultivating the biological capacities necessary for humans to remain intellectually independent, critically reflective, and professionally capable in increasingly AI-mediated societies.

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