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Interdisciplinary Perspective on the Role of Active Learning in Enhancing Memory

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Abstract: Active learning, as delineated through the ICAP framework, differentiates between active, constructive, and interactive modes of engagement, each linked to specific cognitive and behavioural processes that influence knowledge acquisition and retention. While cognitive psychology and neurobiology provide mechanistic explanations for the effectiveness of certain learning behaviours, these insights are seldom systematically integrated within educational frameworks. This theoretical review aims to address this gap by utilising the ICAP hierarchy as an organisational scaffold for synthesising findings from education, cognitive psychology, and neurobiology, and by proposing an integrated model that elucidates how distinct forms of active engagement enhance declarative memory through shared neurocognitive mechanisms. From an interdisciplinary perspective, active learning fosters long-term memory not merely through heightened behavioural engagement, but by aligning curiosity, effort-reward appraisal, and social interaction to activate dopaminergic plasticity pathways. Consequently, the modes of ICAP engagement can be conceptualised as graded modulations of a common neurocognitive cascade: Increasing learner choice and novelty enhances effort–reward appraisal, biases learning toward curiosity and motivation, and thereby facilitates dopaminergic activation, hippocampal and striatal plasticity, and durable memory formation. Within this framework, the active mode initiates engagement with the cascade, the constructive mode stabilises learning through metacognitive monitoring and attentional control, and the interactive mode further amplifies memory by integrating social reward with coordinated regulation of cognitive demands. Collectively, these distinctions elucidate how instructional design can support durable learning by maintaining a favourable effort–reward balance, fostering metacognitive regulation, and leveraging collaboration without exceeding cognitive limits.

Keywords: Active learning, memory, neurobiology, cognitive psychology, interdisciplinary, educational science.

1. Introduction

Active learning has emerged as an important concept in education, significantly improving learning outcomes across diverse disciplines (Fayombo, 2012; Freeman et al., 2014). Unlike traditional lecture-based methods, active learning emphasises cognitive engagement, prompting students to analyse, synthesise, and critically evaluate information rather than passively absorbing it. This approach allows them to construct knowledge through interaction and exploration (Markant et al., 2016; Bonwell & Eison, 1991; King, 1993).

Despite its recognised importance in education, active learning faces a significant challenge: a lack of practical clarity and guidance for educators. The concept remains broadly defined, making it difficult for teachers to implement effectively. To address this, Chi and Wylie (2014) introduced the *Interactive, Constructive, Active, and Passive* (ICAP) framework, which categorises student engagement based on

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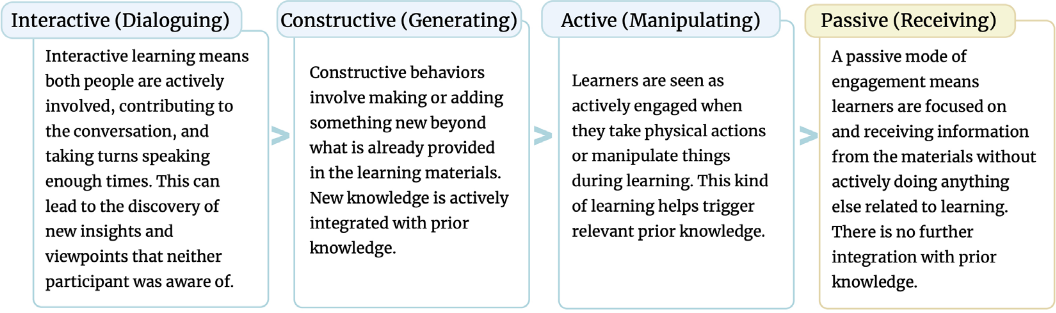
observable behaviours that teachers can identify. This framework highlights distinct modes of engagement, each associated with specific behaviours and processes of knowledge acquisition. The four modes (interactive, constructive, active, and passive) are linked to cognitive processes that drive learning and knowledge transformation, as illustrated in Figure 1 (Chi & Wylie, 2014).



Interactive learning means both people are actively involved, contributing to the conversation, and taking turns speaking enough times. This can lead to the discovery of new insights and viewpoints that neither participant was aware of.

Constructive behaviors involve making or adding something new beyond what is already provided in the learning materials. New knowledge is actively integrated with prior knowledge.

Learners are seen as actively engaged when they take physical actions or manipulate things during learning. This kind of learning helps trigger relevant prior knowledge.

A passive mode of engagement means learners are focused on and receiving information from the materials without actively doing anything else related to learning. There is no further integration with prior knowledge.

Figure 1: *The ICAP framework of Chi and Wylie (2014)*

The ICAP hypothesis posits that the Interactive mode facilitates the highest level of learning, succeeded by the Constructive mode, followed by the Active mode, with the Passive mode yielding the least learning. This implies that various types of observable behaviours result in distinct learning outcomes. The behaviours associated with each mode are indicated in parentheses. The blue boxes denote active learning modes, wherein components of active learning are integrated, whereas the yellow box signifies passive learning. This review particularly emphasises the Interactive, Constructive, and Active modes. This figure was created based on the work of Chi and Wylie (2014) using BioRender.

The cognitive processes underpinning these modes of engagement in active learning enable students to store information in long-term memory and retrieve it efficiently (Nechita, 2019). Numerous studies have underscored the positive impact of active learning on memory, as demonstrated through memory tasks (Markant et al., 2016; Ruggeri et al., 2019). Similar to active learning, the concept of memory is often broadly defined within the literature. In essence, memory pertains to our capacity to retain and recall the knowledge acquired from daily experiences and learning (Benfenati, 2007).

Memory can be broadly divided into short-term memory and long-term memory. Short-term memory encompasses both sensory memory and working memory. Sensory memory captures ephemeral impressions of our perceptions through our senses (Jansson-Boyd & Bright, 2024). Working memory functions as a dynamic, short-term mental space where information and sensory inputs can be processed (Baddeley, 2012).

Long-term memory can be categorised into two primary types: declarative memory and non-declarative memory. Declarative memory includes semantic memory, which predominantly stores factual knowledge and is often referred to as "conscious" memory because its contents can be intentionally accessed and recalled (Kandel & Pittenger, 1999). In contrast, non-declarative memory operates largely outside of conscious awareness and facilitates learning that does not necessitate explicit recall (Benfenati, 2007; Fox et al., 2017). While memory can be classified into various types, several forms share a common process comprising encoding, storage, and recall (Fox et al., 2017). In 1968, Atkinson and Shiffrin introduced the multi-store model to elucidate the process of information storage in the brain. Significant information from sensory memory is filtered through attentional control (Atkinson & Shiffrin, 1968). Working memory is responsible for the temporary storage and processing of this significant information; however, it retains information for only a brief period and is limited in data capacity (Atkinson & Shiffrin, 1968). Information in working memory plays a crucial role in retrieving and integrating knowledge from long-term memory, which functions as the permanent repository for all learned information. This interaction enables the effective utilisation of stored knowledge for cognitive processing, as illustrated in Figure 2 (Atkinson & Shiffrin, 1968; Swiderski, 2011). Ideally, this knowledge is encoded to organise it into meaningful structures and to highlight connections to related information (Atkinson & Shiffrin, 1968). When such organisation is achieved, retrieving knowledge from long-term memory necessitates less cognitive effort (Swiderski, 2011). This review primarily focuses on long-term memory, specifically declarative memory, as it represents the principal objective of formal education, is most closely associated with the knowledge-related learning outcomes defined within the ICAP framework, and is the most extensively characterised form of memory in the neurobiological literature.

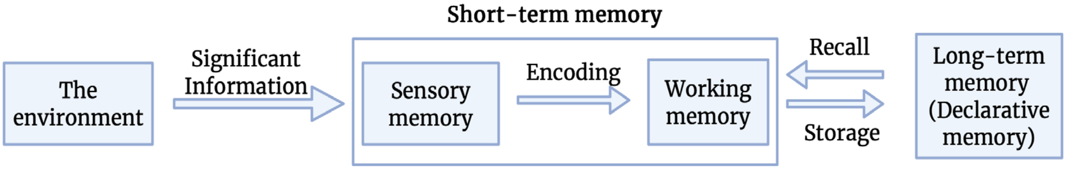


Figure 2: *The multi-store model of memory*

Memory is broadly categorised into short-term and long-term memory. Short-term memory includes sensory memory and working memory, while long-term memory encompasses declarative memory. Declarative memory, which involves the conscious recall of information, is particularly relevant in learning and education. *This figure was created using BioRender.*

1.1 Problem statement

Although educational frameworks such as the ICAP model provide a behavioural taxonomy of engagement, they do not offer a mechanistic account of how these modes map onto specific memory processes. Meanwhile, insights from cognitive psychology and neurobiology explain why certain learning behaviours are effective; however, these explanations are rarely integrated with educational frameworks in a systematic way. Consequently, an interdisciplinary, mechanistic explanation linking ICAP engagement modes directly to memory pathways remains lacking. This theoretical review seeks to address this gap by positioning the ICAP "active–constructive–interactive" hierarchy as an organising scaffold for integrating findings from education, cognitive psychology, and neurobiology. By doing so, the review aims to provide an integrated model explaining how distinct forms of active engagement support (declarative) memory enhancement through specific underlying mechanisms.

The review begins by outlining a theoretical framework that supports learning as an active process, based on the multi-store model, levels of processing, and (social) constructivism. It then examines how characteristics of the learning environment and the learner function as neurobiological triggers that enhance memory storage by linking the ICAP modes to neurocognitive mechanisms. This interdisciplinary analysis lays the groundwork for practical ways to design learning environments that deliberately move students along the ICAP continuum toward deeper and more durable learning.

2. Theoretical Framework: The relation between Active Learning and Memory

Over decades of research, multiple theoretical frameworks have converged on the idea that learners actively engage with, transform, and integrate information to build durable knowledge structures. This perspective is reflected in cognitive theories of memory, constructivist accounts of learning, and contemporary models such as the ICAP framework (Atkinson & Shiffrin, 1968; Chi & Wylie, 2014; Craik & Lockhart, 1972; Piaget, 1971; Vygotsky, 1980). In this section, learning as an active process is examined by integrating theoretical frameworks, including the multi-store model, the levels of processing theory, and (social) constructivism. These theories are then related to the neurobiological mechanisms of learning and memory.

2.1 Theories supporting learning as an active process

Craik and Lockhart (1972) proposed a framework that extended the multi-store model by positing that the strength and durability of a memory are influenced more by the depth of information processing than by the duration of its retention in storage (Craik & Lockhart, 1972). They outlined three levels of processing, each representing a different depth: structural, phonemic, and semantic processing (Craik & Lockhart, 1972). The shallowest level enables basic encoding, resulting in fragile memory that fades quickly. Phonemic processing strengthens memory further but often fails to result in long-term retention. Semantic processing is the deepest and most effective level of processing (Craik & Lockhart, 1972). It involves linking information to existing knowledge by understanding its meaning. This level requires active engagement, encouraging individuals to think critically about the content and connect it to real-life scenarios or personal experiences. By assigning meaningful context to new information, semantic processing creates strong, long-lasting memory traces (Craik & Lockhart, 1972).

Soon after these publications, Piaget's constructivist theory offered a complementary view, highlighting how individuals actively build and integrate knowledge (Piaget, 1971; Piaget & Inhelder, 1972). Constructivism suggests that knowledge consists of mental structures that individuals actively build and refine through interactions with their environment (Piaget, 1971; Piaget & Inhelder, 1972). Each mental structure is an organised framework of information that adapts when exposed to new ideas (Piaget, 1971; Piaget & Inhelder, 1972). This adaptation occurs through processes by which new information is either integrated into existing knowledge structures or leads to the modification and formation of new ones (Piaget, 1971; Piaget & Inhelder, 1972). Social constructivism expanded on Piaget's cognitive constructivism by incorporating Vygotsky's theory. He argued that learning is shaped by social and cultural influences rather than occurring solely within the individual (Vygotskiĭ & Kozulin, 1934; Vygotsky, 1980). A key concept in Vygotsky's theory is thezone of proximal development, which defines the difference between what a student can accomplish independently and what can be achieved with guidance (Vygotskiĭ & Kozulin, 1934; Vygotsky, 1980). This theory suggests that, with the support of a teacher or more knowledgeable peer, students can grasp concepts and develop skills that would otherwise be beyond their reach (Schreiber & Valle, 2013; Vygotskiĭ & Kozulin, 1934; Vygotsky, 1980).

By integrating these theories, it becomes evident that learning is an (inter)active and constructive process, as emphasised by the ICAP framework, wherein learners construct their own interpretations of reality (Chi & Wylie, 2014; Craik & Lockhart, 1972; Piaget, 1971). This concept is consistent with deeper levels of processing, which result in robust and enduring memory traces (Craik & Lockhart, 1972). These traces are created by filtering sensory input through attention, temporarily encoding it in working memory, and, if deemed significant, storing it in long-term memory. Upon retrieval, this well-organised knowledge connects with prior learning, enhancing recall, facilitating application, and reinforcing memory over time (Atkinson & Shiffrin, 1968).

2.2 The neurobiological underpinnings of learning and memory

Learning activates neural circuits in memory-related regions, such as the hippocampus, leading to cellular and molecular changes. The preservation of these changes underpins memory storage (Kandel & Pittenger, 1999; Silva & Josselyn, 2002) (Figure 3). At the cellular level, working memory involves processes such as changes in ion channel conductance, driven by phosphorylation and the influx of calcium ions. This calcium influx prompts the release of neurotransmitters, which activate neighbouring neurons. These neurophysiological changes occur rapidly, typically within minutes, creating a transient form of "molecular memory" (Abel & Lattal, 2001). The molecules involved in these signalling pathways are activated temporarily, with their activity regulated by the kinetics of both phosphorylation and dephosphorylation. This regulation maintains a dynamic balance between the activation and inhibition of learning processes. However, functional changes alone are insufficient for the storage of long-term memories; structural changes are also essential. During memory formation, persistent stimulation triggers signalling pathways, resulting in altered activity of the CREB family of transcription regulators. These regulators are crucial for the conversion of working memory into long-term memory, as their activation leads to altered expression of proteins involved in axon growth and synaptic structure and function (Alberini, 2005; Bozon et al., 2003). These structural changes, collectively known as long-term potentiation, are vital for the long-term storage of memories (Bozon et al., 2003). Consequently, more sustained stimuli result in stronger and more enduring memories of the learned material, aligning with the levels of processing theory proposed by Craik and Lockhart (1972) (Craik & Lockhart, 1972) (Figure 3).

Another concept consistent with this theory is the *synaptic tagging hypothesis*, which suggests that there is a specific time frame following the induction of long-term potentiation during which certain proteins are directed to active synapses. This process ensures the development of a persistent form of potentiation when stronger stimuli, characterised by a higher firing frequency, are encountered (Moncada et al., 2015). A decade after this hypothesis was introduced, researchers expanded it by demonstrating a similar process, termed *behavioural tagging*. This occurs in living organisms during the formation of long-term memory from a weak learning experience, allowing the initially weak memory to be converted into a lasting one when triggered by a stronger learning experience, characterised by a novel or rewarding experience (Moncada et al., 2015).

In summary, learning induces cellular and molecular changes in the hippocampus, which are essential for memory storage. Working memory involves transient processes, while long-term memory requires structural changes such as synaptic remodelling, aligning with the levels of processing theory, which links the deepest level of processing to the strongest memories. Synaptic and behavioural tagging further support this by demonstrating how weak experiences can become lasting memories when reinforced by stronger stimuli, characterised by a higher firing frequency and a novel or rewarding experience. In Figure 3, an integration of memory models and neurobiological mechanisms is illustrated.

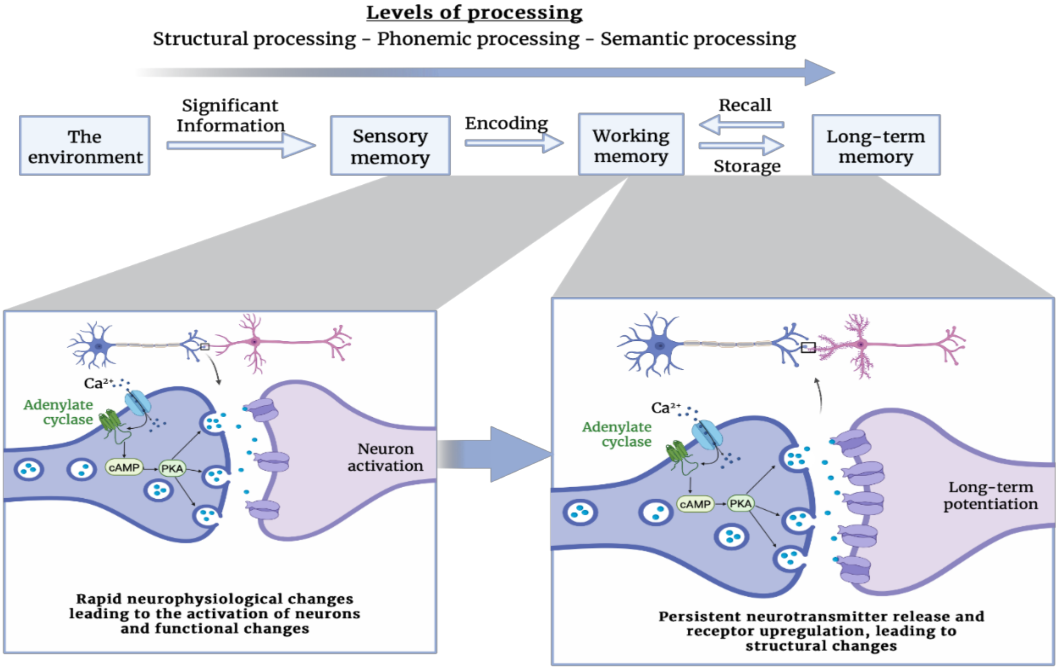


Figure 3: *Integration of memory models and neurobiological mechanisms*

During the formation of working memory, calcium influx stimulates neurotransmitter release, leading to neuron activation. In contrast, long-term memory formation relies on long-term potentiation, where repeated stimulation keeps the neuron active, triggering calcium influx that activates cAMP and PKA. This results in prolonged neurotransmitter release and the strengthening of the synaptic cleft. Consequently, neurons undergo structural changes, forming stronger connections with surrounding neurons. This supports the concept that deeper levels of processing enhance memory more effectively than shallow processing. *cAMP: cyclic adenosine monophosphate; PKA: protein kinase A. This figure was created using BioRender.*

3. Motivation, Curiosity and Novelty as Drivers for Learning to Enhance Memory

Motivation, curiosity, and novelty are recognised as fundamental drivers of effective learning (Gruber et al., 2014; Lisman & Grace, 2005). Motivation provides the foundation for active engagement, influencing the level of attention, effort, and persistence that a learner brings to a task (Oudeyer et al., 2016; Poli et al., 2022). When this motivation is driven by interest or personal relevance, it often gives rise to curiosity, defined as the desire to acquire new knowledge and reduce uncertainty. Curiosity, in turn, directs learners towards information that has the potential to facilitate learning progress, sustaining their engagement in the absence of external rewards (Poli et al., 2022). As learners pursue answers to self-generated questions, they become increasingly receptive to novel information. Novelty captures attention by introducing unfamiliar or unexpected elements, which further stimulate exploration and promote deeper cognitive processing (Houillon et al., 2013; Poli et al., 2022). Collectively, these three elements initiate and support active learning behaviours, as delineated in the ICAP framework, thereby enhancing encoding and memory formation (Chi & Wylie, 2014). In the subsequent sections, each component will be discussed in detail and situated within a broader neurobiological framework that elucidates its contribution to long-term memory consolidation.

3.1 Motivation enhances memory performance depending on effort-reward balance

Motivation and memory are both fundamental aspects of human behaviour and cognition. While motivation drives individuals toward their goals, memory allows them to make decisions based on past experiences (Miendlarzewska et al., 2016). Consequently, motivation can enhance performance when the reward is perceived as being worth the effort and can be either intrinsic, driven by internal goals, curiosity, and the inherent enjoyment or fulfilment of an activity, or extrinsic, driven by external goals and the pursuit of separate outcomes or rewards (Grogan et al., 2022; Miendlarzewska et al., 2016; Ryan & Deci, 2000).

Research shows a positive correlation between active learning and intrinsic motivation (Cicuto & Torres, 2016; Liu et al., 2024). Moreover, studies indicate that students who learn content with intrinsic motivation demonstrate deeper conceptual understanding than those driven by external goals, such as performing well on exams (Benware & Deci, 1984). This aligns with other research suggesting that students motivated by intrinsic rewards also develop greater self-efficacy, a positive predictor of learning outcomes, and are associated with higher levels of behavioural, motivational, and cognitive engagement compared with students who report lower self-efficacy (Bassi et al., 2007; Blain & Sharot, 2021; Linnenbrink & Pintrich, 2003).

Neurobiological research reveals both overlaps and distinctions in how intrinsic and extrinsic motivation are processed in the brain (Duan et al., 2020). Overlapping active brain regions include the ventral tegmental area, which contains dopamine-producing neurons, as well as portions of the hippocampus (Duan et al., 2020). Both the ventral tegmental area and the hippocampus are essential for reward anticipation (Wittmann et al., 2007). Beyond dopamine, other brain chemicals could also affect motivation and memory. For example, the release of noradrenaline in anticipation of a reward or surprise stimulates arousal (Glimcher, 2011). Noradrenaline plays a role in preparing an individual for action (Glimcher, 2011). A task that demands more effort increases noradrenaline activity, while dopamine levels decrease once the effort surpasses a certain threshold. This implies that dopamine is involved in assessing the value of pursuing a goal, whereas noradrenaline provides the energy necessary to act on it (Varazzani et al., 2015). Differences between intrinsic and extrinsic motivation are mostly reflected in brain activation and its timing. When the brain is stimulated by internal rewards, the prefrontal cortex tends to show more activation compared to when external rewards are involved (Chew et al., 2021; Duan et al., 2020). In light of this, active learning may engage the prefrontal cortex more strongly by fostering internal reward processes, thereby supporting deeper conceptual learning. Furthermore, the timing of brain activation differs depending on the type of reward. In the case of external rewards, brain activity occurs before a response is given to the question, whereas with internal rewards, the brain shows increased activity after the answer is provided (Duan et al., 2020). Therefore, while both forms of motivation have been linked to improvements in memory, they may operate through distinct and potentially complementary neural processes that support memory performance.

3.2 Curiosity stimulates long-term potentiation

Motivation grounded in personal interest or perceived relevance gives rise to curiosity, conceptualised as a form of reward motivation that drives the pursuit of novel information to reduce uncertainty (Berlyne, 1950; Harlow, 1953; Kidd & Hayden, 2015; Poli et al., 2022; Tolman, 1926). Research on active learning consistently highlights that it can stimulate and strengthen curiosity in students (Cicuto & Torres, 2016; Liu et al., 2024). Additionally, curiosity has a positive effect on hippocampus-dependent memory, as described by Gruber et al. (2019) and Gruber & Ranganath (2019). They introduced the ‘PACE framework,’ which conceptualises the influence of curiosity on memory as a cyclical process encompassing *Prediction Errors, Appraisal, Curiosity, and Exploration*. Prediction errors emerge when there is a discrepancy between expectations and actual outcomes. This discrepancy signals that something unexpected has occurred, drawing attention to this novel information (Schomaker & Wittmann, 2021a; Tanner et al., 2024). Prediction errors can be categorised as either external (context-based, arising from unexpected events in the environment) or internal (content-based, resulting from knowledge gaps or unmet informational expectations) (Gruber & Ranganath, 2019). The hippocampus is responsible for detecting external prediction errors by identifying novelty through comparisons between prior knowledge and new information (Gruber & Ranganath, 2019; Voss et al., 2017), whereas internal prediction errors originate in the anterior cingulate cortex (Gruber & Ranganath, 2019; Lau et al., 2020; Oosterwijk et al., 2020). Subsequently, these prediction errors activate appraisal processes within the lateral prefrontal cortex. Depending on the evaluation of the situation, appraisal can lead to either anxiety, mediated by the amygdala in response to perceived stress, or curiosity, facilitated by dopaminergic pathways (Gruber & Ranganath, 2019; Noordewier & van Dijk, 2016; Silvia, 2005, 2008). The activation of dopaminergic pathways, in turn, enhances attentional control and stimulates hippocampal activity through synaptic plasticity (Gruber & Ranganath, 2019). While long-term potentiation can occur in the hippocampus without dopamine, it is significantly enhanced when dopamine is present, thereby supporting learning and memory (Bethus et al., 2010; Düzel et al., 2010).

In summary, intrinsic motivation and curiosity can mutually reinforce one another, acting as a driving force for learning. According to the PACE framework, curiosity is triggered when a prediction error occurs, and the situation is appraised as meaningful or interesting. This appraisal acts as a filter, determining whether the novel information is worth exploring. When curiosity is engaged, it activates dopaminergic pathways, which in turn enhance synaptic plasticity in the hippocampus, supporting stronger memory formation. In Figure 4, the integration of curiosity- and motivation-driven memory plasticity is shown.

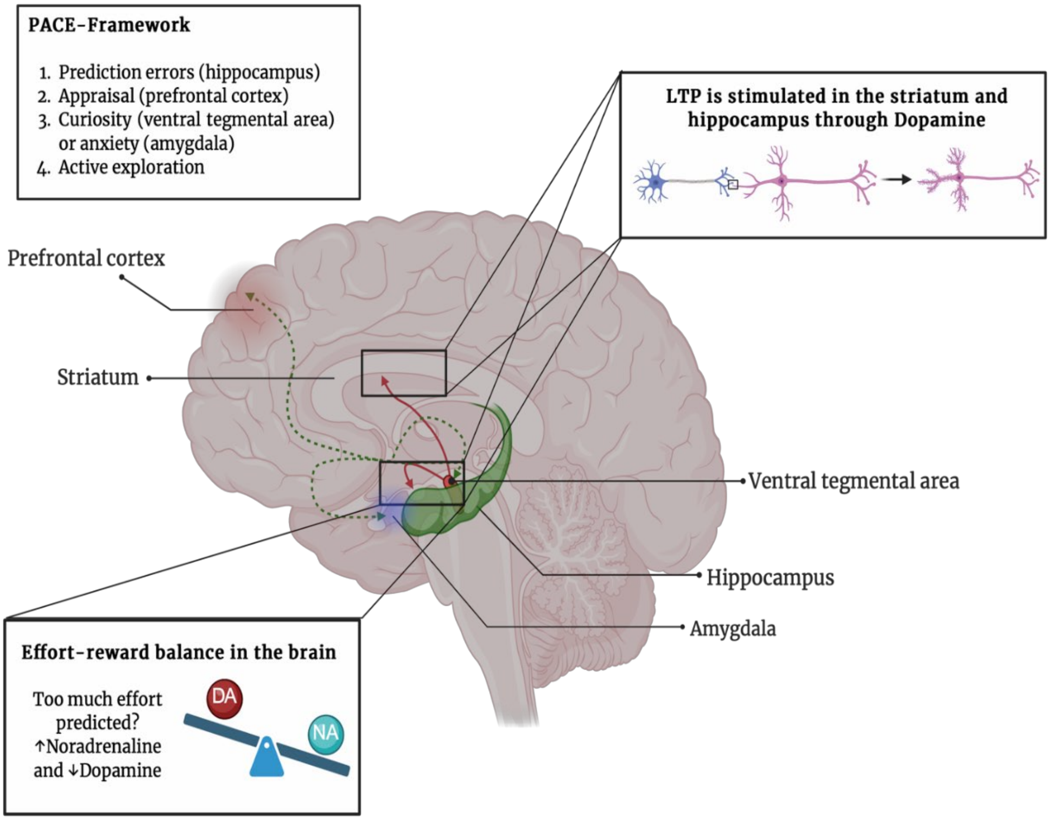


Figure 4: *Curiosity- and Motivation-Driven Memory Plasticity*

Within the PACE framework, the hippocampus is responsible for detecting prediction errors and functions as a crucial region for novelty recognition. This process initiates an appraisal mechanism in the prefrontal cortex, which subsequently results in either an anxiety response, mediated by the amygdala, or a curiosity-driven response, regulated by the ventral tegmental area. The latter response promotes dopamine release, facilitating LTP in the hippocampus and thereby enhancing the consolidation of information into long-term memory. The determination of whether a stimulus elicits anxiety or curiosity is contingent upon the effort-reward balance. When a task is perceived as rewarding in relation to the effort required, motivation increases, resulting in augmented dopamine release. Conversely, if the perceived effort exceeds the anticipated reward, dopamine levels decrease while noradrenaline levels rise, disrupting the optimal balance necessary for effective learning and memory retention. *DA: Dopamine; NA: Noradrenaline; LTP: Long-term potentiation; PACE: Prediction errors, appraisal, curiosity, exploration. This figure was created using BioRender.*

3.3 Novelty stimulates long-term memory through active exploration

Both curiosity and motivation enhance receptiveness to novel information (Poli et al., 2022). Novelty is characterised by an unpredictable event that typically activates emotional arousal and attention (Schomaker & Wittmann, 2021a; Tanner et al., 2024). In academic settings, where students are regularly exposed to new material, attentional control is crucial for filtering information into working memory. Thus, introducing novelty is an effective way to enhance learning and engagement and is frequently employed in educational contexts for its positive impact on memory and student motivation (Davis et al., 2004; Li et al., 2003; Sajikumar, 2004; Sierra-Mercado et al., 2008). Although novelty has been shown to positively affect all types of learning (Dubinsky & Hamid, 2024a), its impact on long-term memory may depend on how it is encountered (Schomaker & Wittmann, 2021b). Research indicates that actively exploring a novel environment through decision-making, in contrast to being passively exposed to it, leads to better declarative memory (Schomaker & Wittmann, 2021b) (Figure 5). Moreover, studies have demonstrated that individuals who actively explored a new environment had better long-term memory for unrelated tasks, such as recalling a list of words, compared to those who merely observed the new environment (Schomaker et al., 2014). This finding is supported by Biel et al. (2019), who showed that exposure to novelty alone is not sufficient to enhance long-term memory; rather, an active task involving the novel stimulus is necessary to promote learning (Biel & Bunzeck, 2019). These findings underscore the importance of engaging with novel stimuli to enhance long-term memory, supporting the *active mode* within the ICAP framework (Chi & Wylie, 2014).

From a neurobiological standpoint, the hippocampus is crucial for detecting novel stimuli. The connection between novelty and learning can be explained through the concept of synaptic plasticity. Neuroscientific research has shown a link between novelty exposure and long-term potentiation (Davis et al., 2004; Li et al., 2003; Sajikumar, 2004; Sierra-Mercado et al., 2008). This connection is further supported by the *behavioural tagging theory*, which suggests that only a novel experience is likely to "tag" active synapses, preparing them for long-term memory formation (Moncada et al., 2015). Moreover, attention itself, activated by the perception of novelty, plays a vital role in encoding new memories. When attention is divided across multiple tasks, memory encoding declines (Craik et al., 1996). Interestingly, this impact of attention was not observed when examining its effect on memory recall. It appears that memory recall is more resistant to distractions than memory storage (Naveh-Benjamin et al., 2000). This aligns with previous models of memory consolidation, which emphasise that attention is essential for filtering information from sensory memory into working memory and, ultimately, for storing it in long-term memory (Atkinson & Shiffrin, 1968).

On a neurophysiological level, novelty-facilitated memory formation is linked to dopamine signalling, which enhances synaptic plasticity within the hippocampus. This is further supported by research showing that dopamine neurons react to novel stimuli and, when synchronised with cortical theta waves, are essential for memory formation (Kamiński et al., 2018; Lisman & Otmakhova, 2001). Moreover, dopamine is vital for synaptic plasticity in the striatum, where long-term potentiation can only occur in its presence (Reynolds & Wickens, 2002) (Figures 4 and 5). Additionally, *the penumbra hypothesis* proposes that the release of dopamine, which typically occurs in response to unexpected events, improves overall memory storage. This enhancement is therefore not limited to the specific stimulus that triggered the dopamine release (Lisman et al., 2011).

Overall, the positive effects of motivation, curiosity, and novelty on memory are closely interconnected and supported by both cognitive and neurobiological mechanisms. When learners encounter novel information, prediction errors elicit curiosity, directing attention to salient stimuli and promoting exploratory behaviour, while effort-reward evaluations activate motivational systems. This attentional engagement facilitates the selection of information into working memory and supports deeper cognitive processing, thereby strengthening long-term memory consolidation. Notably, novel information is more likely to be retained when learning involves active exploration, such as decision-making, questioning, or information seeking. This active engagement, closely linked to both motivation and curiosity, forms a reinforcing loop that supports deep learning over time and is underpinned by dopaminergic signalling, which enhances synaptic plasticity in the hippocampus. Figure 5 presents an integrative framework of motivation, curiosity, and novelty in active learning.

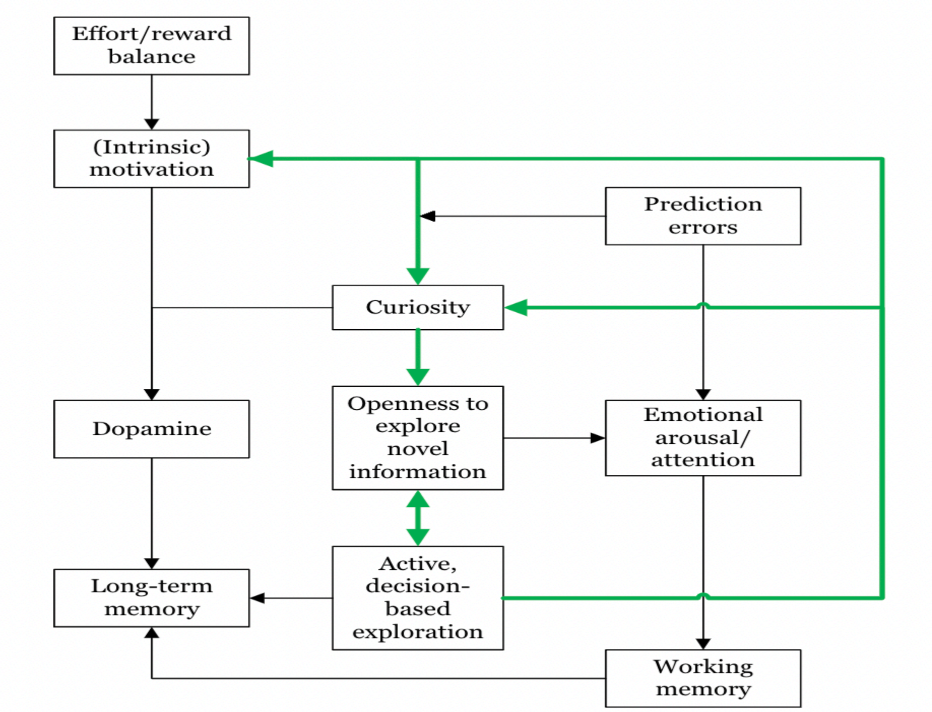


Figure 5: *Integrative framework of motivation, curiosity, and novelty in active learning*

Effort–reward evaluations activate motivational processes, which in turn foster curiosity and increase openness to novel information. Prediction errors play a dual role by capturing attention and triggering curiosity. Similarly, novel stimuli attract attention, facilitating the transfer of information into working memory and promoting long-term memory consolidation. The impact of novelty is further enhanced when it involves active exploration. Such active engagement not only improves memory retention but is also positively associated with both motivation and curiosity, creating a reinforcing loop, as illustrated by the green arrows. Both motivation and curiosity engage dopaminergic pathways, which enhance hippocampal plasticity and support the encoding of durable long-term memories. *This figure was created using Microsoft Visio.*

3. The Role of Self-Directed Learning in Enhancing Attentional Control and Metacognitive Monitoring

Self-directed learning is characterised by a behavioural component in which students take control of their study pace and concentration (Chi & Wylie, 2014; Markant et al., 2014). This approach emphasises the learner's active role in engaging with the material, rather than passively receiving information. As such, self-directed learning is considered a form of active learning (Devi et al., 2016; Markant et al., 2016). This section examines how self-directed learning aligns with the *constructive* mode of learning and how the decision-making processes involved are linked to neurobiological mechanisms that support memory formation.

4.1 Self-directed learning is linked to the constructive mode of learning

Self-directed learning involves two types of decision-making: lower-level and higher-level. Lower-level decisions relate to the timing and duration of each study session, with memory being affected by attention and motivation during those moments (Chun & Turk-Browne, 2007; Markant et al., 2014). In contrast, higher-level decisions involve selecting what to study to optimise learning (Metcalfe, 2002; Metcalfe & Finn, 2008). Research has shown that less familiar information is perceived as more difficult to retain (Bellana et al., 2021). Higher-level decisions about study strategies require learners to assess the difficulty of an item, which is directly tied to the constructivist view of mental structures. According to Piaget's theory, difficulty arises when new information does not fit within existing mental structures, requiring the learner to create or modify their cognitive framework (Piaget, 1971; Piaget & Inhelder, 1972). In this way, higher-level decision-making is linked to constructivism because it necessitates restructuring one's understanding (Piaget, 1971; Piaget & Inhelder, 1972). Thus, learners may opt to review easier material first to enhance retention of, or focus on, challenging information they find difficult to remember (Metcalfe, 2002; Metcalfe & Finn, 2008).

Self-directed learning has been shown to support memory by enabling the adaptive allocation of attention in response to task difficulty, for example, through lower-level decisions such as control over study time (Markant et al., 2014; Tullis & Benjamin, 2011). This finding reinforces the previously discussed positive impact of attentional control on memory. In Figure 6, the relationship between decision-making, self-directed learning, and memory is illustrated using the multistore model.

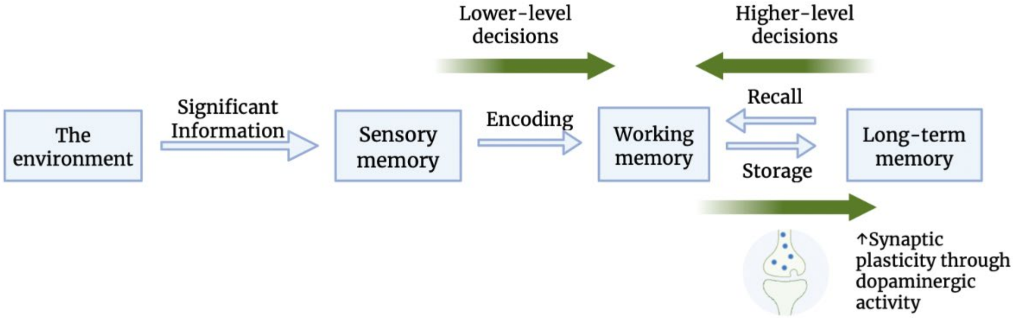


Figure 6: *Decision-making in self-directed learning and memory*

Decision-making is divided into two types: lower-level decisions, which enhance attentional control and facilitate the encoding of information into working memory, and higher-level decisions, which involve metacognitive monitoring and support the retrieval of stored information to assess one's understanding. When new information is perceived as both manageable and engaging, it stimulates curiosity, promoting synaptic plasticity via dopaminergic activity. Green arrows depict the influence of active learning components, while blue arrows represent the structure of the multi-store memory model. *This figure was created using BioRender.*

4.2 Higher-level decisions parallel the effort-reward balance

As mentioned above, the higher-level decisions in self-directed learning are connected to the constructive nature of active learning (Chi & Wylie, 2014; Piaget, 1971). Making these types of decisions requires assessing one's learning progress or current level of understanding, a process known as metacognitive monitoring (Markant et al., 2016). Engaging in metacognitive monitoring can enhance memory, especially when those decisions involve retrieving information from memory (Markant et al., 2016) (Figure 6). However, to make an effective decision, an individual must not only accurately assess their prior knowledge on a given topic but also know how to translate those assessments into study strategies that will yield the greatest learning. In other words, the effort invested in studying must be justified by the potential reward, similar to how the brain balances effort and reward through dopaminergic and noradrenergic activity (Metcalfe, 2009) (Figure 4).

The region-of-proximal-learning framework outlines how metacognitive decisions can be made, suggesting a negative correlation between judgments of prior knowledge and the amount of time spent studying (Metcalfe, 2009). The process begins with the elimination of items deemed already mastered, which leads to reduced study time for those tasks. For moderately difficult tasks, study continues as long as progress is evident. According to the framework, studying halts when no further progress is perceived. Therefore, extremely difficult tasks may lead to cessation if improvement is not felt (Metcalfe, 2009). This is consistent with the effort-reward balance and the previously mentioned PACE framework, which suggests that novel information can trigger anxiety when it is associated with stress and excessive effort, or curiosity when it is perceived as manageable and engaging (Gruber & Ranganath, 2019).

Consequently, the equilibrium between the effort required and the potential reward of a task prior to decision-making integrates the brain's reward system and its capacity to detect novel information through prediction errors (Figures 4 and 5). This notion is further substantiated by the research conducted by Murty et al. (2015), which identified that regions such as the orbital frontal cortex and ventral tegmental area, responsible for evaluating choices, were active during decision-making (Murty et al., 2015). The association between the brain regions implicated in decision-making and those linked to memory, particularly the hippocampal areas, was more pronounced in participants who demonstrated superior recall of the material (Murty et al., 2015). This suggests that even in the absence of a direct reward, the act of making decisions stimulates the brain's reward system and enhances memory (Dubinsky & Hamid, 2024b; Murty et al., 2015) (Figure 6).

In summary, active learning emphasises self-directed behaviour and control over the learning process. Within this framework, the integration of both lower- and higher-level decisions enhances memory by respectively facilitating effective attention coordination and metacognitive monitoring. Attention is critical for memory encoding, a process regulated in part by the brain’s dopaminergic pathways. Furthermore, metacognitive monitoring reinforces learning by activating the brain’s reward system, particularly when decisions are in alignment with an individual's perceived balance between effort and reward. Therefore, self-directed learning amalgamates the beneficial effects of attentional control and decision-making to enhance memory.

4. The Interactive Mode of Active Learning

The social aspect of learning is reflected in the interactive mode of behavioural engagement within the ICAP framework. This section explores interactive learning through collaborative methods, first outlining its cognitive foundations with an emphasis on working memory capacity. It then links social interaction to the neurobiological mechanisms involved in motivation, reward processing, and long-term memory formation.

5.1 Collaborative learning and working memory capacity

For interactive learning to take place, collaboration between students is required. Collaborative learning involves students working as a team to reach a common objective (Du et al., 2022). It emphasises interaction between students and the joint construction of knowledge (Wu, 2023).

Meta-analyses on the benefits of collaborative learning compared to individual learning generally indicate a positive impact on academic achievement (Chen et al., 2018; Kyndt et al., 2013; Rohrbeck et al., 2003; Roseth et al., 2008). However, these benefits are not uniformly demonstrated across all studies, as methodological differences can result in varying findings, with some studies reporting stronger effects than others (Clinton & Kohlmeyer, 2005; Krause et al., 2009; Ramdani et al., 2022; Retnowati et al., 2018). An explanation for these inconclusive results can be found in empirical evidence on the essential components of collaborative learning, suggesting that this type of learning is only effective under certain circumstances (Johnson et al., 1994; Johnson & Johnson, 1999).

For example, collaborative learning is influenced by processes related to metacognition, emotions, and motivation (Haataja et al., 2022; Lobczowski, 2020; Molenaar et al., 2014; Rogat et al., n.d.). In successful collaborative settings, students are engaged in metacognitive interaction, which is defined as a focus on not only their own thought processes but also on those of their peers (Haataja et al., 2022). Engaging in this kind of interaction demands both motivation and effort, but it also offers significant learning advantages (Haataja et al., 2022). From the standpoint of cognitive processing, such metacognitive exchanges help students keep track of their understanding and recognise any errors or gaps in their knowledge (Haataja et al., 2022; Webb, n.d.). This realisation can trigger curiosity and prompt them to actively seek out novel information to improve their understanding (Webb, n.d.). As a result, these interactions can lead to more in-depth reasoning and engagement with others' ideas (De Backer et al., 2017; Järvelä et al., 2021; Teasley, 1997), support the co-construction of knowledge (Hmelo-Silver, 2003; Roschelle & Teasley, 1995), and ultimately enhance memory and learning outcomes (Schnaubert & Bodemer, 2018).

In addition, the cognitive load theory provides a theoretical basis for understanding how collaborative learning further enhances memory. According to cognitive load theory, while long-term memory is essentially limitless, working memory is both limited in capacity and duration (Miller, 1956; Peterson & Peterson, 1959; Sweller, 2011). As a result, working memory is particularly susceptible to cognitive load, which arises when processing new information. If this load exceeds its limits, cognitive overload can occur, hindering learning (Miller, 1956; Peterson & Peterson, 1959; Sweller, 2010, 2011). Building on this framework, the collaborative cognitive load theory proposes that in group settings, cognitive load can be distributed across multiple learners, allowing collaborative groups to function as collective information-processing systems with a shared working memory (Kirschner et al., 2009, 2018). This collective working memory offers greater processing capacity than that of an individual learner, thereby reducing the risk of cognitive overload and explaining the potential advantage of collaborative learning (Kirschner et al., 2009, 2018).Based on this premise, researchers suggest that differences in individual working memory capacity could affect the effectiveness of collaborative learning, potentially impacting group performance (Du et al., 2022). In Figure 7, an integrative framework on the effect of collaborative learning on long-term memory is shown.

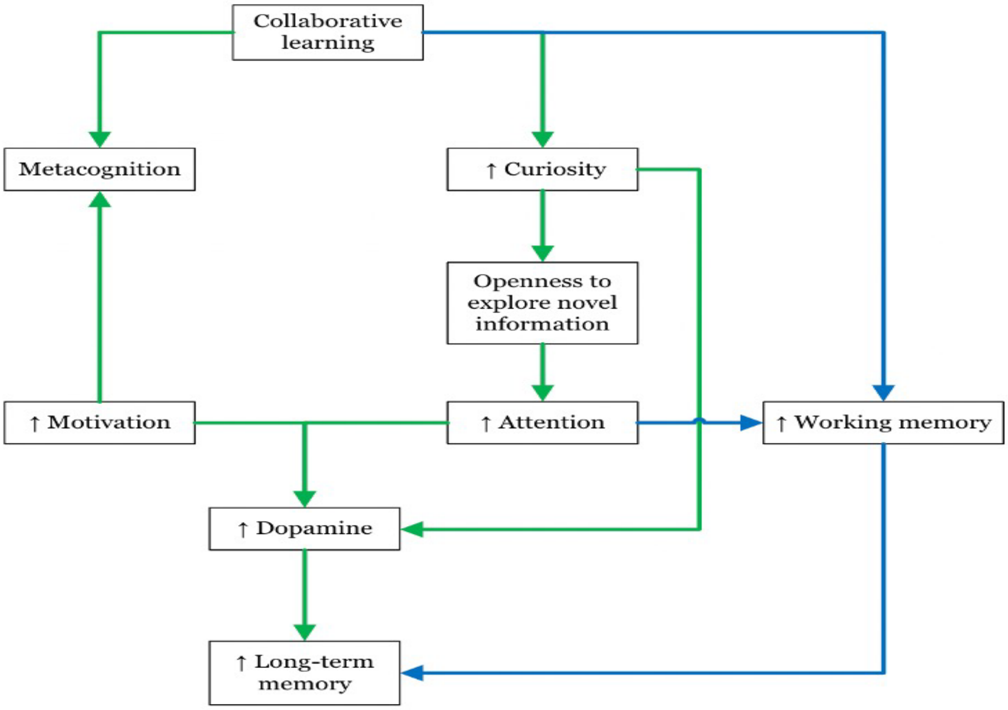


***Figure 7:** The effect of collaborative learning on long-term memory*

The positive effect of collaborative learning on long-term memory can be explained through two interrelated tracks (green and blue). First, collaborative learning sparks both curiosity and metacognitive interaction (the green track). Curiosity enhances receptiveness to novel information and sharpens attention. Both curiosity and attention are tied to the brain's reward system, leading to dopaminergic stimulation and synaptic plasticity. Metacognition, in turn, relies on motivation, which also activates the reward system, further supporting memory formation. The second, blue track follows the logic of collaborative cognitive load theory: by distributing cognitive demands among learners, working memory capacity is expanded. Within this shared space, attention filters out irrelevant input, allowing only meaningful, novel information into working memory. As described in the Atkinson-Shiffrin model, this information can then be transferred into long-term memory. *This figure was created using Microsoft Visio.*

5.2 Social interaction from a neurobiological perspective

From a neurobiological perspective, collaborative interactions among peers activate the brain's dopamine reward system, generating a sense of satisfaction and fulfilment in those engaged in the exchange (Krill & Platek, 2012; Pfeiffer et al., 2014; Redcay et al., 2010; Sakaiya et al., 2013). Furthermore, research in social neuroscience indicates that individuals experience intrinsic rewards when they actively participate in shaping social interactions (Fiske & Dépret, 1996; Schilbach et al., 2013). A social interaction typically involves an initiator, who acts, and a responder, who reacts to the initiator's actions (Schilbach et al., 2013). The initiator, possessing a greater degree of control over the exchange, experiences an increased release of dopamine, which subsequently enhances feelings of confidence and self-worth (Clark & Dumas, 2015). Within a learning environment, students may prefer to assume a leading role in interactions, as this can provide them with a sense of importance, well-being, and increased self-confidence (Clark & Dumas, 2015) (Figure 7). The equilibrium of participation in an interaction depends on the exchange of turns and the continuous flow of mutual feedback. Ideally, each individual should have the opportunity to feel valued and experience a sense of control during the interaction (Clark & Dumas, 2015).

Moreover, even fundamental social interactions, such as maintaining eye contact, are crucial for learning and memory (Pfeiffer et al., 2014). From an evolutionary perspective, gaze plays a pivotal role in directing attention to significant information while also serving a social function that facilitates communication between individuals (Wu et al., 2014). The ventral striatum and the broader reward system are activated when individuals engage in mutual focus of attention (Pfeiffer et al., 2014). This neural activity is further intensified when individuals actively initiate joint attention, a process that is also associated with the engagement of the ventromedial prefrontal cortex (Redcay & Schilbach, 2019; Schilbach et al., 2010). The findings of Kopp & Lindenberger (2011) lend additional support to this notion, demonstrating that joint attention enhances long-term memory in 9-month-old infants. The formation of enduring memory traces is contingent upon the relevance and salience of the information, as indicated by measurements of brain activity (Kopp & Lindenberger, 2011). Consequently, joint attention enhances long-term memory by assisting in the filtering of relevant information and stimulating the brain's dopamine reward system through social engagement. These findings bolster the PACE framework, which posits that prediction errors trigger dopamine-driven curiosity, leading to heightened attentional focus and, ultimately, enhanced long-term memory (Figure 5).

In summary, collaborative learning mitigates cognitive overload by increasing the combined working memory capacity, thus enabling learners to pool their cognitive resources. Moreover, it enhances the formation of long-term memory by fostering factors such as novelty, curiosity, motivation, and metacognition. From a neurobiological standpoint, social collaboration activates the brain's dopamine reward system, which engenders feelings of satisfaction. Even simple social behaviours, such as making eye contact, positively influence this reward system. The stimulation of the brain’s reward pathways promotes memory formation through dopamine-driven synaptic plasticity, resulting in improved long-term memory (Figure 7).

5. Discussion

The ICAP hypothesis offers a widely used behavioural framework for categorising learning engagement, while cognitive psychology and neurobiology provide mechanistic accounts of memory processes that support learning. This review brings these perspectives together by using the ICAP *active–constructive–interactive* hierarchy as an organising framework to link engagement modes to declarative memory mechanisms.

The discussion synthesises the main interdisciplinary findings, addresses key limitations, and considers the practical implications for learning and instruction.

6.1 Summary of main findings

Active learning, as defined by the ICAP framework, is consistently more effective than passive learning. Core drivers of learning include curiosity, motivation, and novelty. Curiosity and motivation activate dopaminergic pathways in the brain, enhancing receptivity to novel information. This effect is especially strong when the effort required for learning aligns with the predicted reward, stimulating the dopaminergic reward system. Activation of this reward system supports synaptic plasticity in the hippocampus and striatum, both of which are involved in long-term memory retention. In turn, novel information enhances attention, helping information reach working memory more efficiently. Additionally, when novelty is combined with active exploration, it further strengthens long-term memory.

The *constructive* mode of active learning promotes curiosity, motivation, and novelty, while also strengthening metacognitive monitoring. This involves actively revisiting and evaluating prior knowledge to determine whether current understanding is sufficient to move forward. Making these judgments independently activates the brain's reward system, which stimulates dopaminergic activity and, in turn, supports synaptic plasticity. Importantly, dopaminergic and noradrenergic modulation do not increase the structural capacity of working memory. Rather, these neuromodulators enhance attentional control and prioritisation of task-relevant information, thereby optimising the efficiency with which limited working memory resources are allocated. Metacognitive monitoring further supports this process by guiding attention toward information that is most relevant for learning within existing capacity constraints.

The *interactive* mode goes a step further, incorporating curiosity, motivation, novelty, and metacognition while adding the positive effect of social interaction. The positive impact of social interaction and collaborative learning on long-term memory can be explained through two interconnected processes. First, collaborative learning stimulates both curiosity and metacognitive engagement. Curiosity increases openness to new information and heightens attentional focus. Both processes are closely linked to the brain's reward system, promoting dopaminergic activity and synaptic plasticity. Metacognitive engagement enhances individual metacognitive monitoring and motivation, thereby further supporting memory formation. The second mechanism follows the principles of collaborative cognitive load theory: by distributing cognitive demands across learners, the capacity of working memory is expanded. In this shared cognitive space, attention more effectively filters out irrelevant information, allowing only meaningful, novel input to enter individual working memory. This information can then be successfully transferred into long-term memory.

6.2 An interdisciplinary viewpoint

The interdisciplinary perspective presented in this paper reveals that active learning enhances long-term memory not merely through increased behavioural engagement, but by aligning curiosity, effort–reward appraisal, and social interaction to engage dopamine-driven neuronal plasticity.

From an educational perspective, active learning is valued for its ability to foster curiosity and intrinsic motivation, both of which support durable learning. Cognitive psychology refines this view by showing that learners' engagement depends on a cost–benefit analysis in which novel information can elicit either curiosity or anxiety, depending on the perceived balance between cognitive effort and expected reward. Neurobiological research builds on these insights by identifying the underlying mechanisms of this appraisal process, including the involvement of the dopaminergic system, the ventral tegmental area, and the hippocampus. When curiosity and motivation are triggered, dopamine release promotes synaptic plasticity in the hippocampus and striatum, thereby strengthening long-term memory. Integrating these findings, ICAP engagement modes can be interpreted as graded modulations of a shared neurocognitive cascade: increasing levels of learner choice and novelty amplify effort–reward appraisal, biasing the system towards curiosity and motivation rather than anxiety. This, in turn, enhances dopaminergic activation, hippocampal and striatal plasticity, and ultimately long-term memory formation. Each ICAP mode can be understood in terms of how strongly and reliably it engages this shared neurocognitive cascade, as shown in Figure 8.

The *active mode* facilitates entry into this cascade primarily by increasing exposure to novelty through task-related action, thereby promoting curiosity-driven engagement and motivation, which leads to hippocampal and striatal plasticity. The *constructive mode* amplifies the neurocognitive cascade through the coordinated engagement of attentional control and metacognitive monitoring. Metacognitive monitoring guides learner choices by refining effort–reward evaluation and directing when and how to engage with a task. This process promotes the integration of new information with prior knowledge via active retrieval and evaluation in working memory. Attentional control complements this by allocating cognitive resources to task-relevant information while selectively filtering novel inputs into the cascade. Together, these processes deepen processing and strengthen long-term memory formation.

The superiority of the *interactive mode* stems from the simultaneous engagement of three mutually reinforcing mechanisms. First, shared cognitive processing reduces individual cognitive load, resulting in a more favourable effort–reward appraisal. Second, social interaction provides an additional source of dopaminergic reward, enhancing motivation and task engagement. Third, metacognitive co-regulation through dialogue and feedback supports sustained monitoring and adjustment of learning strategies. Together, these mechanisms reduce the likelihood of disengagement associated with an unfavourable dopamine–noradrenaline balance and promote more robust and stable memory consolidation through enhanced synaptic plasticity.

More broadly, this synthesis motivates a general principle for active learning: the efficacy of an instructional intervention depends on its ability to reliably initiate and sustain this predictable neurocognitive cascade, thereby supporting durable memory consolidation.

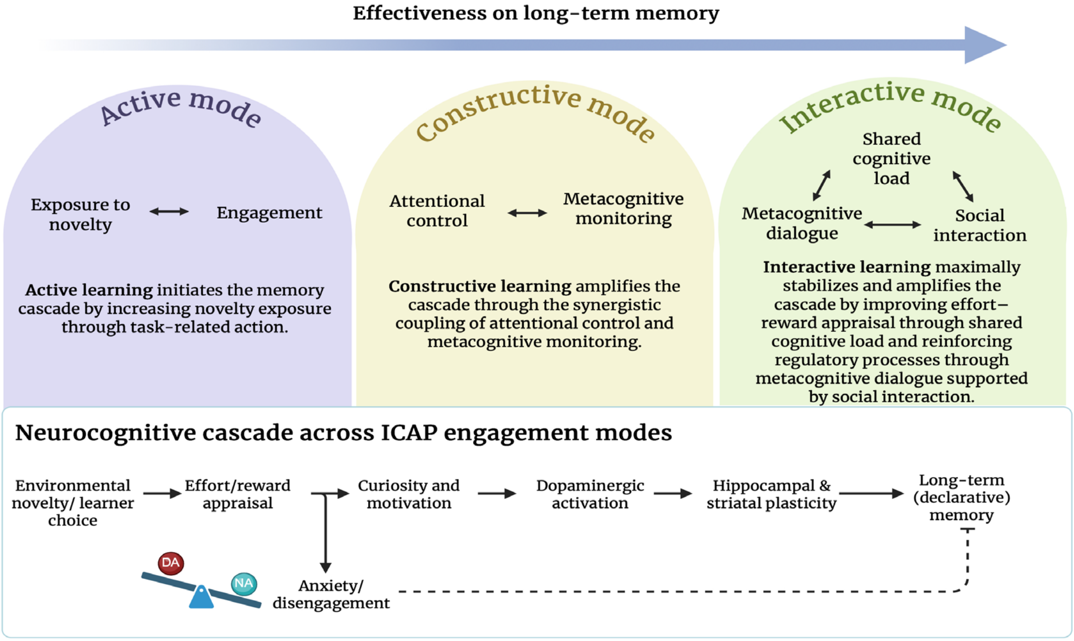


Figure 8: *A synergistic neurocognitive model of ICAP engagement modes*

ICAP engagement modes modulate a shared neurocognitive cascade that links environmental novelty and learner choice to effort–reward appraisal, curiosity, dopaminergic activation, hippocampal and striatal plasticity, and long-term declarative memory. Effort–reward appraisal gates this cascade by determining whether novelty elicits curiosity or anxiety, with effective learning requiring an optimal dopamine–noradrenaline balance. Active learning facilitates entry into the cascade by increasing exposure to novelty through task-related actions. Constructive learning amplifies the cascade through the synergistic interaction of attentional control and metacognitive monitoring, supporting effective regulation and integration of new information with prior knowledge. Interactive learning produces the strongest memory effects by reducing individual cognitive demands through shared cognitive load, thereby improving effort–reward appraisal, while metacognitive dialogue and social reward further stabilise dopaminergic modulation and memory consolidation. *NA = noradrenaline; DA = dopamine. This figure was created using BioRender.*

6.3 Limitations

This review is subject to several limitations that should be considered when interpreting the findings. First, the concept of memory is defined and applied differently across the disciplines included in this review. Educational literature often approaches memory as a broad construct, frequently without distinguishing between specific subtypes such as declarative and non-declarative memory. In contrast, fields such as neurobiology and cognitive psychology adopt more nuanced classifications, with particular emphasis on declarative memory in the educational context. Incorporating such distinctions into educational research could yield more precise insights and help prevent significant findings from being obscured by a general definition.

A second, related limitation is that the review encompasses studies from various disciplines that utilise different methodologies for measuring memory. For instance, educational science often evaluates memory through learning outcomes or performance on memory tasks. Neurobiology, by contrast, frequently employs methods such as fMRI or electrophysiological recordings to examine underlying neural activity associated with memory processes. Cognitive psychology typically investigates memory through experimental paradigms, focusing on recall, recognition, or reaction time tasks to assess specific cognitive mechanisms. While this disciplinary diversity enriches the overall perspective, it also complicates direct comparisons and limits the ability to draw unified conclusions across fields.

Third, the literature search did not concentrate on a specific educational context. Consequently, the included studies span diverse domains, age groups, and instructional settings. This heterogeneity limits the direct applicability of the findings to particular educational scenarios or learner populations and complicates the translation to specific classroom practices.

Lastly, the review primarily focuses on (long-term) memory and does not explicitly address the relationship between memory processes and academic performance. While improvements in long-term memory are pertinent to learning, research on working memory training suggests that the transfer of enhanced memory processes to broad academic achievement is complex and not guaranteed, highlighting a critical area for future translational research (Redick et al., 2015).

6.4 Practical implications

The following section translates the interdisciplinary framework developed in this review into practical implications for educational design, focusing on effort–reward appraisal, working memory capacity, collaborative learning, and metacognitive support.

6.4.1 Translating effort–reward appraisal into instructional design

Effort–reward appraisal operates as the gating mechanism of the neurocognitive cascade underlying active learning. The appraisal of the effort–reward balance determines whether novel information elicits curiosity, associated with dopaminergic engagement, or anxiety, associated with amygdala activation. When novelty is appraised as disproportionately effortful, prediction errors are more likely to bias processing toward anxiety rather than curiosity, disrupting engagement and learning, as described by the PACE framework (Gruber & Ranganath, 2019). Accordingly, instructional challenges should be structured to emphasise attainability and sustained progress. In practice, this can be achieved by clearly specifying learning goals, embedding early success experiences, and making incremental improvements salient.

When novelty is evaluated in a curiosity-biased manner, and engagement is initiated, motivational factors modulate the persistence and intensity of that engagement. Sustained engagement during task execution relies on continued dopaminergic signalling, with intrinsic and extrinsic motivation engaging partially distinct neural processes. Internally generated rewards are associated with heightened prefrontal cortex activation and subsequent reward-related processing, whereas external rewards elicit earlier activation prior to task responses (Chew et al., 2021; Duan et al., 2020). In instances of low intrinsic motivation, modest extrinsic incentives can bolster initial engagement by sustaining reward-related activity. Conversely, when intrinsic motivation is high, extrinsic rewards should be calibrated to serve as informational feedback delivered after task engagement, thereby reinforcing prefrontal cortex-mediated internal reward processes (Duan et al., 2020). Practically, this can be actualised through timely post-task feedback and recognition of progress, signalling successful learning and effort without undermining intrinsic motivation.

As engagement is maintained over time, learning is constrained by limitations in working memory capacity. When cognitive demands exceed available working memory resources, learners may lose their sense of progress, resulting in a breakdown of learning, even in the presence of initial motivation. Sustained learning depends on maintaining a perception of progress within the learner's zone of proximal development (Metcalfe, 2009). When task demands surpass cognitive capacity and effort is no longer perceived as commensurate with reward, disengagement becomes more probable due to an unfavourable dopamine–noradrenaline balance. Therefore, complex material should be segmented into manageable units, supported by structured checkpoints and opportunities to externalise intermediate steps, to preserve progress and mitigate cognitive overload.

Finally, maintaining effective learning across extended tasks requires accurate self-regulation, supported by metacognitive monitoring skills. Metacognitive monitoring guides learners' decisions by refining effort–reward evaluation and regulating task engagement, thereby supporting the neurocognitive cascade underlying long-term memory formation. However, learners often rely on familiarity rather than retrieval success when judging their understanding, leading to systematic overestimation and ineffective regulation of study behaviour (Rawson & Dunlosky, 2007). Educators should therefore design learning activities that explicitly require retrieval-based monitoring, such as formative self-testing, prediction prompts, or explanation tasks, to provide learners with reliable feedback about their state of knowledge and support effective regulation of effort and pacing.

6.4.2 Interactive learning in practice: Social reward and shared cognitive load

Collaborative learning constitutes a distinct practical implication of the interactive mode of active learning because it engages neurocognitive mechanisms that are not activated in individual learning contexts. If neurobiological evidence shows that the initiation of social interaction activates reward-related circuitry, particularly the ventral striatum, then collaborative learning environments should be structured to ensure that all learners actively initiate interactions rather than merely respond. Rotating initiator roles, such as posing questions, proposing solutions, or leading discussions, ensures that intrinsic reward signals associated with social engagement are distributed across group members, thereby enhancing motivation and sustained engagement.

Collaborative learning can also help reduce cognitive load by distributing it across group members. When responsibilities and tasks are shared among group members, learners can engage with more complex content than would be possible individually, resulting in a more favourable effort–reward appraisal and sustained engagement with the task. Educators should therefore design collaborative learning activities that scaffold effective interdependence, for example, by structuring shared goals, assigning complementary roles, and embedding opportunities for face-to-face promotive interaction (Johnson & Johnson, 1999). Teachers can support these conditions by monitoring group dynamics, encouraging equitable participation, and fostering a sense of mutual responsibility, ensuring that collaboration functions as a cognitive and motivational resource rather than a source of extraneous cognitive load.

6.5 Future research directions

An important avenue for future research is to assess whether ICAP engagement modes correspond to graded engagement of a shared neurocognitive cascade. fMRI studies employing matched learning tasks implemented in *active, constructive,* and *interactive* formats could investigate systematic differences in the recruitment of reward-related, control-related, and memory-related brain networks. Based on the present synthesis, interactive tasks are anticipated to elicit stronger or more sustained activation in dopaminergic regions, such as the ventral striatum and ventral tegmental area, alongside increased engagement of prefrontal and hippocampal networks.

Complementary approaches could explore the neurochemical and cognitive mechanisms underlying these effects. Dopamine-related reward and control processes during collaborative versus individual problem-solving could be examined using electrophysiological markers, such as midfrontal theta activity, which has been associated with novelty processing and dopamine-modulated control signals (Kamiński et al., 2018; Lisman & Otmakhova, 2001). Concurrently, experimental manipulations of task complexity and cognitive interdependence could evaluate how collaborative cognitive load distribution influences effort–reward appraisal and disengagement.

Finally, future research should investigate whether increasing levels of active, constructive, or interactive engagement are linked to sustained activation or increased firing frequency in reward-related neural circuits during task execution. Integrating behavioural measures with neural and biochemical indicators would provide a direct test of the neurocognitive cascade proposed in this review.

6. Integrative Conclusion

From an interdisciplinary perspective, active learning enhances memory not only by increasing behavioural engagement but also by aligning curiosity, effort–reward appraisal, and social interaction to recruit dopaminergic plasticity mechanisms. ICAP engagement modes can thus be understood as graded modulations of a shared neurocognitive cascade, whereby increasing levels of learner choice, novelty, and interaction bias effort–reward appraisal towards curiosity and motivation rather than anxiety, thereby strengthening hippocampal and striatal plasticity and long-term memory formation. Within this framework, the active mode initiates entry into the cascade, the constructive mode stabilises learning through metacognitive monitoring and attentional control, and the interactive mode further amplifies memory by integrating social reward with coordinated regulation of cognitive demands. Collectively, these distinctions highlight how instructional design can support durable learning by structuring tasks that maintain a favourable effort–reward balance, support metacognitive regulation, and leverage collaborative interaction without exceeding cognitive limits. Supported by evidence from educational, cognitive, and neurobiological research, these practices provide a robust framework for translating the principles of active learning into practical educational applications that promote deeper and longer-lasting learning outcomes.

7. Declarations

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