Cognitive Neuroscience of Attention and Memory Dynamics

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Article summary

The ability to maintain focus and remember information varies drastically from one moment to the next. Variability in attentional and mnemonic processes is driven both by external factors and also by internal neural states. While a growing body of work in cognitive neuroscience characterizes such fluctuations, many studies do not consider these dynamics. Behavioral and neural measures that track ongoing attention and memory fluctuations and predict upcoming failures demonstrate that these processes vary across multiple time scales—at times in tandem while at other times out of sync. Patterns of synchronous fluctuations reveal that sustained attention fluctuations, in particular, impact working memory capacity—but not precision—as well as long-term memory encoding and retrieval success. Beyond measuring attentional and memory processes over time, perturbing them through closed-loop feedback can reveal insights about these processes individually as well as interactions between them.

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1. Introduction

Attention and memory support nearly every aspect of daily life, from cooking breakfast to commuting to work to relaxing with a book. We remember, for example, the ingredients in a recipe, the quickest route, and the key characters. We engage attention to monitor the pot on the stove, avoid hazards on the road, and notice central events in the story. These mental processes, which shape how we experience and navigate the world, have become two of the most studied topics in cognitive neuroscience. Despite the proliferation of attention and memory research, however, the importance of their dynamics has been underappreciated. That is, we do not attend, encode, and retrieve equally well over time. Rather, our degree of focus and likelihood of storing, maintaining, and retrieving a memory varies from one moment to the next. We argue that not only does characterizing these moment-to-moment fluctuations reveal valuable insights about attention, memory, and their interactions, but that it is inadequate to understand attention and memory without also considering how they vary over time.

Accumulating evidence suggests that attention and memory processes fluctuate in tandem (**Figure 1**). These synchronous dynamics are evident in daily life. While reading a book, for example, attention lapses can interfere with our ability to remember details from a paragraph read just moments ago. On the flip side, recalling a significant argument between two characters may drive attentional engagement when they meet again. Indeed, attention covaries with working memory (deBettencourt et al., 2019), long-term memory encoding (deBettencourt et al., 2018), and long-term memory retrieval (Madore & Wagner, 2022). Characterizing the synchrony between attention and memory dynamics can thus reveal crucial links between these processes.

At the same time, there are also aspects of attention and memory that vary out of sync. While attentional fluctuations substantially impact which items are later recognized (deBettencourt et al., 2018), they appear to be distinct from item memorability (Roberts & Pruin et al., 2025; Wakeland-Hart et al., 2022). Moreover, attention consists of multiple subcomponents, including sustained attention and selective attention, which may interact differentially with memory (Corriveau, Chao et al. 2025; Corriveau et al., 2024; deBettencourt et al., 2021; Mirjalili & Duarte 2025). Further, while attention performance progressively declines over long periods of watch (Mackworth et al., 1948), working memory capacity does not show comparable monotonic decrements over time (Adam et al., 2015; Hakim et al., 2020). As in these examples, identifying moments when attention and memory dynamics decouple can clarify the nature of their relationships.

The interactions between attention and memory are complex and multidirectional. Neither attention nor memory is a unitary construct and their constituent processes may interact in different ways at different times. Fluctuations in one attentional process may influence one type of memory but not another. Memory may guide attention in one situation but not another. Attention may impact memory encoding and retrieval which in turn may affect how attention is deployed in the future. One means of better untangling this web of interactions is identifying when attention and memory dynamics are shared and when they diverge. Moreover, monitoring dynamics in real time presents powerful opportunities for neuroadaptive designs, including closed-loop neurofeedback and real-time triggering, that can reveal causal associations by tracing and manipulating attention and memory. A fuller characterization of dynamics informs our understanding of attention and memory individually as well as when and how they interact in the human mind and brain.

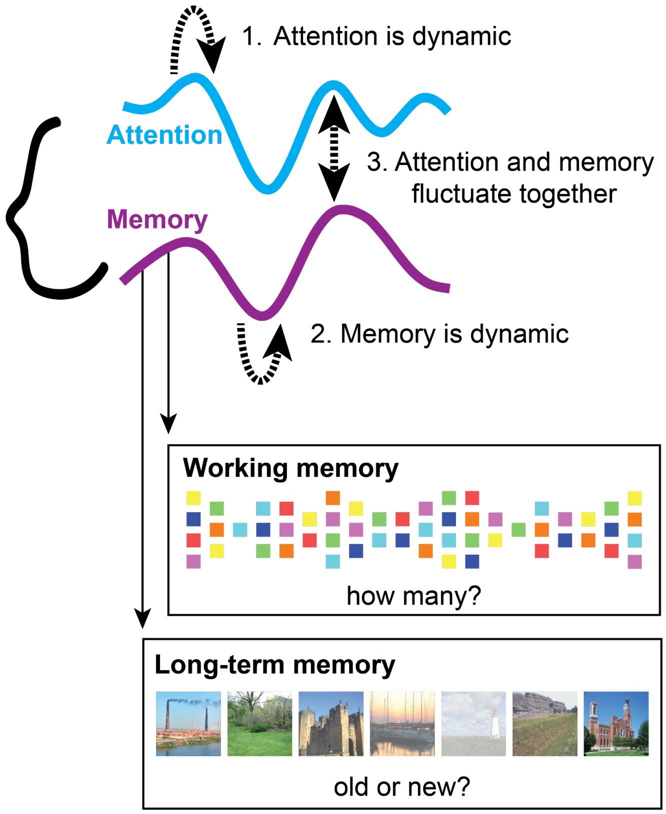

Figure 1. Attention and memory each dynamically fluctuate over time. Measuring these processes concurrently reveals that these fluctuations often occur in tandem, demonstrating profound links between sustained attention and memory, both working memory (how many items held in mind) and long-term memory (whether an item is recognized as old or new). Understanding when and which aspects of attention and memory share dynamics inform our mechanistic understanding of each of these processes as well as how they interact. A complete understanding of attention and memory processes requires studying how they evolve and co-evolve over time.

2. Moment-to-moment fluctuations of attention

Attention waxes and wanes from one moment to the next. We can be engaged one moment and disengaged the next. These moment-by-moment variations in attentional state may be driven by top-down or bottom-up factors or an interaction between the two. Even moments of better attention are multifaceted—the focus of attention can shift between external and internal states, guided by top-down goals or captured by salient information. The dynamic nature of attention may be most apparent in studies of sustained attention, which investigate how we maintain focus over time (Esterman & Rothlein, 2019; Fortenbaugh et al., 2017). In this section, we leverage sustained attention as a case study for a broader understanding of attentional dynamics.

In sustained attention paradigms, participants are typically presented with a steady stream of stimuli. They are asked to detect rare targets (i.e., oddballs) that occasionally but infrequently occur during the stimulus stream. A key finding is that attention often lapses, as indexed by moments when participants fail to detect a rare stimulus. Continuous performance tasks (CPTs) provide a temporally rich readout of behavioral responses, including accuracy and response times (RTs). Notably, performance declines on sustained attention tasks over extended periods of time, an effect known as the vigilance decrement (Mackworth, 1948). Atop slow vigilance decrements, behavioral indices of attentional state (e.g., accuracy, RT speed, RT variability) also reveal how attention dynamically fluctuates over shorter timescales, ranging from seconds to tens-of-seconds (Castellanos et al., 2005; Rosenberg et al., 2025; Terashima et al., 2021). These behavioral indicators—including fast (Corriveau, Chao et al., 2025; deBettencourt et al., 2018) and erratic (Esterman et al., 2013; Rosenberg et al., 2013) responding—predict when attention failures are most likely to occur. Although in many tasks fast RTs indicate engaged focus, in CPTs, speeding is a hallmark of automated, mindless responding. Erratic RTs likewise indicate suboptimal focus, potentially reflecting effortful performance more reliant on top-down control (Chidharom et al. 2025).

While response speed and variability forecast upcoming attention failures in CPTs, neurophysiological measures offer opportunities to examine brain activity that precedes and predicts lapses in a wider variety of tasks and contexts. In particular, cognitive neuroscience techniques with high temporal resolution, such as electroencephalography (EEG), can measure the oscillatory brain dynamics before lapses. Scalp EEG studies, for example, observe increases in alpha power (approximately 8-12 Hz) and decreases in theta power (approximately 4-7 Hz) before attentional lapses (Clayton et al., 2015; Mazaheri et al., 2009; O'Connell et al., 2009). This is consistent with observations that alpha power decreases prior to successful visual perception (Ergenoglu et al., 2004; Hanslmayer et al., 2007; van Dijk et al., 2008) and theta power increases to support cognitive control (Cavanagh & Frank, 2014). Studies measuring intracranial EEG can access activity in higher frequencies as well as in specific functional networks, revealing high frequency broadband (70-170 Hz) activity differences in the default mode network (DMN) and dorsal attention network (DAN) before attention lapses (Kucyi et al., 2020). Although functional magnetic resonance imaging (fMRI) has a much lower temporal resolution, comparisons of fMRI activity before lapses vs. correct responses have revealed reduced stimulus-specific activity and increased DMN, frontal, and parietal activity before lapses (Weissman et al., 2006). Finally, attention lapses are preceded by smaller pupils and linked to specific neuromodulatory states related to norepinephrine and locus coeruleus function (Unsworth & Robison, 2016a). As such, behavioral and neurophysiological tools provide complementary insight into when a lapse is likely to occur.

Momentary lapses occur in the context of slower-fluctuating sustained attentional states (Rosenberg et al., 2025). These states—often discretized into "in-the-zone" states of stable, successful responding and “out-of-the-zone” states of erratic, error-prone performance (Esterman et al., 2013; 2014b; Rosenberg et al., 2013)—are characterized by univariate and multivariate differences in brain activity (deBettencourt et al., 2015; Esterman et al., 2013; Rosenberg et al., 2015). That is, although sustained attention task performance overall engages canonical attention regions, including the prefrontal and parietal cortices as well as subcortical structures (Corbetta & Schulman, 2002; Langer & Eickoff, 2013), the relative contribution of different brain regions and networks varies within in-the-zone and out-of-the-zone states.

Repeated evidence demonstrates that in-the-zone attentional states are characterized by increased DMN and decreased DAN activity (Esterman et al., 2013; Fortenbaugh et al., 2018; Kucyi et al., 2016; 2017) and co-fluctuation (a time point-by-time point measure of two regions' covarying activity; Jones et al., 2024). These attentional states also map onto DMN- and DAN-dominated brain states (patterns of activation and coactivation that cluster together in a low-dimensional neural representational space), respectively (Song et al., 2023; Yamashita et al., 2021). Although counterintuitive at first glance given the popular but simplistic conception of the DMN as a “mind wandering” or “off-task” network, increases in DMN activity are thought to reflect more automatic, practiced processing during in-the-zone states. In contrast, increased DAN activity in *worse* attentional states may reflect increased reliance on attentional control during these moments. First, during better attentional performance, these networks are more anticorrelated (Kucyi et al., 2020; Seeburger et al., 2024). Second, interactions between brain regions and networks beyond the DMN and DAN reflect evolving attentional states (Song & Rosenberg 2021). Data-driven analytic approaches have revealed, for example, large-scale functional networks whose dynamics predict attentional state changes during more artificial laboratory-based tasks (Jones et al., 2024; Kardan et al., 2022; Rosenberg et al., 2020) and more naturalistic scenarios such as watching movies (Song et al., 2021; Zuberer et al., 2021). Finally, information processing differs between in-the-zone and out-of-the-zone states. The fidelity of neural representations increases under better attentional states (Jackson et al., 2017; Rothlein et al., 2018). Heightened sustained attention is likewise accompanied by greater evidence of distractor processing, suggesting that, in these periods, successful performance is possible without actively filtering task-irrelevant information (Esterman et al., 2014b). Taken together, this evidence suggests that shifting attentional states are reflected in the activity and functional connectivity of widespread brain networks.

The behavioral and neuropsychological work discussed so far reveals correlates of attentional lapses and states. Causal approaches, however, offer a more direct way to explore the role of neural activity in sustained attention dynamics. For example, increasing attention via neuropharmacological manipulations also results in increased strength of and activity in networks correlated with better attention (Lyu, Corriveau, et al., in prep; Manza et al., 2025; Rosenberg et al., 2016). The opposite is also true: decreasing attention with anesthetic agents results in decreased strength of attention-related networks (Chamberlain & Rosenberg, 2022; Rosenberg et al., 2020). In addition, methodological innovations enable researchers to monitor in real time the activity within specific brain networks (Sitaram et al., 2017; Stoeckel et al., 2014; Sulzer et al., 2013). The time-varying dynamics of sustained attention can be fed back to participants in real time via closed-loop neurofeedback, thereby directly modulating brain activity and enhancing sustained attention performance (deBettencourt et al., 2015; Mennen et al., 2021). This real-time fMRI approach offers a promising avenue to directly test and modulate distributed patterns of functional connectivity that support sustained attention (Scheinost et al., 2020; Yamashita et al., 2017). By directly altering brain function, causal methods move beyond observation to actively test how neural representations support sustained attention behavior.

In sum, the dynamic nature of attention can be powerfully assayed through the lens of sustained attention. These studies reveal how attention varies over different time scales within individuals.

Dynamics can be measured via behavior, including lapses, and tracked with cognitive neuroscience tools. These tools reveal that successfully sustaining attention encompasses multiple complex processes, including maintaining goal representations, detecting rare items, and inhibiting distracting information.

3. Moment-to-moment fluctuations of memory

Much like sustained attention, memory performance fluctuates over time. For example, recall the last time you met a new group of new people. You may have continued the conversation with one person’s name in mind but another’s—shared only seconds later—woefully forgotten. Such memory variability may be due to differences in the information itself (such as how salient or memorable it is; Bainbridge, 2019) as well as how it is encoded, maintained, or retrieved. Another non-exclusive possibility is that memory fluctuations are driven by shifting attentional, affective, and cognitive states that influence our ability to remember. Here, we examine this moment-to-moment variability in working memory and long-term memory before considering their interactions with fluctuating attention.

3.a Working memory dynamics

Over the course of an experiment, working memory performance changes. This is evident in variability across trials in both the number of items held in working memory (i.e., memory capacity; Adam et al., 2015; deBettencourt et al., 2019; Kozlova et al., PsyArXiv) as well as the the fidelity of a single representation (i.e., memory precision; Zhang & Luck, 2008). At the same time, working memory tasks give rise to canonical brain signatures, including EEG delay signatures (Luria et al., 2016; Vogel & Machizawa, 2004) and distributed fMRI brain activity in stimulus-specific and control regions (Christophel et al., 2017; Curtis & D’Esposito 2003;

D'Esposito & Postle 2015). By examining how these brain signatures covary with capacity and precision, cognitive neuroscience sheds light on the mechanisms that give rise to working memory dynamics. For example, working memory trials on which people remember fewer items are associated with reduced measures of preparatory activity (Murray et al., 2011) and delay activity in EEG (Adam et al., 2018) and fMRI (Pessoa et al., 2002) as well as smaller pupil size (Robison & Unsworth, 2019). More successful trials are also reflected in better multivariate representations (Bettencourt & Xu, 2016; Rahmati et al., 2018; Sprague et al., 2016; Wan et al., 2024). Causally implicating these neural substrates and oscillatory signatures are studies that demonstrate how transcranial magnetic stimulation (TMS) modulates working memory performance (Hamidi et al., 2008 & 2009; Riddle et al., 2020). In summary, working memory is inconsistent over time and investigating these inconsistencies can reveal important information about the neural underpinnings of working memory.

Although some momentary memory lapses—like forgetting someone's name as soon as they say it—can happen unexpectedly, there is evidence that often such failures are not isolated events, but rather reflect ongoing dynamics shaped by both pretrial states and recent content. Prior to stimulus presentation, neural activity, including posterior alpha (Myers et al., 2014) and frontal theta (Adam et al., 2015; 2018), predict upcoming working memory performance. That is, EEG provides access into general control states that may predetermine success. In addition, specific content from prior trials can influence working memory on an upcoming trial (Kiyonaga et al., 2017). Demonstrating the lingering effects of preceding trials on current neural representations, evidence for prior stimulus representations has been decoded from neuroimaging and electrophysiological data, including EEG (Bae and Luck, 2019; Zhang & Lewis-Peacock, 2024), fMRI (St. John-Saaltink et al., 2016; Sheehan & Serences, 2022), MEG (Hajonides et al., 2023) and spiking activity (Barbosa et al., 2020). That is, like attention lapses, working memory failures likely reflect slower-frequency dynamics.

Although we have so far focused on trial-to-trial working memory dynamics—which typically occur on the order of seconds to tens of seconds—a growing body of work investigates cognitive and neural dynamics *within* trials as information is held in mind during a delay period. This work reveals time-varying modulation of cognitive and neural stimulus representations on the order of milliseconds to seconds (Adam et al., 2022; Buschman & Miller, 2022; Stokes, 2015). Additionally, working memory behavioral performance, eye gaze, pupil size, and neural activity can be modulated while information is actively being held in mind during a delay interval by retrospective cues (Griffin & Nobre, 2003; Souza & Oberauer, 2016; van Ede et al., 2019; Zokaei et al., 2019). Thus, dynamics of working memory occur at a wide range of temporal scales. A comprehensive model of working memory must account for, and understand what gives rise to, these dynamics.

3.b Long-term memory dynamics

One of the hallmark characteristics of long-term memory is that it is imperfect; we do not remember everything we encounter. For instance, how many new acquaintances' names do you remember hours, days, and weeks later? Experimentally, the stimulus properties, cognitive states, and neural signatures of this phenomenon have been examined by contrasting brain activity and behavior surrounding remembered vs. forgotten items, known as the subsequent memory effect (Paller & Wagner, 2002). Some variance in what we remember can be driven by features of the item itself, for example, its valence or memorability (Bainbridge, 2019). However, memory is also critically shaped by internal states present when information is encountered, processed, and retrieved.

Lingering mnemonic states that influence whether an item will be remembered can be detected even before a stimulus appears. For example, memory judgments for an upcoming item can be biased by retrieval states from the previous trial (Duncan et al., 2012; Patil & Duncan, 2018). EEG provides powerful and temporally resolved insight into these prestimulus states. Using multivariate analysis of EEG, it is possible to decode retrieval states and predict memory outcomes (Long & Kuhl, 2019). In addition, oscillatory activity during the prestimulus period is associated with memory performance. Theta power prior to an item predicts long-term memory encoding (Fell et al., 2011; Fellner et al., 2013; Guderian et al., 2009; Merkow et al., 2014) and retrieval (Addante et al., 2011). Additionally, lower prestimulus alpha power at encoding is associated with successful long-term memory (Weidemann & Kahana, 2021). Prestimulus activity can also be measured by evoked brain activity, including EEG waveforms (Otten et al. 2006) and fMRI stimulus-related activity (Turk-Browne et al., 2006). In sum, prestimulus neural activity reflects ongoing mnemonic states that shape the likelihood of remembering.

An important observation is that mnemonic states unfold over longer timescales than single trials. A well-documented finding from free recall paradigms is the temporal clustering of nearby items (Howard & Kahana, 2002; Manning et al., 2014; Polyn & Kahana, 2008). This behavior is attributable to slow fluctuations in internal context, measurable by multivariate analysis of EEG (Manning et al., 2011) and fMRI (Chan et al., 2017; Polyn et al., 2005). Items encoded simultaneously can also become contextually bound together (Gardner-Medwin, 1976; Horner & Burgess, 2013) and correlated with fMRI activity within the hippocampus (Horner et al., 2015). These dynamics may serve a key adaptive purpose, segmenting information that is presented over time into events (DuBrow et al., 2017; Shin & DuBrow, 2021). Thus, state dynamics over longer timescales critically shape whether and how we remember information.

The identification of dynamic memory states presents a powerful opportunity for causal manipulation and real-time intervention. Memory encoding can be deliberately triggered during optimal or suboptimal moments, based on ongoing brain states (Rudoler et al., 2024; Salari and Rose, 2016; Yoo et al., 2012). Brain stimulation offers another way to manipulate memory (Hebscher & Voss, 2020; Yeh & Rose, 2019; Zhao & Woodman, 2021), and can be particularly powerful when paired with real-time decoding (Ezzyat et al, 2018; Kragel et al., 2025). Real-time decoding also enables adaptive interventions, such as prioritizing poorly encoded information for restudying (Fukuda & Woodman, 2015). In addition, real-time fMRI and neurofeedback can bias memory reactivation and retrieval (deBettencourt et al., 2019; Koizumi et al., 2016; Peng et al., 2024; Taschereau-Dumouchel et al., 2018). Identifying and intervening upon mnemonic state dynamics offers a window into how our memory can be shaped over time.

4. Considering attention and memory dynamics together

While there is consensus that both attention and memory exhibit intrinsic fluctuations, most often these fluctuations are examined in isolation. In the following sections, we describe work that combines concurrent measurements of attention and working and long-term memory to examine whether, when, and how their dynamics interact. By investigating these processes in tandem, we examine their complex and evolving relationships.

4.a Dynamics reveal that attention and working memory are tightly coupled

Attention and working memory are closely conceptually related as working memory involves selective attention to perceptual information and internal representations of items held in mind (Adam & deBettencourt, 2019; Awh et al., 2006; Chun, 2011; Cowan 1998; Oberauer, 2019). Despite this close connection, most conceptualizations of attention and working memory also acknowledge that these constructs are not synonymous. Here, we first consider the relationship between attention and working memory through shared variance across individuals and similar neural representations. Then, we discuss how interleaving attention and working memory tasks provides critical insight into when and how their dynamics are intertwined.

Both attention and working memory abilities vary enormously across the population. Leveraging this variation reveals that attention and working memory abilities are correlated across individuals: Individuals who are better at sustaining attention also have higher working memory capacity (Kane et al., 2007; Unsworth et al., 2010; Unsworth & Robison, 2020). Neural analyses also demonstrate how sustained attention and working memory are related across individuals. Functional-connectivity-based models trained to predict individual differences in one domain generalize to predict individual differences in the other (Avery et al., 2020; Kardan et al., 2022; Yoo et al., 2022). That is, behavioral and neural analyses of individual differences reveal a close link between sustained attention and working memory.

Another way to examine shared neural mechanisms is by testing whether attention and working memory engage similar cognitive and neural processes. This can be observed indirectly by the impact on performance of simultaneous dual attention and working memory tasks. Engaging in a distracting attention task while maintaining items in working memory reduces memory performance (Souza & Oberauer, 2017). Analyses of neural data can also reveal commonalities between these processes. First, neuroimaging and electrophysiological recordings from humans and non-human primates suggest that items elicit similar neural responses whether they are perceptually attended or maintained in working memory (Awh & Jonides, 2001; Gazzaley & Nobre, 2012; Ikkai & Curtis, 2011; Panichello & Buschman, 2021). Likewise, regions implicated in one process show overlapping activity in another: the frontal eye fields and intraparietal sulcus, for example, support goal-directed attention and are activated during working memory maintenance (Pessoa et al., 2002). Second, changes in common neural features predict fluctuations in *both* attention and working memory. For example, increased frontal theta power and decreased posterior alpha power predict better attention and working memory performance (Adam et al., 2015; 2018; Myers et al., 2014; van Ede et al., 2017).

Thus, attention and working memory abilities are correlated across individuals and also implicate similar neural substrates. In addition, both attention and working memory change across multiple time scales. But are those dynamics themselves linked? This question has been challenging to answer, as dynamics have traditionally been observed using different stimuli in distinct paradigms. We propose the most compelling way to answer this is by concurrently and even simultaneously tracking attention and working memory fluctuations. If attention and working memory co-fluctuate, this suggests an intricate link between them.

A study by deBettencourt et al. (2019) investigated whether sustained attention and working memory exhibit simultaneous dynamics by interleaving sustained attention and working memory tasks. Moments of better sustained attention (slower, more careful responding) correlated with moments of better working memory (more items remembered). Furthermore, this work presented a key innovation to directly leverage ongoing sustained attention. Fluctuations of sustained attention fluctuations were monitored in real time to specifically probe working memory when attention was extremely high or low (**Figure 2**). Participants remembered more items when probes appeared in a high vs. low attentional state, revealing that working memory and sustained attention dynamics are themselves deeply intertwined.

A follow-up study replicated these behavioral links between attention and working memory and explored pupillary correlates (Keene et al., 2022). This work also developed real-time pupil triggering, such that working memory probes were triggered when pupil size was exceptionally large or small. These observations that sustained attention and working memory covary together in time provide strong evidence that these constructs rely on a common resource store that dictates ability from moment to moment. Furthermore, the technological development of real-time triggering designs make important suggestions about how to leverage these dynamics to enhance attention and working memory behavior.

Examining attention and working memory dynamics in tandem also reveals dissociations in these processes. While attentional dynamics correlate with the *number* of items in working memory on a given trial (capacity), they are not related to the *precision* of working memory representations (deBettencourt et al., 2019). This finding is in line with previous work that capacity and precision may comprise separable features of working memory (Fukuda et al., 2010; Murray et al., 2011). Furthermore, while attention and memory share some neural mechanisms, EEG (Hakim et al., 2019) and fMRI (Sheremata et al., 2018) findings also show dissociation in neural activity underlying these constructs. Indeed, working memory likely comprises multiple subcomponents, including attentional control (Adam et al., 2015; Hakim et al., 2020). Although attention can be deployed to representations in working memory, items need not be the focus of attention to be remembered (Olivers et al., 2011; Lewis-Peacock et al., 2012; LaRocque et al., 2015). Finally, subjective self-reports of moment-to-moment fluctuations of attentional states may be associated with working memory performance fluctuations (Unsworth & Robison, 2016b), but they may reflect distinct attentional states (Chidharom et al., 2025). Thus, examining the shared dynamics of attention and working memory can shed light on the intricate and complex relationship between the subcomponents of these processes.

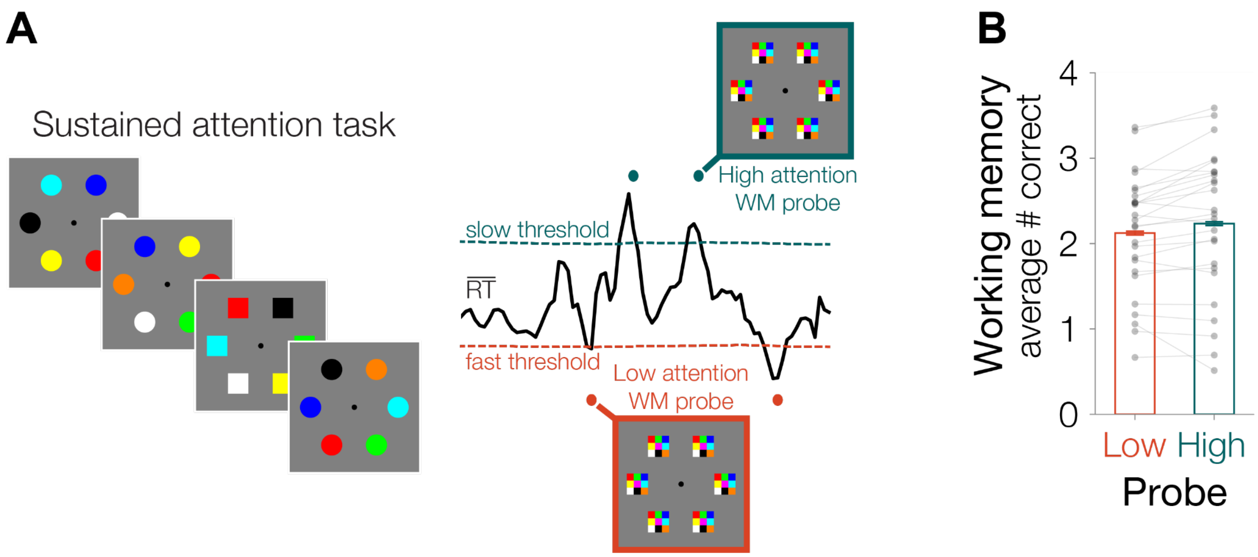

Figure 2. Linking attention and working memory dynamics (A) A real-time triggering approach explores synchronous fluctuations in attentional state and working memory (WM) capacity. A sustained attention task was used to monitor fluctuations of attention in real time based on the speed of responding (fast or slow). This method enabled researchers to probe WM during moments of high and low sustained attention. Such real-time monitoring techniques are valuable tools for exploring cognitive dynamics and developing individualized and adaptive systems that respond to moment-to-moment changes in attentional state **(B)** WM performance was better during periods of better sustained attention, as participants recalled more colors correctly when attention was high (p<.01). These findings directly linked momentary lapses of sustained attention with the amount of information held in mind. Figure adapted from deBettencourt et al., 2019.

4.b Attention dynamics drive long-term memory

We might assume that paying better attention to something will help us remember it later on, but until recently surprisingly little work had tested this relationship empirically. Rather, understanding how fluctuating attentional states drive memory has been a challenge for the field. Here we will examine the relationship between sustained attention and long-term memory through their shared dynamics.

Attention and long-term memory share common sources of variability at both behavioral and neural levels. Across individuals, higher sustained attention is correlated with better long-term memory performance (Corriveau, Chao et al., 2025; deBettencourt et al., 2021), though this relationship may be particularly strong among children and young adults (Decker et al., 2023b; Tran et al., 2025). Factor analyses suggest that sustained attention ability may, in fact, be more similar to long-term memory than to other attentional components like attentional control (Zhao et al., bioRxiv). Additionally, the recruitment of overlapping brain mechanisms for attention and long-term memory supports the close relationship between these functions (Aly & Turk-Browne 2017; Chun & Turk-Browne, 2007; Kuhl & Chun, 2014; Long et al., 2018). Retrieving locations from long-term memory activates similar multivariate representations as attending to spatial locations, evident in both EEG alpha topography (Sutterer et al., 2019) and fMRI activity in retinotopic regions (Vo et al., 2022). In addition, EEG activity patterns related to retrieval state are activated during a spatial attention task (Long 2023). Memory encoding recruits activity in the parietal cortex, specifically regions canonically associated with attention (Hutchinson et al., 2014; Turk-Browne et al., 2013; Uncapher et al., 2011; c.f. Hutchinson et al., 2009). On the other hand, attention is represented in the hippocampus, a region tightly linked with long-term memory (Aly & Turk-Browne 2016b; Cordova et al., 2019; Dudovic et al., 2011). Moreover, some of the shared relationship between attention and memory may be mediated by reliance on shared neuromodulatory indices (Decker & Duncan, 2020; Tarder-Stoll et al., 2020).

Trial-level fluctuations of attention within individuals also predict variability in long-term memory performance (deBettencourt et al., 2021; Mirjalili & Duarte, 2025). Activity in frontoparietal attention network regions predicts successful long-term memory encoding (Turk-Browne et al., 2013), as do attention-related patterns of activity in the hippocampus (Aly & Turk-Browne, 2016a). Attentional state prior to retrieval, indexed by posterior alpha power and pupil size, predicts memory success (Madore et al., 2020). These findings all support the idea that long-term memory shares representations with attention more broadly, and particularly sustained attention.

More recently, research has directly examined how moment-to-moment fluctuations of sustained attention relate to long-term memory (**Figure 3**). Findings show that periods of better sustained attention lead to better memory (deBettencourt et al., 2018). This observation has since been replicated and extended by a growing body of research (Corriveau, Chao et al., 2025; Corriveau et al., 2024; Decker et al., 2023b; Wakeland-Hart et al., 2022). Findings robustly show that higher sustained attentional state, measured by more accurate, slower, and less variable responding, covaries with better recognition memory for stimuli that appear during those moments.

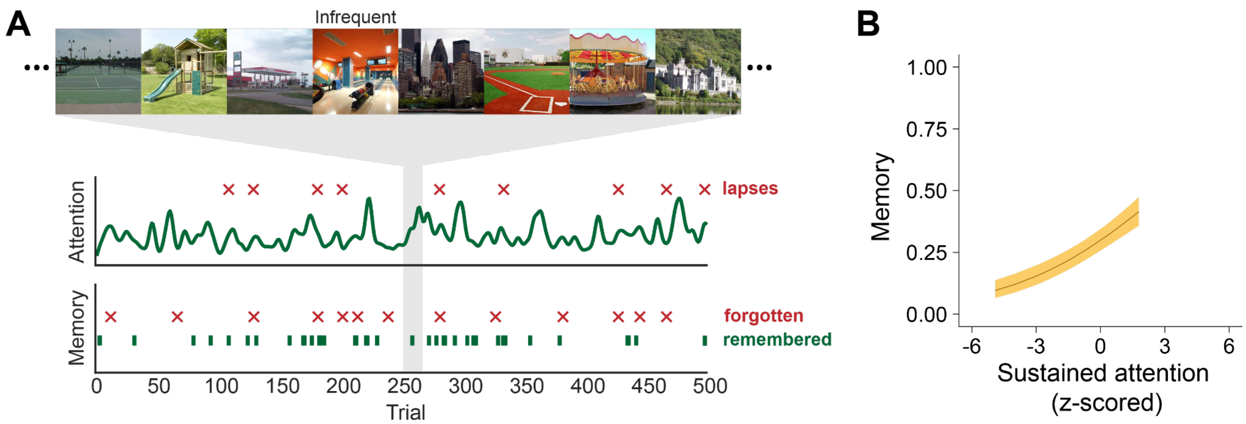

Figure 3. Predicting long-term memory from moment-to-moment fluctuations in sustained attention **(A)** An experiment links sustained attention dynamics with long-term memory. Attentional state was tracked using trial-by-trial fluctuations in behavioral responses. Attention dynamics not only predicted lapses in attention in the moment but also critically related to which items were remembered or forgotten later on. **(B)** Recognition memory was significantly better on trials with higher attentional states (*p*<0.001), showing that attention dynamics strongly impact what we remember. This suggests that even subtle fluctuations in attentional state play a profound role in memory formation. Figure adapted from Corriveau, Chao et al., 2025.

One study by deBettencourt et al. (2018) exploited attentional fluctuations to demonstrate the direct link between sustained attention and memory. Response speed was monitored in real time to determine moments when participants were most likely to be in an engaged state (showing slow RTs) or a disengaged attentional state (showing fast RTs). During these moments, probes were inserted requiring participants to change their prepotent response. Not only did the manipulation work—participants were more likely to lapse during worse attentional states—but memory was also worse for probe items presented in poor attentional states. This work was expanded upon to show that attentional states are independent from memorability (Wakeland-Hart et al., 2022). Leveraging both attention and memorability in real time offers a powerful strategy to individually tailor which information is encoded when (Roberts & Pruin et al., 2025). These findings not only establish a direct link between attention and memory dynamics but also showcase the power of real-time, adaptive cognitive interfaces to dissect and unravel the complex relationship between attention and memory.

Attentional fluctuations at encoding also have residual effects on memory encoding of information outside the focus of attention. Work by Corriveau and Chao et al. (2025) presented pairs of images during the sustained attention task, one of which was task-irrelevant. Increases in attentional state not only predicted better memory for the task-relevant images but also for the irrelevant images. A conceptual replication of this work utilized multisensory audio-visual stimuli (Corriveau et al., 2024). Successful recognition of a task-relevant stimulus (e.g., a picture) predicted memory for its irrelevant pair (e.g., a sound), suggesting that sustained attentional state at encoding affected relevant and irrelevant stimuli similarly. Together, these findings suggest that better sustained attention does not sharpen filtering, but rather reflects a greater overall capacity of the attentional system.

Sustained attention paradigms, particularly their ability to reveal attention dynamics, are valuable for examining whether and how attention impacts memory and learning more broadly. For example, the attentional boost effect describes a phenomenon in which rare targets transiently improve memory for information encountered at the same time (Lin et al., 2010; Swallow & Jiang, 2010). The proposed mechanism for this effect suggests that detecting rare targets transiently and broadly boosts perceptual processing, facilitating encoding for the context that accompanies the target (Swallow & Jiang, 2013). However, while the detection of rare targets improves recognition memory, it does not alter temporal memory (Wang & Egner, 2023). Also, sustained attention does not appear to impact temporal clustering of memory recall (Jayakumar et al., 2023). Finally, this approach also extends beyond memory, for example to examine the relationship with learning. There is evidence that attentional state impacts the ability to learn statistical regularities, with participants exhibiting faster responses for anticipated stimuli under high attentional states (Zhang & Rosenberg, 2024; although, see Decker et al., 2023a). There is also evidence for a close relationship between sustained attention and reward (Esterman et al., 2014a; Trach et al., 2025).

5. Toward a dynamic framework for cognition

Attention and memory are two of the most studied constructs in cognitive psychology and neuroscience. However, this work often assumes both functions are stable and binary—i.e., information is either attended or unattended, remembered or forgotten—and disregards the fact that they fluctuate over time. Past work has been fruitful for characterizing attentional and mnemonic processes as a whole, and assuming stability may have been useful for identifying trademark properties of these functions. With this groundwork laid, we propose that future research consider changes in attention and memory over time to more fully understand these inherently dynamic functions. In particular, methods incorporating cognitive dynamics may seek to answer a host of open questions.

How can dynamic interactions advance models of attention and memory?

Incorporating the dynamic properties of both attention and memory into computational models offers new opportunities to better capture the complexity of cognition and behavior. Recent work shows that modeling attentional features improves computational models of memory performance (Adam et al., 2015; Hakim et al., 2020) as well as machine learning decoding (Mirjaili & Duarte, 2025). More broadly, fluctuating attentional states during encoding and retrieval may account for memory variability that has often been attributed to memory processes alone, suggesting a need to revise memory theories accordingly. Conversely, memory retrieval can shape future attentional deployment, implying that dynamic models of attention should also incorporate memory-based influences. In addition, attention and memory fluctuations are observed and change over an enormous range of timescales (Rosenberg et al., 2025), ranging from sub-second (i.e., theta) rhythms (Biba et al., PsyArXiv; Fiebelkorn & Kastner, 2019; Landau & Fries, 2012) to the lifespan, as both attention and memory generally peak in early to middle adulthood (Alloway & Alloway, 2013; Fortenbaugh et al., 2015; Ronnlund et al., 2005). Modeling the bidirectional, time-varying interactions between attention and memory may provide a more unified framework for understanding human cognition. Joint measurement of attention and memory dynamics will be critical for uncovering the extent to which observed mnemonic and attentional phenomena emerge from shared underlying fluctuations, distinct mechanisms, or their interaction.

How can understanding attention and memory dynamics inform technology and translation?
A deeper understanding of attention and memory dynamics could have broad impacts, with applications across technology, education, and healthcare. Attention and memory have already inspired key innovations in artificial intelligence (Lindsay, 2020), and a fuller understanding and implementation of their dynamic properties may lead to more flexible and adaptive AI architectures. In education, attention and memory are essential for achieving learning goals, and tailoring instructional strategies to account for their natural fluctuations could significantly enhance educational effectiveness. In health care, attention and memory impairments are implicated in a range of psychiatric and neurological disorders, suggesting that tracking and modeling their fluctuations could support early detection and personalized interventions. Ultimately, insights into the dynamic nature of attention and memory could drive innovations across domains, shaping tools that are more responsive to the complexity of human cognition.

How can brain-computer interfaces harness attention and memory dynamics in real time?

Understanding the dynamic nature of attention and memory unlocks powerful opportunities for real-time prediction and intervention. Because cognitive states naturally fluctuate over time, knowing the current state can offer strong predictive leverage for anticipating what comes next. When attention wanes, catastrophic lapses become more likely, working memory capacity shrinks, and long-term memory formation is impaired. Advanced signal processing and analytic frameworks now allow researchers to track these fluctuations in real time using cognitive neuroscience and behavior tools (Shelat et al., 2024). Real-time monitoring of behavioral and neural signals enables researchers not just to observe, but to intervene in the moment. Approaches such as real-time triggering, neuroadaptive task designs, and closed-loop neurofeedback leverage continuous readouts of cognitive state to dynamically adjust stimuli, optimize performance, or directly modulate neural activity (**Figure 4)**. By moving beyond static snapshots and toward real-time dynamic monitoring, we can begin to both predict—and ultimately shape—the unfolding trajectory of mental processes.

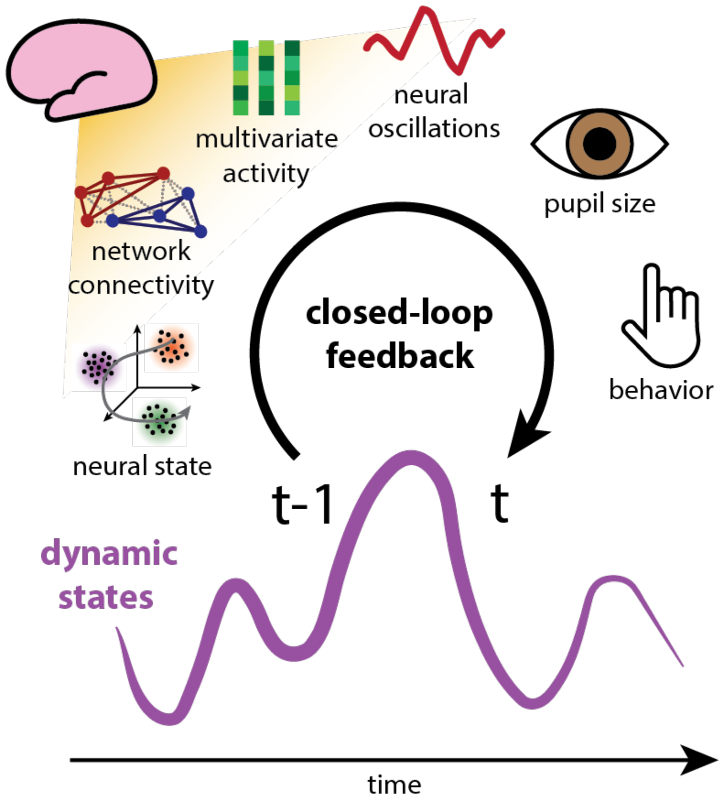

Figure 4. Adaptive designs enable the tracking of dynamic states in real time. Patterns of brain activity and behavior provide insight into ongoing processes which can be used to trigger timely interventions or guide real-time changes in the environment. Such closed-loop interfaces not only deepen our understanding of the complex and intricate relationship between attention and memory but also offer a powerful framework for probing the dynamic nature of cognition itself.

6. Conclusion

While we all have personal experience with what it feels like to attend and remember—as well as what it feels like when these abilities fail—the cognitive and neural dynamics underlying these phenomena are complex. Successful attention and memory may arise from some combination of external factors and drifting internal states whose interactions dictate ongoing cognition. Investigating fluctuations in attention and memory provides a critical lens into understanding these processes in isolation, as well as their interaction. The advancement of cognitive neuroscience techniques enables the possibility of probing, leveraging, and perturbing brain states to better understand how slowly-evolving states affect cognition and behavior. Therefore, while the dynamics of attention and memory may shape daily experience, neuroscience may also hold the keys to shaping cognitive dynamics in turn.

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