TARGETED REACTIVATION OF MEMORIES: INSIGHTS FROM SLEEP AND POST-SLEEP EEG IN HUMANS

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Summary

Sleep is a fundamental biological process that supports various cognitive functions, particularly memory. Non-rapid eye movement (NREM) sleep, one of its primary stages, is closely linked to memory consolidation, the process by which newly acquired memories are stabilized and integrated into lasting neural representations.

Among the memories that benefit most from sleep are episodic memories, which allow us to recall past experiences along with their spatial and temporal contexts. These memories underpin everyday cognitive tasks, including navigation, planning, and decision-making. Targeted memory reactivation (TMR) has emerged as an established approach for examining how sleep supports these memories. TMR involves presenting sensory cues, such as sounds and odors associated with learned material, to promote the reactivation of specific memories. While animal studies have demonstrated the replay of spatial and sequential experiences during sleep, research is still uncovering how these processes unfold in the human brain.

This thesis investigates two aspects of spatial memory processing in humans: the reactivation of complex spatial and sequential memories during NREM sleep using TMR, and the influence of TMR on neural activity during post-sleep memory retrieval.

To address these aims, two EEG studies were conducted. The first study examined whether image- and head orientation-related neural activity could be identified in sleep EEG following TMR, and whether this activity followed a structured, sequential pattern. Participants learned image sequences associated with specific head orientations, each linked to a sound cue. During their following NREM sleep, half of these cues were replayed to trigger reactivation, along with an unrelated control sound. Memory for the sequences was tested before sleep, after waking, and again after a 24-hour delay. Results indicated that TMR selectively supported the retrieval of head orientations that had been weakly encoded, with improvements evident only during delayed testing. Multivariate decoding analysis of sleep EEG revealed that both image category and head orientation-related activity could be decoded following TMR cues. However, decoding time courses did not follow a clear sequential pattern, and classifiers trained on wake localizer data did not generalize from wake to sleep. These findings suggest either flexible dynamics of reactivation during sleep or limitations in the current approaches and methods for capturing sequential memory processing.

The second study examined the impact of TMR on neural activity during post-sleep memory retrieval. Participants learned associations of object images and head orientations, each paired with a sound cue. During NREM sleep, selected cues corresponding to specific head orientations were replayed, along with a control cue. Post-sleep testing included both object recognition and the recall of associated head orientations. Results showed that TMR led to performance declines, suggesting that associating multiple memories with the same cue might produce interference rather than improvement. EEG analyses using event-related potentials (ERPs) and time-frequency representations (TFRs) showed no overall cueing effects on post-sleep neural dynamics. However, an interaction between cueing and head orientation in ERP data suggested that spatial memory neural dynamics were modulated by prior cueing. Notably, subtle head movements emerged during successful retrieval, despite explicit instructions to remain still during the task. This observation may reflect an embodied dimension of spatial memory retrieval.

Together, these two studies provide a complementary view of how spatial memories are processed across sleep and subsequent wakefulness. This thesis demonstrates that complex spatial memory representations can be decoded from EEG during sleep, and that TMR can modulate spatial memory performance in a selective and context-dependent manner, enhancing weaker memories while suppressing competing associations. These findings underscore that TMR effects depend on encoding strength, associative overlap, and task demands. Moreover, they emphasize the embodied aspect of spatial memory retrieval, opening new directions for integrating bodily signals into the study of spatial memories. Methodologically, this work highlights the challenges in decoding across brain states and the need to account for differences between wake and sleep neural dynamics. Together, these insights can inform the design of future TMR protocols, particularly those targeting spatial and embodied aspects of memory.

Overall, this thesis advances our understanding of how targeted reactivation during sleep shapes the consolidation and retrieval of spatial memories, offering new insights into the conditions that determine its effects on behavioral and neural dynamics. It further highlights the potential role of embodied processes and the methodological considerations involved in studying memory across brain states.

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1. GENERAL INTRODUCTION

1.1. Sleep and Memory Consolidation

Every day, we encounter a vast amount of information and experiences, yet only some of them persist as lasting memories. How does the brain decide what to retain and what to forget? Understanding the processes that shape memory has long been a central question in cognitive neuroscience. Increasing evidence suggests that the answer lies not only in how information is encoded during wakefulness, but also in how the brain processes memories during sleep, a period recognized as essential for memory consolidation (Diekelmann & Born, 2010; Rasch & Born, 2013).

To understand the relationship between sleep and memory, it is important to consider the dynamics of sleep itself. Sleep is a fundamental biological process observed in many species, from vertebrates to invertebrates (Cirelli & Tononi, 2008). It is characterized by a temporary loss of consciousness and decreased responsiveness to external stimuli. In mammals, sleep consists of two primary stages: rapid eye movement (REM) sleep and non-rapid eye movement (NREM) sleep. NREM sleep includes lighter stages (N1 and N2) and slow wave sleep (SWS, or stage N3). Sleep cycles through these stages, with SWS dominating the initial hours of the night and progressively diminishing in duration and intensity. Conversely, REM sleep becomes more frequent in the latter part of the night (Rasch & Born, 2013).

During sleep, newly acquired memories are stabilized and integrated into long-term storage. Among the different memory types, episodic memory is particularly dependent on sleep for successful consolidation (for a comprehensive review, see Rasch & Born (2013)). It enables individuals to remember and mentally relive previous experiences and is fundamental to an organism’s adaptive response to changing environmental demands (Murty et al., 2016; Tulving, 1993). Memory processing is typically divided into three primary stages: encoding, consolidation, and retrieval. When new memories are encountered, they are initially encoded, allowing them to be registered in the memory system (Liu et al., 2021). These newly acquired memories then require consolidation to be stabilized and strengthened, thereby reducing their susceptibility to interference and forgetting (Squire et al., 2015). Finally, memories are retrieved from long-term storage when needed (Dudai, 2002).

Memory consolidation typically occurs during sleep, which provides an ideal window for this process, as it minimizes external sensory input and engages neural mechanisms that stabilize recently encoded memories. This offline processing ensures that encoding and consolidation processes do not interfere with each other (Diekelmann & Born, 2010). Through consolidation, memory accessibility improves during subsequent wakefulness, meaning that memories can be efficiently retrieved when needed (Stickgold & Walker, 2013).

During the NREM stage of sleep, synchronized brain activity supports the transfer of memory representations between the hippocampus and learning-related neocortical areas. This process is guided by the interaction of key oscillations, named neocortical slow oscillations (SOs, 0.5-1 Hz), thalamocortical sleep spindles (12-16 Hz), and hippocampal sharp-wave ripples (80-120 Hz). When these rhythms align, they support memory reactivation, contributing to the stabilization of memories and integrating them into stable cortical networks (Girardeau & Lopes-dos-Santos, 2021; Latchoumane et al., 2017; Schreiner et al., 2021, 2024; Sirota et al., 2003; Staresina et al., 2015).

These oscillations each play distinct yet complementary roles in supporting consolidation. Slow oscillations provide time windows for regulating cortical and subcortical excitability, guiding transitions in membrane potential between states of neuronal silence (downstates) and excitation (upstates) (Amzica & Steriade, 2002; Isomura et al., 2006; Steriade et al., 1993;

Timofeev, 2011). They also trigger the occurrence of thalamocortical sleep spindles, which usually coincide with their upstates (Helfrich et al., 2018). Spindles, in turn, are known to contribute to synaptic plasticity by enabling calcium to enter dendrites (Rosanova & Ulrich, 2005; Seibt et al., 2017). Meanwhile, hippocampal ripples, which typically align with the troughs of spindles, are closely associated with the reactivation of memory traces (Ngo et al., 2020; Schreiner et al., 2024). Ensuring the transfer of memory representations from the hippocampus to the cortex, the interaction between these oscillations supports memory consolidation during sleep (Schreiner & Staudigl, 2020).

Before discussing how the reactivation process can be experimentally manipulated and detected using different methods, it is important to define two key terms. In human studies, memory reactivation refers to the recurrence of neural activity patterns that were present during the initial learning phase (Genzel et al., 2020). Replay, a term originally rooted in rodent studies investigating hippocampal firing sequences, is also applied in human studies and describes a specific form of reactivation that preserves the temporal and spatial structure of the original experience, even when the timing is compressed or altered (Genzel et al., 2020; Schreiner & Staudigl, 2020).

Understanding these processes could inform experimental methods to support learning and memory during sleep. With these concepts clarified, the next section introduces targeted memory reactivation (TMR), an experimental approach used to modulate reactivation during sleep.

1.2. Targeted Memory Reactivation (TMR)

Building on evidence that sleep oscillations are linked to memory processes, research has explored ways to modulate reactivation during sleep. Targeted Memory Reactivation (TMR) is utilized as a powerful technique in which external sensory cues, such as odors or sounds linked to prior learning experiences, are presented during sleep to trigger memory reactivation (Oudiette & Paller, 2013). By re-exposing participants to these cues, TMR has been shown to enhance and selectively prioritize subsequent recall for cued items – those presented during sleep – compared to uncued items (Göldi & Rasch, 2019). However, evidence also suggests that TMR can not only strengthen but also weaken or even induce forgetting of memories, depending on the nature of the memory associations and study goals (Joensen et al., 2022; Oyarzún et al., 2017; Schreiner et al., 2024).

1.2.1. TMR Effects on Different Types of Memory

Since its first demonstration in humans by Rasch et al. (2007), which revealed improved spatial learning after an associated rose odor cue was presented during SWS, TMR has been applied to different types of memory, including declarative (Rudoy et al., 2009; Schreiner & Rasch, 2015), procedural (Rakowska et al., 2021; Schönauer et al., 2014), and emotional memories (Hutchison et al., 2021; Yuksel et al., 2025).

Declarative memory encompasses facts and events that can be consciously retrieved (Sridhar et al., 2023). TMR has been applied across various declarative memory paradigms, including object-location associations, where sounds paired with image locations are replayed during sleep to strengthen memory traces (Rudoy et al., 2009). Notably, this benefit was observed even when images and cues lacked a clear semantic relationship (Antony et al., 2018). Moreover, Schechtman et al. (2021) showed that TMR effectively strengthened object-location memory regardless of the number of images (1, 2, or 6) associated with a given cue.

Another well-documented application of TMR is in vocabulary learning, where reintroducing words during sleep enhances recall. Schreiner & Rasch (2015) demonstrated that listening to Dutch words during sleep improved the recall of their German translations compared to uncued words. TMR has also been used to reinforce spatial memory, such as associating words to spatial locations in the visual field –left or right– (Bar et al., 2020) and linking images to distinct real-world head orientations using differently positioned screens (Schreiner et al., 2024), which will be discussed in detail in later sections.

Although most of the research on TMR has focused on declarative memory, its effects have also been examined in the context of non-declarative memories. Procedural memories are a form of implicit memory that involves acquiring perceptual and motor skills through repeated practice (Censor et al., 2012; Hong et al., 2019). Studies applying TMR to motor tasks, such as the serial reaction time task (SRTT), have reported mixed results (Rakowska et al., 2024). While some findings suggest that TMR improves motor sequence learning, with effects emerging 24 hours later and persisting for several days (Rakowska et al., 2021), other studies have found no significant effects, particularly in older adults (Nicolas et al., 2024). These findings indicated that the impact of TMR on procedural memories may depend on factors such as task-specific factors, the timing of assessment, and age-related differences in performance.

TMR has also been explored as a tool for modulating emotional memories, with potential clinical implications for conditions such as post-traumatic stress disorder (Van Der Heijden et al., 2022). Studies found that pairing negative memories with positive cues during sleep can modulate emotional responses, such as reducing the perceived aversiveness of negative words (Xia et al., 2023) and lowering arousal in response to negative images (Hutchison et al., 2021).

Taken together, these findings replicated across different memory domains have established TMR as a potential approach for memory enhancement and clinical interventions (Göldi & Rasch, 2019; Whitmore et al., 2022).

1.2.2. The Effectiveness of TMR during NREM versus REM Sleep

TMR is most commonly applied during NREM sleep, as numerous studies have consistently demonstrated its robust benefits for memory consolidation in different types of memories. A meta-analysis comprising 91 studies (N = 2,004) found that TMR during NREM significantly improved memory retention, while TMR during REM or wakefulness showed no significant benefit (Hu et al., 2020).

Although REM sleep has been investigated less frequently in TMR research, some evidence suggests it may contribute to memory processing, particularly for procedural (Abdellahi et al., 2024) and emotional memories (Hutchison et al., 2021; Kim et al., 2020). However, TMR during NREM sleep has also been shown to enhance these types of memories (Cairney et al., 2014; Rakowska et al., 2021), highlighting the primacy of NREM in consolidation.

Some studies proposed that REM sleep has a complementary role rather than directly enhancing consolidation induced by TMR. For instance, Yuksel et al. (2025) reported that TMR during REM impaired emotional memories, while TMR benefits during SWS were strongest when followed by more time spent in REM sleep. Similarly, Sifuentes Ortega et al. (2023) found that memory benefits from NREM-TMR were enhanced when REM followed NREM rather than preceding it. These findings suggest that while TMR during NREM strengthens memories, REM sleep may contribute to refining or regulating them. In summary, NREM sleep plays a primary role in TMR-induced memory benefits, while REM sleep may contribute to their subsequent regulation.

1.3. EEG Decoding Approaches to Track Reactivation

Although TMR has been shown to influence neural activity during sleep and improve subsequent memory performance, identifying neural patterns that reflect reactivation remains a central challenge (Belal et al., 2018). Addressing this challenge requires analytical approaches that can capture content-specific neural activity. Accordingly, there has been growing interest in identifying neural signatures of reactivation in sleep and memory research (Grootswagers et al., 2017; Schreiner et al., 2021).

Traditional EEG analyses have provided important insights into the oscillatory mechanisms involved in memory consolidation, such as slow oscillations, spindles, and their coupling (Hahn et al., 2020; Helfrich et al., 2018; Mikutta et al., 2019). However, these methods do not reveal whether specific content is being reactivated. To address this, researchers increasingly employ machine learning-based decoding techniques. In this framework, a classifier is trained to recognize distinct neural responses linked to specific stimulus categories encountered during learning. The trained classifier is then applied to EEG data recorded during sleep to detect whether similar neural patterns re-emerge, which serves as evidence of memory reactivation (Denis & Cairney, 2023).

Decoding approaches can be used to track both endogenous memory reactivation, which often aligns with the coupling of SO-spindle events (Schreiner et al., 2021), and TMR-induced reactivation, in which cue-triggered neural responses are analyzed (Cairney et al., 2018; Schreiner & Rasch, 2015; Wang et al., 2019).

The integration of EEG decoding with TMR has advanced the study of memory reactivation during sleep. Research analyzing EEG responses following TMR cues has successfully classified reactivated stimulus features, such as stimulus category (Cairney et al., 2018) and object locations (Wang et al., 2019). More recent work has extended this approach to complex spatial representations, demonstrating that head orientation-related activity can be reliably decoded following TMR cues (Schreiner et al., 2024). Beyond these wake-trained classifiers, another study has trained and tested classifiers within sleep data to decode the category of previously learned images, capturing learning-related processing within sleep (Schönauer et al., 2017).

The use of classification methods to investigate how specific memory traces are reactivated during sleep enhances our understanding of sleep-dependent memory consolidation, while TMR provides a powerful tool to control and examine which memories are reactivated during this process.

1.4. The Reactivation of Sequential and Spatial Memories During Sleep

Episodic memories involve the spatial and temporal organization of experiences, allowing individuals to encode and retrieve events within their broader context (Dickerson & Eichenbaum, 2010; Tulving, 1972, 1993). An important aspect of episodic recall is remembering not only individual elements of an event but also their sequential relationships and spatial context. The ability to retrieve events in the right order helps to maintain the integrity and coherence of events over time, supporting everyday functions such as navigation and planning (Bellmund et al., 2020; Drosopoulos et al., 2007; Huang et al., 2018).

Rodent studies have revealed that the sequences of hippocampal place cells, which encode an animal's path through an environment, are replayed during rest and sleep (Diba & Buzsáki, 2007; Foster & Wilson, 2006). As the animal explores, these place cells initially fire in patterns that correspond to specific locations in the environment. During replay, these neuronal sequences recur either in a forward direction (matching the original experience) or in the backward direction (reverse order). This reflects the flexible nature of memory retrieval, supporting cognitive functions such as navigation and planning (Carr et al., 2011; Ólafsdóttir et al., 2018).

Human memory reactivation similarly involves the replay of previously experienced events (Wimmer et al., 2020). The direction of replay – forward or backward – may be influenced by retrieval goals, such as requiring them to be recalled in the original order or prioritizing more recent memories for retrieval (Huang et al., 2018). Sleep further supports this process by consolidating temporal sequences, reinforcing the relationships between individual elements, and preserving the correct order in which events were encoded (Drosopoulos et al., 2007).

Spatial information is another fundamental component of episodic memories, supporting our ability to navigate environments and recall specific event locations (Bird & Burgess, 2008). While rodent research has shown spatial reactivation through hippocampal place cell activity (Diba & Buzsáki, 2007; Klinzing et al., 2019), human research similarly offers evidence that spatial memories undergo reactivation during offline periods, particularly during sleep (Schreiner et al., 2024). For example, Creery et al. (2022) demonstrated improved spatial memory performance when auditory cues linked to object locations were presented during NREM sleep. Similarly, Shimizu et al. (2018) found improved recall accuracy following the cueing of learned spatial locations during sleep. Nevertheless, different neural dynamics may underlie this process across species. While studies in rodents have associated spatial replay with hippocampal sharp-wave ripples (SWRs) (Buzsáki, 2015; Papale et al., 2016; Pezzulo et al., 2019), human studies using MEG and intracranial EEG have emphasized the role of high-frequency activity in the medial temporal lobe (Creery et al., 2022; Liu et al., 2019), with spindle-locked ripples also reported to correlate with memory reactivation (Schreiner et al., 2024).

Despite growing evidence for the reactivation of spatial and sequential components of memory during sleep, most human studies have focused on these aspects in isolation. However, real-world episodic memories typically involve not only what happened and where, but also when and in what order. Understanding how sleep supports the integration of these dimensions remains an open question to advance theories of memory consolidation.

1.5. Neural Signatures of Memory Reactivation and Retrieval

Similar to reactivation, memory retrieval processes are associated with distinct neural activity patterns, reflected in fluctuations in power across different frequency bands. These oscillatory changes, observed as increases or decreases in post-stimulus power relative to a baseline period before stimulus onset, provide insights into the neural dynamics underlying memory access (Hanslmayr et al., 2012; Pfurtscheller & Aranibar, 1977). For instance, theta (4-8 Hz) and gamma (30-100 Hz) oscillations are often associated with successful memory encoding and retrieval (Noh et al., 2018; Wynn et al., 2024), as they support the integration of memory traces through neural synchronization (Herweg et al., 2020; Nyhus & Curran, 2010). Reductions in alpha (8-12 Hz) and beta (13-30 Hz) power, referred to as desynchronization, have been linked to increased cortical excitability and reduced interference from irrelevant information, facilitating access to stored memories (Hanslmayr et al., 2012).

While neural dynamics of memory retrieval have been extensively studied, less is known about how retrieval processes are modulated by prior sleep. Sleep is thought to support memory consolidation, and TMR during NREM sleep has been shown to enhance memory-related oscillatory activity (Schechtman et al., 2021; Schreiner & Rasch, 2015; Wang et al., 2019). However, whether TMR influences neural activity during post-sleep retrieval remains an open question. Clarifying this relationship is crucial for understanding how cued reactivation influences the later accessibility of memories.

A prior study by Schreiner et al. (2015) suggests that TMR during NREM sleep can modulate subsequent retrieval-related neural activity, with cued memories exhibiting enhanced theta power compared to uncued memories. However, this study focused on vocabulary learning and was conducted during nap sleep, leaving it unclear whether similar effects generalize to nighttime TMR or more complex memory representations like spatial memories.

In addition to oscillatory dynamics, event-related potentials (ERPs) may offer perspective on neural markers of post-sleep retrieval. For instance, the well-documented "old-new" effect, which differentiates between previously encoded and novel information, was found to be more pronounced following sleep than after wakefulness, suggesting that sleep enhances access to stored memories (Mograss et al., 2006). Examining retrieval-related neural patterns during post-sleep in conjunction with TMR can enhance our understanding of how memories are reorganized and accessed following consolidation.

1.6. Objectives of the Thesis

Despite significant advances in sleep and memory research, several questions remain unanswered. It is still unclear whether sequential-spatial memories undergo reactivation during sleep and, if so, whether this reactivation follows a systematic temporal order. Additionally, the impact of TMR on neural dynamics of post-sleep retrieval and the role of spatial information in shaping these retrieval processes remain to be fully understood.

This thesis addresses these questions through two complementary studies. Study 1 investigates the reactivation of sequential-spatial memories, in which participants learned sequences of images associated with specific head orientations in a real-world spatial context. These associations were later cued during NREM sleep using TMR. Employing EEG decoding approaches, we aimed to identify image and head orientation-related activity from sleep EEG, and examine their temporal dynamics, providing insights into the neural representations underlying memory reactivation during sleep.

Study 2 explores the effects of TMR on post-sleep memory retrieval EEG dynamics using a spatial memory task that involves object-head orientation associations. As in the first study, each association was linked to sound cues that were later presented during NREM sleep. EEG analyses focused on how cueing influenced neural activity during post-sleep retrieval and head orientation-related markers of memory.

Together, these studies aim to clarify how TMR influences the reactivation of spatial memories during sleep and the neural processes that support their subsequent retrieval. This work seeks to advance our understanding of how spatial information is processed and stabilized across sleep-dependent memory consolidation.

2. STUDY 1:

IDENTIFYING IMAGE AND HEAD ORIENTATION-RELATED MEMORY REACTIVATION DURING SLEEP IN HUMANS

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2.1. Abstract

Sleep is thought to support memory consolidation by reactivating prior experiences. While animal studies have demonstrated the replay of sequential-spatial trajectories during sleep, human research has largely focused on the reactivation of single-item associations. This study addressed this gap by investigating whether sequential-spatial memories can be reactivated following targeted memory reactivation (TMR) during non-rapid eye movement (NREM) sleep. Twenty-four participants learned 24 sequences of four images each, linked to distinct real-world head orientations and paired with unique sound cues. This was implemented by viewing images on monitors positioned at different angles around them. Memory performance was assessed before and after sleep, and again 24 hours after the initial post-sleep retrieval. During NREM sleep, half of the previously learned sound cues were replayed to trigger memory reactivation. TMR selectively benefited weakly encoded head orientation associations, with this effect emerging during the delayed retrieval session. Multivariate decoding analysis of sleep EEG revealed that image category and head orientation-related activity could be reliably decoded following TMR cues. However, the temporal dynamics of decoding accuracy did not reflect a structured sequential pattern, and classifiers trained on wake localizer data did not generalize to sleep. These findings suggest that TMR during NREM sleep can benefit weakly encoded spatial memories and that spatial representations can be reliably decoded from sleep EEG, but also point to limitations in detecting temporal structure or in the classification of neural representations from wake to sleep.

Keywords: targeted memory reactivation (TMR), sleep EEG, multivariate decoding, sequential-spatial memory, head orientation, memory consolidation

2.2. Introduction

Sleep plays an essential role in strengthening and stabilizing memories by reactivating prior experiences, particularly during non-rapid eye movement (NREM) sleep (Diekelmann & Born, 2010; Klinzing et al., 2019; Rasch & Born, 2013). Decoding memory content from EEG signals has been proposed as a valuable method for understanding the processes of memory consolidation. This method enables the detection of distinct neural patterns associated with previously learned content (Belal et al., 2018; Schönauer et al., 2017; Wang et al., 2019).

Decoding techniques, such as Multivariate Pattern Analysis (MVPA) (Grootswagers et al., 2017) and Representational Similarity Analysis (RSA) (Kriegeskorte, 2008), have been widely used in memory research during both wakefulness and sleep. For instance, using MVPA, researchers reported that brain patterns specific to stimuli spontaneously recur during both awake resting states and sleep (Deuker et al., 2013). Another study demonstrated that multivariate pattern classification can successfully differentiate between stimulus categories (e.g., faces and houses) during both NREM and rapid eye movement (REM) sleep (Schönauer et al., 2017).

Targeted memory reactivation (TMR) has been utilized to investigate how the reactivation of memories contributes to memory consolidation. This technique involves associating learned material with specific sensory cues, such as sounds and odors, in wakefulness and reintroducing these cues during subsequent sleep to trigger memory reactivation (Hu et al., 2020; Lewis & Bendor, 2019; Schreiner & Rasch, 2015). TMR provides more control over the timing and selection of memories being retrieved (Oudiette et al., 2013), enabling researchers to analyze brain activity elicited by these cues to decode the reactivated memory content (Belal et al., 2018; Schreiner et al., 2018; Wang et al., 2019). Successful examples include decoding stimulus categories such as objects and scenes (Cairney et al., 2018), as well as lateralized object location information (Wang et al., 2019). A recent study from Schreiner et al. (2024) further demonstrated the successful decoding of head orientation-related information following TMR cues during NREM sleep, highlighting the potential of TMR to elicit the reactivation of spatial cues.

TMR has been demonstrated to enhance memory retention by selectively reactivating memories during sleep, leading to better memory performance for cued items compared to uncued items (Göldi & Rasch, 2019). It has also been shown that the extent of these benefits may depend on the initial strength of encoded memories. For instance, TMR has been found to preferentially benefit weaker memory representations, as these memories have greater potential for improvement through reactivation during sleep (Cairney et al., 2016; Denis et al., 2021). In contrast, well-encoded memories show less improvement due to limited room for further performance gains (Creery et al., 2015).

Episodic memory enables the recollection of past events, which are organized along both spatial and temporal dimensions (Eichenbaum, 2017b). In animal models, spatial navigation is commonly used to study episodic memory, as it naturally involves trajectories of events. For instance, hippocampal place cells fire in a sequential manner as animals move through an environment, encoding spatial trajectories (Diba & Buzsáki, 2007; O'Keefe & Dostrovsky, 1971). These sequences are later replayed in the same or reverse temporal order during rest and sleep, a process thought to support memory consolidation (Lee & Wilson, 2002; Skaggs & McNaughton, 1996; Wilson & McNaughton, 1994). The organization of events in time and space is a function of episodic memory that distinguishes it from other types of memory.

In humans, episodic memory similarly depends on the sequential organization of events.

For instance, compared to wakefulness, sleep has been found to enhance memory for forward associations in word triplets, suggesting that sleep-dependent consolidation preserves the temporal sequence of events (Drosopoulos et al., 2007). Conversely, an EEG study demonstrated backward replay of sequentially encoded items during wakefulness, with recent memories being prioritized for consolidation and replayed in a compressed manner (Huang et al., 2018). Similarly, Wimmer et al. (2020) found that during memory retrieval, sequential replay of episode elements occurs in a compressed manner, and the direction of replay depends on retrieval goals. Specifically, forward replay occurred when retrieving later elements, while backward replay occurred when retrieving preceding elements. These findings highlight the flexible and dynamic nature of sequential memory reactivation across both sleep and wakefulness.

Previous research on spatial memory reactivation has primarily focused on decoding single-item associations (Schreiner et al., 2024). Therefore, less is known about how sequences of spatial cues are reactivated and temporally organized during sleep. Understanding this could offer valuable insights into how the human brain processes complex spatial memories over time. Recent advancements in decoding techniques have enabled researchers to track the temporal dynamics of reactivation (Abdellahi et al., 2024; Schreiner et al., 2021). Michelmann et al. (2018) used phase similarity and regression-based techniques to examine sequential replay, reporting forward replay patterns of movie scenes during awake retrieval. This work illustrates the potential of multivariate methods to reveal the fine-grained temporal dynamics of human memory processes.

Building on these findings, the present study aims to determine whether spatial information can be decoded from sequential memories and to explore the temporal dynamics of decoding during NREM sleep. To this end, head orientations are incorporated as spatial context. Similar to animal studies showing that head direction cells support navigation by linking head orientation to future locations and guiding movement, recent human research suggests that head orientations can serve as contextual cues, becoming part of the memory trace being reactivated (Schreiner et al., 2024).

Twenty-four healthy participants (mean age: 23.89 ± 3.98; 15 female) performed a spatial memory task comprising 24 sequences, each linking four images to specific real-world head orientations. Each sequence was associated with a sound cue later used for TMR during NREM sleep, designed to trigger the reactivation of associated memories. Memory performance was assessed before and after sleep, as well as 24 hours after the first morning retrieval session, to evaluate the potential delayed effects of TMR, as suggested by prior research (Cairney et al., 2018; Rakowska et al., 2021).

We hypothesized that image and head orientation-related information could be reliably decoded during NREM sleep following the TMR cues. Behaviorally, we expected that TMR would improve memory performance for cued memories, preferentially favoring weakly encoded sequences. Furthermore, we anticipated that the temporal dynamics of decoding would exhibit a forward pattern, consistent with the sequential organization of memories.

2.3. Methods

2.3.1. Participants

24 healthy participants (right-handed, mean age: 23.89 ± 3.98; 15 female) participated in the study. They had either normal or corrected-to-normal vision. 16 additional participants were excluded due to insufficient sleep or technical issues. Screening questionnaires were completed by the participants, including information on their sleep patterns, overall health status, and use of stimulants. These questionnaires were utilized to confirm that participants had regular sleep schedules, were not using any medications, and did not have neurological or psychiatric disorders. Overall, participants reported good sleep quality. Participants were instructed to wake up by 7 a.m. and refrain from caffeine on the day of the experiment. They were also advised to abstain from alcohol the evening before the experiment. Compensation was provided for the participation, either in the form of course credits or monetary payment. This study was approved by the ethics committee of the Department of Psychology at Ludwig–Maximilian University, Munich.

2.3.2. Experimental Procedure

Paradigm Overview

The procedure started with an adaptation nap session in the sleep lab to familiarize participants with the lab environment a few days before the main experiment. On the day of the main experiment, preparation started at 5 p.m. with the application of polysomnographic recordings, including electroencephalography (EEG) and electrooculography (EOG). Participants performed the tasks on a computer with five monitors with different orientations (-60°, -30°, 0°, 30°, and 60°). First, the experiment began with the *localizers and controls* task, followed by the main memory task (see below for details). In the memory task, participants learned 24 distinct sequences, each comprising four images that were linked to specific real-world head orientations (HOs). These images were presented on four peripheral screens (-60°, -30°, 30°, and 60°), and participants turned their heads towards the screen to view the images. Each sequence was preceded by a unique sound (a German verb) serving as a reminder cue during retrieval and TMR. Memory performance was tested before and after a night of sleep, as well as 24 hours after first morning retrieval. Participants went to sleep around midnight. During NREM sleep, half of the previously learned sounds were presented to prompt reactivation of associated sequences. After 7 hours of sleep, participants were awakened to reassess their memory performance. Motion tracking and eye-tracking were recorded during awake parts of the experiment.

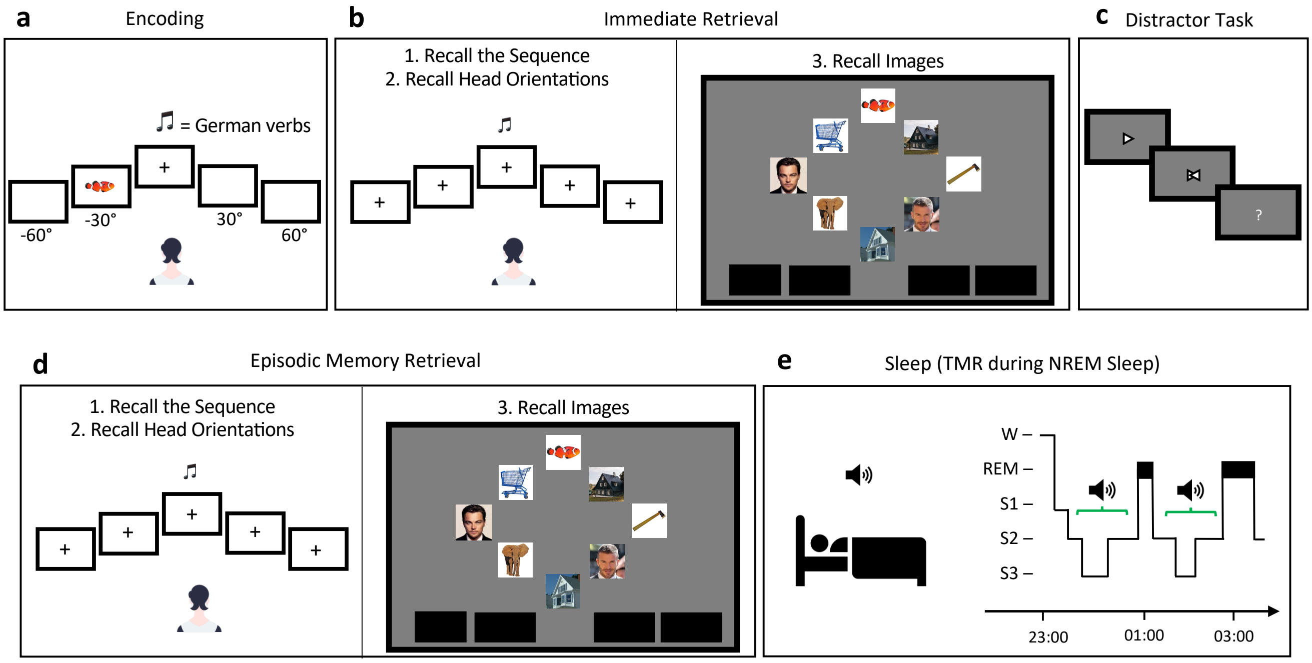

Figure 1. Experimental design. Participants performed a memory task on a computer with five monitors positioned at different orientations (-60°, -30°, 0°, +30°, and 60°). **a. Encoding phase:** Participants learned 24 sequences (3 blocks x 8 sequences), each consisting of four images – one from each of four categories: animals, objects, houses, and famous faces – presented on peripheral screens. Each sequence was preceded by a unique auditory cue (a German verb). Participants turned their heads toward the corresponding screen to view each image. After seeing the sequence, the cue was repeated, and participants verbally recalled their self-generated story linking the sequence while performing the associated head orientations (without seeing the images). The original sequence was then replayed for verification, and participants indicated whether it matched their recalled sequence. **b. Immediate retrieval**: Following encoding, participants heard the same sound cue and imagined the associated sequence for 12 seconds while fixating on a central fixation cross. They then performed the learned head orientations without seeing the images (Head Orientation Task). Next, they completed the **Image Sorting Task**, selecting and ordering the correct four images from a set of eight (four targets and four distractors) using on-screen placeholders. This task was performed on the central screen. **c. Distractor Task**: After each block, participants performed a 3-minute distractor task in which they indicated the direction of briefly presented arrows followed by a mask. **d. Episodic memory retrieval:** Participants completed an episodic memory task for the 8 sequences learned. This followed the same three-step procedure as immediate retrieval: covertly retrieving the sequence, the head orientation task, and the image sorting task. Identical retrieval procedures were conducted during the post-sleep and 24-hour delay sessions, with all 24 sequences tested in randomized order rather than by block. **e. Sleep with TMR:** Participants slept in the lab and received TMR during NREM sleep. Half of the previously learned sounds (12 sound cues) and a novel control sound were repeatedly played to induce reactivation of the associated sequences. The example hypnogram illustrates that sound cues were delivered during NREM sleep.

Stimuli

Each sequence included four images, one image from each of the following categories: animals, objects, houses, and famous faces. The images were obtained from various sources: animals (Konkle & Caramazza, 2013; Russo & Wu, 2022), objects (Hebart et al., 2019), houses (Ahmed & Moustafa, 2016), and famous faces (Mehta, 2017).

German verbs were used as the auditory stimuli. They were recorded in the sleep laboratory with a speech therapy student at Ludwig-Maximilian University in Munich. The verbs were two-syllable, simple action verbs with concrete meanings, each lasting 600 milliseconds.

Localizer and Control Tasks

Participants performed multiple localizers and control tasks that included measures of cardboard glasses head movements, sounds, eye movements, head movements, head movement cognition, and images.

Cardboard glasses head movements: Participants wore cardboard glasses before entering the experimental room to prevent them from seeing the setup. They were seated in front of the experimental computer with five monitors. An experimenter guided them throughout the task to perform sequences of four head movements (left, far left, right, far right). Participants were instructed to look straight ahead and then perform the specified head orientation. Once the experimenter confirmed the correct direction based on where the laser pointer on the glasses aimed on the screen, participants paused for approximately 2 seconds at that position to get a feeling of that specified head orientation. They completed three practice trials, receiving feedback on their movements. Each practice trial began with a brief tone signaling the start of the following sequence. The main task had three blocks of 15 sequences each, with a short beep indicating the start of a new sequence, while a higher beep indicated the end of a block. To start the next block, participants pressed the spacebar. At the end of the task, a "tadaa" sound was played, signaling the completion of the task, after which the experimenter removed the glasses.

Sounds: Participants listened to German verbs that comprised sounds that were later used in the memory task (each 600 milliseconds) while looking at the center screen. A fixation cross was presented before and after each sound (duration: 1 ± 0.1 seconds). Each block consisted of 28 sounds.

Eye movements: Participants performed 24 sequences of eye movements by following fixation crosses displayed on nearby peripheral screens (-30° and +30°), without turning their heads. After each sequence of eye movements, they turned their gaze to the middle screen.

Head movements: Participants performed sequences of four head movements, turning their heads clearly toward four screens, depending on where the fixation cross appeared (duration: 3 seconds ± 0.1). After each sequence of four images, they returned their heads to the center screen. Each block consisted of 24 unique sequences.

Head movement cognition: Participants kept their heads as still as possible, fixating their eyes on a fixation cross in the middle of the center screen. Fixation crosses then appeared on the four peripheral screens (duration: 3 seconds ± 0.1). Participants were asked to imagine turning their heads to the respective screen without moving. Each block consisted of 24 unique sequences.

Images: Images of animals, objects, famous faces, and houses, including images used later in the memory task, were presented on the center screen. Participants indicated whether the picture was shown for the first or second time by pressing the left (first) or right (second) arrow key. Each block consisted of 144 images.

Memory Task

The memory task included several phases, beginning with a practice phase to familiarize participants with the procedure. In the practice phase, participants engaged in tasks identical to the main memory task, but with colored shapes serving as stimuli instead of image categories used in the memory task. After three practice trials, the main memory task started.

Encoding

The memory task consisted of three blocks, each with eight sequences, for a total of 24 sequences. During encoding, each sequence started with the presentation of a German verb sound (duration: 0.6 seconds). A fixation cross appeared before and after the sound (duration: 0.45 ± 0.1 seconds). Four images of a sequence were displayed one at a time in a randomized order on four peripheral screens, with each image on a different screen (Fig. 1a). Participants viewed each image by turning their heads to the corresponding screen and fixating for the duration of image presentation (2 seconds), then returned to the central screen before moving to the next image. They were instructed to learn the German verb, the images in the correct order, and their associated head orientations. Participants were encouraged to create a vivid story from each sequence for later recall. Next, the German verb sound was played again, and fixation crosses appeared on all screens. Participants verbalized their created story while performing the head orientations of the learned sequence without seeing the images. The sequence of images was then presented again on the screens for participants to verify their story against the correct sequence.

Immediate Retrieval

Following encoding, participants entered the immediate retrieval phase (Fig. 1b). After hearing the associated German verb, they were instructed to imagine the sequence for 12 seconds without moving their head or eyes, fixating on the center screen with the fixation cross. Then, they performed the head orientation task: after the sound presentation, all screens were presented with a fixation cross, and participants performed the head orientations of the encoded sequence, pausing for 2 seconds in each direction. In case they were unsure of the sequence, they were instructed to guess. After performing head orientations, they pressed the space bar to move to the image sorting task.

In the image sorting task, participants saw four images of the sequence and four new images as distractors arranged in a circle (Fig. 1b). Below the circle of images, black screen placeholders were provided. Participants were instructed to select the correct images in the correct order and place them on the correct screen placeholders using the mouse cursor. This process was repeated for eight sequences in each block.

Upon completing the eight sequences, participants engaged in a three-minute distractor task (Fig. 1c). In this task, an arrow appeared in the center of the screen, followed by a mask. When a question mark appeared, participants indicated the arrow's orientation (up, down, right, or left). After the distractor task, the episodic memory task for the corresponding block started.

Episodic Memory Task

During the episodic memory task, participants recalled all eight sequences from the encoding in randomized order and performed the same three-step procedure as during immediate retrieval (Fig. 1d). The sound was presented at the beginning of each step: recalling the sequence in 12 seconds without moving the head or eyes, performing head orientations, and image sorting. Participants' confidence ratings were collected on a scale from 1 (very unsure) to 5 (very sure) following the head orientation task and image sorting task. This process continued until all sequences in a block were tested.

Post-sleep and 24-hour delay retrieval tasks followed the same episodic memory procedure, and participants recalled all sequences after hearing 24 verbs in a randomized order, rather than performing them in blocks as in the pre-sleep retrieval.

Famous Faces Task

After the 24-hour delay episodic memory task, participants performed a face recognition task involving a series of famous faces to measure their familiarity with the faces. The task started with a fixation cross presented at the center of the screen for 0.6 seconds. Each face then appeared in the center of the screen along with the question, "Do you recognize this person?". Below the question, three options were displayed for participants to select with a button press: recognized the person (left arrow key), recognized the person but could not remember their name (down arrow key), or did not recognize the person (right arrow key). Participants were instructed to respond as quickly as possible, with a maximum of 10 seconds to answer for each face.

The following data were not used in the analysis of this research and were designed for other research questions: cardboard glasses head movements, eye movements, sounds, head movement cognition localizers, as well as the famous faces task.

Targeted Memory Reactivation

Targeted Memory Reactivation (TMR) was implemented during NREM sleep (Fig. 1d). The sound cues were selected from half of the previously learned sequences, which comprised half of the remembered sequences and half of the forgotten sequences based on participants' pre-sleep memory performance. A sequence was considered remembered if both aspects –images and head orientations– were accurately recalled, and forgotten if either aspect was recalled inaccurately. Additionally, the selection was balanced according to the starting screen of sequences. A total of 12 experimental sounds, along with one control sound not associated with learning, were repeatedly presented during NREM sleep at 6 ± 0.2-second intervals using a loudspeaker. On average, there were 74.83 ± 13.49 repetitions per stimulus. Sound presentation was stopped whenever arousals, awakenings, or signs of REM sleep were detected.

EEG Data Acquisition

To record the EEG, an EEG system with 65 Ag/AgCl electrodes and a 10/20 system layout was used (ANT Neuro Enschede, Netherlands). Impedances were kept below 20 kΩ. EEG signals were sampled at a rate of 1000 Hz and referenced online to electrode CPz. Horizontal and vertical electrooculography (EOG) were recorded for polysomnography.

Sleep Staging

Sleep architecture was determined offline by two independent raters based on standard criteria outlined in the ASSM Manual for Scoring Sleep (Iber, Ancoli-Israel, Chesson, & Quan, 2007). Sleep stages were scored in 30-second epochs by assigning a stage to each epoch: Wake, Stage 1 (N1), Stage 2 (N2), Stage 3 (N3), and REM (Rapid Eye Movement). If two or more stages occurred within a single epoch, the stage comprising the majority of the epoch was assigned. Additionally, epochs containing arousals and movements were marked.

The stages were defined as follows:

Epochs were characterized as wakefulness based on the presence of alpha waves, eye blinks, or eye movements. Sleep stage N1 was identified by slow eye movements and low-amplitude, mixed-frequency EEG activity. N2 was distinguished by the appearance of K-complexes and spindles, while N3 was marked by prominent slow-wave activity. Finally, REM sleep was characterized by rapid eye movements and low-amplitude, mixed-frequency EEG activity.

2.3.3. Data Analysis

Behavioral Analysis

Memory performance was calculated for pre-sleep, post-sleep, and 24-hour delay sessions. Initially, sequence performance was evaluated based on participants' accuracy in remembering images and head orientations. A sequence was considered remembered if all images or head orientations were recalled accurately; otherwise, it was considered forgotten.

Due to missing data in one session, three participants were excluded from the image sorting analysis, resulting in 21 participants for this measure. Additionally, seven participants were excluded from the head orientation analysis due to technical issues with head motion tracking, resulting in 17 participants included in that analysis.

To further analyze image sorting and head orientation performances in detail, weakly encoded sequences were distinguished. Sequences were classified as weak if only one or two images or orientations out of four were accurately recalled. Only subjects with weakly encoded sequences were included in the analysis.

EEG Data Preprocessing

Preprocessing of EEG data was performed using the Fieldtrip toolbox in MATLAB (Oostenveld et al., 2011). All data were downsampled to 200 Hz. Pre-sleep EEG data, including localizers and memory tasks, were segmented into epochs spanning -1.5 to 4.5 seconds around the stimulus onset. TMR data were segmented into epochs covering -1 to 4 seconds around the TMR onset. Using visual inspection, EEG artefacts were removed, and noisy EEG channels were identified and replaced with interpolated values generated from neighboring channels using a weighted average approach. Independent component analysis (ICA) was conducted to identify and remove components linked to eye blinks and lateral eye movements.

Sleep-EEG Analysis

To analyze sleep EEG data, event-related potentials (ERPs) and time-frequency representations (TFRs) were computed to investigate neural responses after cueing during sleep. Initially, specific channels (M1, M2, EOG, and Iz) were removed, and the data were re-referenced to the average reference (avgRef). The data were time-locked to the presentation of TMR cues and segmented into trials based on the contrasts of interest.

Trial selection and definition for ERP and TFR analyses proceeded as follows: First, trials were grouped according to experimental versus control sounds. Next, remembered versus forgotten trials were contrasted according to participants' pre-sleep memory performance. Only sequences that were fully remembered with both correct images and head orientations were categorized as remembered.

Event-related Potentials (ERPs)

Event-related potentials (ERPs) were analyzed to examine neural responses during post-sleep memory retrieval, comparing cueing conditions (experimental versus control) and performance conditions (remembered versus forgotten). A low-pass filter with a cut-off frequency of 30 Hz was applied to the data. Following trial segmentation (as detailed in the EEG Data Analysis section), baseline correction was applied using a baseline period from -0.5 to 0 seconds relative to stimulus onset. Time-locked analysis was conducted to assess the mean neural responses across conditions, focusing on the interval from -0.5 seconds to 3 seconds around the stimulus onset.

Time-frequency Representations (TFRs)

To investigate neural dynamics across cueing conditions (experimental versus control) and performance conditions (remembered versus forgotten), time-frequency representations were calculated using Fieldtrip. Frequency decomposition of the data was performed using Fourier analysis with a fixed-length sliding time window of 0.5 seconds. A single Hanning taper was applied to each window, covering a time range from -1 to 4 seconds relative to stimulus onset, and yielding a frequency range from 2 to 30 Hz. Power values were then z-scored across time [− 1 to 4 s].

Detection of Slow Oscillations (SO) and Sleep Spindles

The detection of SOs and sleep spindles was performed using established algorithms (Ngo et al., 2013; Staresina et al., 2015). Initially, sleep data were prepared by removing specific channels (EOG and Iz) and re-referencing the signal against mastoid channels (M1, M2). Only artifact-free segments from NREM sleep stages 2 and 3 were considered. Stimulus categories were defined based on memory performance, distinguishing TMR trials associated with remembered and forgotten sequences. For SO detection, data were band-pass filtered between 0.3 and 2 Hz. Slow oscillations were identified based on negative peak and peak-to-peak amplitude within a duration window of 0.8-2 seconds. The detection of sleep spindles was carried out by band-pass filtering the data between 12 and 18 Hz, with the duration criterion ranging from 0.5 seconds to 3 seconds. An amplitude threshold was applied per channel, defined as 1.5 times the median of the root mean square (RMS) envelope calculated with a 200-ms sliding window.

The co-occurrence of SO and spindle events was analyzed by examining their simultaneous occurrence within each trial, focusing on central electrodes (Cz and C4). The number of SOs, spindles, and SO-spindle complexes was then calculated relative to the total number of trials, allowing for comparison of their occurrences in remembered versus forgotten conditions. To assess differences between these conditions, Wilcoxon signed-rank tests were conducted.

Multivariate Decoding Analysis

To examine the image category-related and head orientation-related representations in the sleep EEG signal, multivariate classification of EEG data was conducted utilizing the MATLAB-based MVPA Light toolbox (Treder, 2020). A multiclass Linear Discriminant Analysis (LDA) classifier was employed. Before each classification analysis, channels M1, M2, EOG, and Iz were removed, and the data were re-referenced to an average reference (avgRef).

For classification within sleep, the sleep data were locked to the TMR cues, with the time of interest defined as -0.5 seconds before and 2 seconds after stimulus onset. The data were z-scored across all trials at each time point. To investigate whether image category-related and head orientation-related activity could be identified within sleep, the classifier was trained and tested on sleep data. For the decoding of images, the classifier was trained on four categories of images: animals, objects, houses, and famous faces. For the decoding of head orientation-related activity, the classifier was trained on four different head orientations (-60°, -30°, 30°, and 60° from center). Data were smoothed using a running average window of 150 ms. The dataset was divided into training and test sets using 5-fold cross-validation to prevent overfitting. Due to the inherent variability in cross-validation caused by random trial assignment, the analysis was repeated five times, and the results were averaged. Statistical significance was assessed by comparing the classification results to a chance level (0.25). Furthermore, the same classification analysis procedure was applied for trials with and without spindle occurrences.

To ensure sufficient data for classification, participants were only included if they had a minimum of 30 trials in each of the four categories (image categories or head orientations). Based on this criterion, 18 participants were included in the image category decoding, and 22 participants were included in the head orientation decoding analysis. When the decoding was restricted to trials with or without spindle occurrences, fewer trials remained. Applying the same inclusion criterion, 11 participants were retained for this analysis.

Next, a time-by-time classification analysis was computed focusing on identifying wake-related representations of image categories and head orientations during sleep. A classifier was trained on the localizer data and tested on sleep data. For head orientations, data were trained on instances where participants performed head turns towards the screen with a fixation cross, fixating for 2 seconds. Image categories were trained on the image presentation onset. Both the localizer data and sleep data were z-scored across trials. Data were smoothed using a running average window of 150 milliseconds. For this analysis, 18 participants were included in the image category decoding, and 9 participants were included in the head orientation decoding, based on the same inclusion criterion as in the other decoding analyses (a minimum of 30 trials per category in each decoding analysis). Due to the smaller number of available trials in the head orientation localizer (24 sequences, 3 blocks), combined with artifact rejection, some participants lacked sufficient data for all orientation classes, resulting in additional exclusions compared to image decoding.

Temporal Dynamics of Memory Reactivation

To examine the temporal dynamics of memory reactivation during sleep, we adapted an approach introduced by Michelmann et al (2018), which aimed to assess the replay of episodic content using phase similarity between encoding and retrieval. In our study, we used within-sleep decoding accuracy values to track the evolution of decoding over time for four sequentially learned items, for both images and head orientations.

For each participant, decoding accuracy time series for the four items were normalized by subtracting the minimum value of each item's time course. These normalized values were then cumulatively summed and divided by the total sum to obtain relative cumulative decoding curves. For each time window, we also ranked the cumulative sums of the four items/head orientations to examine if there was a consistent order of items from 1 to 4.

2.3.4. Statistical Analysis

Behavioral analysis was conducted to assess the effect of test time (pre-sleep/post-sleep/24-hour delay) and cueing (cued/uncued) on memory performance using a 3x2 repeated measures ANOVA (rmANOVA). For analyzing the improvement of weak sequences based on cueing conditions, the distribution of these sequences was quantified across the retrieval sessions. Using Wilcoxon signed-rank tests, the relative improvement of cued versus uncued sequences was compared across different measurement times (post/pre-sleep, 24-hour delay/pre-sleep, 24-hour delay/post-sleep). For the behavioral analyses, results were considered significant if the p-value was less than 0.05.

Statistical comparisons of ERPs and TFR data were performed using a non-parametric cluster-based permutation test using the Fieldtrip toolbox (Oostenveld et al., 2011). The analyses were conducted at the group level using dependent-samples t-tests. Monte Carlo simulations were used to calculate cluster p-values (alpha = 0.05, two-tailed) based on the permutation distribution.

In all classification analyses, Fieldtrip's cluster-based permutation test was used. Dependent-samples t-tests were utilized to identify clusters of contiguous time points per electrode across participants. The values were thresholded at $p = 0.05$. The cluster statistic was defined as the maximum sum of all t-values within a cluster (maxsum). Monte Carlo simulations, with 1000 randomizations, were used to calculate the cluster p-value (alpha = 0.05, two-tailed) based on the permutation distribution. These analyses were conducted at the group level. The input data consisted of either classification values over time (decoding within sleep) or time x time classification values (cross-state decoding by training on localizer data and testing on sleep). Cluster-based permutation tests were applied to test classification accuracy against a chance level (0.25).

For the statistical testing of temporal dynamics of decoding analysis, linear regression was used on the cumulative decoding values at each time point, using the item indices (1 to 4) as predictors. The resulting slopes quantified the relationship between item position and decoding strength at each time point. A negative slope indicates stronger decoding for earlier items, which would then be indicative of forward replay (Michelmann et al., 2018).

A cluster-based permutation test was performed to test the statistical significance of the slopes. First, t-statistics were computed by comparing the slopes to zero at each time point (two-tailed one-sample t-test). Consecutive significant time points were grouped into clusters. For each cluster, the sum of the t-statistics was calculated. A null distribution was generated by randomly shuffling the subject labels (1,000 permutations) and recalculating the maximum cluster sum for each permutation. Then, these observed clusters were compared against this null distribution. Clusters with p-values below 0.05 were considered statistically significant.

2.4. Results

2.4.1. Behavioral Results

Overall memory performance

Memory performance was assessed for head orientation and image sorting tasks across pre-sleep, post-sleep, and 24-hour delay sessions. A sequence was classified as remembered in a given task if all four images or head orientations were correctly recalled. To investigate differences in memory performance across test times (pre-sleep, post-sleep, and 24-hour delay) and TMR conditions (cued and uncued), a 3 × 2 repeated measures ANOVA was computed.

Memory performance for the head orientation task (n = 17) is depicted in Figures 2a and 2b. There were no significant effects of test time ($F_{2, 32} = 2.81$, $p = 0.075$) or cueing ($F_{1, 16} = 0.88$, $p = 0.36$), and no significant interaction effect was found ($F_{2, 32} = 0.81$, $p = 0.45$). For the image sorting task (n = 21) (Figs. 2c-d), memory performance declined significantly across sessions ($F_{2, 40}$

= 15.02, p < 0.001). No main effect of cueing ($F_{1, 20} = 0.38$, p = 0.55), or interaction effect between cueing and test time could be demonstrated ($F_{2, 40} = 0.88$, p = 0.43).

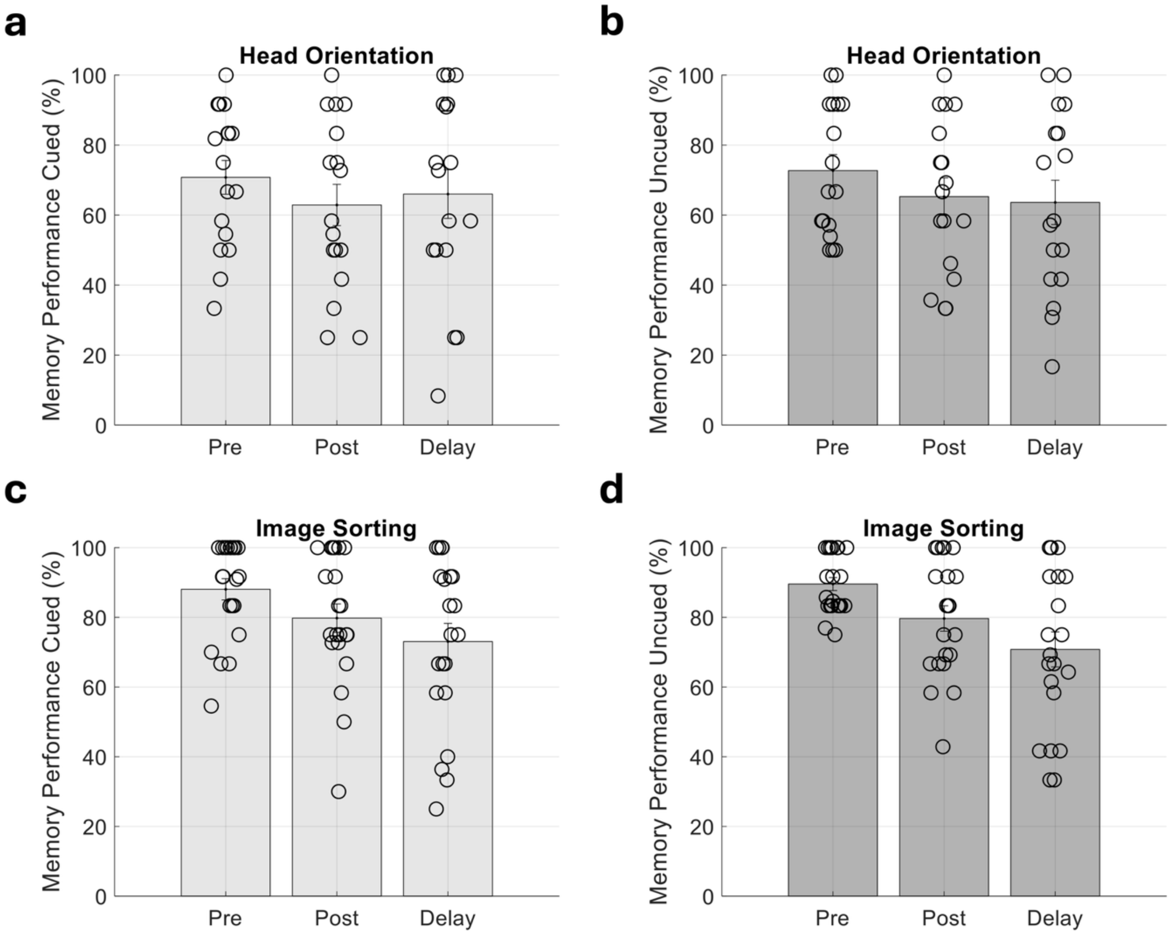

Figure 2. Memory performance for head orientation and image sorting tasks across pre-sleep, post-sleep, and 24-hour delay sessions. **a.** and **b.** depict memory performance for the head orientation task under cued and uncued conditions. A 3 x 2 repeated measures ANOVA showed no significant main effects of time or cueing and no interaction effect. **c.** and **d.** demonstrate memory performance for the image sorting task under cued and uncued conditions. Memory performance significantly decreased across sessions ($F_{2, 40} = 15.02$, p < 0.001). No main effect of cueing or interaction effect between cueing and test time was found. Bar graphs illustrate the mean (± SEM across participants) in percentage of memory performance. Circles overlaid on bar graphs represent individual participant data.

Memory performance in weak sequences

To investigate whether TMR selectively improves weakly encoded sequences, we analyzed sequences in which only one or two items or orientations out of four were correctly recalled. The number of weak sequences in the cued and uncued conditions was quantified and compared across measurement times (post-sleep/pre-sleep, 24-hour delay/pre-sleep, 24-hour delay/post-sleep) using Wilcoxon signed-rank tests. Results for both the head orientation and image sorting tasks are presented in Fig. 3. A higher number of weak sequences at a later test indicates more forgetting. For the head orientation task (Fig. 3a-c), Wilcoxon signed-rank tests comparing cued and uncued conditions showed a significant difference in 24-hour delay/pre-sleep (W = 10, n = 15, p = 0.02, Fig. 3b) and 24-hour delay/post-sleep comparisons (W = 2, n = 13, p = 0.001, Fig. 3c), indicating that cued weak sequences demonstrated greater performance improvement or stabilization compared to uncued sequences. In contrast, there were no significant differences between cued and uncued sequences in any comparison for the image sorting task (all p-values > 0.05, Fig. 3d-f).

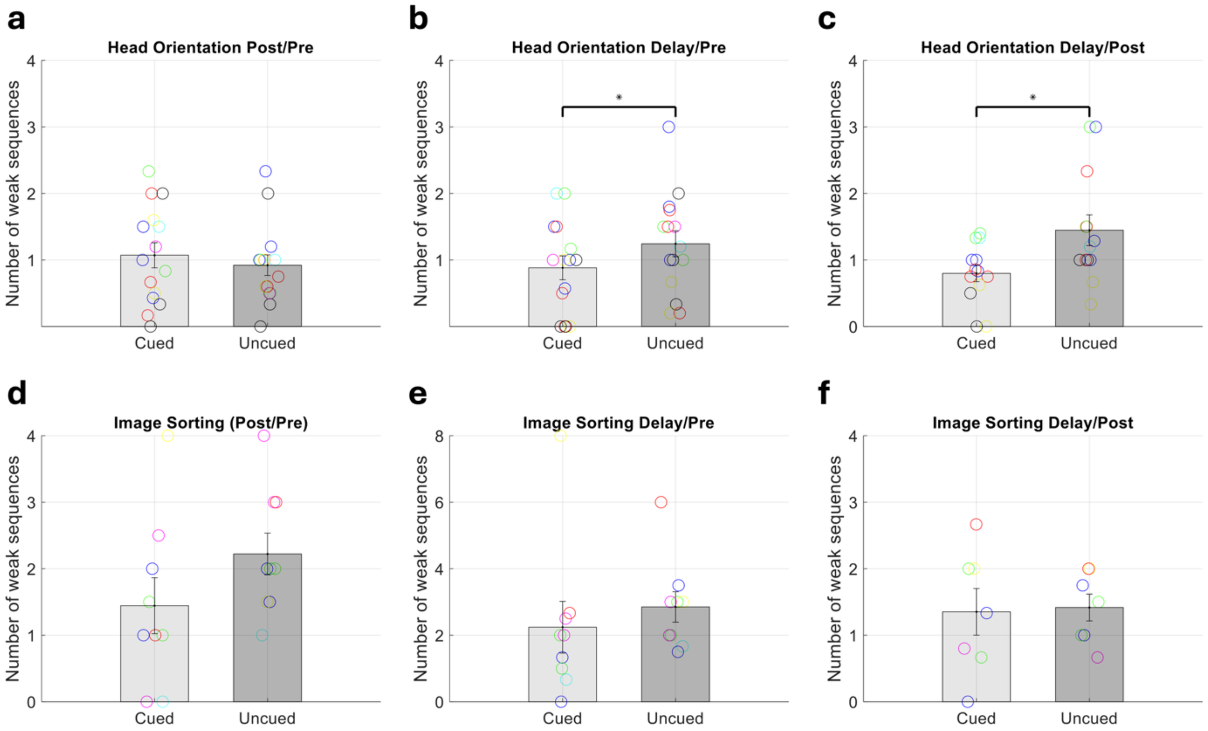

Figure 3. Number of weak sequences in cued and uncued conditions for head orientation (a-c) and image sorting tasks (d-f) across test intervals: post-sleep/pre-sleep **(a, d)**, 24-hour delay/pre-sleep **(b, e)**, and 24-hour delay/post-sleep **(c, f)**. In the head orientation task, the significantly greater number of weak sequences in uncued versus cued conditions at both the 24-hour delay/pre-sleep (p = 0.02) and 24-hour delay/post-sleep (p = 0.001) intervals indicates enhanced memory stabilization or improvement in cued sequences. In the image sorting task, no significant differences were observed between cued and uncued conditions (all p-values > 0.05).

Bar graphs illustrate the mean number of weak sequences (± SEM across participants). Colored circles overlaid on bar graphs represent individual participant data.

2.4.2. Sleep EEG

Event-related potentials (ERPs)

To investigate neural responses to TMR cues in sleep EEG, ERPs were computed for the following contrasts: experimental versus control to assess the influence of cueing during sleep, and remembered versus forgotten to compare ERP responses based on pre-sleep memory performance. In both contrasts, cluster-based permutation tests (two-sided) did not reveal significant differences in ERPs (all p-values > 0.025, Fig. 4a-b). This analysis served as a sanity check, confirming the presence of an ongoing ERP pattern following TMR cues, particularly the occurrence of K-complexes after the sound presentation.

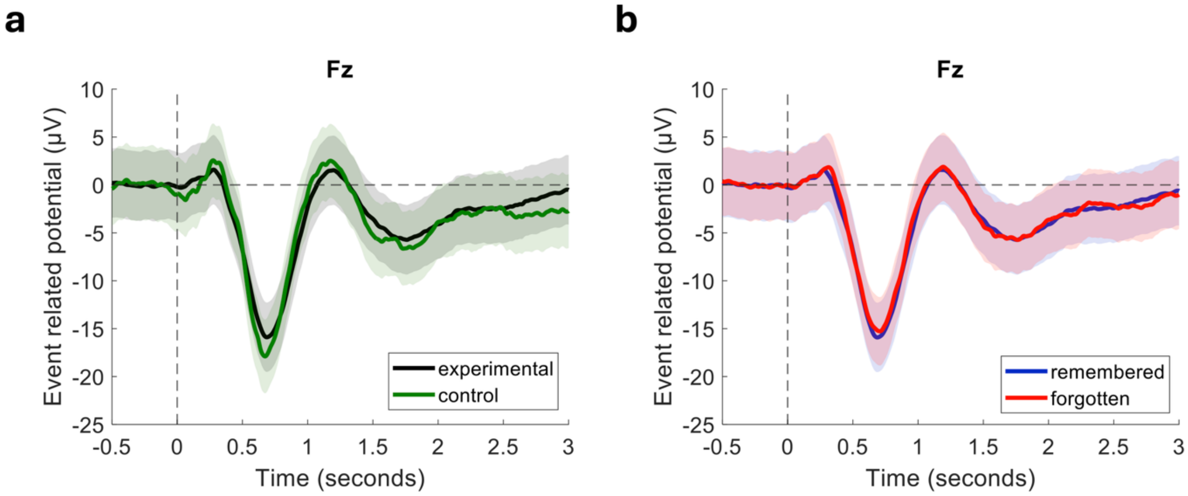

Figure 4. ERPs following TMR onset. a. Grand average ERP waveforms at electrode Fz for experimental (black) and control (green) cues. **b.** Grand average ERP waveforms at electrode Fz for cues associated with remembered (black) and forgotten (red) sequences according to pre-sleep performance. Shaded areas indicate the standard error of the mean (SEM).

Time-frequency representations (TFRs)

Next, TFRs were computed to explore changes in neural activity during sleep across the experimental versus control and remembered versus forgotten contrasts. Both experimental and control cues demonstrated increases in slow oscillation (1-4 Hz) and spindle band (12-18 Hz) activity following TMR cues (Figs. 5a & 5b). However, the differences between neural responses in experimental versus control conditions were not significant (all p-values > -0.025, two-sided cluster-based permutation test, Fig. 5c). Similarly, no distinct neural patterns emerged when comparing cues associated with remembered versus forgotten sequences based on pre-sleep memory performance (all p-values > 0.025, two-sided cluster-based permutation test, Fig. 6c).

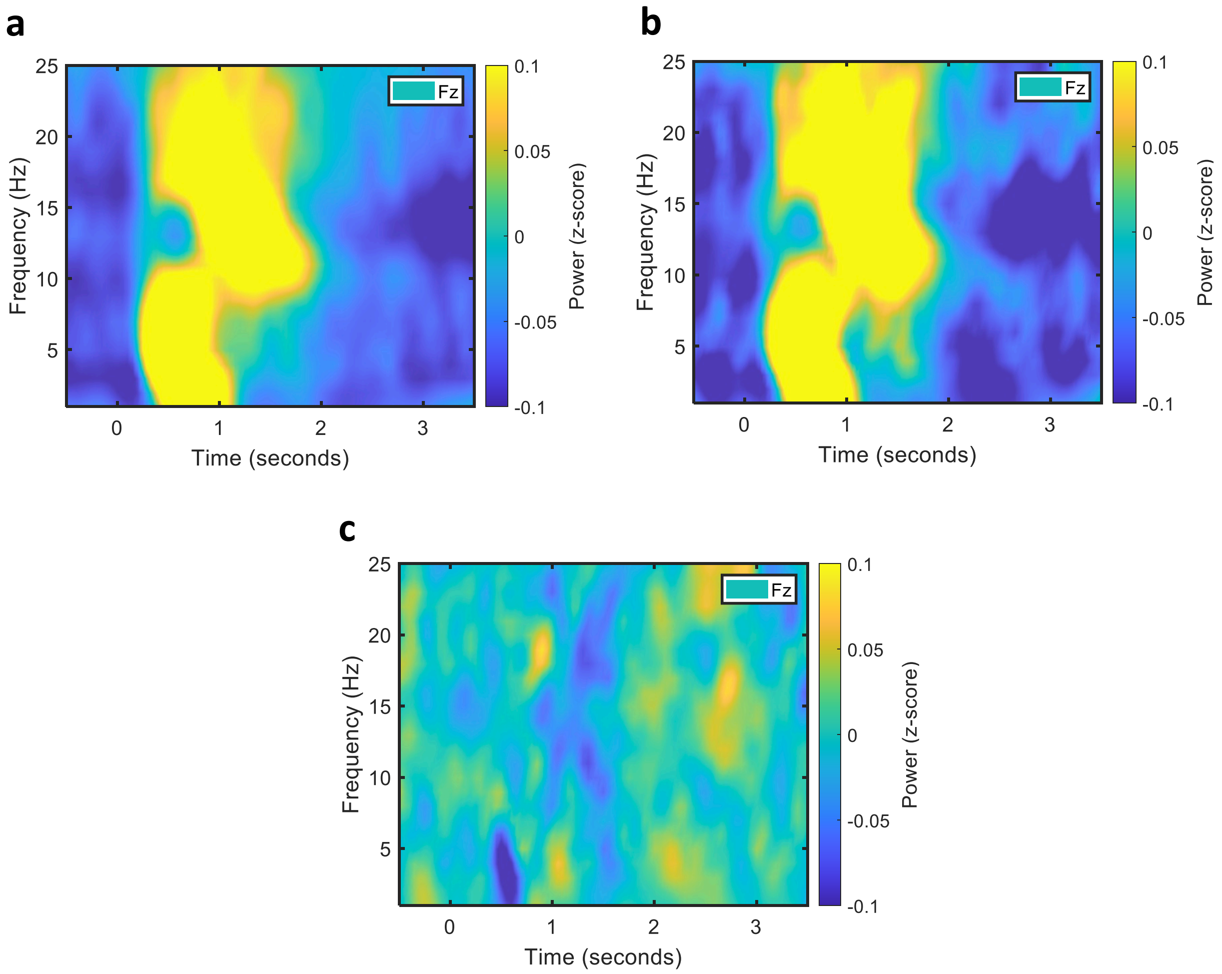

Figure 5. EEG power for experimental and control cues following TMR onset. a. Grand average TFR for experimental cues. **b.** Grand average TFR for control cues. Increases in slow oscillation (1-4 Hz) and spindle band (12-18 Hz) activity were observed in both conditions following TMR cues. **c.** Difference of grand averages between experimental and control cues. Data from Fz is plotted as a representative electrode. No significant differences in power were observed comparing experimental and control cues across the frequency bands (1-25 Hz) and time (-0.5 s to 3.5 s) investigated (p > 0.025, two-sided cluster-based permutation test).

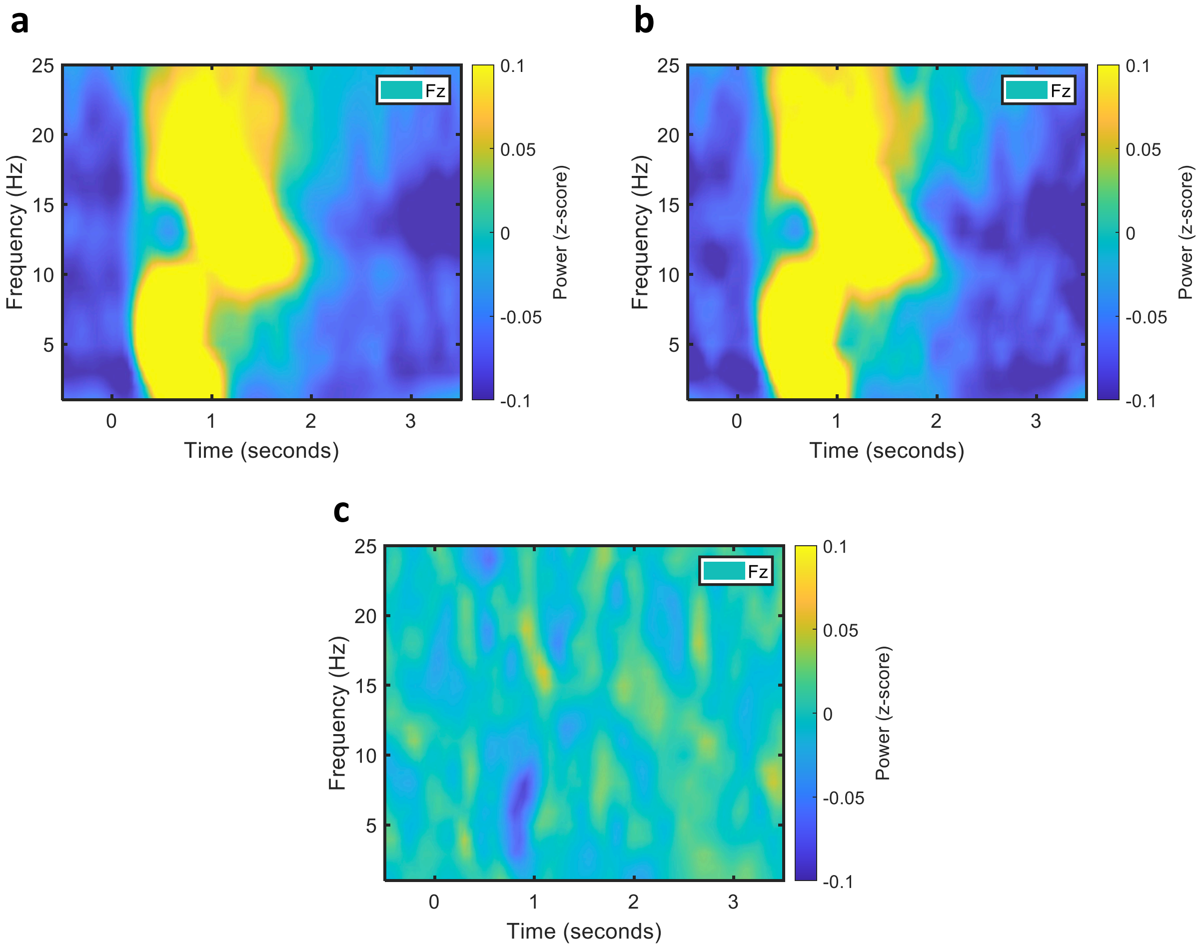

Figure 6. EEG power following TMR onset for cues associated with remembered and forgotten sequences. a. Grand average TFR for cues associated with remembered sequences. **b.** Grand average TFR for cues associated with forgotten sequences. Increases in slow oscillation (1-4 Hz) and spindle band (12-18 Hz) activity were observed in both conditions following TMR cues. **c.** Differences in grand averages between remembered and forgotten conditions. Data from Fz is plotted as a representative electrode. No significant difference in power was observed between remembered and forgotten conditions across the frequency bands (1-25 Hz) and time (-0.5 s to 3.5 s) investigated ($p > 0.025$, two-sided cluster-based permutation test).

2.4.3. Multivariate Decoding Analysis

Multivariate decoding was performed using the MVPA Light toolbox in MATLAB to examine whether head orientation-related and image category-related activity could be decoded during sleep. EEG data were time-locked to the TMR cues, and a classifier was trained and tested on the sleep data. A multiclass linear discriminant analysis (LDA) was conducted separately for head orientations (four classes) and image categories (four classes).

Each analysis employed 5-fold cross-validation and was repeated five times to ensure stability. At each time point, the classifier attempted to predict the correct class label for held-out trials based on the EEG patterns observed following the TMR cue. This procedure provided a time-resolved measure of how accurately stimulus-specific activity can be decoded from sleep EEG. Based on the inclusion criterion of having at least 30 trials per class (see Methods), decoding analyses were conducted on n = 22 participants for head orientations and n = 18 for image categories. The results showed that both head orientation and image category-related activity could be decoded following TMR cues. By comparing the classification results to chance levels (0.25) using a two-sided cluster-based permutation test, head orientation-related activity showed a significant, above-chance classification for all four orientations (n = 22, first and second orientations: $p = 0.02$; third and fourth: $p < 0.001$, Fig. 7a). Image category-related activity was partially decodable (n = 18, Fig. 7b), specifically for the second item ($p < 0.001$) and the third item ($p = 0.02$) in the sequence.

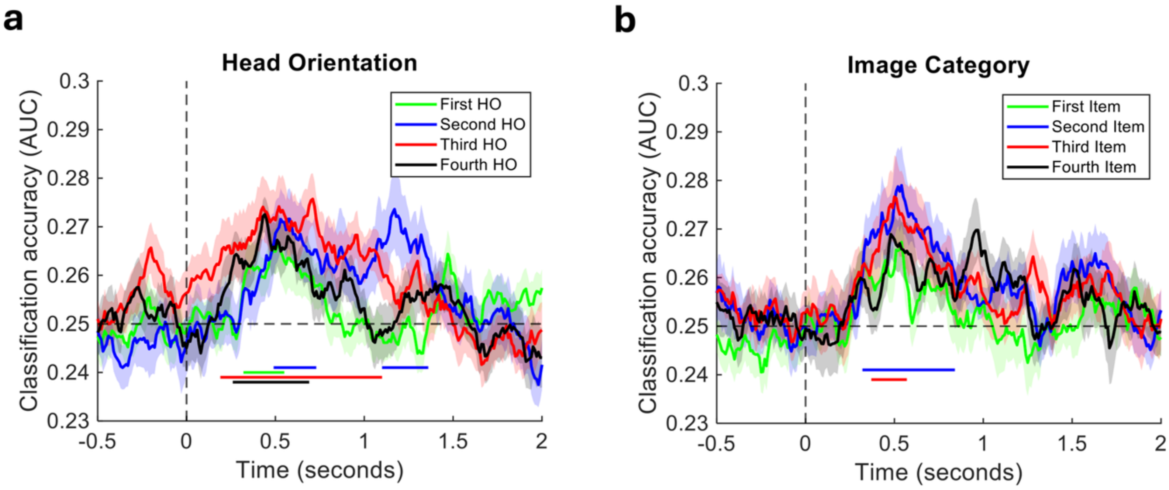

Figure 7. Multivariate decoding during sleep. a. Classification accuracy (± SEM across participants) of head orientation-related activity for four head orientations (HO): first (green), second (blue), third (red), and fourth (black). Significant above-chance decoding was observed for all four head orientations (first and second orientations: $p = 0.02$; third and fourth: $p < 0.001$, two-sided cluster-based permutation test). **b.** Classification accuracy (± SEM across participants) of image category-related activity for four items. Significant decoding accuracy was identified for the second ($p < 0.001$) and third items ($p = 0.02$) in a sequence. The horizontal dashed line indicates chance-level performance (0.25). The vertical dashed line at time zero represents the

onset of the TMR cue. The color-coded horizontal lines below the curves show the temporal extent of significant decoding results.

2.4.4. Slow Oscillations (SOs), Spindles, and SO-Spindle events

Slow oscillations (SOs), spindles, and SO-spindle co-occurrences following TMR cues were detected from central electrodes (Cz, C3, and C4) and analyzed in relation to participants' pre-sleep memory performance. The number of occurrences was computed and compared between TMR trials linked to remembered and forgotten sequences. These comparisons were then tested using Wilcoxon signed-rank tests. The results showed a significant increase in spindle occurrences for remembered compared to forgotten sequences ($W = 227$, $N = 24$, $p = 0.028$, Fig. 8b). However, no significant differences were observed for the number of SOs ($W = 145$, $N = 24$, $p = 0.88$, Fig. 8a) or SO-spindle events ($W = 186$, $N = 24$, $p = 0.304$, Fig. 8c) between remembered and forgotten conditions.

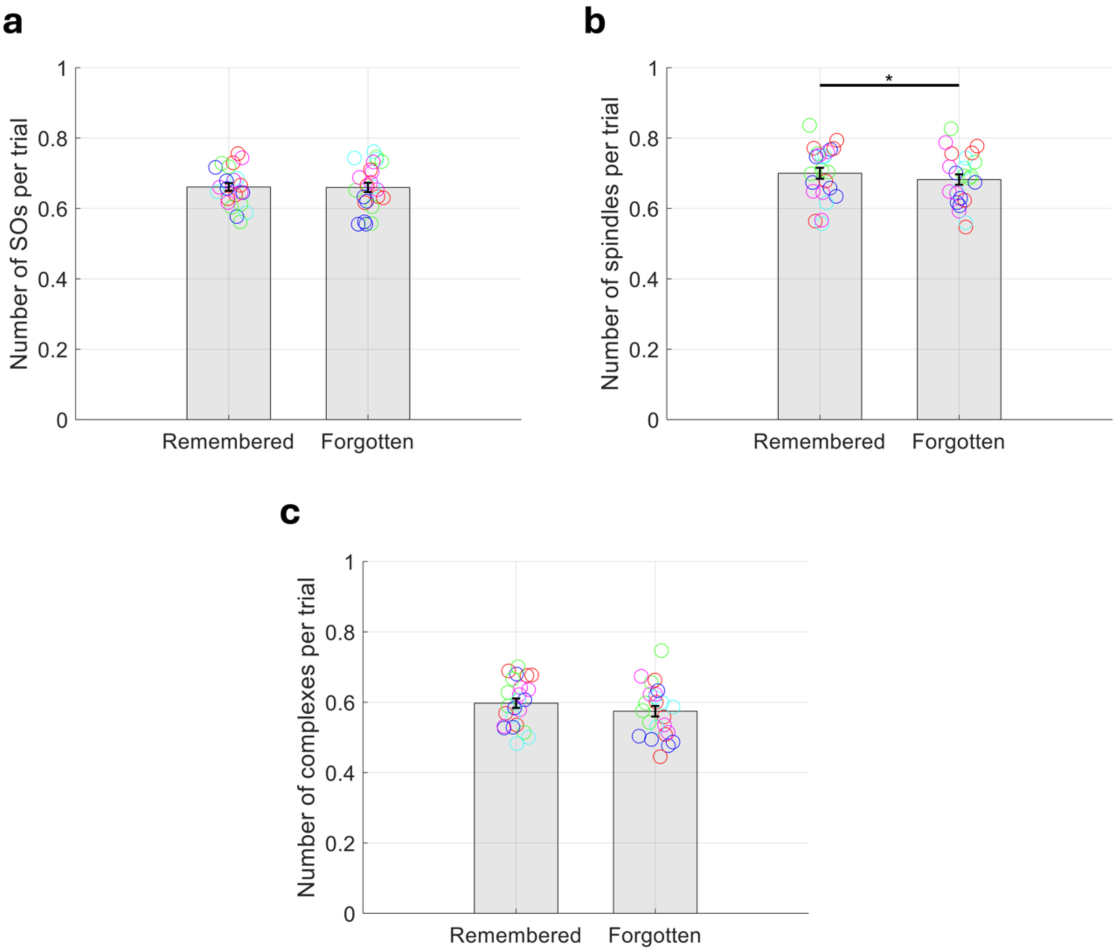

Figure 8. Number of SOs, spindles, and SO-spindle events following TMR cues in remembered and forgotten conditions. a. Number of SOs per trial for remembered and forgotten conditions. No significant difference was found between the conditions. **b.** Number of spindles per trial for remembered and forgotten conditions. Remembered trials showed a significantly higher number of spindles compared to forgotten (W = 227, N = 24, p = 0.028). **c.** Number of SO-spindle co-occurrences per trial for remembered and forgotten conditions. No significant differences were observed between the conditions. Bar graphs illustrate the mean number of events per trial (± SEM across participants). The colored circles represent individual participant data. The star highlights the significant difference.

Decoding within sleep associated to spindle events

Given the significant increase in the number of spindles observed in remembered trials compared to forgotten ones, suggesting that spindles may play a role in memory consolidation, decoding analysis within sleep was repeated, focusing on TMR trials containing spindle events and trials without spindle events. Participants were included in this analysis if they had at least

30 trials per class after filtering for spindle presence (see Methods), resulting in a final sample of n = 11.

Trials containing spindle occurrences exhibited statistically significant classifier performance for the first (p = 0.024) and second (p = 0.012) head orientations (Fig. 9a, cluster-based permutation test against a chance level of 0.25). In contrast, trials without spindle occurrences did not reach significance when tested against the chance level (all p-values p > 0.025, Fig. 9b, cluster-based permutation test against a chance level of 0.25).

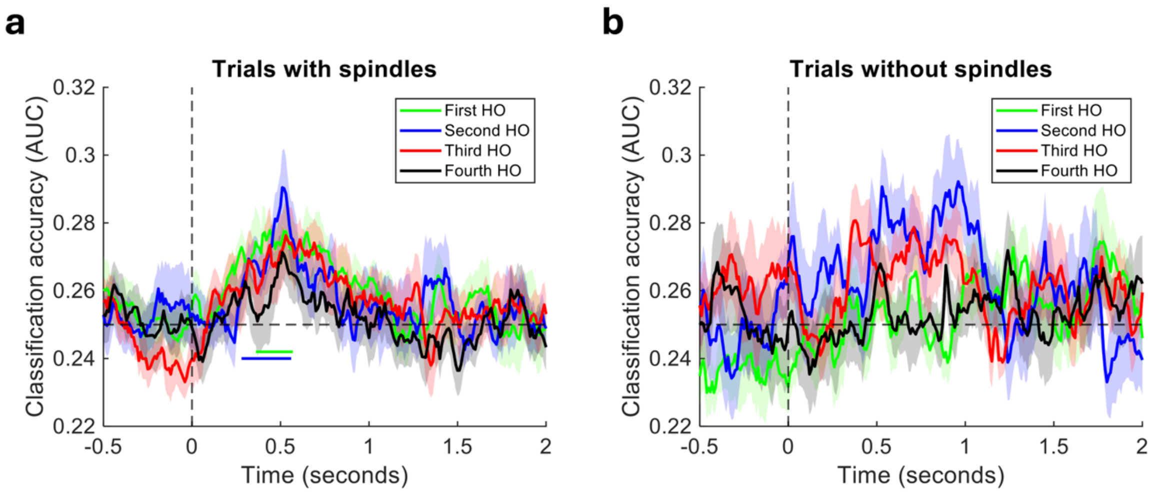

Figure 9. Multivariate decoding of head orientation-related activity during sleep for trials with and without spindle occurrences. a. Classification accuracy (± SEM across participants) for head orientation (HO)-related activity in trials with spindles. Significant above-chance decoding was observed for the first (green, p = 0.024) and second head orientations (blue, p = 0.012) based on a two-sided cluster-based permutation test against a chance level of 0.25. **b.** Classification accuracy (± SEM across participants) for head orientation-related activity in trials without spindles. No significant decoding was found for any of the orientations (all p-values p > 0.025). The horizontal dashed line indicates chance-level performance (0.25). The vertical dashed line at time zero represents the onset of TMR. The color-coded horizontal lines below the curves show the temporal extent of significant decoding results.

2.4.5. Decoding Wake-Related Memories During Sleep

Next, the potential reactivation of wake-related memory representations during sleep was investigated for head orientations and image categories. The same inclusion criterion as in all decoding analyses was implemented (a minimum of 30 trials per class), resulting in n = 9 for head orientation decoding and n = 18 for image category decoding. Fewer participants were included in the head orientation analysis due to a smaller number of trials in the localizer and additional exclusions after artefact rejection.

For head orientations, the classifier was trained on data from the head orientation localizer task, where participants fixated on the fixation cross on the corresponding screen. The training was specific to sequence order; when analyzing the first orientation in sequences, the classifier was trained on data from the first fixation event, the second one on the second fixation event, and so forth. For image categories, the classifier was trained on the data from the image localizer task time-locked to image onset. The trained classifiers were then tested on sleep data to assess the reactivation of these representations.

The significance of the classifier performance was tested using a two-sided cluster-based permutation test against a chance level of 0.25. No significant decoding accuracy was observed for either head orientations or image categories during sleep (all p-values > 0.025). The results are illustrated in Figures 10a-d for head orientations and Figures 11a-d for image categories. These findings suggest that wake-related neural representations of both head orientations and image categories were not decodable from sleep EEG data, indicating potential limitations in capturing wake-related memory processing from sleep EEG.

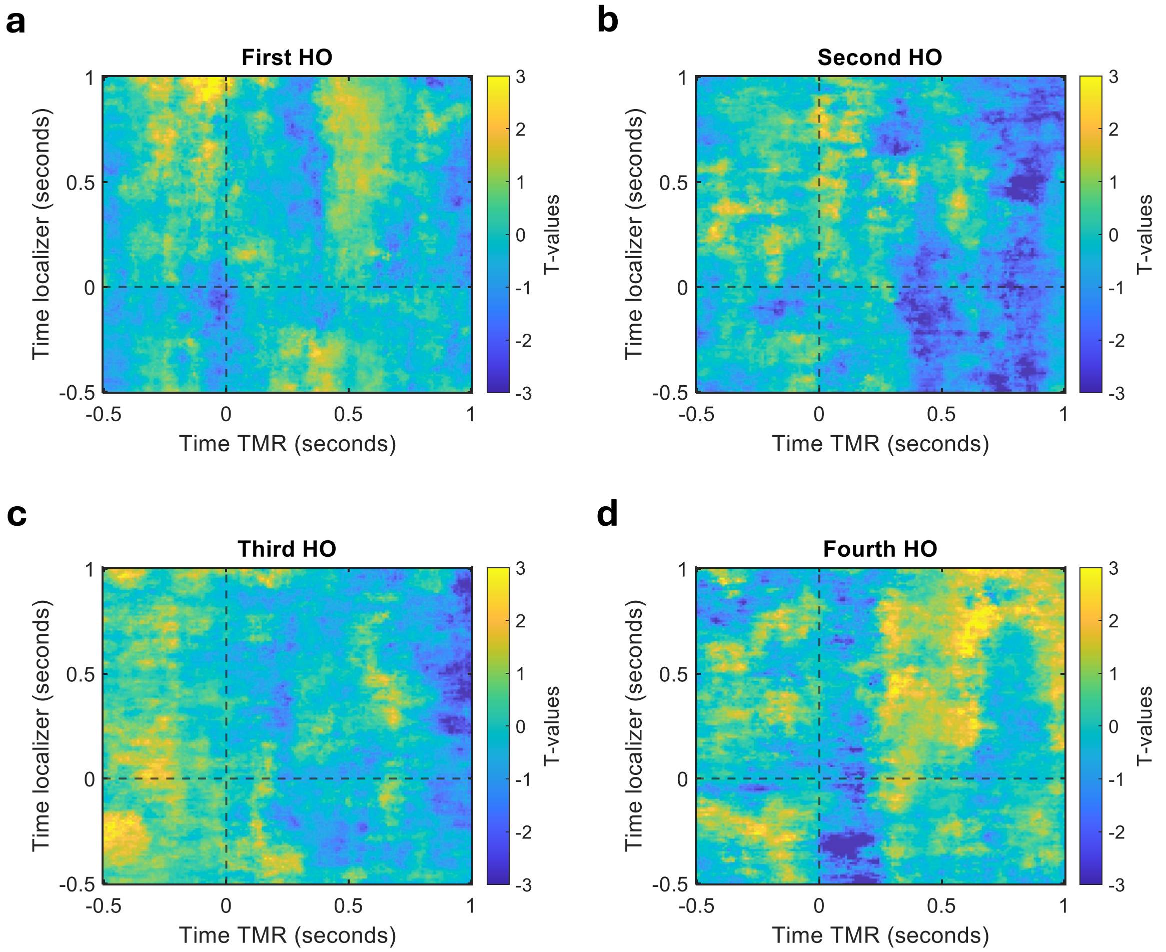

Figure 10. Decoding head orientation-related activity during sleep. Time-generalization matrices demonstrating classifier performance for head orientations in a sequence (first to fourth head orientation (HO) in a sequence). The color scale represents t-values comparing classifier performance to chance-level. Head orientation-related activity training on localizers was not decodable during TMR, as indicated by the absence of consistent warm clusters across time points (all p-values > 0.025, two-sided cluster-based permutation test).

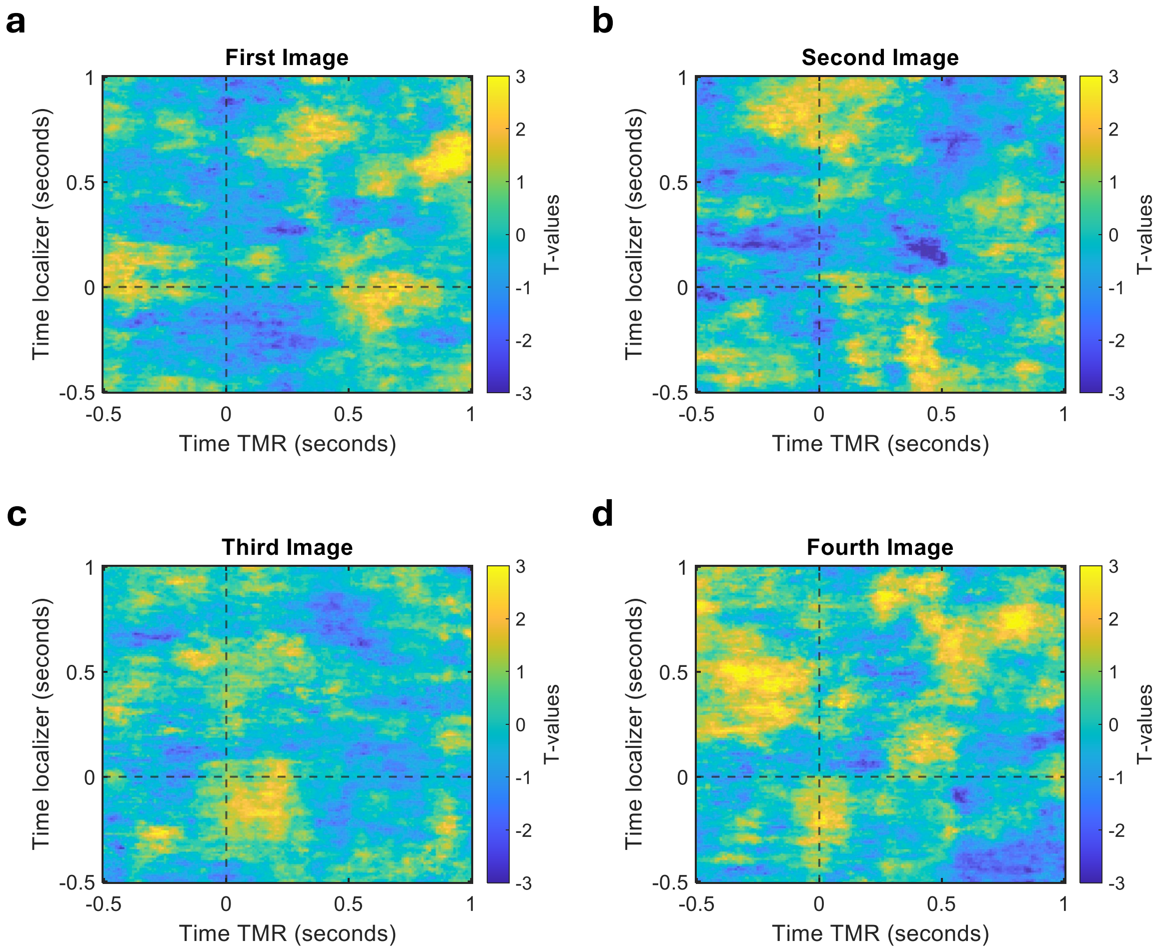

Figure 11. Decoding image category-related activity during sleep. Time-generalization matrices demonstrating classifier performance for image categories in a sequence (first to fourth item in a sequence). The color scale represents t-values comparing classifier performance to chance levels. Image category-related activity training on localizers was not decodable during TMR, as indicated by the absence of consistent warm clusters across time points (all p-values > 0.025, two-sided cluster-based permutation test).

2.4.6. Temporal Dynamics of Memory Reactivation During Sleep

To test whether decoding accuracy followed a systematic pattern over time relating to the sequential order, the temporal dynamics of memory reactivation for sequential images and head orientations were investigated by adapting the approach of Michelmann et al. (2018). Cumulative sums of classification values from within-sleep decoding results were computed over time across four items and head orientations, and then normalized (Figs. 12a and 13a). Linear regression was applied to these cumulative sums at each time point, using item indices as predictors. The resulting regression slopes represent the rate of change in decoding accuracy over time (Figs. 12c and 13c), a negative slope indicating higher accuracy for earlier items and a positive slope indicating higher accuracy for later items in a sequence (Michelmann et al., 2018).

To assess statistical significance, a cluster-based permutation test was performed. At each time point, slopes were compared to zero using a two-tailed one-sample t-test. Consecutive significant time points were grouped into clusters. For each cluster, the sum of the t-statistics was calculated. A null distribution was generated by randomly shuffling the subject order (1,000 permutations) and calculating the maximum cluster sum for each permutation. The observed cluster-level statistics were compared against the null distribution. No significant clusters were identified in the analysis of slopes over time for either head orientations (Fig. 12d) or image categories (Fig. 13d; all p-values > 0.05), suggesting no systematic changes in the temporal dynamics of memory reactivation.

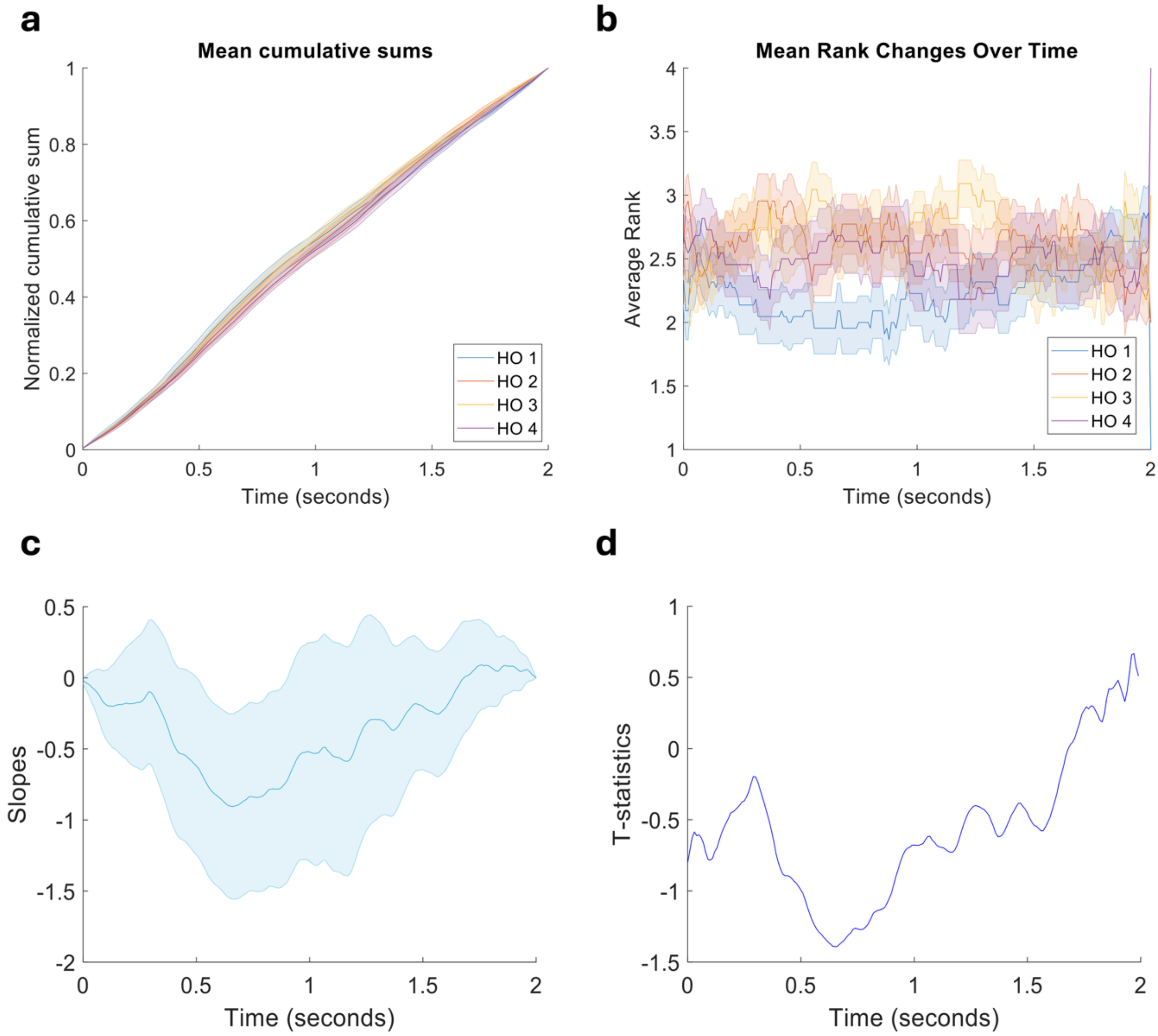

Figure 12. Temporal dynamics of head orientation (HO) decoding accuracy. a. Cumulative sum of classification values over time (normalized) for four head orientations (HO 1-4). **b.** The average rank of cumulative sums for each head orientation over time. **c.** Regression slopes derived based on the cumulative sums at each time point, representing the change in decoding accuracy over time. Shaded areas indicate the standard error of the mean (SEM). **d.** T-statistics resulting from testing the slopes against zero at each time point. No significant clusters were identified, suggesting an absence of consistent temporal dynamics in decoding accuracy.

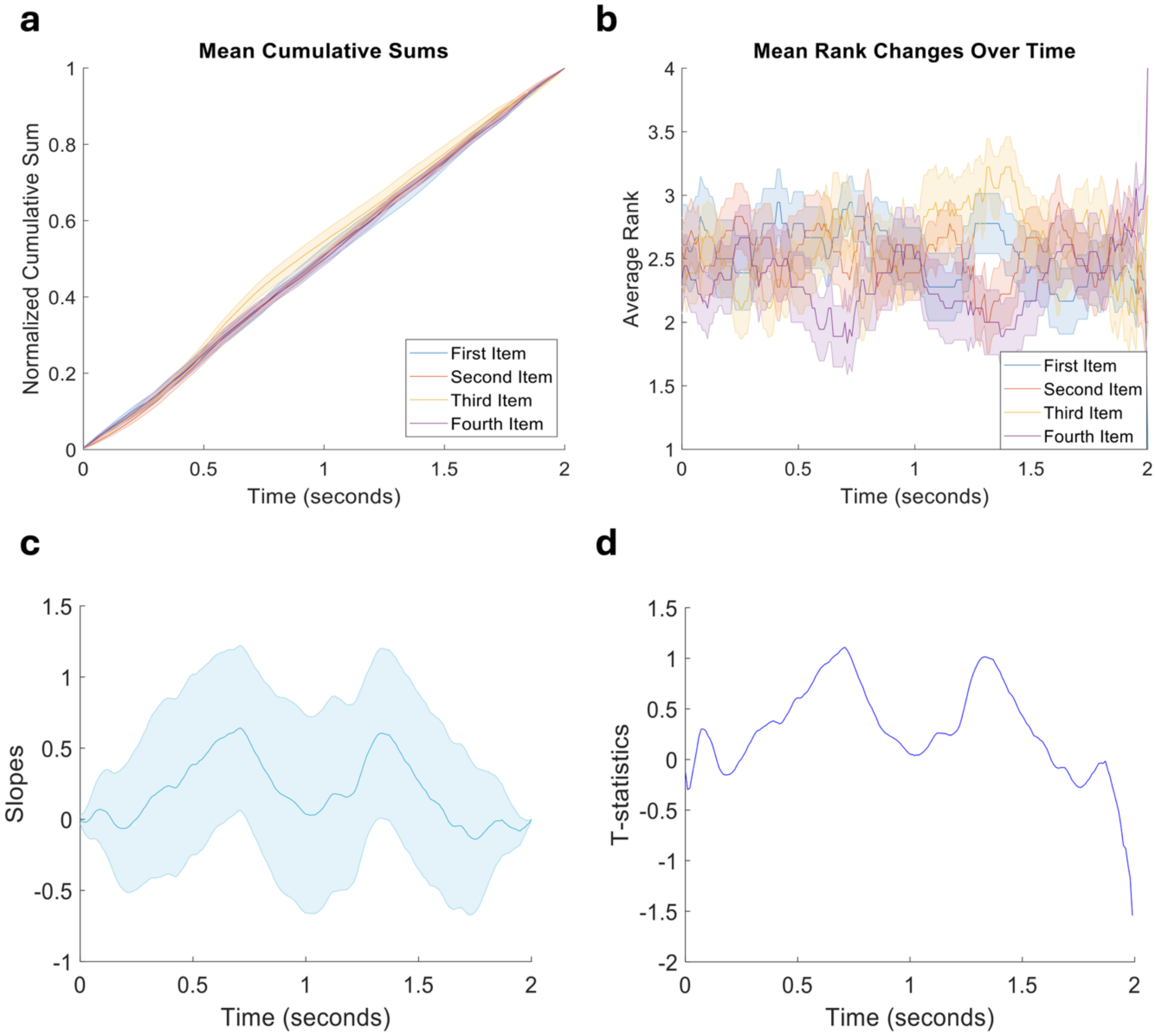

Figure 13. Temporal dynamics of image category decoding accuracy. a. Cumulative sum of classification values over time (normalized) for four images in a sequence. **b.** The average rank of cumulative sums for each image over time. **c.** Regression slopes derived based on the cumulative sums at each time point, representing the change in decoding accuracy over time. Shaded areas indicate the standard error of the mean (SEM). **d.** T-statistics resulting from testing the slopes against zero at each time point. No significant clusters were identified, suggesting an absence of consistent temporal dynamics in decoding accuracy.

2.5. Discussion

Our study revealed several key findings. TMR selectively improved head orientation memory performance for weakly encoded sequences, with effects becoming evident in the 24-hour delayed retrieval session. Decoding analyses, in which classifiers were trained and tested on sleep EEG data following TMR cues, revealed distinct neural activity patterns that reliably differentiated head orientations for all sequence items, whereas image category decoding was limited to the second and third items in a sequence. Importantly, decoding performance was significant only in trials with spindle occurrences but not in those without, highlighting the relevance of these oscillations in memory processing. Furthermore, analyses of the temporal dynamics of decoded neural activity, which examined variations in decoding accuracy over time, indicated no systematic changes in decoding performance for either image or head orientations. Finally, classifiers trained on wake localizer tasks for image and head orientation-related activity did not show significant decoding when tested on sleep data.

Our findings demonstrate that multiple aspects of memory, including image and head orientation-related activity, can be decoded from sleep EEG following TMR cues. The ability to decode both features provides a unique opportunity to examine how these interconnected memory components are processed during sleep. Notably, head orientations were consistently decoded across all sequence items, while image decoding was only successful for the second and third items. This suggests that different memory features may follow distinct neural patterns during sleep. One possible explanation is that spatial information serves as a structural framework for organizing memory traces (Eichenbaum, 2017b), leading to more stable reactivation of head orientations.

For images, significant decoding was observed for the middle sequence items (2nd and 3rd items). This pattern suggests that the first and last items in a sequence may have initially been more strongly encoded, potentially due to primacy and recency effects that enhance memory strength (Glanzer & Cunitz, 1966). As a result, middle items may have benefited more from processing during sleep. Previous research suggests that sleep preferentially stabilizes weaker representations by strengthening their neural traces and integrating them into memory networks (Denis et al., 2021). Since middle items may not benefit as much from primacy and recency effects during encoding, their initial representations could be less robust, making them more susceptible to reactivation during sleep. This finding suggests that serial position in a sequence may influence how memory components are processed during sleep, potentially due to differences in their initial encoding strength.

It is also important to note that the decoding peak occurred ~0.5 seconds after TMR onset. This timing is consistent with prior studies reporting early phases of cue-induced reactivation. It aligns with theoretical models suggesting that TMR cues first elicit a partial reactivation in cortical regions and may then engage hippocampal replay mechanisms (Lewis & Bendor, 2019). For example, Cairney et al. (2018) reported distinct time points of memory-related neural activity at both ~0.5 and ~2 seconds post-cue, based on increased discriminability between object-scene categories. Similarly, Schreiner et al. (2018) found that reinstatement of memory-related phase patterns occurred immediately after cue onset, followed by two additional peaks at ~2 and ~3 seconds. Lewis & Bendor (2019) interpreted these findings as reflecting a sensory-driven initial cortical response followed by hippocampally driven reactivation. However, in our data, no additional decoding peaks were observed beyond this initial response. This may indicate that memory processing in our paradigm was limited to an early phase, or that any later occurrences were too temporally variable or weak to be reliably detected using our decoding approach.

Our findings demonstrate increased spindle activity following TMR cues in remembered sequences compared to forgotten ones, suggesting a link between spindles and memory retention. It is well-established that sleep oscillations are linked to memory consolidation processes (Mölle et al., 2009; Staresina et al., 2015). Among these oscillations, sleep spindles are thought to enhance memory reactivation by facilitating the communication between hippocampal and cortical regions, a process essential for integrating memories into long-term storage (Latchoumane et al., 2017; Maingret et al., 2016). Moreover, coupling of spindles with slow waves has been linked to improved reactivation efficacy, and this interaction is thought to coordinate reactivation with optimal plasticity windows (Hahn et al., 2020; Schreiner et al., 2021; Staresina et al., 2015). Furthermore, we found that the presence of spindles following TMR cues predicted decoding success for head orientations. Decoding was only successful in trials where the spindles were present, while trials without spindles did not show above-chance classification results. This aligns with previous research demonstrating that TMR-induced spindle activity supports memory reactivation (Antony et al., 2019; Cairney et al., 2018; Ngo & Staresina, 2022; Schreiner et al., 2024).

However, an important consideration for this finding is the unequal trial numbers between the spindle and non-spindle conditions, highlighting the need for cautious interpretation. To ensure balanced trial numbers across image categories and head orientations, the dataset was adjusted so that all conditions had an equal number of trials available for decoding. Since trials without spindles were already less frequent than those with spindles, this approach created an imbalance between spindle and non-spindle conditions. If the same adjustment were applied to spindle occurrence, it would have further reduced the number of available trials, potentially compromising classification performance. Therefore, while our findings suggest that spindles facilitate memory reactivation, it remains unclear whether the absence of significant decoding in the non-spindle condition reflects a lack of memory processing or reduced statistical power.

In addition to within-sleep decoding, we investigated whether memory representations could be detected in the sleep EEG when trained on wake localizer data. Decoding memory-related activity across brain states enables the investigation of whether and how neural representations established during wakefulness are reactivated during sleep (Deuker et al., 2013; Schreiner et al., 2021; Wang et al., 2019). However, decoding previously learned information from sleep EEG is methodologically challenging. In our study, training classifiers on wake localizer data and testing on sleep data did not result in reliable decoding of either image-related or head orientation-related activity.

This null result may stem from several factors. First, memory-related brain activity can vary both between trials within the same participant and between participants. This variability introduces differences in the timing and strength of reactivation signals. Since EEG-based classification methods require the detection of stable and consistent patterns, the inter-subject and inter-trial variability reduces the classifier's ability to learn and generalize from the data (Van Bree et al., 2024). Second, differences in the time-frequency characteristics of EEG activity between wakefulness and sleep introduce variability, further complicating the identification of consistent reactivation patterns (Schönauer et al., 2017). For instance, sleep EEG is characterized by slower frequencies with increased amplitude, while wake EEG typically shows low-amplitude, high-frequency activity (Cirelli & Tononi, 2015; Rasch & Born, 2013). These differences can complicate the direct comparison or transfer of classifiers across states.

Nevertheless, several studies have successfully applied cross-state decoding to detect sleep-related reactivation of memory traces trained on wakefulness (Schreiner et al., 2021, 2024; Wang et al., 2019). For instance, Schreiner et al. (2021) employed a localizer-trained classifier and demonstrated successful decoding of stimulus categories from spontaneous reactivation during sleep, specifically aligned to the SO-spindle coupling. In the context of TMR-induced reactivation, Schreiner et al. (2024) trained classifiers on EEG data recorded during retrieval phases and reported cue-locked reactivation of head orientation-related activity during NREM sleep. These studies highlight the potential of cross-state decoding methods. However, these results may depend on their approaches, such as using single-item associations and precise alignment with sleep oscillations. In our paradigm, the complex nature of sequential-spatial associations, combined with the lack of alignment with sleep oscillations, may have limited the classifier's ability to generalize from wake to sleep.

A key question in our study was whether the processing of sequential memories during sleep follows a structured temporal trajectory, as theories of memory reactivation propose that past experiences are reinstated in a structured manner (Eichenbaum, 2017a). To track temporal dynamics, we adapted a method from Michelmann et al. (2018), who investigated the progression of episodic memory replay over time by computing cumulative phase similarity values between encoding and retrieval in video episodes. In our study, instead of phase similarity, we computed cumulative classification values across sequential images or head orientations from within-sleep decoding results to track how decoding accuracy evolved.

However, our analysis did not reveal a systematic pattern of decoding accuracy across the 0-2 second post-cue window for either images or head orientations. It is important to note that Michelmann et al. (2018) focused on awake retrieval rather than sleep, and reported that replay does not always follow a strict temporal order but can occur flexibly depending on task demands. Although cueing was applied to trigger reactivation in a controlled manner, the precise timing of reactivation relative to the cue may differ across trials, making it difficult to detect consistent temporal trajectories at the group level.

Prior research also suggests that reactivation during sleep may occur temporally compressed (Abdellahi et al., 2024) or be aligned with sleep oscillations, such as the coupling of slow oscillations and spindles (Schreiner et al., 2021). Our analysis was designed to track decoding dynamics relative to TMR cues but did not specifically target alignment with oscillatory events. Together, these factors may have contributed to the absence of a consistent temporal pattern in our decoding results. These considerations highlight the need for further research to disentangle how the temporal progression of reactivation unfolds during sleep.

Behaviorally, we demonstrated a significant TMR benefit for sequences of head orientations that were weakly encoded before sleep. This selective enhancement suggests that reactivation during sleep may help stabilize fragile spatial associations that would otherwise be prone to forgetting. While previous research has demonstrated that TMR preferentially strengthens weaker memory traces (Cairney et al., 2016; Denis et al., 2021), the present findings extend this line of work to sequential-spatial memories involving head orientation cues.

The delayed emergence of cueing effects aligns with previous findings indicating that TMR-induced reactivation may initiate memory processes that require additional offline consolidation to become evident (Cairney et al., 2018; Rakowska et al., 2021). For example, Cairney et al. (2018) reported no immediate cueing benefit following a 90-minute nap, and effects were only present the next morning after a full night's sleep without further TMR. Similarly, Rakowska et al. (2021) found that TMR benefits on procedural memories emerged 10 days after encoding but not immediately after sleep. Therefore, an additional night of sleep in our study may have contributed to the delayed strengthening process.

Ceiling performance in the image sorting task likely obscured potential cueing effects, highlighting a common issue in TMR studies, where strong initial encoding may diminish the effect of TMR on memory performance (Creery et al., 2015). Accounting for initial encoding strength when assessing behavioral cueing effects provided a more detailed understanding of memory retention in our study.

Several methodological factors should be considered when interpreting our findings. While undersampling was applied in all decoding analyses to ensure a balanced number of image categories and head orientations, this approach resulted in an imbalance of trial numbers in spindle and non-spindle trials. Examining spindle occurrences in decoding was not a primary focus of this study. Therefore, trial numbers were not pre-adjusted for this comparison. Future studies could address this by incorporating spindle occurrence as a factor in the initial experimental design, collecting larger datasets, and ensuring sufficient trials for all conditions.

This would allow for balanced comparisons and provide clearer insights into the spindles' role in TMR-induced memory processing during sleep.

Moreover, decoding across wakefulness and sleep presents methodological challenges. We addressed this by carefully selecting training time points from the localizer data sets, aligning the classifier training with stimulus onset for image presentation and head fixation periods of head orientations. Despite these attempts, decoding accuracy remained low when tested on sleep data. Future studies could address these limitations by implementing methods such as time-lagged decoding (Liu et al., 2019), aligning decoding analyses with sleep oscillations (Schreiner et al., 2021), or using subject-specific classifiers (Rudoler et al., 2024) to detect memory-related patterns during sleep.

Our study contributes to the literature on sleep-dependent memory consolidation in the context of sequential-spatial memories. By successfully decoding head orientation-related activity during sleep, we extend previous findings (Schreiner et al., 2024) and emphasize the feasibility of decoding spatial information from sequential memories. Together with the observed cueing effect on head orientation performance, these findings support the idea that spatial information provides a framework for memory organization (Eichenbaum, 2017a). Additionally, we highlight the role of sleep spindles in memory processing and discuss key methodological challenges in decoding wake-trained representations during sleep.

To further advance our understanding of sequential memory consolidation, future studies should examine whether reactivation during sleep is influenced by the behavioral relevance and structural features of memory components. For instance, whether spatial orientation is task relevant, whether some items are more strongly linked through contextual or temporal associations during encoding, and how an item's position in a sequence affects the likelihood of being reactivated. Examining these factors may clarify how sleep selectively supports the reactivation of sequential-spatial memories and broaden our understanding of sleep-dependent memory consolidation.

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3. STUDY 2:

NEURAL DYNAMICS OF POST-SLEEP MEMORY RETRIEVAL

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3.1. Abstract

Sleep supports memory consolidation and retrieval, yet the effects of targeted memory reactivation (TMR) on post-sleep retrieval dynamics remain unclear. This study examined whether TMR during NREM sleep modulates EEG activity during post-sleep retrieval in the context of spatial memories. Twenty-five healthy participants learned to associate 168 object images with four distinct real-world head orientations, each linked to a specific sound cue. During NREM sleep, two of the learned sounds (linked to left and right orientations) were replayed as TMR cues, while a third sound unrelated to learning served as a control. Participants were tested on recognition memory (old-new judgments of the objects) and associative memory (recalling the associated head orientations). EEG analyses employing ERPs and TFRs revealed no overall cueing effects on post-sleep neural activity. However, ERP data showed an interaction between cueing and spatial memory, suggesting differential modulation of spatial retrieval processes. Subtle head turns accompanied by successful retrieval suggest a potential embodied component in spatial memory retrieval, even when participants were instructed to remain still. Additionally, we replicated the traditional old/new effect and identified differences related to memory performance (hits versus misses) in both ERP and time-frequency measures. The findings highlight the importance of examining retrieval processes after sleep and suggest that spatial context and bodily signals may contribute to memory access, even without consistent cueing-related benefits.

Keywords: post-sleep memory, targeted memory reactivation, memory retrieval, EEG retrieval dynamics, microscopic head movements

3.2. Introduction

Memory consolidation is a critical process that involves the stabilization of memories during sleep and their accessibility during wakefulness (Creery et al., 2022). Post-sleep memory retrieval offers a unique window to assess the effects of memory consolidation on neural dynamics supporting the long-term accessibility of memories.

Memory retrieval has been previously linked to dynamic neural oscillations, characterized by neural synchronization and desynchronization (Jutras & Buffalo, 2010). For instance, alpha (8-12 Hz) and beta (13-35 Hz) power decreases have been associated with successful memory recall (Griffiths et al., 2019; Li et al., 2024). These decreases in power are thought to reflect neural desynchronization, which may promote access to stored memory representations (Hanslmayr et al., 2012). In contrast, theta (~5 Hz) and gamma (>40 Hz) frequencies often exhibit increases, indicating synchronized activity that facilitates memory reactivation (Nyhus & Curran, 2010; Wynn et al., 2024). These observations in neural dynamics provide a framework for investigating similar mechanisms in post-sleep retrieval.

Targeted memory reactivation (TMR) has emerged as a valuable tool to investigate sleep-dependent memory consolidation. It uses sensory cues during sleep to selectively reactivate previously learned content (Oudiette & Paller, 2013). The application has been commonly employed during NREM sleep, a stage critical for memory consolidation. Studies have shown that reactivation during NREM sleep enhances subsequent recall of memories (Hu et al., 2020; Rasch et al., 2007; Rudoy et al., 2009). However, there have also been detrimental effects of TMR reported when multiple associations were formed and led to memory interference (Antony et al., 2018; Joensen et al., 2022; Oyarzún et al., 2017; Schreiner et al., 2024).

In addition to its effects on memory performance, TMR has been shown to modulate neural activity during sleep by enhancing memory-related oscillatory dynamics such as theta (4-8 Hz) and sleep spindle (12-16 Hz) activity (Denis & Payne, 2024; Wang et al., 2019). Although these effects are well-documented, the impact of TMR on neural dynamics during post-sleep memory retrieval has received limited attention (Schreiner et al., 2015). Exploring this link can provide insights into how promoting memory reactivation during sleep can modulate neural processes supporting memory retrieval.

Schreiner, Göldi and Rasch (2015) provided early insights by investigating how TMR modulates retrieval-related brain responses after sleep. Their findings demonstrated that cueing foreign vocabulary during sleep not only improved the later recall of word translations but also enhanced EEG theta activity in the subsequent recognition memory task, potentially indicating a neural marker for strengthening memory. This study primarily focused on simple verbal associations and was conducted during nap sleep. Therefore, it remains unclear whether TMR similarly impacts neural dynamics when retrieving complex associative memories, such as object-location associations, after a full night of sleep.

In addition to exploring oscillatory dynamics, studies employing event-related potentials (ERPs) in recognition memory paradigms have provided valuable insights into the neural processes that support memory retrieval. These studies consistently reported that the brain's response to previously acquired stimuli (old items) differs from its response to novel stimuli (new items). This phenomenon is termed the "old-new effect" in memory research and is characterized by a more positive ERP response to familiar stimuli, typically starting around 300-400 ms post-stimulus onset (Danker et al., 2008; Finnigan, 2002; Noh et al., 2018). Whether TMR affects these ERPs remains largely unknown in the context of post-sleep memory retrieval.

Our study aims to examine the influence of TMR on EEG neural dynamics during post-sleep memory retrieval. Twenty-five healthy subjects engaged in a spatial memory task associating real-world head orientations with images of objects. These head orientations were paired with sound cues, which were later used for TMR during NREM sleep. Memory performance was tested before and after sleep while EEG was recorded, enabling a comprehensive examination of post-sleep EEG dynamics and their association with retrieval outcomes.

To investigate whether TMR modulates EEG neural dynamics associated with memory beyond the sleep period, we analyzed event-related potentials (ERPs) and time-frequency representations (TFRs) of EEG activity. Specifically, we explored whether distinct neural patterns reflected item familiarity, successful memory retrieval, and head orientation-related dynamics. By investigating these neural dynamics, this study aims to clarify how targeted reactivation of memories during sleep influences post-sleep retrieval processes.

3.3. Methods

3.3.1. Participants

25 healthy participants (right-handed, mean age: 25.2 ± 0.6; 16 female) participated in the study. They had either normal or corrected-to-normal vision. 14 additional participants were excluded due to insufficient sleep or technical issues. Before the experiment, participants completed screening questionnaires to collect information on their sleep patterns, overall health status, and usage of stimulants. These evaluations confirmed that they did not have any neurological or psychiatric conditions, nor were they using any medications. All participants reported having good sleep quality. Participants were instructed to wake up by 7 a.m. and avoid caffeine consumption on the experiment day. Additionally, they were told to avoid alcohol the night before the experiment. Written informed consent was obtained from the participants after explaining the study procedures in detail. The participants were compensated for their

participation with either course credits or monetary compensation. This study was approved by the ethics committee of the Department of Psychology at Ludwig–Maximilian University, Munich.

3.3.2. Experimental Procedure

Paradigm Overview

Participants came to the sleep lab for an adaptation nap session to familiarize themselves with the lab environment several days before the main experiment. On the day of the experiment, the procedure started at 7 p.m. with the application of polysomnographic recordings, including electroencephalographic (EEG) and electrooculography (EOG). The training task started around 8 p.m., and it was followed by the memory task. Participants went to sleep around 11 p.m. Sound cues that were previously associated with learned content (animal sounds) were presented to the participants during NREM sleep (N2 and SWS stages). These cues were repeatedly presented for about 60 minutes. Participants were awakened after 6 to 7 hours of sleep to reassess their memory performance.

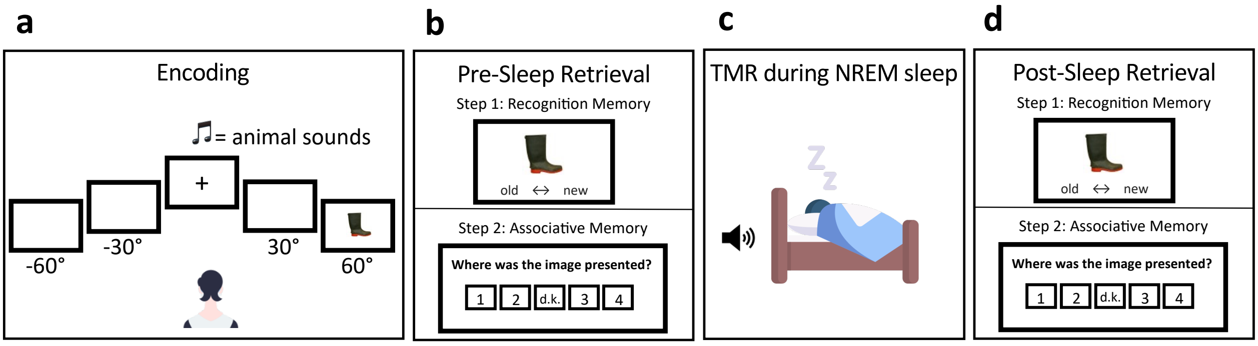

Figure 14. Experimental Design. Participants performed a memory task on a computer with five monitors positioned at different orientations (-60°, -30°, 0°, +30°, and 60°). **a. Encoding phase:** Participants learned 168 images of objects, each presented on one of four peripheral screens. Each trial began with a fixation cross and the presentation of one of four animal sounds (each associated with a specific screen). Participants turned their heads toward the screen where the image was presented and were instructed to learn both the object and the head orientation. **b. Pre-sleep retrieval:** Using the central screen, participants were presented with images, comprising the learned 168 images and 84 new foil images. For each image, they indicated whether it was "old" or "new" (recognition memory). If the image was judged as old, participants indicated the associated head orientation (associative memory) using a button press, without executing the head orientation, or chose "don't know" when unsure. **c. TMR during NREM sleep:**

Two of the previously learned sounds (one linked to left-sided and one to right-sided head orientations), along with one control sound not used during learning, were repeatedly presented for 60 minutes. **d. Post-sleep retrieval:** Participants completed the same recognition and associative memory procedures as in pre-sleep retrieval, using a new set of foils.

Stimuli

336 images of objects, including images of animals, food, clothing, tools, or household items, presented on a plain white background. These images were taken from (Konkle et al., 2010). Five different animal sounds were used, including a cow’s moo, a parrot’s squawk, a cat's meow, a sheep's baa, and a cuckoo's sound.

Training

The training procedure started with a fixation cross in the center screen with a duration of 1.5 ± 0.1 seconds. After the fixation cross disappeared, one of four animal sounds was presented for 600 ms. Then, the cross reappeared on one of four surrounding screens (-60°, -30°, 30°, and 60° from center; the screen-to-eye distance was ~1 meter) for 2.5 seconds. At the beginning, four sounds were randomly chosen and assigned to each screen, which remained fixed throughout the experiment. Participants were instructed to turn their heads towards the screen with the fixation cross and maintain fixation for 2.5 seconds. Following this, the fixation cross reappeared on the center screen for 1.5 (± 0.1) seconds, and participants returned their head to the central screen position. This training, comprising 160 trials in 4 blocks, was designed to establish strong associations between sound cues and head orientations.

Memory Task

Participants were tasked to learn 168 images of objects along with their associated head orientations (Fig. 1a). A fixation cross appeared at the beginning of each trial (duration: 1.5 ± 0.1 seconds). Then, one of four animal sounds from the training session was played (duration: 600

ms), followed by the presentation of an object image on the corresponding screen for 4 seconds. Half of the objects were animate and half were inanimate. The participants were already familiar with the sound-screen associations from the training. They were instructed to turn their head towards the screen where the image was presented, and to remember the image and its position. After this, a question appeared at the center of the screen, asking participants to indicate whether the previously displayed object was animate or inanimate by pressing a button.

This pre-sleep memory test comprised 168 images seen during training (referred to as old items) along with 84 new images (foils). Following a fixation cross of 1.5 (± 0.1) seconds, the image was displayed on the center screen (Fig. 1b). After 1 second, participants were tasked with recognizing whether the image belonged to the "old" set (part of the learning material) or the "new" set (not seen during learning) within the next 10 seconds. If participants responded with "new," they proceeded directly to the next trial. If they responded with "old," they were required to indicate the corresponding head orientation of that object image by pressing a button (Fig. 1b). At the end of each trial, participants provided a confidence rating in their head orientation decision on a scale ranging from 0 (very uncertain) to 4 (very certain). The post-sleep memory retrieval followed the identical procedures as the pre-sleep memory test, except that it utilized 84 new foil images (Fig. 1d).

Targeted Memory Reactivation

For targeted memory reactivation (TMR), two sounds were randomly chosen from the four previously presented during encoding, one sound linked to left-sided head orientations (screens positioned at -60° and -30°) and one associated with right-sided head orientations (screens positioned at 30° and 60°). An additional fifth animal sound was utilized as a control stimulus, which was not a part of the training. In total, three cues were presented repeatedly during NREM sleep with an interval of 5.5 ± 0.2 seconds using a loudspeaker. The application lasted for a maximum of 60 minutes with 182.6 ± 31.41 repetitions per stimulus. Throughout the application, sound presentation ceased upon the emergence of arousals, awakenings, or REM sleep indicators.

EEG Data Acquisition

An EEG system with 65 channels (ANT Neuro Enschede, Netherlands) was employed to record the EEG (65 Ag/AgCl electrodes, 10/20 system layout). Impedances were maintained below 20 kΩ. EEG signals were sampled at a rate of 1000 Hz referenced online to electrode CPz. In addition, horizontal and vertical electrooculography (EOG) were recorded for polysomnography purposes. Two independent raters determined the sleep architecture offline based on standard criteria.

3.3.3. Data Analysis

EEG Data Preprocessing

EEG data underwent pre-processing using the Fieldtrip toolbox in MATLAB, designed for EEG/MEG analysis (Oostenveld et al., 2011). All EEG data were downsampled to 200 Hz. TMR data and post-sleep EEG data were segmented into epochs covering -1 to 3 seconds around the stimulus onset. Visual inspection was employed to identify noisy EEG channels, which were then eliminated and replaced with interpolated values generated from neighboring channels using a weighted average approach. Additionally, EEG artefacts were removed using visual inspection. The retrieval data underwent independent component analysis (ICA) to identify and remove components linked to eye blinks and eye movements. Post-sleep data were epoched in two different ways for further analysis: from the onset of recognition memory (old-new question), and associative memory (head orientation question).

Event-related potentials (ERPs) and time-frequency representations (TFRs) were employed for analyzing the post-sleep EEG data using the Fieldtrip toolbox within MATLAB. Initially, EEG data were preprocessed by removing specific channels (M1, M2, Iz) and re-referenced to the average reference (avgRef). EEG data were segmented into trials based on the contrasts of interest.

Trial selection and definition for ERP and TFR analyses proceeded as follows: To delineate the contrast between old and new items in recognition memory, trials were categorized based on memory performance (only correctly recognized and correctly rejected items). To evaluate the difference between cued and uncued trials, selection was made based on whether they were cued during sleep or not, and this difference was investigated following the image onset (recognition memory test) and the onset of the head-orientation question (associative memory test). Furthermore, hits versus misses were analyzed according to participants' memory performance in the post-sleep recognition memory test. Moreover, ERPs and TFRs were computed for trials associated with the left versus right-sided screens during the associative memory test. Finally, separate contrasts were conducted for cued and uncued trials associated with the left versus right-sided screens in the associative memory test.

Participants with fewer than 15 trials in any condition were excluded from the respective analyses, resulting in a final sample of 15 participants for the hits versus misses contrast in the recognition memory test.

Event-related Potentials (ERPs)

Event-related potentials (ERPs) were analyzed to examine neural responses during post-sleep memory retrieval, focusing on the discrimination between contrasts of interest (e.g., cued versus uncued). Following trial segmentation (as detailed in the EEG Data Analysis section), baseline correction was applied using a baseline period from -0.3 to 0 seconds relative to stimulus onset.

Time-locked analysis was conducted to assess the mean neural responses across different trial conditions.

Time-Frequency Analysis (TFRs)

Time-frequency analysis was conducted on post-sleep memory retrieval data to explore oscillatory dynamics across different conditions. Frequency decomposition was performed using Fourier Analysis with a fixed-length sliding time window of 0.5 seconds and a single Hanning taper. The analysis covered a time range from -1 to 1 second relative to stimulus onset and a frequency range of 2 to 30 Hz. Power spectra were averaged across trials for each condition and baseline-corrected using relative change with a baseline period from -0.5 to 0 seconds before stimulus onset.

High-frequency activity was analyzed using wavelet convolution with 10 cycles per frequency across a range of 30 to 70 Hz (in 5 Hz steps). Power estimates were computed in 50-ms steps over a time window from -1 to 1 second relative to stimulus onset and baseline-corrected using relative change from a pre-stimulus period of -0.5 to 0 seconds.

Head Orientation Analysis

Although the associative memory task was performed on the central screen and responses were indicated by a button press, participants’ head orientation traces were analyzed to detect potential micro-movements during the recall of head orientations. Participants were instructed to keep their heads still throughout the task.

Head orientation traces were time-locked to image onset and analyzed over a window from -1.5 to 4.5 seconds to account for the self-paced transition between the recognition and associative memory tests. A baseline period from -0.5 to 0 seconds before the image onset was used to compute relative deviations in head orientation.

Trials were categorized based on participants' responses in the associative memory task to assess whether subtle head movements corresponded to their reported memory for head orientations. All four screen positions were treated as separate conditions for visualization and grouped into two categories for statistical testing: "left" (-60° and -30°) and "right" (30° and 60°). Head orientation data were averaged within each trial and condition.

3.3.4. Statistical Analysis

Behavioral data were analyzed using a 2 x 2 repeated-measures ANOVA to examine the effects of test time (pre-sleep/post-sleep) and cueing (cued/uncued) on memory performance, separately for recognition and associative memory retrieval. Additionally, an exploratory 2 x 2 repeated measures ANOVA was conducted to assess the effects of spatial orientation (left/right) and test time on memory performance. A significance threshold of $p < .05$ was applied to all behavioral analyses.

For statistical comparisons of ERPs and TFR data, non-parametric cluster-based permutation tests were employed using the Fieldtrip toolbox (Oostenveld et al., 2011). Both analyses were conducted at the group level within a latency window spanning 0 to 1 second. Dependent-samples t-tests identified clusters of adjacent time-frequency points ($p = 0.05$), with Monte Carlo simulations determining cluster p-values (alpha = 0.05, two-tailed) under the permutation distribution (1,000 permutations).

Additionally, a 2 x 2 factorial design was employed to investigate the interaction effect between cueing condition (cued/uncued) and spatial location (left/right) using ERPs. Grand averages were computed separately for each combination of cueing condition and spatial location. Subsequently, differences in ERP responses and TFRs were calculated between cued and uncued conditions for both left and right stimulus locations. Statistical analysis was then performed using a cluster-based permutation test to examine the interaction effect between cueing condition and spatial location. The analysis was conducted at the group level, using dependent-samples t-tests to compare the differences in ERP responses and TFRs between cueing conditions for left and right stimulus locations.

For the statistical comparison of head orientation traces, non-parametric cluster-based permutation tests were conducted using the Fieldtrip toolbox (Oostenveld et al., 2011). The analyses were performed at the group level across the time window from -1.5 to 4.5 seconds. Dependent samples t-tests identified clusters of adjacent time points (cluster-forming threshold p = 0.05), and Monte Carlo simulations (1,000 permutations) were used to compute cluster-level p-values under the null distribution (alpha = 0.05, two-tailed).

3.4. Results

To investigate the EEG neural dynamics underlying memory retrieval after sleep, post-sleep EEG data were analyzed using event-related potentials (ERPs) and time-frequency representations (TFRs) across frequency bands of interest (2-30 Hz). The analyses focused on the following contrasts: cued-uncued, old-new, hits-misses, and left-right. Additionally, the left-right contrast (distinguishing items presented on one of the left-sided versus right-sided screens) was further investigated in the high-frequency band (30-70 Hz).

3.4.1. Behavioral Results

As previously reported (Schreiner et al. 2024), TMR had a detrimental effect on memory performance in this study. To investigate the differences in memory performance across test times (pre/post) and TMR conditions (cued/uncued), a 2x2 ANOVA was computed. During the recognition memory test, no significant main effect of test time ($F_{1,24}$=0.29; p=0.59) or an interaction effect between test time and cueing was observed ($F_{1,24}$=0.08; p = 0.77, Fig. 2a).

However, in the associative memory test, there was a significant main effect of test time ($F_{1,24}$ = 19.24; $p < 0.001$), indicating that participants' memory performance declined significantly throughout sleep. Moreover, a significant interaction between test time and cueing was found ($F_{1,24}$=5.48; p = 0.028, Fig. 2b). Specifically, performance for cued items declined more from pre- to post-sleep compared to uncued items in the associative memory test (Fig. 2b).

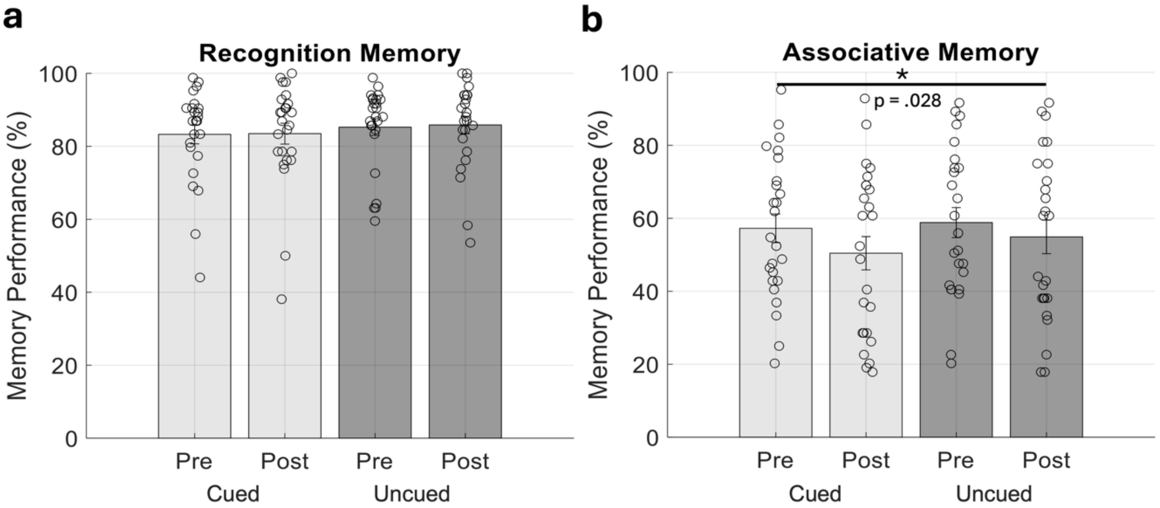

Figure 2. Behavioral Results for pre- and post-sleep in cued and uncued conditions. a. Recognition memory performance showed no significant change from pre- to post-sleep, with no significant main effect of test time or interaction between them. **b.** Associative memory performance revealed a significant interaction between test time (pre/post) and cueing (cued/uncued), with a decline in memory performance for cued items compared to uncued from pre- to post-sleep. Bar graphs illustrate the mean (± SEM across participants) in percentage of memory performance. Dots represent the individual memory performance of participants (N = 25). The star highlights the significant interaction ($F_{1,24}$= 5.48; p = 0.028).

3.4.2. Old versus New

ERPs were computed to explore the neural differences between items successfully identified as old (previously encountered) and new during the recognition memory test. Old items elicited less negative-going activity compared to new items, starting at 187 ms after image onset (Fig. 3a). A cluster-based permutation test (two-sided) revealed a significant difference between conditions ($p < 0.001$). The observed difference was most prominent from 187 ms to 1 second, suggesting differential processing of familiar versus new information during this period. The topographic scalp map (Fig. 3b) shows the distribution of ERP amplitude differences, with the strongest effects observed over frontal and central electrodes in this latency range.

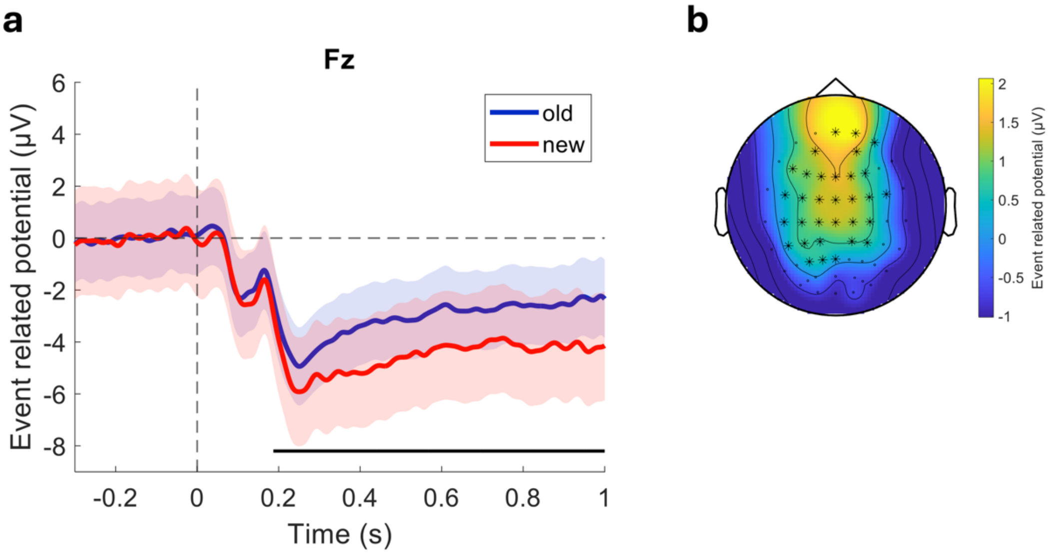

Figure 3. ERPs for old and new conditions during the recognition memory test. a. Grand average ERP waveforms at electrode Fz for old items (blue) and new items (red) following the image onset, showing less negative-going activity for old items starting at 187 ms. Shaded areas indicate the standard error of the mean (SEM). The black horizontal line indicates the time window of the significant difference (two-sided cluster-based permutation test, p < 0.001). **b.** The topographic scalp map displays the grand average difference between old and new conditions during the time interval showing significant differences (187 ms to 1 sec.). The largest differences were observed over frontal and central electrodes, where enhanced activity for old items was most prominent. Channels contributing to the significant effect are marked for visual reference.

Next, time-frequency representations of power were computed to compare old and new conditions during the recognition test. Grand averages for old items (Fig. 4a) and new items (Fig. 4b) were calculated. A two-sided cluster-based permutation test comparing the two conditions revealed a significant difference between the conditions (p = 0.018). This effect was expressed in the alpha and beta frequency ranges, with differences most prominent between 650 and 800 ms after stimulus onset (Fig. 4c). The observed pattern was primarily distributed over central and left-parietal electrodes (Fig. 4d).

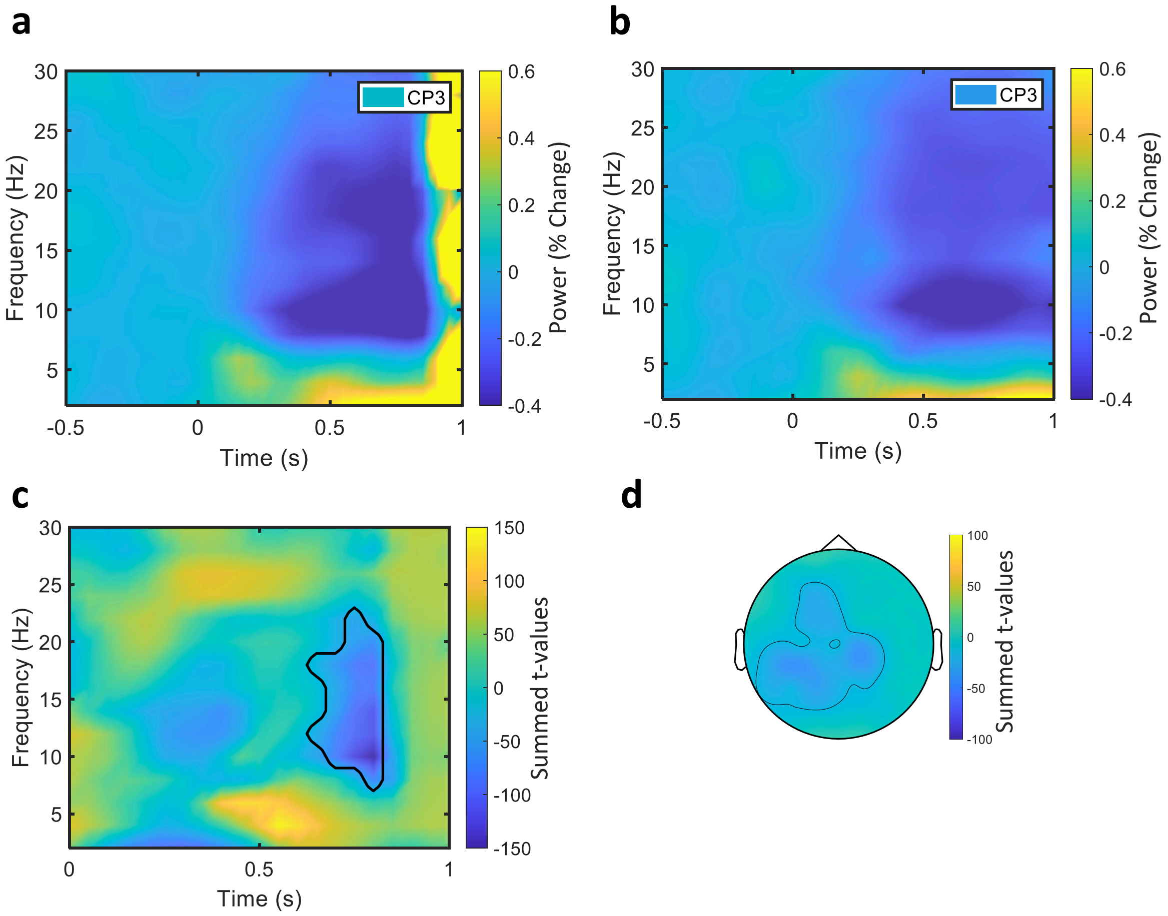

Figure 4. TFRs of EEG power for old and new conditions during the recognition memory test. a. Grand average TFRs for old items. **b.** Grand average TFRs for new items. Data from electrode CP3 is plotted as a representative site. **c.** A two-sided cluster-based permutation test revealed a significant difference between conditions (p = 0.02, based on summed t-values), with the largest differences observed in the alpha-beta frequency range between 650 ms and 800 ms after image onset. **d.** The scalp topography of summed t-values during this time-frequency window, showing that the observed differences were most prominent over central and left-parietal electrodes.

3.4.3. Hits versus Misses

To uncover neural signatures associated with memory performance, grand averages of ERPs evoked by hits and misses were computed during the recognition memory test. A cluster-based permutation approach (two-sided) showed a significant difference between conditions (p = 0.02), with the largest amplitude differences occurring between 573 ms and 641 ms post-stimulus onset (Fig. 5a). The observed difference was most pronounced over central electrodes (Fig. 5b) though the spatial extend of this effect was not statistically tested.

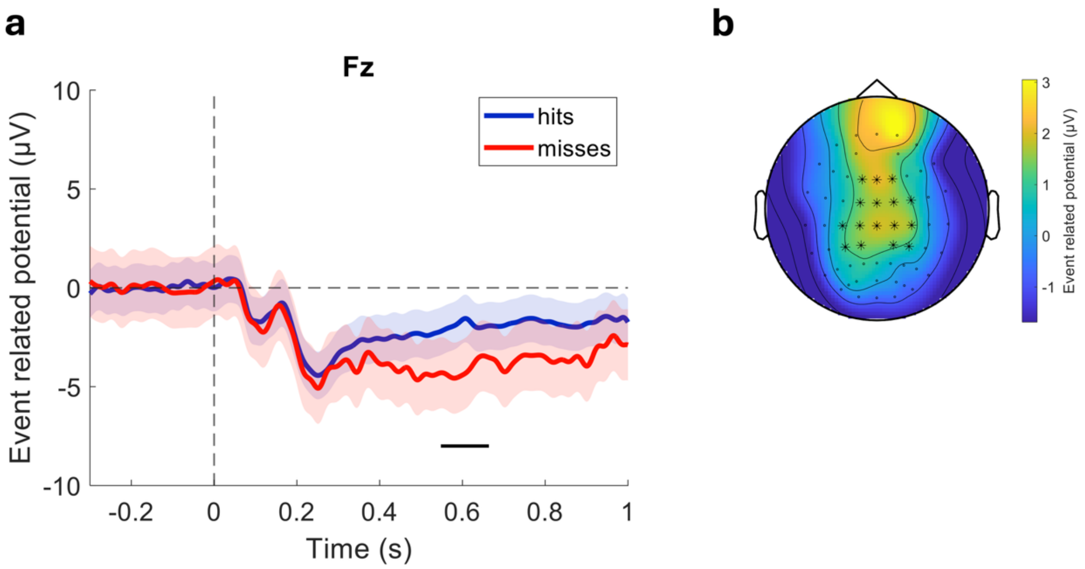

Figure 5. ERPs for hits and misses during the recognition memory test. a. Grand average ERP waveforms at electrode Fz for hits (blue) and misses (red) following image onset. A two-sided cluster-based permutation test revealed a significant difference between hits and misses ($p = 0.02$), with the largest amplitude differences between 573 ms and 641 ms. Data from electrode Fz is plotted as a representative electrode within the observed effect. Shaded areas represent the standard error of the mean (SEM). The black horizontal line represents the time window corresponding to the significant result. **b.** The scalp topography demonstrates the distribution of grand average ERP differences during this time window, with the largest differences appearing over central electrodes. Channels are marked for visual reference.

Time-frequency representations of power for hits versus misses were analyzed. A two-sided cluster-based permutation test based on a dependent samples t-test indicated a significant difference between the conditions ($p = 0.003$), with the strongest differences emerging in the beta frequency range. This effect in spectral power was most evident between 100 ms and 850 ms following image onset (Fig. 6d). The centro-parietal scalp region showed the most prominent differences, as illustrated by the topography of summed t-values in Fig. 6e.

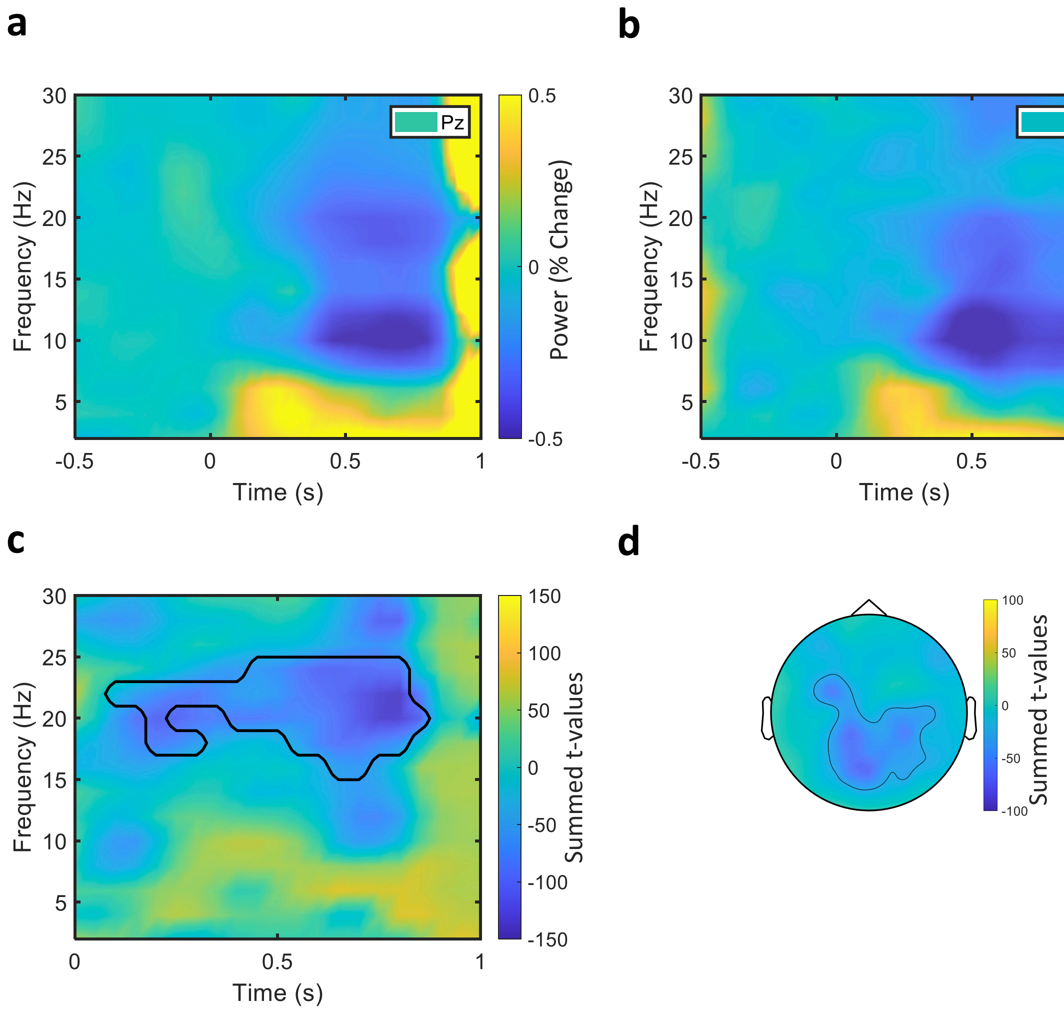

Figure 6. TFRs of EEG power for hits and misses during the recognition memory test. a. Grand average TFR for hits. **b.** Grand average TFR for misses. **c.** Summed t-values resulting from the cluster-based permutation test (two-sided) comparing hits and misses in the frequency bands of interest (2-30 Hz), highlighting a significant difference between conditions ($p = 0.003$), with the largest differences observed in the beta band from 100 ms to 850 ms after image onset. **d.** The scalp topography of summed t-values during this time window, showing the strongest differences over centroparietal electrodes.

3.4.4. Cued versus Uncued

To investigate the impact of TMR cueing on ERP patterns, grand average ERP amplitudes evoked by cued and uncued trials were computed. Data were locked to the onset of images for the recognition memory test (Fig. 7a) and the head-orientation question onset for the associative memory test (Fig. 7b). A cluster-based permutation test (two-sided) was used to compare the grand averages of the two conditions. In both recognition and associative memory tests, no significant differences in ERP amplitudes were observed between cued and uncued trials (all p-values > 0.025, two-sided dependent samples t-test), suggesting that TMR during NREM sleep did not reliably modulate evoked neural responses during post-sleep memory retrieval.

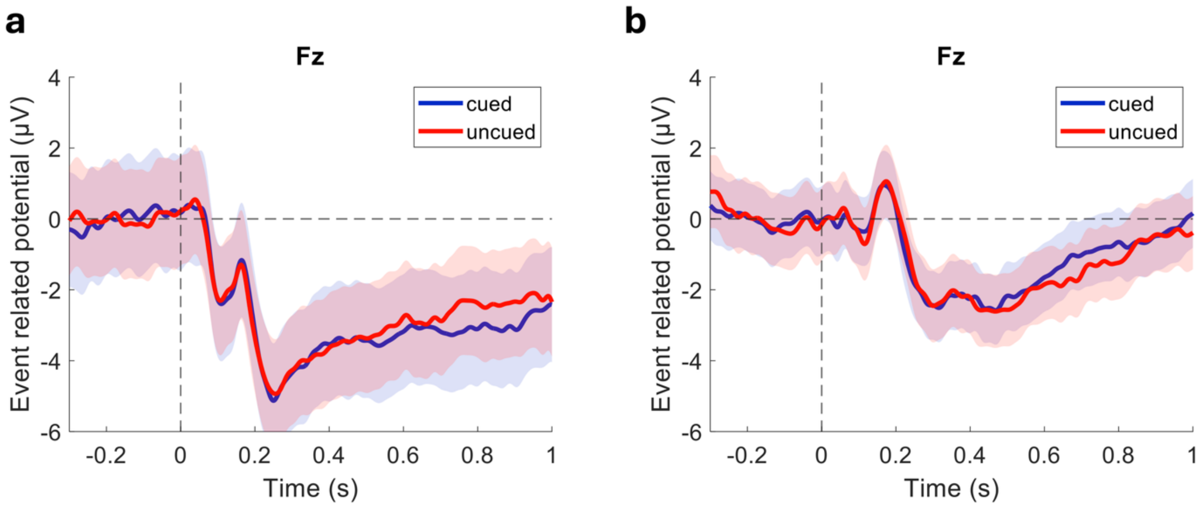

Figure 7. ERPs for cued versus uncued conditions. Grand average ERP amplitudes evoked by cued (blue) and uncued (red) trials **a.** following the onset of images during the recognition memory test **b.** following the head-orientation question onset in the associative memory test. Data from electrode Fz is plotted as a representative electrode. Shaded areas represent the standard error of the mean (SEM). A cluster-based permutation test (two-sided) did not reveal any significant differences in ERP amplitudes between cued and uncued trials for either recognition or associative memory tests (all p-values > 0.025).

Time frequency representations (TFRs) were computed to assess power differences between cued and uncued conditions for the recognition memory test (Fig. 8) and the associative memory test (Fig. 9). In the recognition test, the TFRs for cued condition (Fig. 8a) showed a tendency toward enhanced power in the theta band (4-8 Hz) and decreased power in the alpha band (8-12 Hz). However, these effects did not reach statistical significance (p > 0.025). A cluster-based permutation test (two-sided) comparing cued and uncued conditions across the frequency bands of interest revealed no significant differences (all p-values > 0.025). These findings suggest that TMR cueing during NREM sleep did not reliably modulate EEG power during post-sleep memory retrieval.

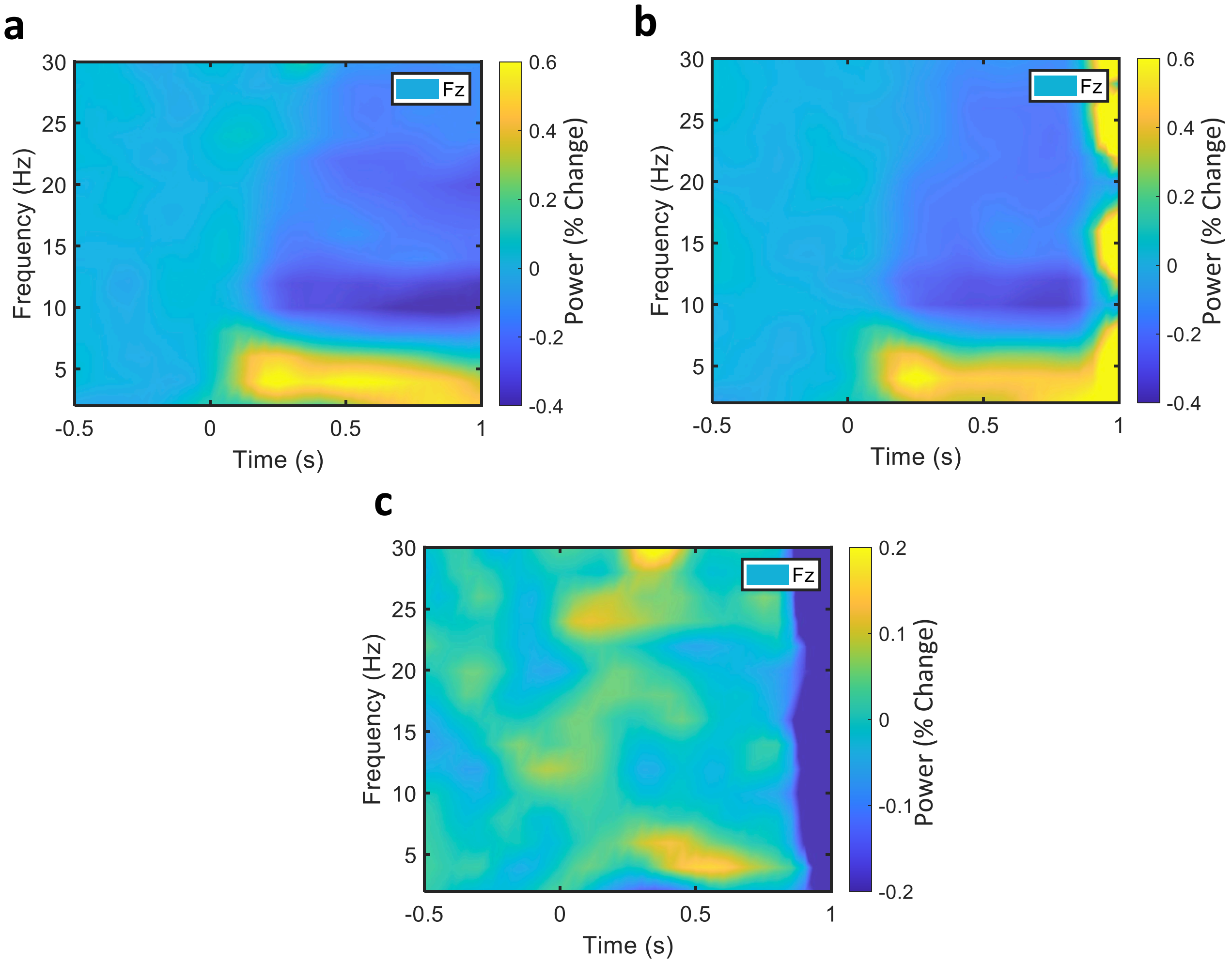

Figure 8. TFRs of EEG power for cued and uncued conditions during the recognition memory test at electrode Fz. a. Grand average TFRs for cued items. **b.** Grand average TFRs for uncued items. **c.** Differences of grand averages between cued and uncued trials. Data from electrode Fz is plotted as a representative site. No significant differences were observed between cued and uncued conditions across the 2-30 Hz frequency range ($p > 0.025$, two-sided cluster-based permutation test), suggesting that cueing did not reliably modulate EEG power during post-sleep retrieval.

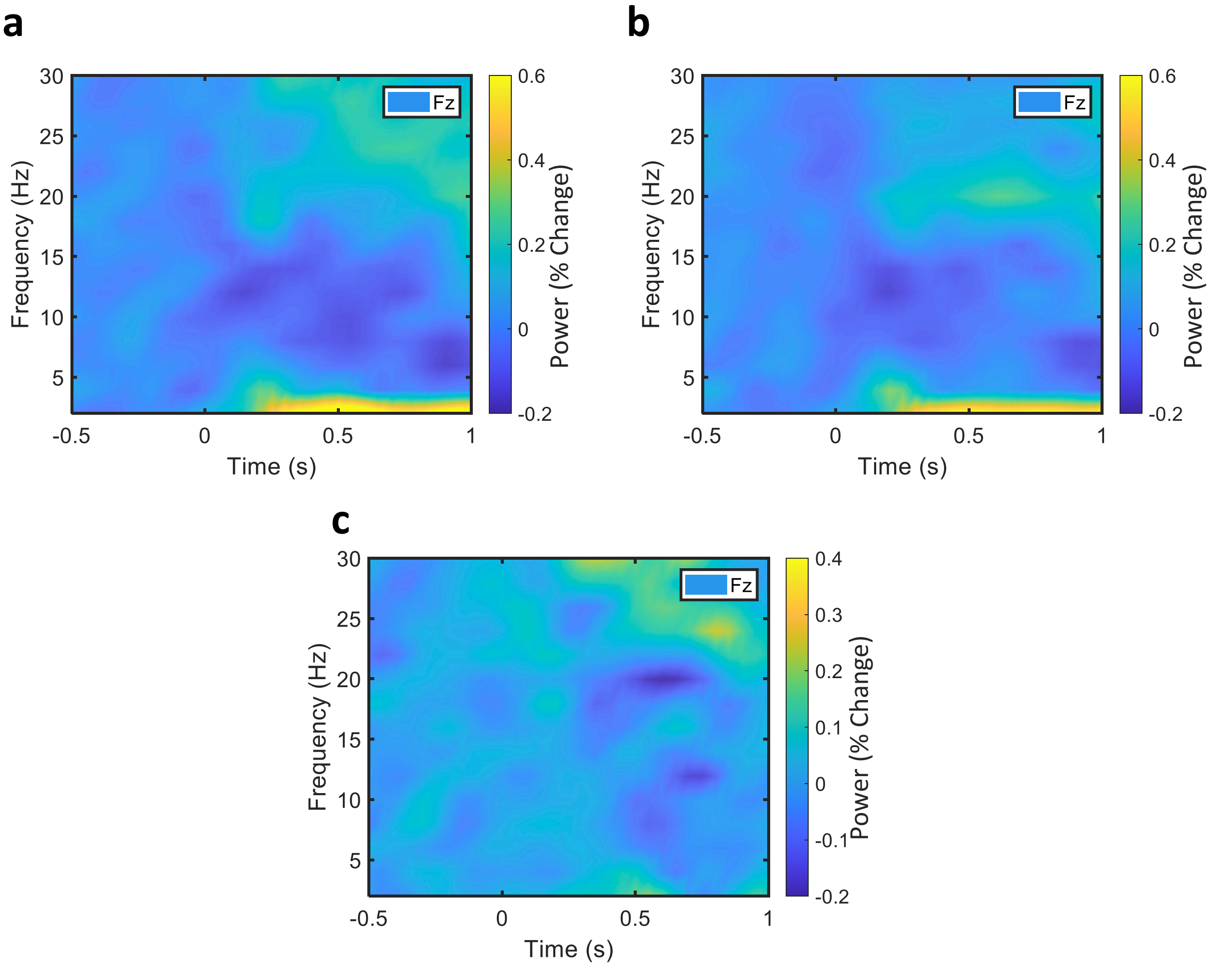

Figure 9. TFRs of EEG power for cued and uncued conditions during the associative memory test at electrode Fz. a. Grand average TFRs for cued items. **b.** Grand average TFRs for uncued items. **c.** Differences of grand averages between cued and uncued trials. Data from electrode Fz is plotted as a representative site. No significant differences were observed between cued and uncued conditions across the 2-30 Hz frequency range ($p > 0.025$, two-sided cluster-based permutation test), suggesting that cueing did not reliably modulate EEG power during post-sleep retrieval.

3.4.5. Left versus Right

The left-right contrast was assessed in the associative memory test, where participants indicated the associated head orientation for recognized items. This analysis aimed to determine whether spatial orientations elicited differential neural responses. ERPs were computed for trials associated with the left (-60°, -30°) and right-sided (30°, 60°) orientations. A cluster-based permutation test (two-sided) revealed a significant difference between conditions ($p < 0.001$), indicating that EEG responses differed between left- and right-sided items. The largest differences were observed over right-frontal (Figs. 10a-10b) and left-parietal electrodes (Figs. 10c-10d), highlighting lateralized neural processing of spatial associations (Fig. 10).

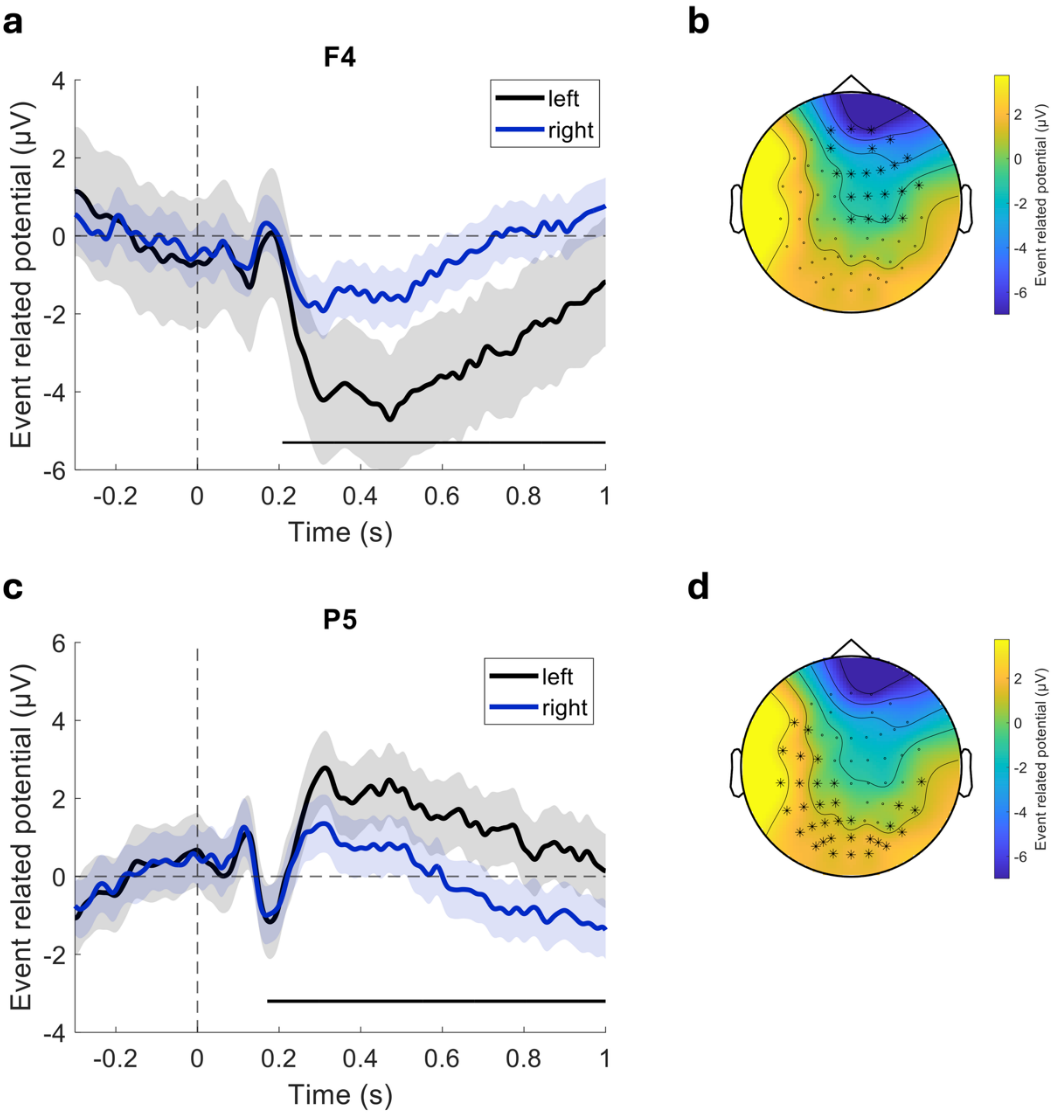

Figure 10. ERPs for left and right-sided items during the associative memory test. a. Grand average ERP amplitudes recorded from electrode F4 for left (black) and right-sided (blue) items, locked to the onset of the associative memory test. A two-sided cluster-based permutation test revealed a significant difference between conditions, with a negative cluster ($p < 0.001$) and a positive cluster ($p < 0.001$). **b.** Scalp topography of grand average differences during the significant time window, highlighting the negative effect over right-frontal electrodes. **c.** Grand average ERP waveforms recorded from electrode P5 for left (black) and right-sided (blue) items. **d.** The scalp topography of grand average differences during the significant time window, showing the positive effect over the left-parietal electrodes. Shaded areas in panels **a** and **c** represent the standard error of the mean (SEM). Black horizontal lines indicate the significant time windows. Data from electrodes F4 and P5 are plotted as representative electrodes from the effect contributing to the significant result.

To further explore the significant ERP difference between left- and right-sided items, we assessed the memory performance for these items. Participants' associative memory performance was analyzed using a 2 x 2 ANOVA with factors of spatial orientation (left/right) and time (pre/post). Similar to the overall memory performance (Fig. 1b), there was a significant decrease in performance after sleep in both conditions ($F_{1,24}$= 19.31; p < 0.001, Fig. 11). However, no significant main effect of spatial orientation ($F_{1,24}$= 0.004; p = 0.95) or interaction effects ($F_{1,24}$= 1.80, p = 0.19) were found.

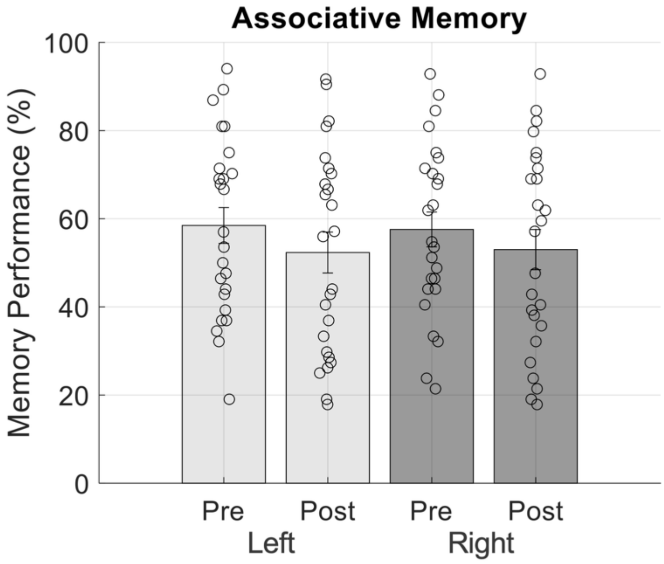

Figure 11. Behavioral Results for left and right-sided trials during the associative memory test. A 2x2 ANOVA with factors of spatial location (left/right) and test time (pre-post) revealed a significant decrease in associative memory performance over the course of sleep (p < 0.001). No significant main effects or interaction effects were found, indicating that the decline in performance was not dependent on spatial location. Bar graphs illustrate the mean (± SEM across participants) in percentage of memory performance. Dots represent the individual memory performance of the participants (N = 25).

Left versus Right – High-Frequency Band Activity

Next, time-frequency representations of high-frequency band activity (30-70 Hz) were analyzed for left- and right-sided trials during the associative memory task. This analysis aimed to examine whether differences in spatial orientation were accompanied by variations in high-frequency activity, which may reflect subtle motor activity. Note that participants were instructed to look straight ahead and avoid head movements during the task. The results revealed increased power for the left-sided trials over lateral parieto-occipital electrodes (PO7 and PO8) (Fig. 12d). However, this difference did not reach statistical significance after cluster-based correction (Fig. 12c, p > 0.025).

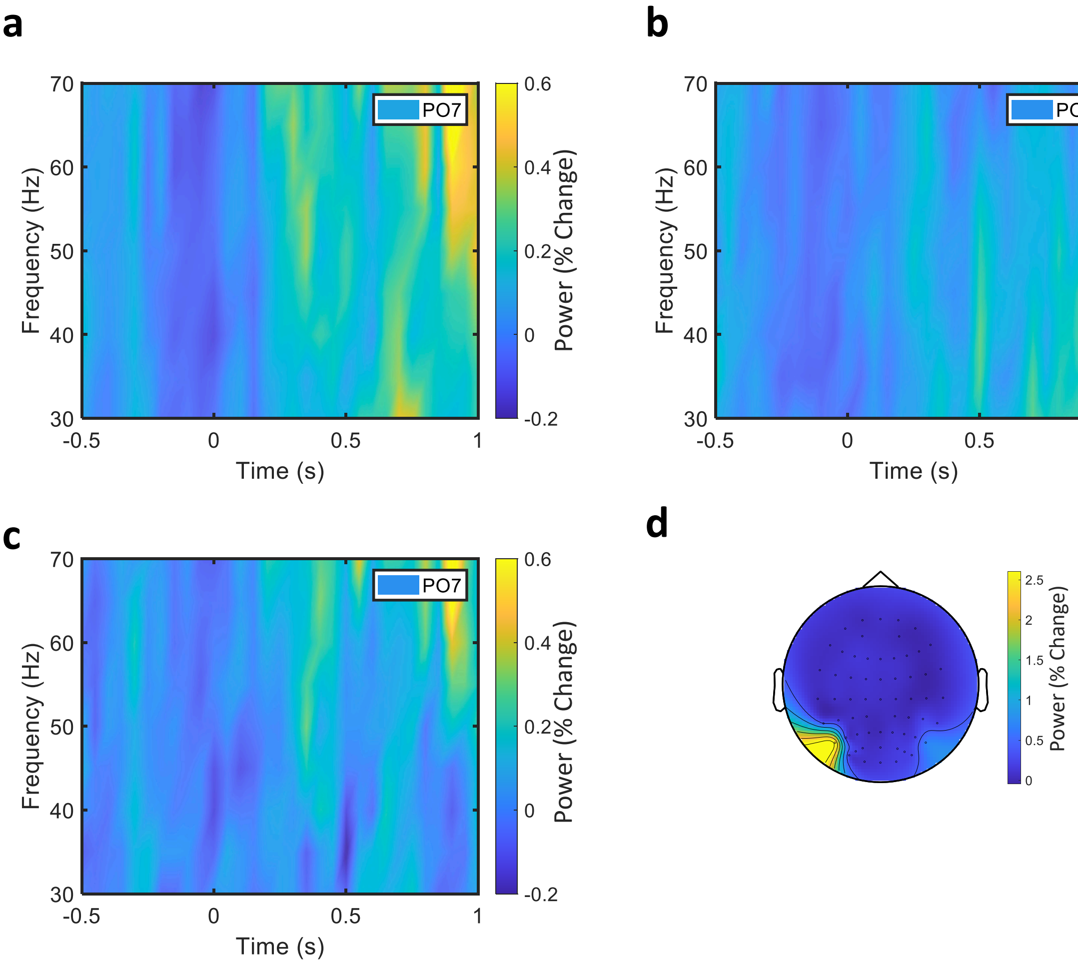

Figure 12. TFRs of high-frequency EEG power (30-70 Hz) for left and right-sided items during the associative memory test, recorded from electrode PO7. a. Grand average TFRs for the left-sided items. **b.** Grand average TFRs for the right-sided items. **c.** Differences in grand average TFRs between left- and right-sided trials. **d.** Topography demonstrates the differences in high-frequency power, with predominant activity in electrodes PO7 and PO8, which may reflect contributions from neck muscle activity. While high-frequency power was enhanced for the left-sided items in the 55-70 Hz range, this difference did not reach significance (p > 0.025, two-sided cluster-based permutation test).

Head Orientation Traces

To further explore the left versus right contrast and examine whether subtle head movements may reflect spatial memory recall, head orientation data were analyzed during the retrieval phase. Despite participants being instructed to look straight ahead and respond on the central screen using button presses, we assessed whether subtle head movements aligned with previously learned spatial locations.

Head orientation traces were averaged for “left” (-60° and -30°) and “right” (30° and 60°) conditions. A cluster-based permutation test revealed a significant difference between left and right conditions during the recognition memory test (p = 0.015, Fig. 13a), with the cluster spanning approximately from 3.9 to 4.5 seconds post-stimulus.

However, when the same analysis was time-locked to the onset of the associative memory question, this difference was longer significant (p = 0.18, Fig. 13b). Additionally, a complementary analysis was conducted during the associative memory test using the -0.5 seconds preceding the recognition test as the baseline. The difference between the two conditions remained non-significant (p = 0.13, Fig. 13c).

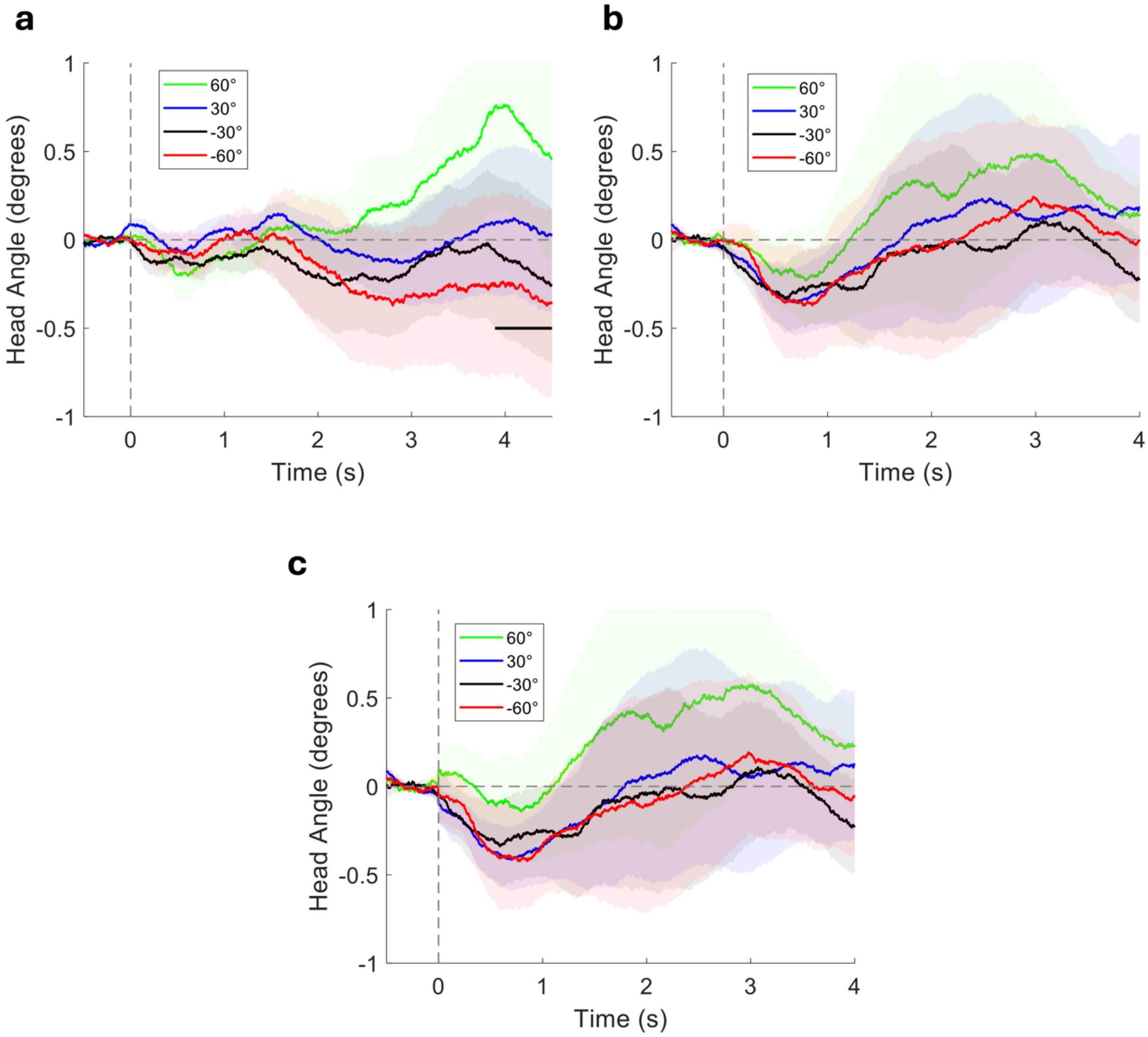

Figure 13. Mean horizontal head orientations for four head orientations. a. Head movement traces locked to the recognition memory test. A significant difference was observed between left and right head orientations (p = 0.015, cluster-based permutation test). The black horizontal line represents the time interval associated with the significant difference. **b.** Head movement traces aligned to the associative memory test onset. No significant differences were observed between left- and right-sided trials (p = 0.18, cluster-based permutation test) **c.** Head movement traces during the associative memory test, computed using the baseline of the recognition memory test. No significant differences were observed between left- and right-sided trials (p = 0.13, cluster-based permutation test). A head angle of 0° corresponds to participants fixating on the center screen, with negative angles indicating leftward deviations and positive angles indicating rightward deviations. Shaded areas represent the standard error of the mean (SEM). Head orientation data were available for 15 participants.

Left versus Right – Cued versus Uncued

To further explore differences in neural responses for left- and right-sided items, we investigated whether cueing modulated these spatial effects. A 2 x 2 interaction was computed between spatial orientation (left/right) and cueing (cued/uncued). During the recognition test, no interaction effect was observed ($p > 0.025$, Fig. 14a). However, during the associative memory test, where participants indicated the corresponding head orientation, a significant interaction emerged. ERP differences between left- and right-sided items were more pronounced in the uncued condition, suggesting that cueing modulated spatial retrieval processes (Fig. 14b). A two-sided cluster-based permutation test resulted in two time intervals with significant differences. The first effect occurred between 446-769 ms ($p = 0.007$), and the second between 880-1000 ms ($p = 0.015$).

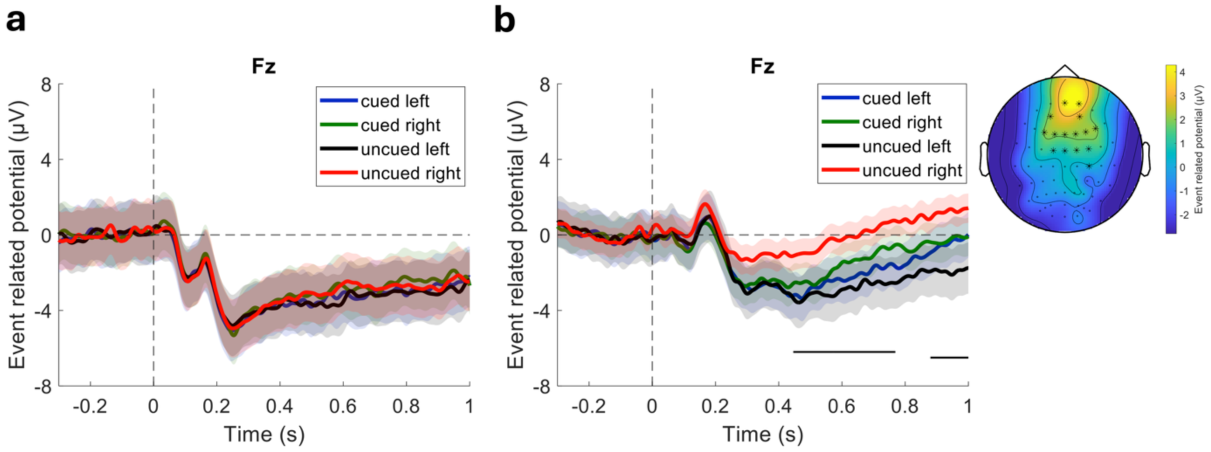

Figure 14. ERPs for left and right-sided items under cued and uncued conditions. a. Grand average ERP waveforms during the recognition memory test recorded at electrode Fz for cued left (blue), cued right (green), uncued left (black), and uncued right (red) items. No significant interaction was observed between spatial orientation and cueing (all p-values > 0.025, two-sided cluster-based permutation test). **b.** Grand average ERP waveforms during the associative memory test. Shaded areas represent the standard error of the mean (SEM). Two time windows showed significant differences between left- and right-sided uncued trials based on a cluster-based permutation test: 446-769 ms ($p = 0.007$) and 880-1000 ms ($p = 0.015$). The inset scalp topography demonstrates the ERP differences during these intervals, highlighting the contributing electrodes predominantly over frontal regions.

3.5. Discussion

Our findings revealed distinct ERP and TFR dynamics during post-sleep memory retrieval following a TMR protocol. While TMR did not significantly influence overall post-sleep EEG activity, it selectively modulated head orientation-related neural responses. Additionally, our results indicated neural markers associated with item familiarity and successful memory retrieval. Importantly, spatial memory information remained robust after sleep, and an exploratory analysis demonstrated that retrieval of this information was accompanied by subtle head movements, suggesting a potential link with embodied memory mechanisms.

At the behavioral level, TMR did not enhance memory performance but led to deterioration in associative memory performance, while recognition memory performance remained unaffected (see Schreiner et al. 2024). This detrimental effect may result from retrieval competition among multiple targets associated with a single cue, where stronger cue-target associations are preferentially reactivated and potentially outcompete weaker ones (Antony et al., 2018; Joensen et al., 2022; Oyarzún et al., 2017). It suggests that TMR can lead to selective strengthening or weakening of memory traces, depending on task design and cueing strategy.

Building on our understanding of TMR's effect on memory performance, we investigated its influence on post-sleep EEG dynamics. We found no significant impact of cueing on overall ERP or TFR patterns. To our knowledge, Schreiner et al. (2015) is the only other study to examine post-sleep neural dynamics in the context of a TMR protocol. Following a vocabulary learning task and cueing word translations during sleep, they reported enhanced theta activity for cued words compared to uncued words. This effect was attributed to enhanced memory strength and lexical integration of new words promoted by cueing during sleep. While our study also observed post-sleep increases in theta activity, these increases did not significantly differ between cued and uncued conditions.

Key methodological and conceptual differences between Schreiner et al.’s study and ours may explain these distinct findings. First, Schreiner et al. focused on word pairings, likely engaging lexical processes linked to theta activity. Our study examined spatial memory by linking head orientation to object associations. The mechanisms underlying spatial memory tasks may differ from those of linguistic associations. Second, they employed a nap paradigm to assess memory retrieval shortly after learning, whereas our study extended this research by testing participants after a full night of sleep. Naps typically do not include a complete cycle of sleep stages due to their shorter duration (Ong et al., 2017). In Schreiner et al.’s study, nap sleep may have resulted in theta-related memory processes being more prominent during retrieval due to the relatively recent consolidation of learned information. On the other hand, in our study, the prolonged consolidation period of a full night's sleep might have reduced theta effects, as full-night sleep provides a longer duration for memory consolidation and integration processes (Van Schalkwijk et al., 2019). Lastly, our study involved a more complex task design to retrieve object-head orientation associations. Increased task complexity and cognitive demands may influence neural dynamics differently. These differences highlight the importance of considering the duration of the consolidation period and task differences when interpreting the neural effects of TMR.

Although we did not observe an overall effect of TMR on post-sleep neural dynamics, we identified its selective impact on head orientation-related responses. Specifically, ERPs computed for items presented on the left versus right revealed a significant interaction between cueing and orientation during the associative memory test. Moreover, this finding was consistent with TMR’s differential effects on memory performance, which indicated better performance for uncued items. These preserved ERP patterns may reflect the neural reactivation of spatially encoded associations, with TMR cues selectively modulating the retrieval of this information. Notably, the ERP differences could not be explained by behavioral performance differences between left and right items, since memory performance did not significantly differ between these orientations.

To further explore this distinct observation between left and right conditions, we considered the potential contribution of involuntary muscle activity while retrieving head orientation-related information, despite participants being instructed to look straight during retrieval. This was motivated by the possibility that subtle movements, even in the absence of intentional motion, could influence neural responses. Additionally, we aimed to check whether participants followed the instructions to look straight or might have moved their heads unintentionally toward the remembered head orientation.

Muscle activity, if present, is typically reflected in the EEG high-frequency band above 30 Hz (Muthukumaraswamy, 2013). Although we observed markers of enhanced power in the high-frequency band (between 55-70 Hz) for left versus right, this difference was not significant. The most pronounced differences were over lateral parieto-occipital electrodes (PO7 and PO8), areas that are potentially sensitive to residual neck muscle activity. These results suggested a trend for further investigation.

We then analyzed deviations in head orientation during the associative memory task to explore potential motor contributions to the observed neural dynamics. Our motivation for this analysis stemmed from research demonstrating the role of microscopic expressions, such as microsaccades -small, involuntary eye movements during fixation- in cognitive processes. For instance, Van Ede et al. (2019) showed that microsaccades align with the axis of memorized content during working memory tasks, even when object location is not explicitly asked, suggesting they track the rehearsal of spatial information. Similarly, microsaccades were used to decode the contents held in working memory, even when participants were instructed to fixate their eyes on a central point and actively discouraged from moving them (Linde-Domingo & Spitzer, 2023). These findings suggest the involuntary expression of memory content through the oculomotor system. Building on this, we investigated in our spatial memory paradigm whether subtle head shifts might similarly contribute to the expression of memory content.

We observed significant differences in head orientation deviations for left and right conditions approximately 4 seconds after the image onset in recognition memory, suggesting that microscopic head movements may reflect the brain's representation of spatial information associated with head orientation knowledge. Importantly, this significant time frame overlaps with the associative memory phase, as participants were instructed to indicate their recognition memory choice (old/new) 1 second after the image presentation and then proceeded immediately to the associative memory test. However, when the data were locked to associative memory onset, the observed differences were no longer significant. This variation in results could arise from the baseline periods. The recognition memory onset had a clearer baseline before the image onset, whereas associative memory could be influenced by the self-paced transition from recognition memory and associative memory, which may have introduced variability in the timing and dynamics of memory processing. Nevertheless, the observed subtle head movements could still indicate internal spatial processing associated with the representation of head orientation knowledge.

Although our study was not initially focused on motor behavior, this factor may explain the differential findings observed for head orientations. Importantly, for this analysis, the deviations in orientations were categorized based on participants' remembered responses rather than the original stimulus orientation. Therefore, the observed pattern suggests a potential link between orientation deviations and memory-related processes.

The present study has also provided insights into item familiarity and successful memory retrieval during the recognition memory test. Consistent with prior research, we observed higher ERP amplitudes for successfully identified old items compared to new items. This finding reflects the well-documented "old/new effect" in recognition memory paradigms, which highlights the neural differentiation between successfully retrieving familiar stimuli and processing new stimuli (Danker et al., 2008; Tsivilis et al., 2015).

The significant ERP difference observed between old and new items from 187 ms to 1 second likely comprises two stages of recognition memory retrieval. The early portion of this effect may capture processes related to familiarity-based retrieval, typically observed around 300-500 ms post-stimulus onset (Bridger et al., 2012; Curran, 2000). The sustained portion of the effect extends to the time windows associated with recollection (500-800 ms), likely reflecting recognition processes accompanied by recollection-related activity (Tsivilis et al., 2015).

Mograss, Godbout, and Guillem (2006) explored the old/new effect in the context of both sleep and wake conditions. Their results showed larger ERP differences for old and new items after sleep, with distinct early frontal and later posterior ERP components. This suggests that sleep, compared to wakefulness, enhances episodic memory recognition processes by strengthening memory traces. While our study did not directly compare sleep and wake conditions or include sleep condition without TMR, the observed effects after sleep are consistent with the idea that sleep contributes to the refinement and strengthening of memory traces (Klinzing et al., 2019), supporting the successful recognition process.

Complementing these ERP findings, our investigation also revealed significant alpha-beta (8-30 Hz) desynchronization for old items versus new items, with this effect predominantly observed over the left parietal region. This pattern has been consistently linked to successful memory formation during encoding and deeper levels of information processing during retrieval. It is often interpreted as a neural signature of active memory construction, reflecting the engagement of more elaborate retrieval processes when recalling old items compared to indicating novel stimuli (Hanslmayr et al., 2012).

Further support for successful memory retrieval emerged from the hits (correctly recognized items) versus misses (forgotten items) contrast. Hits elicited more positive ERP amplitudes around 600 ms, with a central topography for this significant difference. Additionally, beta-band desynchronization was significantly greater for hits compared to misses, with a central-left parietal topography. These ERP and oscillatory patterns align with prior research linking successful memory to a late positive component in ERPs (Yang et al., 2019) and desynchronization in alpha-beta bands (Griffiths et al., 2019).

The findings from the old-new contrast and the hits-misses comparison indicate that both ERP and TFR markers may serve as indicators of successful memory retrieval, highlighting the role of a combination of neural processes supporting recognition memory.

Our findings should be considered in the context of specific methodological limitations. TMR’s detrimental effect on memory performance may have reduced the likelihood of observing cueing-related differences in the post-sleep neural activity, highlighting the importance of considering behavioral outcomes when interpreting the neural effects.

Both behavioral and neural responses to TMR are likely influenced by task-specific factors such as the complexity of the design, cognitive demands, and the type of associations involved. Our spatial associative memory task involving head orientation-image associations may have introduced additional motor encoding demands compared to verbal or semantic associations. This highlights the importance of considering how task structure may interact with reactivation and retrieval processes. The potential role of embodied elements in memory retrieval could be explored more systematically in future studies.

We computed head orientation deviations to provide insights into potential embodied expressions during spatial retrieval. However, the absence of electromyographic (EMG) recordings may have limited our ability to determine whether high-frequency EEG activity reflects muscular activity or neural signals. Future studies may benefit from integrating EMG recording to disentangle motor from cognitive contributions.

The lack of a direct comparison with a sleep condition without TMR restricts our ability to isolate the specific contributions of targeted cueing from those of general sleep-based consolidation. Including a no-cue control condition would improve the interpretability of TMR's effects on post-sleep neural dynamics.

Finally, individual variability in sleep architecture and cue responsiveness may have contributed to variability in our results. Some participants may be more receptive to cueing than others, depending on sleep stage dynamics and individual thresholds for stimulus processing during sleep.

The current study advances the field by extending the TMR protocol to spatial memory tasks involving head orientations and examining its effects on memory retrieval after a full night of sleep. Although cueing did not significantly modulate post-sleep neural dynamics overall, this null finding highlights the need to refine specific aspects of TMR protocols to enhance their effectiveness across different phases of memory processing. Factors such as cue timing and the initial encoding strength may influence the long-term effects of TMR.

Furthermore, subtle head movements emerged as a potential embodied expression of spatial memory, offering new perspectives on how bodily signals may contribute to the successful retrieval of memories. Our findings also confirmed distinct neural dynamics associated with familiarity, recollection, and retrieval success.

Future research should systematically investigate how different cueing strategies influence post-sleep retrieval in spatial memory tasks and further explore how TMR affects time-frequency characteristics of EEG activity during the retrieval of different types of memories. In addition, studies combining neural and physiological measures can help understand the role of subtle bodily movements in the expression of spatial memory during retrieval.

Moreover, direct comparisons between sleep conditions with and without TMR will be essential to isolate the specific impact of TMR and general sleep-related consolidation. These efforts can establish the foundation for developing TMR-based interventions targeted at improving memory processes in real-world settings.

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4. GENERAL DISCUSSION

This thesis investigated how targeted memory reactivation (TMR) during non-rapid eye movement (NREM) sleep contributes to the consolidation of spatial memories, drawing insights from both sleep and post-sleep retrieval phases. To this end, two complementary EEG studies were conducted: one focused on memory reactivation during sleep in the context of sequential-spatial memories, and the other investigated the neural dynamics of post-sleep memory retrieval following TMR. This discussion begins with a summary of the main findings from these studies, followed by an exploration of their theoretical implications. Methodological limitations are then addressed, and potential directions for future research, including practical implications, are proposed.

4.1. Summary of Findings

4.1.1. Study 1: Identifying Image and Head Orientation-Related Memory Reactivation During Sleep in Humans

4.1.1.1. Study Aims

In Study 1, we investigated whether TMR during NREM sleep can reactivate item- and spatial context-related representations in sequential memories. Specifically, we sought to decode neural patterns associated with different image categories and head orientations following auditory cues presented during sleep. Additionally, we explored whether the temporal dynamics of decoding align with the original sequence structure encoded during learning.

4.1.1.2. Main Findings

We found that TMR selectively benefited head orientation memory performance for weakly encoded sequences, and this effect emerged during the retrieval session following an additional night of sleep. We successfully decoded neural patterns related to image categories and head orientations following TMR cues when training and testing within sleep data. Importantly, successful decoding of head orientations was consistent across all items in a sequence, which suggested a strong reinstatement of the spatial context associated with each item. We have also reported that head orientation decoding was linked to spindle activity: trials containing spindle activity showed significant classification performance for head orientations, while trials with no spindles did not. However, we found no evidence for a structured temporal order of decoding accuracy across items, suggesting that reprocessing during sleep may not strictly follow the original encoding order of the sequences. Finally, classifiers trained on localizer data failed to generalize to sleep. We speculate that memory representations during sleep may rely on distinct neural dynamics from those during wakefulness, a topic discussed in more detail in the following sections.

4.1.1.3. Novelty & Relation to Previous Work

This study improves our understanding of how sleep supports memory by demonstrating that TMR during NREM sleep may help stabilize spatial memories through reprocessing. Specifically, the reliable decoding of head orientations within sleep suggests that spatial information-related activity was present in response to auditory cues, which may reflect memory-related processing during sleep. These findings go beyond previous work decoding individual item-cue associations in spatial memories using head orientations (Schreiner et al., 2024), by showing that TMR can elicit item-specific spatial information for each element within a learned sequence.

One of our key contributions is that behavioral TMR effects are selective for weakly encoded spatial memories and become evident only after 24 hours, consistent with previous delayed consolidation effects reported (Cairney et al., 2018; Rakowska et al., 2021). This suggests that TMR may initiate processes during sleep that support consolidation over subsequent nights rather than resulting in immediate behavioral gains.

The findings also emphasize the role of spindles in memory processing. Extending prior studies linking TMR to increased spindle activity (Antony et al., 2019; Cairney et al., 2018; Ngo & Staresina, 2022; Schreiner et al., 2024), our results suggest that spindle occurrence following TMR cues contributes to the reprocessing of spatial context. While other oscillations, such as slow oscillations and theta rhythms, have also been associated with memory consolidation and may support spatial processing (Herweg et al., 2020; Ng et al., 2025), we focused on spindles because their occurrence significantly increased after TMR cues in remembered versus forgotten sequences. This pattern suggests a relationship between spindles and successful spatial memory processing.

4.1.2. Study 2: Neural Dynamics of Post-Sleep Memory Retrieval

4.1.2.1. Study Aims

The second study examined the influence of TMR on the neural dynamics of post-sleep memory retrieval. We analyzed EEG markers of successful memory retrieval, spatial memory, and subtle head movements as potential embodied indicators of successful remembering. This allowed us to explore both neural and behavioral signatures of spatial memory retrieval.

4.1.2.2. Main Findings

By analyzing event-related potentials (ERPs) and time-frequency representations (TFRs) of post-sleep retrieval, we found no significant influence of cueing on neural activity compared to uncued memories. However, we observed neural responses related to head orientations and an interaction with cueing, suggesting preserved spatial information after sleep. The interaction was also in line with our behavioral results, which showed better performance for uncued memories. Moreover, we replicated the well-established old-new effect in both ERP and TFR data and identified neural dynamics related to the successful memory retrieval. Additionally, subtle head movements during retrieval were linked to successful remembering, suggesting a role of microscopic movements for memory processes.

4.1.2.3. Novelty & Relation to Previous Work

This work expands the scope of TMR research by investigating post-sleep retrieval, a phase that remained underexplored compared to the investigation of encoding and sleep phases (Johnson et al., 2015; Oudiette & Paller, 2013). Unlike prior work using a simpler associative memory task in a nap paradigm (Schreiner et al., 2015), we examined complex spatial associations following a full night of sleep.

Together, the findings suggest that post-sleep retrieval may involve neural dynamics related to different aspects of memory, including familiarity, recollection, and spatial context. Specifically, contrasts analyzed between old and new items (familiarity), hits and misses (recollection), and left versus right-side associated trials (spatial context) revealed distinct neural patterns, even in the absence of a general TMR effect on post-sleep neural activity.

The observation of preserved spatial information indicates that memory traces linked to spatial context may remain stable after sleep and potentially be modulated by cueing.

Furthermore, the results suggest a possible role of embodied memory processes – bodily signals that accompany or reflect internal cognitive states (Barsalou, 2008)– in spatial memory retrieval, as subtle head movements were linked to successful recall. This finding adds to a growing body of work suggesting that bodily signals may reflect covert aspects of memory retrieval in episodic memory contexts (Johansson & Johansson, 2014; Wynn & Schacter, 2024).

4.2. Theoretical Implications

4.2.1. Extending Models of TMR And Memory Consolidation

The active systems consolidation theory remains one of the most prominent frameworks for understanding sleep-related memory consolidation. It posits that NREM sleep supports the transfer of memories from the hippocampus to neocortical networks, supported by the coordinated activity of sleep oscillations such as slow oscillations (SOs), spindles, and sharp-wave ripples (Rasch & Born, 2013). This process helps transform transient memory representations into more stable, long-term traces. Our findings build on this widely supported theoretical foundation and extend it to TMR-induced memory consolidation in the context of spatial and sequential memories.

Our findings emphasize the significance of spindle activity in the reprocessing of spatial memory traces, suggesting that spindle-containing trials during NREM sleep may offer windows of enhanced plasticity for reinforcing spatial context, aligning with prior work that shows spindles facilitating synaptic plasticity (Rosanova & Ulrich, 2005; Seibt et al., 2017).

Another key implication of our work is that TMR does not equally benefit all memories. Instead, its impact appears to depend on factors such as initial encoding strength and memory competition between overlapping associations. In Study 1, TMR during NREM sleep benefited weaker spatial memories, consistent with the idea that strongly encoded memories may be more stable and thus less susceptible to further enhancement through reactivation during sleep (Creery et al., 2015), while weaker memories remain more responsive to reactivation-based improvement (Cairney et al., 2016; Denis et al., 2021).

This adaptive nature of TMR may also operate at the level of sequence structure and could help explain our finding in Study 1 that middle items (2nd and 3rd in a sequence) were significantly decoded for images, whereas first and last items were not. We interpret this as a possible indication that TMR may preferentially support elements at greater risk of weakening within sequences, such as middle items, while the first and last items may be more resilient to forgetting due to primacy-recency effects (Glanzer & Cunitz, 1966). We acknowledge that differences in neural variability in reactivation strength across positions could also account for this pattern and should be examined in future work. This result also aligns with our behavioral finding that weak sequences benefit from TMR, as such sequences could be particularly dependent on the successful reactivation of fragile elements. Future work should investigate whether weak sequences are indeed characterized by weaker middle items and how this relationship contributes to the consolidation process.

Notably, the influence of TMR is not always uniform and may result in detrimental effects under certain conditions. This was observed in Study 2, where TMR during NREM sleep impaired behavioral performance, which we interpret as the outcome of retrieval competition when multiple associations are associated with the same cue. This can then lead to interference between competing memory representations (Schreiner et al., 2024; Xia et al., 2024). Instead of being uniformly adaptive, our results highlight that the impact of TMR is highly context-dependent and influenced by the structure and strength of encoded associations, as well as the competitive dynamics among the associations.

In summary, our findings suggest that TMR can interact differently with sleep-related memory processes depending on the memory context. The contrasting outcomes of two studies underscore that both encoding strength and associative structure of memories must be carefully considered when designing TMR protocols to enhance or weaken memories.

4.2.2. Integration of Spatial and Sequential Information in Memory Reactivation

Real-world memories typically consist of sequences of interrelated events with spatial and temporal dimensions (Bellmund et al., 2020). Rather than isolating single-item associations, in Study 1, we focused on how spatial and sequential elements of memories are reactivated during sleep.

The analysis of within-sleep EEG decoding showed that both item-related and spatial context-related activity could be decoded. Importantly, decoding was significant for all head orientations in a sequence, suggesting that spatial context may anchor the context for reprocessing, binding elements into coherent memory traces. This supports the broader view that memory consolidation involves binding multiple aspects of an experience, including spatial and contextual relationships (Tulving, 1972; Eichenbaum, 2017).

Despite the reliable decoding of head orientation-related activity, there was no structured temporal pattern in decoding accuracy. This challenges the assumption that past experiences are reinstated in a temporally organized manner (Eichenbaum, 2017b).

Instead, the results suggest that memory reprocessing during sleep may be more flexible and context-dependent than following structured awake retrieval dynamics. However, it is important to note that this conclusion is based on our approach, adapted from Michelmann et al. (2018), and other methods may reveal a finer temporal pattern.

Together, our results demonstrate that both spatial and item-related information were decodable during sleep within a sequential-spatial memory paradigm, even though the temporal organization of this decoding appears to be more flexible than expected. Our findings extend prior evidence that NREM sleep supports the consolidation of spatial memories. Studies using TMR have shown enhanced stabilization of cued spatial memories (Creery et al., 2022; Rudoy et al., 2009; Schreiner et al., 2024; Shimizu et al., 2018), while studies without TMR have similarly demonstrated that spontaneous reactivation during sleep can also modulate spatial memory (Deuker et al., 2013; Peigneux et al., 2004). Building on this body of research, our study implemented a more complex sequential-spatial context, offering insights into how both item-specific and spatial representations may be maintained during sleep.

4.2.3. The Investigation of Post-Sleep Retrieval

Research investigating sleep-related memory consolidation has predominantly focused on behavioral outcomes of TMR and the neural responses following cueing during sleep, such as increases in theta and spindle activity (Denis & Payne, 2024; Schreiner & Rasch, 2015; Wang et al., 2019). In contrast, post-sleep retrieval remains understudied, even though it is critical to understand how targeted reactivation during sleep modulates the neural dynamics supporting later memory retrieval. Previous work on memory retrieval has demonstrated that oscillatory dynamics, such as alpha/beta desynchronization and theta/gamma synchronization, play a key role in the successful recall of memories (Hanslmayr et al., 2012; Nyhus & Curran, 2010). In Study 2, we addressed this gap by investigating how memory traces influenced by TMR application are reflected in post-sleep retrieval neural dynamics, providing insights into the long-term consequences of memory reactivation.

The present findings from Study 2 suggest that spatial memory representations related to head orientations can remain preserved after sleep. The observation of no general TMR effect on neural dynamics differs from prior work that reported increased theta and gamma power for cued items in a vocabulary learning paradigm (Schreiner et al., 2015). The differences may be attributed to increased task complexity and the spatial nature of the task used in our study, which may engage distinct consolidation processes. Moreover, the persistence of a clear old/new effect in our data suggests that sleep may preserve core features of recognition memory, possibly through systems-level consolidation processes that strengthen memory traces through hippocampal-neocortical networks during sleep (Diekelmann & Born, 2010).

In summary, we highlight the need to consider task complexity, memory type, and retrieval demands when interpreting the impact of TMR on post-sleep neural dynamics. Since these factors can influence how memories are reactivated and expressed after sleep, accounting for them can enhance the design of TMR protocols aiming to selectively shape memory processes.

4.2.4. The Role of Embodied Processes in Memory

The idea that successful retrieval may involve embodied components has gained increasing attention in cognitive neuroscience (Barsalou, 2008; Dijkstra et al., 2007). Many studies suggest that bodily signals, such as eye movements, can reflect memory reinstatement, including in long-term and episodic memory tasks (Johansson & Johansson, 2014; Wynn & Schacter, 2024). Extending this framework, we propose that subtle head movements, even when subjects were instructed to keep a straight head position, may similarly support the retrieval of spatial memory content. This aligns with the idea that different forms of covert bodily behavior may reveal the internal processes of memory retrieval (Barsalou, 2008).

We observed a tendency for increased high-frequency activity at posterior electrodes located near the base of the skull (PO7 and PO8), along with subtle head movements during the retrieval of spatial information. These micromovements were specific to successful memory retrieval, indicating that spatial recall may involve embodied elements and reflect subtle motor-related processes, such as muscle activity associated with head orientation. Together, these observations suggest that post-sleep retrieval may engage sensorimotor components and express memory traces consolidated during sleep.

Together, we propose that integrating embodied cognition into sleep and memory research can clarify how sensorimotor signals support the successful retrieval of spatial memories. Since sleep is a critical period for consolidation, investigating bodily signals during post-sleep retrieval may reveal whether sensorimotor components from learning are preserved. Identifying which embodied aspects are stabilized during sleep could enrich our understanding of how retrieval dynamics are modulated through offline consolidation. This approach offers a more integrative approach for studying memory processes across the brain and body.

4.3. Methodological Considerations and Limitations

4.3.1. Cueing Strategies and Timing

It is essential to reflect on key methodological choices when interpreting our findings. One important factor is the cueing strategy, as both the sleep stage and delivery method of TMR cues can influence their effectiveness (Carbone et al., 2024; Ngo & Staresina, 2022; Oudiette & Paller, 2013). Most studies use sleep-stage-specific cueing, typically targeting NREM sleep, which is characterized by oscillatory activity that supports memory consolidation (Diekelmann & Born, 2010; Klinzing et al., 2019; Rasch & Born, 2013).

Another strategy within this framework is phase-locked cueing, where TMR cues are delivered during specific phases of SOs, particularly during the UP states. These UP states reflect periods of high neuronal excitability and tend to coincide with spindle generation (Ngo & Staresina, 2022; Shimizu et al., 2018). Aligning cues with the time windows for excitability has been shown to induce memory reactivation more effectively than cueing during DOWN states of SOs or at random times (Klinzing et al., 2019; Ngo & Staresina, 2022; Xia et al., 2023).

In our study, we delivered TMR cues during stable NREM epochs identified in real-time, during both N2 and slow-wave sleep (SWS). While this broader approach allowed us to capture memory dynamics in a wider sleep window, it did not target specific phases of SOs.

SOs are present across both N2 and SWS stages, but their dynamics differ in terms of density and their coupling with spindles (Carbone et al., 2024; Mölle et al., 2011). Therefore, the phase-locked cueing approach may offer more precise control over reactivation timing and could enhance cueing outcomes. Since we did not observe a general behavioral benefit of TMR on memory performance in Study 1, it is possible that phase-specific cueing would have resulted in stronger effects.

At the same time, current literature provides limited evidence for behavioral differences between cueing during N2 and SWS. For example, Wick & Rasch (2023) and Carbone et al. (2024) found no significant behavioral differences when TMR was applied in either stage, despite reporting different oscillatory responses. However, the lack of clear differences in behavioral outcomes for cueing in either NREM substage suggests that our broader NREM cueing strategy remains a methodologically valid approach. Nevertheless, future studies could benefit from directly comparing stage-specific and phase-locked strategies for optimizing cueing efficacy.

It is also worth noting that our focus on NREM sleep does not account for the possible contributions of REM sleep. As outlined in the general introduction, REM sleep has been associated with the consolidation of emotional and procedural memories (Abdellahi et al., 2024; Hutchison et al., 2021; Kim et al., 2020) and suggested to play a complementary role in refining memories consolidated during NREM (Sifuentes Ortega & Peigneux, 2024; Yuksel et al., 2025). However, the benefits of TMR during REM and whether REM sleep contributes to memory reactivation in a similar manner to NREM are debated (Hu et al., 2020). Since spatial memories have been primarily shown to benefit from cueing during NREM (Rudoy et al., 2009; Schreiner et al., 2024; Shimizu et al., 2018), our decision to apply TMR during NREM sleep aligns with previous findings. Nevertheless, the potential role of REM in consolidating spatial and associative memories remains an open question for future research.

4.3.2. Reflecting on EEG Analysis Choices

In the present study, we implemented two approaches for decoding: within-sleep decoding and a cross-state approach in which classifiers were trained on wake localizer data and tested on sleep data. Only the within-sleep decoding revealed significant results, demonstrating that neural activity patterns associated with different image categories and head orientations re-emerged during sleep following TMR cues.

Memory reactivation is commonly defined as the recurrence of neural patterns from prior learning (Denis & Cairney, 2023; Genzel et al., 2020). While our within-sleep decoding does not establish a direct link to learning-phase neural activity, the consistent stimulus-specific patterns following TMR cues suggest that neural representations related to memory can re-emerge during sleep. This provides indirect but systematic evidence for reactivation processes during sleep, although it does not confirm reactivation as strictly defined by cross-state decoding.

While EEG-based decoding holds promise for investigating memory reactivation, it remains a methodologically challenging approach. A central limitation is in interpreting what specific memory content is being reactivated. Although classifiers can detect neural patterns associated with prior learning, the reactivation signals are often subtle and can be masked by noise or background activity. Moreover, individual differences in the strength or timing of reactivation may further reduce the detectability of consistent neural patterns across participants (Van Bree et al., 2024).

Despite these challenges, EEG-based decoding remains a valuable method when carefully aligned with the study design. Advances in alignment with sleep oscillatory events (Schreiner et al., 2021), temporal modeling of reactivation (Liu et al., 2019), or exploring the use of subject-specific classifiers (Rudoler et al., 2024) may offer potential approaches to increase decoding sensitivity in future studies.

Another challenge in decoding memory-related activity is decoding across different brain states. In our study, classifiers trained on wake localizer data did not generalize well to sleep data, likely due to differences in neural dynamics between these states (Schönauer et al., 2017). However, several studies have successfully demonstrated reactivation using cross-state decoding methods (Cairney et al., 2018; Schreiner et al., 2021, 2024; Wang et al., 2019). These findings emphasize the feasibility of this approach. Thus, the absence of significant decoding accuracy in our study does not necessarily imply the absence of reactivation. Instead, it may reflect limitations in classifier sensitivity, parameter choices, insufficient trial numbers, or the reactivation formats not well captured by the current analysis pipeline.

4.3.3. Sample Characteristics

Our participant sample primarily consisted of university students between the ages of 18-35. While this age range was appropriate for our research aims, which focused on sleep-dependent memory consolidation in healthy young adults, it limits the generalizability of our results to broader populations. Age-related changes in sleep architecture and memory processing may influence reactivation and consolidation outcomes. Whether similar results could be observed in older adults or across different developmental stages is an open question for future research. Although we controlled for prior sleep habits, individual variability in responsiveness to auditory cues during sleep may still have influenced the consistency of memory processing among participants. Differences in sleep architecture, such as the phase of slow oscillations during cue presentation, the presence or timing of spindles, and the overall NREM structure, can vary between participants and are known to influence the efficacy of TMR (Antony et al., 2019; H.-V. V. Ngo & Staresina, 2022). These factors were beyond the scope of our research but represent promising targets for aiming to characterize cueing effectiveness.

We have previously implemented the same TMR paradigm used in Study 2 in a clinical sample (epilepsy patients) and observed comparable results in behavioral and reactivation patterns (Schreiner et al., 2024). While this suggests that TMR can be applied beyond healthy subjects, no such comparison was conducted for Study 1, which focused on sequential-spatial memories. Therefore, the generalizability of those findings to broader populations, such as clinical groups, remains uncertain. Examining whether memory dynamics are consistent across different populations may inform the translational potential of TMR-based interventions.

4.4. Future Directions and Applications

4.4.1. Future Directions in Research

Future research should refine experimental paradigms to better understand the conditions under which TMR is most beneficial. Our findings suggest that TMR effects are influenced by encoding strength and associative interference, with greater benefits observed for weakly encoded sequences and detrimental effects when competing associations are formed. Future studies should consider these factors to better understand how memory structure and strength modulate cueing outcomes and reactivation efficacy.

Moreover, future studies should include a no-cue control condition to further isolate the effects of TMR on spatial memory consolidation. This would help differentiate spontaneous memory processes from cue-induced reactivation and clarify the contribution of cueing to behavioral and neural outcomes on both sleep and post-sleep retrieval.

When examining how TMR affects post-sleep neural dynamics, it is also important to consider the memory type targeted. Evidence on post-sleep retrieval neural dynamics comes from studies focusing on vocabulary learning (Schreiner et al., 2015), while our study extends this work by investigating spatial memories. Prior studies have shown that TMR can produce different behavioral and neural outcomes across memory domains (Cairney et al., 2018; Hutchison et al., 2021; Rakowska et al., 2021). These differences likely reflect distinct consolidation mechanisms involved in each memory type, such as hippocampal-neocortical interactions for declarative memories and sensorimotor or limbic processes for procedural and emotional memories (Rasch & Born, 2013). Considering these differences could help clarify how cueing influences subsequent neural activity after TMR during sleep.

From a methodological perspective, while EEG offers high temporal resolution, its limited spatial precision can pose challenges in localizing the neural sources underlying reactivation. Although source localization techniques are available for EEG, combining it with other imaging methods such as functional magnetic resonance imaging (fMRI) or magnetoencephalography (MEG) could enhance spatial accuracy and help identify brain regions involved in reactivation. This spatial information may be valuable for understanding how different memory components are represented and reactivated during sleep.

Furthermore, incorporating electromyography (EMG) recordings could assist in detecting and controlling for neck muscle activity, which could be confounded with neural signals during the reactivation of head orientations during sleep. This would enable better control of movement-related signals and help dissociate them from neural contributions to the EEG signal.

4.4.2. Real-world Applications

TMR is increasingly being explored beyond laboratory settings as a tool for mental health conditions, educational contexts, and at-home cognitive interventions. For instance, studies have shown that pairing TMR with positive information –such as affirming personality traits or emotionally positive cues– can enhance positive self-relevant memories (Yao et al., 2024), improve self-esteem (Chen et al., 2023), and reduce physiological markers of anxiety (Borghese et al., 2022). These findings highlight the potential of TMR in mental health applications.

In educational settings, TMR has been successfully applied to improve language learning (Neumann et al., 2020) and the retention of academic material in school settings (Vidal et al., 2022). Moreover, effects of TMR have been observed in both laboratory conditions and home-based environments using mobile applications and wearable devices (Göldi & Rasch, 2019; Whitmore et al., 2022). This further supports the feasibility of implementing TMR in real-world applications. Exploring the neural and embodied dynamics of reactivation and retrieval processes will further advance the design of effective, real-world TMR applications across diverse memory domains.

5. CONCLUSION

This thesis explored how targeted memory reactivation (TMR) during NREM sleep contributes to the consolidation and subsequent retrieval of spatial memories. Specifically, it examined both memory reactivation during sleep and the influence of TMR on retrieval-related neural dynamics after sleep. These questions were addressed through two EEG studies: one investigated the reactivation of sequential-spatial associations during sleep, and the other focused on the neural dynamics during post-sleep retrieval. The findings demonstrate that TMR can modulate spatial memories, particularly those involving real-world head orientations, as reflected in neural activity during both sleep and wakefulness, as well as in behavioral performance.

Categorical and spatial information could be identified from sleep EEG using multivariate decoding, suggesting that TMR elicits neural activity linked to memory content. However, the absence of a consistent temporal decoding structure, together with the lack of cross-state generalization from wake to sleep, suggests that reactivation may operate in a more flexible and context-dependent manner than previously assumed. The findings underscore the need for more tailored analytical methods to capture the dynamics of sequential reactivation.

Behaviorally, the effects of TMR differed depending on task context and memory structure. While cueing enhanced memory performance for weakly encoded spatial memories in one study, it impaired performance in another study when multiple associations competed for the same cue. This variability highlights that the impact of TMR is not uniform and is influenced by factors such as encoding strength, the structure of associations, and interference between competing memories.

The investigation of post-sleep retrieval further demonstrated that spatial memory representations are preserved after sleep, as reflected by both differences in neural activity for head orientations and the emergence of subtle head movements during successful recall. This embodied aspect of memory retrieval introduces a novel angle for future studies, suggesting a potential relationship between sensorimotor processes and the retrieval of spatial memories.

In sum, this thesis provides an in-depth investigation of how TMR modulates the reactivation and retrieval of spatial memories across sleep and wake states. By combining behavioral, neural, and embodied measures, it advances current models of memory reactivation and contributes to both theoretical and methodological developments. These findings not only deepen our understanding of sleep-dependent consolidation but also hold promise for informing practical applications of TMR in educational, clinical, and cognitive enhancement contexts.

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Author Contributions

Study 1: Identifying Image and Head Orientation-Related Memory Reactivation During Sleep in Humans

Merve Kutlu, Thomas Schreiner, Julia Schaefer, Tobias Staudigl

M.K.: formal analysis, methodology, investigation, interpretation of results, data curation, writing — original draft, writing — review and editing

T.Sc.: conceptualization, methodology

J.S.: methodology, investigation

T.St.: conceptualization, methodology, interpretation of results, writing — review and editing, supervision, project administration, and funding acquisition

My contribution to this manuscript in detail:

For this manuscript, I contributed to the implementation and adaptation of the experimental paradigm and coordinated the sleep-EEG recordings, including participant recruitment and data collection. I performed EEG preprocessing, developed analysis pipelines, conducted statistical analyses, and visualized the results. Additionally, I interpreted the outcomes and drafted the manuscript, which I subsequently revised and refined based on feedback from my supervisor.

Merve Kutlu Tobias Staudigl

Study 2: Neural Dynamics of Post-Sleep Memory Retrieval

Merve Kutlu, Thomas Schreiner, Tobias Staudigl

M.K.: formal analysis, methodology, investigation, interpretation of results, data curation, writing — original draft, writing — review and editing

T.Sc.: conceptualization, methodology, investigation

T.St.: conceptualization, methodology, interpretation of results, writing — review and editing, supervision, project administration, and funding acquisition.

My contribution to this manuscript in detail:

For this manuscript, I contributed to the data collection for a project that had already been developed. I focused on the post-sleep part of the data, where I conducted the analyses, performed the statistical testing, and visualized the results in figures. I also interpreted the findings and drafted the manuscript, which I subsequently revised and refined in collaboration with my supervisor.

Merve Kutlu Tobias Staudigl

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