MEMORY
2026, VOL. 34, NO. 10, 1276–1289
https://doi.org/10.1080/09658211.2026.2733322

Routledge
Taylor & Francis Group

OPEN ACCESS Check for updates

Sleep benefits cross-dimensional binding of spatial context in episodic memory

Sabrina Shakoor, Edgar Erdfelder and Beatrice G. Kuhlmann

Department of Psychology, School of Social Sciences, University of Mannheim, Mannheim, Germany

ABSTRACT

The active systems consolidation hypothesis predicts that sleep compared to wakefulness benefits context binding in episodic memory for retention intervals of up to 12 h. Extending previous research on sleep benefits in item-context associative memory, we investigated whether sleep also improves bound source memory for cross-dimensional context associations. In a source-monitoring experiment, we used intentionally learned pictures as items and incidentally learned horizontal and vertical screen positions as context dimensions to compare cross-dimensional binding in spatial source memory for retention intervals filled with natural night sleep versus daytime wakefulness. In line with the active systems consolidation hypothesis, multinomial modelling analyses revealed a significant sleep benefit in bound source memory for horizontal and vertical spatial locations of items. Hence, not only memory for item-context associations but also memory for cross-dimensional context associations benefits from sleep.

ARTICLE HISTORY
Received 1 December 2025
Accepted 10 August 2026

KEYWORDS
Episodic memory; source memory; consolidation during sleep; memory binding; multinomial processing tree modelling

Research in neuroscience and psychology has shown that sleep compared to wakefulness during a retention interval benefits episodic memory in a subsequent test (for a meta-analysis, see Berres & Erdfelder, 2021). As such, episodic memory includes not only memory for past events and experiences but also for their context (e.g., their spatial location; Tulving, 2002), often collectively referred to as the source of information (Johnson et al., 1993).[1] During encoding, the content of memories (i.e., item memory) appears to be bound to its unique context (i.e., source memory) by the hippocampus (e.g., Dudai et al., 2015; Mitchell & Johnson, 2009). As detailed below, this source binding process is assumed to benefit from subsequent sleep (e.g., Feld & Born, 2017; Klinzing et al., 2019). Specifically, according to the active systems consolidation hypothesis[2] (Born & Wilhelm, 2012; Diekelmann & Born, 2010; Feld & Born, 2017; Inostroza & Born, 2013; Klinzing et al., 2019; Rasch & Born, 2013), hippocampal memory representations are replayed during sleep by reactivating specific neuronal firing patterns (Klinzing et al., 2019; Lewis & Durrant, 2011; O'Neill et al., 2010; Pfeiffer, 2020; Wilson & McNaughton, 1994). These local synaptic upscaling processes, which occur especially during slow-wave sleep (SWS), strengthen synaptic connections in the hippocampus, thereby stabilising hippocampal memory representations. In parallel, diminished neuronal firing rates renormalise the strength of synaptic connections across all cortical and subcortical areas (Feld & Born, 2017; Klinzing et al., 2019). It is assumed that the combination of this global synaptic downscaling process together with local synaptic upscaling processes results in a net strengthening of episodic context-bound hippocampal memory representations for retention intervals of up to approximately 12 h (Klinzing et al., 2019). Thus, the active systems consolidation hypothesis predicts that sleep compared to wakefulness within a 12-h retention interval strengthens associations between the components of a memory representation that were established earlier during encoding.

Prior research has investigated sleep benefits in item-context binding, that is, the binding of item information to a source (e.g., a sound or a spatial location) without further differentiating dimensions within that source (e.g., pitch and loudness, horizontal and vertical positions). In the following section, we briefly review the literature on sleep benefits in item-context binding. We then turn to the present study, which tests whether sleep benefits found in item-context binding (spatial location) also extend to cross-dimensional binding of multiple dimensions within a source (horizontal and vertical positions).

CONTACT Sabrina Shakoor sabrina.shakoor@uni-mannheim.de Department of Psychology, School of Social Sciences, University of Mannheim, A5, 6, Room B116, Mannheim 68159, Germany; Edgar Erdfelder erdfelder@uni-mannheim.de Department of Psychology, School of Social Sciences, University of Mannheim, A5, 6, Room B118, Mannheim 68159, Germany; Beatrice G. Kuhlmann kuhlmann@uni-mannheim.de Department of Psychology, School of Social Sciences, University of Mannheim, L13, 15-17, Room 425, Mannheim 68161, Germany

Supplemental data for this article can be accessed online at https://doi.org/10.1080/09658211.2026.2733322

© 2026 The Author(s). Published by Informa UK Limited, trading as Taylor & Francis Group
This is an Open Access article distributed under the terms of the Creative Commons Attribution-NonCommercial-NoDerivatives License (http://creativecommons.org/licenses/by-nc-nd/4.0/), which permits non-commercial re-use, distribution, and reproduction in any medium, provided the original work is properly cited, and is not altered, transformed, or built upon in any way. The terms on which this article has been published allow the posting of the Accepted Manuscript in a repository by the author(s) or with their consent.

Sleep benefits in item-context binding

Only a few studies have investigated sleep benefits in memory for item-context associations as tested in source-monitoring paradigms and have yielded mixed results (for a more detailed review, see Berres et al., 2025). For example, comparing natural nighttime sleep and daytime wakefulness, Mawdsley et al. (2014) and Lewis et al. (2011, Experiment 1) observed significant sleep-induced source memory benefits for word-position and object-background photo associations. In contrast, Wang et al. (2017) found no significant sleep benefit in children's source memory for word-pair-temporal context associations, although memory for word pairs as well as for the temporal context was better after sleep compared to wakefulness. Mixed results also emerged for nap study designs, comparing naps versus wakefulness during the day or early evening. Whereas van der Helm et al. (2011) and Lewis et al. (2011, Experiment 2) observed significant sleep benefits in source memory for word-context and object-background photo associations, Wang and Fu (2009) as well as Köster et al. (2017) found no significant sleep-induced source memory benefits for picture-background colour associations. Similarly, split-night studies yielded mixed support for the active systems consolidation hypothesis, which predicts higher importance of SWS-rich early sleep versus REM-rich late sleep for memory consolidation. In line with the active systems consolidation hypothesis, Groch et al. (2015) and Sopp et al. (2017) showed worse memory for frame colour and spatial position of neutral pictures after REM-rich compared to SWS-rich sleep. By contrast, Rauchs et al. (2004) observed better memory for word-position associations after REM-rich rather than after SWS-rich sleep.

One possible reason for the inconsistent findings could be the use of source memory measures that confound multiple cognitive processes, such as memory and guessing (cf. Batchelder & Riefer, 1990; Bröder & Meiser, 2007). To address this point, Berres et al. (2025) used multinomial processing tree (MPT) models of source monitoring (Batchelder & Riefer, 1990; Bayen et al., 1996; Meiser & Bröder, 2002) to test the sleep-strengthens-source-memory hypothesis in a recent study. As such, MPT models are formal mathematical measurement models that are well developed and understood (for reviews and a tutorial on MPT models, see Batchelder & Riefer, 1999; Erdfelder et al., 2009; Riefer & Batchelder, 1988; Schmidt et al., 2025). These models explain observed categorical behavioural data by estimating outcome probabilities of hypothesised underlying processes such as item memory, source memory, and different types of guessing, which are represented as nodes in a tree structure (for an example, see Figure 1). Importantly, by disentangling source memory from item memory and guessing, MPT models of source monitoring provide more rigorous and less contaminated measures of source memory (cf. Batchelder & Riefer, 1990; Bayen et al., 1996; Meiser & Bröder, 2002).

In two source-monitoring experiments conducted online, Berres et al. (2025) used intentionally learned pictures as items and incidentally learned screen positions and frame colours as source dimensions to compare memory for item-context and cross-dimensional context associations after 12-h retention intervals filled with either natural night sleep or daytime wakefulness. Specifically, in Experiment 1, the spatial position of pictures on a computer screen (left vs. right) was manipulated to examine sleep-induced memory benefits for item-context associations. In line with the active systems consolidation hypothesis, the results showed a significant sleep benefit in item-context binding. In Experiment 2, the spatial position (left vs. right) and the frame colour (blue vs. yellow) of pictures were orthogonally manipulated. It was investigated whether sleep also improves cross-dimensional binding, that is, bound source memory for the combination of spatial position and frame colour. Whereas the sleep benefit in item-context binding for spatial positions replicated, no sleep benefit was observed in item-context binding for frame colour. Further, no cross-dimensional binding of position and frame colour occurred, independent of sleep. The authors proposed a floor effect in incidental encoding of colour associations as an explanation for this finding and argued that relevant context features must be sufficiently salient and well encoded for cross-dimensional binding as well as for the sleep benefit to occur (Berres et al., 2025).

Consequently, it is still an open question whether sleep compared to wakefulness also strengthens bound source memory for cross-dimensional context associations. To fill this gap, we tested this core assumption of the active systems consolidation hypothesis by conducting a conceptual replication of Berres et al.'s (2025) Experiment 2 with key changes that allowed us to further examine sleep's role in strengthening cross-dimensional binding.

The present study

The current experiment largely followed Experiment 2 in Berres et al. (2025; for more details see its preregistration on the Open Science Framework, OSF, https://osf.io/gctzn) with one major exception: Instead of presenting pictures left versus right and in a blue versus yellow frame, pictures were presented left versus right and top versus bottom. This experimental manipulation is well established for investigating spatial source memory (cf. Cansino et al., 2002; Groch et al., 2015; Simon et al., 2018; Zhao & Vogel, 2025). In these studies, spatial source memory is commonly analysed in terms of quadrants (e.g., left-top; bound source memory). However, it is also possible that participants remember only one of the two dimensions (e.g., left; unbound source memory). Thus, horizontal and vertical locations can give rise to bound or unbound representations in context memory. By focusing on quadrants, the scoring methods of previous studies ignored this possibility and were also not further

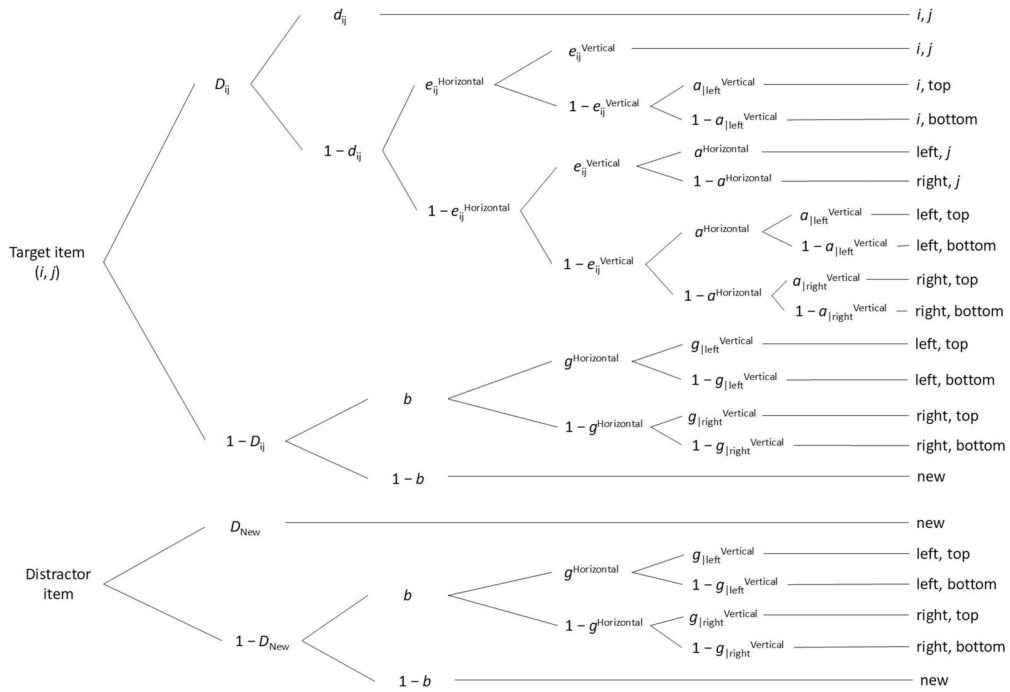

Figure 1. Multinomial Model of Multidimensional Source Monitoring. Note: D_{ij} = probability of correctly recognising a target item in sources *i* (i.e., "left" or "right" on the horizontal source dimension) and *j* (i.e., "top" or "bottom" on the vertical source dimension) of both source dimensions; D_{new} = probability of correctly identifying a distractor item as "new"; d_{ij} = probability of correctly identifying the source combination *i*, *j* of a recognised item (i.e., "left and top", "left and bottom", "right and top", or "right and bottom", respectively); $e_{ij}^{Horizontal}$ = probability of correctly identifying the source (i.e., left, right) on the horizontal source dimension of a recognised item; $e_{ij}^{Vertical}$ = probability of correctly identifying the source (i.e., top, bottom) on the vertical source dimension of a recognised item; $a^{Horizontal}$ = probability of guessing "left" on the horizontal source dimension of a recognised item; $a_{|left}^{Vertical}$ = probability of guessing "top" on the vertical source dimension if the target item was correctly identified as "old" and assigned to source "left"; $a_{|right}^{Vertical}$ = probability of guessing "top" on the vertical source dimension if the target item was correctly identified as "old" and assigned to source "right"; *b* = probability of guessing that an unrecognised item is "old"; $g^{Horizontal}$ = probability of guessing "left" on the horizontal source dimension if the unrecognised item was guessed to be "old"; $g_{|left}^{Vertical}$ = probability of guessing "top" on the vertical source dimension if the unrecognised item was guessed to be "old" and assigned to source "left"; $g_{|right}^{Vertical}$ = probability of guessing "top" on the vertical source dimension if the unrecognised item was guessed to be "old" and assigned to source "right". Adapted from "Analyzing Stochastic Dependence of Cognitive Processes in Multidimensional Source Recognition", by T. Meiser, 2014, *Experimental Psychology,* 61(5), p. 408 (https://doi.org/10.1027/1618-3169/a000261). Copyright 2014 by Hogrefe Publishing.

validated as measures of bound source memory. As outlined below, our approach is based on a validated multinomial model that jointly considers bound and unbound representations in context memory. Based on this model, we can assess whether both representations are required for capturing spatial source memory in this experimental paradigm. This allows a more fine-graded analysis by differentiating between sleep effects on bound and unbound source memory.

We chose spatial context dimensions – horizontal and vertical screen positions – for two additional reasons. First, to avoid the problem Berres et al. (2025, Experiment 2) encountered with manipulating frame colour, we aimed to avoid floor effects in incidental encoding of either context dimension. In two experiments with incidental source learning, Berres et al. (2025) observed that spatial positions receive sufficient incidental processing to gain sufficiently high memory strength at encoding, so that floor effects are unlikely in this case. Second, horizontal and vertical item positions are prototypical examples of integral stimulus dimensions as defined by Garner (1974). As such, these dimensions are perceived holistically and "in a more unitary fashion" (Grau & Kemler Nelson, 1988, p. 348) than separable dimensions like horizontal position and frame colour as used by Berres et al. (2025, Experiment 2). Importantly, it has been shown that, at encoding, the hippocampus is equally involved in word-word, picture-picture, and word-picture binding (Park & Rugg, 2011). Sleep effects on this source binding process should therefore apply to any sufficiently encoded combination of context dimensions, regardless of whether they are integral or separable. If integral dimensions such as horizontal and vertical positions receive sufficient processing at encoding, it is thus likely that a bound cognitive representation is established (cf. Garner & Felfoldy, 1970, Experiment 3), which then may or may not be retained across the subsequent retention interval filled with sleep versus wakefulness. For this reason, the use of integral dimensions as stimuli provides an ideal basis for testing the sleep-strengthens-bound-source-memory hypothesis specifically.

Following Berres et al. (2025, Experiment 2), we report commonly used behavioural measures of item and source memory for comparison with previous studies,

although our main data analysis rests on the MPT model of multidimensional source monitoring (Meiser, 2014; see the Method section for detailed descriptions). This model provides uncontaminated measures of item memory, bound source memory, unbound source memory, and guessing. According to the active systems consolidation hypothesis, bound source memory, in particular, should be larger after a 12-h retention interval containing sleep versus wakefulness.

Method

We applied a (2 × 2) × 2 mixed factorial design with horizontal (left vs. right) and vertical screen position (top vs. bottom) as within-subject factors and condition (wake vs. sleep) as between-subjects factor. Participants were randomly assigned to a wake or a sleep condition. In the wake condition, participants learned the material in the morning and were tested in the evening after a 12-h retention interval of daytime wakefulness. By contrast, participants in the sleep condition learned the material in the evening and were tested 12 h later in the morning after a period of nighttime sleep.

Participants

We strove for a sample of 130 participants based on the a priori power analysis reported in Berres et al. (2025). Specifically, the MPT-based power analysis conducted in multiTree (Moshagen, 2010) with a conventional α-level of .05 and an assumed difference of .10 between the sleep and wake condition in item memory (D), bound source memory (d), and unbound source memory parameters ($e^{\text{Horizontal}}$, e^{Vertical}) yielded power values of .99 (D), .78 (d), .67 ($e^{\text{Horizontal}}$), and .61 (e^{Vertical}) for a sample size of 130 participants, 120 target items, and 60 distractor items (Berres et al., 2025). Because data collection was slow, we collected the targeted sample size in three waves from fall 2022 to spring 2023, from fall 2023 to winter 2023, and from summer 2024 to fall 2024 via campus advertisement and mailing lists of the University of Mannheim, social media, and personal contacts. To participate in the online experiment, participants had to be between 18 and 35 years old, speak German fluently, and have no colour blindness or neurological disorders. In addition, we excluded participants with high average daytime sleepiness, which may be related to sleep disorders, as indicated by a sum score > 10 on the Epworth Sleepiness Scale (ESS; Bloch et al., 1999; Johns, 1991).

In total, 185 participants ($n_{\text{wake}} = 86$, $n_{\text{sleep}} = 99$) completed the experiment successfully and were rewarded with either €10 or corresponding course credits. Note that the experiment was successfully completed only if all parts of the experiment (i.e., registration, learning, and testing session) were completed within the set time frames and at least 50% of the responses in the orienting task were correct. We also applied the same exclusion criteria as Berres et al. (2025): Thirty-six participants were excluded because they indicated that they were distracted or interrupted during the experiment. Furthermore, 12 participants had to be excluded because the retention interval was not within 11–13 h. In addition, two participants of the wake condition were excluded because they napped during the retention interval. We also excluded two participants with a larger false-alarm rate than hit rate. Another two participants were excluded because they reported technical problems. Finally, one participant switched devices during the experiment, which could affect the display and performance of the online experiment and was thus excluded. In sum, 55 participants were excluded, leaving 130 participants ($n_{\text{wake}} = 54$, $n_{\text{sleep}} = 76$) for analysis.[3] Participants were between 18 and 33 years of age ($M = 22.67$ years, $SD = 3.33$), 101 (77.69%) were female. For more detailed sample characteristics, we refer to Table S1 in the supplemental materials. Performance in the orienting task was near perfect, well above the minimally required 50% correct responses ($M_{\text{total}} = M_{\text{wake}} = M_{\text{sleep}} = 99.58\%$), indicating high attention to the spatial positions of the items during the learning phase.

In their analysis, Berres et al. (2025) further excluded participants with substantial alcohol consumption during the retention interval. By contrast, we included all 130 participants in the main analysis and conducted a sensitivity analysis for which we excluded four participants who indicated alcohol consumption ($n_{\text{wake}} = 2$, $n_{\text{sleep}} = 2$; see Table S2 in the supplemental materials for sample characteristics). Importantly, the sensitivity analysis yielded results comparable to the results of the main analysis reported here (see Tables S3 to S5 in the supplemental materials).

Material

As stimulus material, we used the coloured version of 184 object drawings from the multilingual picture databank (MultiPic; Duñabeitia et al., 2018). This stimulus material was also utilised in Experiment 2 by Berres et al. (2025), however, in their study grey-scaled instead of coloured to draw attention to the experimental manipulation of frame colour. Previous research showed better memory for coloured material compared to grey-scaled (e.g., Spence et al., 2006; Wichmann et al., 2002; for a review, see Dzulkifli & Mustafar, 2013). For this reason and because we did not manipulate frame colour, we opted for the coloured version of the object drawings.

For each participant, we randomly chose 120 target pictures of the 184 drawings and displayed them either on the left or the right side and on the top or bottom of the screen (i.e., 30 pictures each were displayed at the 10% and 90% position on the x- and y-axis). Consequently, each combination of horizontal and vertical position appeared equally often (i.e., 30 times). Furthermore, we randomly selected another 60 pictures as distractors and presented the remaining four pictures as buffer items in

the beginning of the learning phase to prevent primacy effects. Because of the 12-h retention interval, no recency buffer was included. Following Berres et al. (2025), the data analysis does not contain the responses to the four buffer items. We provide a list of the 184 pictures on the OSF (https://osf.io/v78y5/?view_only=7fae4b70acc34741ac90d614342602bc).

Procedure

The experiment closely resembles Experiment 2 described in Berres et al. (2025) and was thus also conducted as an online experiment, using the same online study builders, that is, SoSci Survey (Leiner, 2020) and lab.js (Henninger et al., 2022). In total, the online experiment consisted of three parts: registration, learning, and testing session. In the following, we will describe each part in detail. Unless explicitly stated otherwise, the procedure in the current experiment is identical to the procedure of Experiment 2 in Berres et al. (2025).

Registration

Participants gave informed consent and filled out the Epworth Sleepiness Scale (ESS), which was not included in Berres et al. (2025). Subsequently, participants were randomly assigned to either the wake or sleep condition if they met all participation requirements (see the Participants section for a detailed description). According to their assigned experimental condition, participants had to pick a date and time for the first session (i.e., wake condition: 7 am to 10 am; sleep condition: 7 pm to 10 pm). They were informed that the second session starts 12 h later.

Learning session

Participants received the access link to the learning session via email 15 min before the start time they had selected during registration. Following Berres et al. (2025), participants were explicitly instructed to study the presented pictures for a later recognition test (i.e., intentional learning of items). By contrast, sources were learned incidentally without any encoding instruction. Although this approach creates a more realistic setting for investigating everyday source monitoring, it also increases the risk of floor effects in source memory. For this reason, we adopted the orienting task used by Berres et al. (2025) in which participants indicated the spatial position of a presented picture by pressing the correct button during picture presentation in the learning phase. As the presented picture and the corresponding correct button were both positioned in the same quadrant (see Figure 2A), an additional motor component was likely involved in picture-position learning. This probably increased the likelihood of binding at encoding as intended. Moreover, the orienting task requires attending to relevant source information but involves no rehearsal (Boywitt & Meiser, 2012; Berres et al., 2025). Due to these two characteristics (i.e., motor component, source attention without rehearsal), the orienting task is well-suited for preventing floor effects in incidental source learning. Note that differences in memory performance between the wake and sleep condition cannot be explained by the orienting task as it was performed by all participants in the experiment. To summarise, participants were explicitly informed and thus aware of the relevance of the pictures but not of the pictures' spatial position for a later memory test.

For the study phase, 124 randomly selected pictures (i.e., 4 buffer and 120 target items) were sequentially presented on the left or right side and at the top or bottom of the screen for 5 s each. Since screen sizes vary among participants in online experiments, we displayed the pictures at the 10% and 90% position on the x- and y-axis. In addition, the screen was divided into four corresponding sections by a centred horizontal and vertical line located at the 50% position on the x- and y-axis (see Figure 2A). This learning setup deviates from Berres et al.'s (2025) Experiment 2, where coloured instead of grey-scaled pictures (see the Material section for more details) were presented left versus right at the 10% and 90% position on the x-axis and in a blue versus yellow frame without any horizontal or vertical dividing lines. As in Experiment 2 of Berres et al. (2025), every picture presentation was followed by an interstimulus interval of 1 s (i.e., blank white screen for 500 ms followed by a fixation cross for 500 ms). While a picture was presented on the screen, participants performed the aforementioned orienting task. Specifically, within the 5 s picture-presentation time, participants were required to press the correct button for the combination of horizontal and vertical position. The four buttons were displayed at the centre of the screen in the corresponding section and labelled "left + top", "left + bottom", "right + top", and "right + bottom" (see Figure 2A). This differs from Berres et al.'s (2025) Experiment 2 in which the buttons for spatial position shown in grey and labelled "left" and "right" were displayed on the bottom of the screen next to the buttons for frame colour shown in the respective colour and labelled "blue" and "yellow". Following Berres et al. (2025), only participants who provided at least 50% correct answers were invited to the testing session 12 h later.

Testing session

Again, participants received the access link via email 15 min before the automatically calculated start time. For testing, the 120 target items were intermixed with 60 distractors and presented in the upper middle of the screen. Below the picture, in the lower middle of the screen, the question "Have you seen this picture before?" was displayed followed by four buttons labelled "Yes, left + top", "Yes, left + bottom", "Yes, right + top", and "Yes, right + bottom". Below these buttons, one button labelled "Was not shown" was displayed (see Figure 2B). Participants responded by pressing the appropriate button.

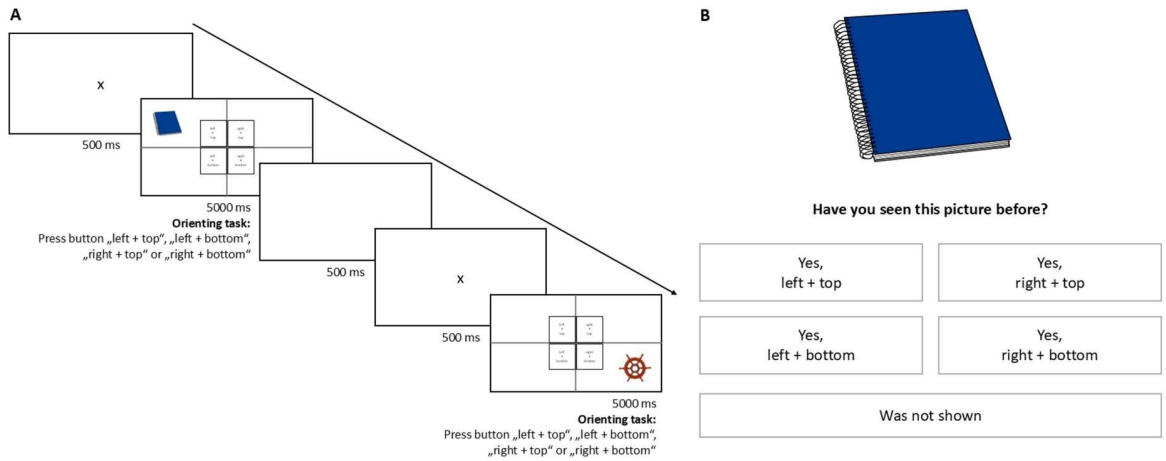

Figure 2. Learning and testing procedure of the online experiment. Note: The learning session contained 124 coloured object drawings (i.e., 4 buffer and 120 target items) presented left versus right and top versus bottom. For each of the 180 items in the testing session (i.e., 120 target items intermixed with 60 distractor items), participants were asked "Have you seen this picture before?" to make a "Yes, left + top", "Yes, left + bottom", "Yes, right + top", "Yes, right + bottom", and "Was not shown" decision by pressing the button with the fitting label. This was followed by control and demographic questions. Panel A: Orienting task during the study phase. Panel B: One-step item and source memory test in the testing session. See the online article for the colour version of this figure.

This testing setup deviates from Berres et al.'s (2025) Experiment 2, in which stimuli were presented in the middle of the screen with two buttons below. The button labels "old" and "new" were switched in position between participants. If participants answered "old", they were asked about the spatial position and frame colour. Participants responded by pressing one of four buttons labelled "left plus blue", "left plus yellow", "right plus blue", and "right plus yellow". The buttons were arranged in a square grid with labels for the spatial position (i.e., left, right) presented always on the respective side and labels for the frame colour (i.e., blue, yellow) varied between participants. Thus, in contrast to Berres et al. (2025), item memory and source memory in the present study were tested conjointly without varying the labels of the buttons between participants. In the current experiment, the labels of the four location response buttons in the test were static and always corresponded to the respective screen position to avoid confusion. As in Experiment 2 of Berres et al. (2025), this memory test was followed by control and demographic questions, including the exclusion criteria (e.g., distraction, technical problems; cf. Berres et al. 2025). Finally, participants were thanked and debriefed.

Measures

Following Berres et al. (2025), we report hit rates, false-alarm rates, sensitivity index *d'* and response bias *c* for item memory next to the average conditional source identification measure (ACSIM) for source memory to allow comparisons with previous studies. Our main data analysis, however, rests on the MPT model of multidimensional source monitoring (Meiser, 2014). Below, we provide a detailed description of all measures applied.

Standard measures of item and source memory

Item memory measures. Hit rates are defined as the proportion of target items correctly identified as "old" whereas false-alarm rates are defined as the proportion of distractor items falsely identified as "old". Sensitivity index *d'* and response bias *c* from the signal detection theory (SDT; Stanislaw & Todorov, 1999) denote target-distractor discriminability and general response tendency, respectively. Specifically, larger positive values of *d'* indicate better discrimination between target and distractor items. For *c*, larger positive values indicate a stronger "new"-response bias, larger negative values indicate a stronger "old"-response bias, and values close to zero indicate no response bias (Stanislaw & Todorov, 1999).

Source memory measures. The average conditional source identification measure (ACSIM) is defined as the proportion of correct source attributions for all target items correctly identified as "old", averaged across two sources (e.g., top, bottom) of a source dimension (e.g., vertical position; Murnane & Bayen, 1996). In case all target items correctly identified as "old" are assigned to the same source (e.g., top) of a source dimension (e.g., vertical position), ACSIM is not defined. In such cases, the conditional source identification measure (CSIM) is reported, which is defined as the averaged proportion of correct source attributions for all target items correctly identified as "old" (Murnane & Bayen, 1996). Larger positive ACSIM and CSIM values indicate better source-identification performance, which is often interpreted as indicating better source memory (albeit confounded with guessing).

Multidimensional source monitoring model

As in Experiment 2 of Berres et al. (2025), we used a reparameterised variant of Meiser and Bröder's (2002)

multidimensional source monitoring model (see Meiser, 2014) to measure item memory, bound source memory (i.e., spatial location in the horizontal-vertical plane), unbound source memory, and guessing separately in the wake and in the sleep condition (see Figure 1). Specifically, with probability D_{ij}, participants recognise a target item presented in horizontal position *i* (e.g., "left" or "right") and vertical position *j* (e.g., "top" or "bottom") as "old". With probability D_{New}, a distractor item is detected as "new". The correct horizontal-vertical position combination of recognised items is identified with probability d_{ij}. In case the combination is not identified ($1 - d_{ij}$), the horizontal position *i* or the vertical position *j* can be identified independently with probabilities $e_{ij}^{Horizontal}$ and $e_{ij}^{Vertical}$, respectively. Participants are assumed to guess if item memory ($1\text{-}D_{ij}$), bound source memory ($1\text{-}d_{ij}$), and unbound source memory ($1\text{-}e_{ij}^{Horizontal}$, $1\text{-}e_{ij}^{Vertical}$) fail. If item memory is successful but bound and unbound source memory fail for either or both dimensions, source *i* (e.g., "left") of the horizontal dimension is guessed with probability $a^{Horizontal}$. Similarly, source *j* (e.g., "top") of the vertical dimension is guessed with probabilities $a_{|left}^{Vertical}$ and $a_{|right}^{Vertical}$ for targets assigned to left versus right horizontal positions, respectively. In case item memory fails, participants guess "old" with probability *b*. With probability $g^{Horizontal}$, participants guess source *i* (e.g., "left") of the horizontal dimension for unrecognised target or distractor items identified as "old". In addition, they guess source *j* (e.g., "top") of the vertical dimension with probabilities $g_{|left}^{Vertical}$ and $g_{|right}^{Vertical}$ for unrecognised target or distractor items assigned to left versus right horizontal positions, respectively (Meiser, 2014).

As illustrated in Figure 1, the most general version of the multidimensional source memory model allows parameters to differ between item types and sources. To identify the most parsimonious submodel that fits the data, we tested parameter invariance for item memory, followed by source memory, and finally guessing parameters. The following parameter constraints were imposed successfully for both the wake and the sleep condition (cf. Meiser, 2014; Meiser & Bröder, 2002): First, we equated item memory parameters D_{ij} across horizontal and vertical dimensions and constrained D_{New} to be equal, resulting in a single item memory parameter *D*. Second, we did the same for bound source memory parameters d_{ij}, resulting in a single bound source memory parameter *d*. Similarly, we equated unbound source memory for horizontal (parameter $e_{ij}^{Horizontal}$) and vertical positions (parameter $e_{ij}^{Vertical}$) across vertical (parameter $e^{Horizontal}$) and horizontal source dimensions (parameter $e^{Vertical}$), respectively (Meiser, 2014; Meiser & Bröder, 2002). Third, we imposed additional constraints on source guessing parameters (i.e., $a^{Horizontal} = g^{Horizontal}$, $a_{|left}^{Vertical} = g_{|left}^{Vertical}$, $a_{|right}^{Vertical} = g_{|right}^{Vertical}$), resulting in three guessing parameters, namely, the probability of guessing "left" on the horizontal dimension of a recognised or unrecognised item that was guessed to be "old" ($g^{Horizontal}$), the probability of guessing "top" on the vertical source dimension if the item was correctly identified as "old" or guessed to be "old" and assigned to source "left" ($g_{|left}^{Vertical}$) or "right" ($g_{|right}^{Vertical}$), respectively. This most parsimonious model version was used for data analysis.

Several methods exist to fit MPT models to empirical data (e.g., Heck et al., 2018; Moshagen, 2010; Nestler & Erdfelder, 2023; Schmidt et al., 2025; Singmann et al., 2024). Here, we applied both complete and partial pooling to check whether our results are robust against different distributional assumptions involved. Specifically, the complete pooling approach is based on observed category frequencies aggregated across participants. This aggregated model-based analysis provides MPT-parameter estimates via the maximum likelihood (ML) method, as implemented in the multiTree software (Moshagen, 2010). In contrast, the partial pooling approach combines information on the individual and group level, thereby explicitly accounting for individual differences between participants. We employed a hierarchical Bayesian model-based analysis that uses Markov-chain Monte Carlo (MCMC) methods to provide individual and group-level parameter estimates. Specifically, the latent-trait approach (Klauer, 2010) as implemented in the R package TreeBUGS (Heck et al., 2018) was applied.

Results

For all frequentist analyses, we set a significance level of $\alpha = .05$. In a first step, we analysed effects of sleep versus wakefulness on commonly used behavioural measures of item and source memory. For hit and false alarm rates, *d'* and *c* measures of item recognition and ACSIM-based source memory for horizontal and vertical positions, Table 1 shows means, standard errors, and *t*-test results. Importantly, all two-tailed *t* tests for two independent

Table 1. Results of item- and source-memory analyses.

Dependent variable	Wake		Sleep			
	M	*SE*	*M*	*SE*	*t*(128)	*p*
Item memory						
Hit rate	0.70	0.02	0.73	0.02	1.11	.271
False-alarm rate	0.16	0.02	0.17	0.02	0.40	.692
Sensitivity index *d'*	1.76	0.11	1.79	0.11	0.18	.855
Response bias *c*	0.31	0.06	0.22	0.06	1.33	.186
Source memory						
ACSIM, horizontal	0.71	0.02	0.73	0.01	1.02	.311
ACSIM, vertical	0.66	0.02	0.69	0.01	1.59	.114
ACSIM, right-top	0.70	0.02	0.72	0.01	1.00	.321
ACSIM, left-top	0.70	0.02	0.72	0.01	0.84	.400
ACSIM, left-bottom	0.67	0.02	0.70	0.01	1.55	.124
ACSIM, right-bottom	0.66	0.02	0.70	0.01	1.66	.099

Note: Means and standard errors of the mean are shown for the wake ($n = 54$) and sleep condition ($n = 76$), as well as the results of two-tailed *t* tests comparing the two independent groups. Sensitivity index *d'* was calculated by $Z_{hit\ rate} - Z_{false\text{-}alarm\ rate}$. Response bias *c* was calculated by $-0.5 * (Z_{hit\ rate} + Z_{false\text{-}alarm\ rate})$. In both cases, *Z* denotes the probit transformation (e.g., Stanislaw & Todorov, 1999). We also used the log-linear rule (i.e., adding 0.50 to hits, false alarms, misses, and correct rejections; Hautus, 1995) to obtain estimates of *d'* and *c* even in case of extreme hit rates and false alarm rates of 0 or 1. ACSIM = average conditional source identification measure.

groups showed no statistically significant differences in item memory and source memory after sleep versus wakefulness, $t(128) \leq 1.59$, $p \geq .114$ (see Table 1). In addition, ACSIM-based source memory was also analysed by a mixed ANOVA using ACSIM for horizontal versus vertical positions as two levels of a single within-subject factor and wake versus sleep as between-subjects factor. We found a statistically significant main effect in source memory, with better memory for horizontal ($M = .72$, $SE = .01$) than for vertical positions ($M = .68$, $SE = .01$), $F(1, 128) = 53.12$, $p < .001$, $\eta_p^2 = .29$. Although source memory was descriptively slightly higher in the sleep condition, neither the main effect of the wake versus sleep condition, $F(1, 128) = 1.81$, $p = .180$, nor the interaction effect of source memory for the horizontal versus vertical position with the wake versus sleep condition was statistically significant, $F(1, 128) = 0.64$, $p = .427$.

As discussed in The Present Study section, source memory in the current experiment can also be analysed in terms of quadrants. We therefore calculated ACSIM-based source memory for each quadrant and analysed it with a mixed ANOVA using the four quadrants as levels of a single within-subject factor and wake versus sleep as between-subjects factor. Similar to the analysis of horizontal versus vertical positions described above, we found a statistically significant main effect in source memory, with better memory for left- and right-top (both $M = .71$, $SE = .01$) than for left- and right-bottom positions (both $M = .69$, $SE = .01$), $F(3, 384) = 11.16$, $p < .001$, $\eta_p^2 = .080$. Again, despite descriptively slightly higher ACSIMs in the sleep condition, both the main effect of the wake versus sleep condition, $F(1, 128) = 1.81$, $p = .180$, and the interaction effect of source memory for the four quadrants with the wake versus sleep condition were not statistically significant, $F(3, 384) = 1.02$, $p = .384$.

To summarise, using commonly applied memory measures, we found no statistically significant evidence for sleep benefits within a 12-h retention interval. Note, however, that ACSIM-based source memory confounds memory and guessing processes and does not fully delineate bound and unbound source memory.

In a second step, we tested our predictions more rigorously by using the validated MPT model of multidimensional source monitoring (Meiser, 2014) which provides less contaminated measures of item and (bound as well as unbound) source memory. Here, the question of whether sleep improves cross-dimensional binding (i.e., bound source memory, parameter d) was of particular interest.

The most parsimonious model version (see the Method section) fitted the aggregated data well, $G^2(24) = 21.98$, $p = .581$. Table 2 provides the ML parameter estimates, standard errors, and 95% confidence intervals for the experimental conditions. For item memory (parameter D), we found no statistically significant difference between the sleep and wake condition, $\Delta G^2(1) = 3.00$, $p = .083$. However, bound source memory (parameter d) showed a statistically significant difference, $\Delta G^2(1) = 10.96$, $p < .001$, and was about 11% larger in the sleep than in the wake condition. This significant sleep benefit in bound source memory parameter d is in line with the active systems consolidation hypothesis. By contrast, there was no statistically significant sleep benefit for unbound source memory parameters $e^{\text{Horizontal}}$, $\Delta G^2(1) = 0.02$, $p = .901$, and e^{Vertical}, $\Delta G^2(1) = 0.03$, $p = .869$.

Note that both bound source memory (parameter d) and unbound source memory for horizontal positions (parameter $e^{\text{Horizontal}}$) were significantly larger than zero in both the wake and sleep conditions, d: $\Delta G^2_{\text{Wake}}(1) = 72.00$, $p < .001$, $\Delta G^2_{\text{Sleep}}(1) = 121.10$, $p < .001$; $e^{\text{Horizontal}}$: $\Delta G^2_{\text{Wake}}(1) = 67.72$, $p < .001$, $\Delta G^2_{\text{Sleep}}(1) = 73.56$, $p < .001$. By contrast, unbound source memory for vertical positions (parameter e^{Vertical}) in wake and sleep conditions was not statistically different from zero, $\Delta G^2_{\text{Wake}}(1) = 3.40$, $p = .07$, $\Delta G^2_{\text{Sleep}}(1) = 2.84$, $p = .09$. The likely reason for this result is a floor effect in unbound source memory for vertical positions, reflected in low estimates of correctly identifying the source (i.e., top, bottom) if the target item was correctly identified as "old", wake: $e^{\text{Vertical}} = 0.09$, sleep: $e^{\text{Vertical}} = 0.08$ (see Table 2).

Regarding guessing parameters, the probability of guessing an item is "old" (parameter b) was significantly higher in the sleep than in the wake condition, $\Delta G^2(1) = 9.24$, $p = .002$.[4] For all other guessing parameters, we

Table 2. Parameter estimates of the multinomial model of multidimensional source monitoring for aggregated data.

Parameter	Wake			Sleep		
	MLE	*SE*	95% CI	MLE	*SE*	95% CI
D	.54	.01	[.52, .55]	.56	.01	[.54, .57]
d	.37	.03	[.32, .42]	.48	.02	[.44, .53]
$e^{\text{Horizontal}}$	.30	.04	[.23, .38]	.30	.04	[.22, .37]
e^{Vertical}	.09	.05	[.00, .18][a]	.08	.04	[.00, .16][a]
$g^{\text{Horizontal}}$	.50	.01	[.48, .52]	.50	.01	[.48, .52]
$g^{\text{Vertical}}_{\|\text{left}}$	.52	.01	[.49, .54]	.51	.01	[.48, .53]
$g^{\text{Vertical}}_{\|\text{right}}$	.59	.01	[.56, .62]	.56	.01	[.54, .59]
b	.34	.01	[.32, .36]	.38	.01	[.37, .40]

Note: For the aggregated model-based analysis, maximum likelihood estimates (MLE), standard errors (*SE*), and 95% confidence intervals (CI) are reported. D = probability of correctly identifying a target item as "old" and a distractor item as "new"; d = probability of correctly identifying the source combination of a target item; $e^{\text{Horizontal}}$ = probability of correctly identifying the source (i.e., left, right) on the horizontal source dimension if the target item was correctly identified as "old"; e^{Vertical} = probability of correctly identifying the source (i.e., top, bottom) on the vertical source dimension if the target item was correctly identified as "old"; $g^{\text{Horizontal}}$ = probability of guessing "left" on the horizontal source dimension if the target item was correctly identified as "old" or if the unrecognised item was guessed to be "old"; $g^{\text{Vertical}}_{|\text{left}}$ = probability of guessing "top" on the vertical source dimension if the target item was correctly identified as "old" and assigned to source "left" or if the unrecognised item was guessed to be "old" and assigned to source "left"; $g^{\text{Vertical}}_{|\text{right}}$ = probability of guessing "top" on the vertical source dimension if the target item was correctly identified as "old" and assigned to source "right" or if the unrecognised item was guessed to be "old" and assigned to source "right"; b = probability of guessing that an item is "old".

[a]Asymptotic confidence interval boundaries with values below .00 or above 1.00 were set to 0 and 1, respectively, because the parameter space limits the range of admissible values to [.00, 1.00].

Table 3. Hierarchical Bayesian parameter estimates of the latent-trait version of the multinomial model of multidimensional source monitoring.

Parameter	Wake			Sleep		
	M	*SD*	95% BCI	*M*	*SD*	95% BCI
D	.53	.03	[.46, .60]	.57	.03	[.50, .63]
d	.28	.05	[.16, .37]	.42	.04	[.34, .49]
$e^{\text{Horizontal}}$	.29	.06	[.17, .40]	.25	.05	[.14, .36]
e^{Vertical}	.06	.05	[.00, .17]	.04	.03	[.00, .18]
$g^{\text{Horizontal}}$	.49	.01	[.47, .52]	.49	.01	[.47, .51]
$g^{\text{Vertical}}_{\text{left}}$	.52	.02	[.49, .55]	.50	.01	[.47, .53]
$g^{\text{Vertical}}_{\text{right}}$	.60	.02	[.55, .64]	.57	.02	[.54, .60]
b	.27	.04	[.19, .35]	.33	.03	[.27, .39]

Note: For the latent-trait model (Klauer, 2010), posterior means (*M*), posterior standard deviations (*SD*), and 95% Bayesian credibility intervals (BCI) of the probability transformed group-level parameters as estimated with TreeBUGS (Heck et al., 2018) are reported. There was good MCMC chain convergence ($\hat{R} < 1.05$) and model fit (wake condition: $p_{T1} = .49$, $p_{T2} = .49$; sleep condition: $p_{T1} = .57$, $p_{T2} = .70$). D = probability of correctly identifying a target item as "old" and a distractor item as "new"; d = probability of correctly identifying the source combination of a target item; $e^{\text{Horizontal}}$ = probability of correctly identifying the source (i.e., left, right) on the horizontal source dimension if the target item was correctly identified as "old"; e^{Vertical} = probability of correctly identifying the source (i.e., top, bottom) on the vertical source dimension if the target item was correctly identified as "old"; $g^{\text{Horizontal}}$ = probability of guessing "left" on the horizontal source dimension if the target item was correctly identified as "old" or if the unrecognised item was guessed to be "old"; $g^{\text{Vertical}}_{|\text{left}}$ = probability of guessing "top" on the vertical source dimension if the target item was correctly identified as "old" and assigned to source "left" or if the unrecognised item was guessed to be "old" and assigned to source "left"; $g^{\text{Vertical}}_{|\text{right}}$ = probability of guessing "top" on the vertical source dimension if the target item was correctly identified as "old" and assigned to source "right" or if the unrecognised item was guessed to be "old" and assigned to source "right"; b = probability of guessing that an item is "old"; $\hat{R}$ = potential scale reduction factor (Gelman & Rubin, 1992); p_{T1} = posterior predictive p-value for the mean; p_{T2} = posterior predictive p-value for the covariance.

found no statistically significant differences between sleep and wake conditions, all $\Delta G^2(1) \leq 1.90$, $p \geq .168$.

Finally, we performed a hierarchical model-based analysis using Klauer's (2010) latent-trait model as implemented in TreeBUGS (Heck et al., 2018) for partial pooling to check the robustness of our results. Importantly, the estimated group-level means of the hierarchical MPT model (see Table 3) resembled those reported for the aggregated model-based analysis (see Table 2). In line with Erdfelder et al. (2024) and Singmann et al. (2024), we therefore conclude that the basic result pattern does not depend on whether complete or partial pooling methods are used for data analysis.

Discussion

In line with the active systems consolidation hypothesis, we found convincing evidence that sleep compared to wakefulness within a 12-h retention interval improves cross-dimensional binding. Using a multinomial modelling approach, we showed for the first time that sleep benefits bound source memory for horizontal and vertical positions. This finding extends previous research which focused almost exclusively on sleep benefits in item-context binding without differentiating between dimensions that constitute a source.

In their Experiment 2, Berres et al. (2025) investigated whether sleep within a 12-h retention interval strengthens bound source memory for spatial position and frame colour. However, most likely due to insufficient encoding of colour associations, they found no significant sleep benefit for either frame colour or bound source memory of horizontal spatial position and frame colour, which were both at floor independent of sleep. In the current work, we made sure that the context receives sufficient processing at encoding. We therefore manipulated horizontal and vertical spatial positions, which represent integral stimulus dimensions (Garner, 1974; Garner & Felfoldy, 1970) and thus provide a high likelihood of binding at encoding. Using these context dimensions, we indeed found substantial cross-dimensional binding in both the sleep and the wake condition and a significant sleep benefit in bound source memory (parameter d). Importantly, both spatial dimensions were actually processed, rather than a single dimension of spatial location. This is evident from the fact that participants sometimes remembered only one of the two integral stimulus dimensions, as reflected in $e^{\text{Horizontal}}$ and e^{Vertical}. Whereas unbound source memory for horizontal positions is significantly above zero in both the wake and sleep condition, unbound source memory for vertical positions is not statistically different from zero. This result pattern can be explained by a more salient left-right difference compared to the top–bottom difference in our experiment. To reiterate, we used relative positioning for picture presentation to account for different screen sizes in the online experiment. As typical screens have a larger width than height, relative positioning typically resulted in a larger difference and thus better encoding of horizontal than vertical positions. A feasible solution to avoid this in future experiments would be the use of absolute positioning for pictures within a quadratic container for which relative positioning is used. However, despite the floor effect in e^{Vertical}, our results show that spatial context features are remembered not only in combination (e.g., left-top) but also separately (e.g., left). As such, this finding underlines the usefulness of considering horizontal and vertical locations as two dimensions of spatial location and analysing them separately rather than only examining them in terms of quadrants. Overall, our finding regarding d emphasises the importance of sufficient encoding strength for relevant episodic information when investigating sleep benefits: If both context dimensions receive sufficient encoding strength, then a significant sleep benefit in bound source memory d emerges.

Importantly, previous research has shown that the hippocampus is equally involved in binding stimuli of the same (e.g., word pairs, picture pairs) or different study material (e.g., word-picture pairs; Park & Rugg, 2011). Therefore, it is likely that our findings generalise to any sufficiently encoded combination of context dimensions, regardless of whether they are integral or separable. To reiterate, in the current work, we used – based on previous

research – integral stimulus dimensions such as horizontal and vertical spatial positions to ensure a high likelihood of binding at encoding. It thus remains to be investigated whether separable stimulus dimensions also produce a sleep benefit in cross-dimensional binding. To test this, we suggest using stimulus-related contextual features with directly perceivable multidimensional structures (e.g., brightness and size of an item, cf. Grau & Kemler Nelson, 1988) which are inherently associated with a high likelihood of item-context binding at encoding (Spencer & Raz, 1995). In a subsequent step, contextual features with different sensory modalities (e.g., visual, auditory) can be examined. Note, however, that this may require employing different learning instructions and associative encoding strategies, as sufficient memory strength at encoding appears to be crucial for the sleep benefit in cross-dimensional binding to occur (cf. Denis et al., 2020; Muehlroth et al., 2020; Rauchs et al., 2011).

Some of the prior studies report a significant sleep benefit in ACSIM-based source memory (e.g., Berres et al., 2025; Mawdsley et al., 2014; van der Helm et al., 2011). In particular, Berres et al. (2025) found a significant sleep benefit in ACSIM-based source memory and in MPT model-based unbound source memory for horizontal positions in both experiments. In the present study, ACSIM-based source memory for horizontal versus vertical positions as well as for the four quadrants was descriptively higher after sleep versus wakefulness (see Table 1), but these differences were not statistically significant. The discrepancy between our current findings and previous results is likely due to differences in guessing patterns. Indeed, here we observed a larger, albeit not significant descriptive tendency to guess "top" for the newly included horizontal source dimension in the wake versus sleep condition (see the results for parameters $g_{|\text{left}}^{\text{Vertical}}$ and $g_{|\text{right}}^{\text{Vertical}}$ in Tables 2 and 3). In addition, the most parsimonious model version (see the Method section) was used to analyse the present data. By contrast, this model version showed a misfit in Berres et al.'s (2025) Experiment 2, requiring separate source guessing parameters for recognised (i.e., $a_{|\text{left}}^{\text{Colour}}$, $a_{|\text{right}}^{\text{Colour}}$) and unrecognised items (i.e., $g_{|\text{left}}^{\text{Colour}}$, $g_{|\text{right}}^{\text{Colour}}$) in their analysis of position-colour attributions. Thus, variations in guessing patterns likely contributed to differences in ACSIM-based source memory. In addition, it is important to note that ACSIMs do not target bound source memory specifically. Although ACSIM for quadrants may be seen as tapping into bound source memory, it ignores additional contributions of residual unbound source memory for both spatial dimensions to correct quadrant responses on the source-monitoring test. Indeed, our model-based analysis showed above-chance significant residual unbound source memory for horizontal spatial positions. Further, it is well known that commonly used behavioural measures of source memory such as ACSIM confound memory and guessing to some degree (Bröder & Meiser, 2007; Murnane & Bayen, 1996) and thus are noisy measures of source memory. Thus, strictly speaking, ACSIM is a questionable measure of bound source memory, irrespective of whether it was calculated based on horizontal versus vertical positions or the four quadrants.

Moreover, we found no significant sleep benefit for unbound source memory parameters $e^{\text{Horizontal}}$ and e^{Vertical}, which differs from the results for unbound source memory for the horizontal position (e^{Position}) reported in Berres et al. (2025). In the current study, cross-dimensional binding at encoding was successful, as indicated by significant bound source memory d (see Table 2). By contrast, in Experiment 2 of Berres et al. (2025), cross-dimensional binding failed likely due to a floor effect in incidental encoding of colour associations. In case of successful source memory binding during encoding as in the current work (see parameter d), the unbound source memory parameters $e^{\text{Horizontal}}$ and e^{Vertical} reflect only *residual* item-context binding for correctly recognised items with failed or forgotten cross-dimensional binding. In Berres et al. (2025), however, the unbound source memory parameter e^{Position} in Experiment 2 captured the full item-position binding effect since bound source memory parameter d was essentially zero in their study. Because of these differences in d between studies, the unbound source memory parameters of the present study and the study by Berres et al. (2025) cannot be directly compared.

Although our sample size ($N = 130$, $n_{\text{wake}} = 54$, $n_{\text{sleep}} = 76$) is comparable in size to Berres et al. (2025; Experiment 1: $N = 132$, $n_{\text{wake}} = 65$, $n_{\text{sleep}} = 67$; Experiment 2: $N = 134$, $n_{\text{wake}} = 62$, $n_{\text{sleep}} = 72$), fewer observations might be available to detect potential differences in unbound source memory parameters due to successful cross-dimensional binding in the current study. To check this assumption, we conducted post hoc power analyses for the aggregated model-based analysis in multiTree (Moshagen, 2010). Specifically, we used $N = 130$ to compute the total number of observations given 120 target and 60 distractor items per participant. Moreover, we used the wake-condition estimates as baseline parameters while assuming a hypothetical gain of .10 for the sleep condition compared to the wake condition in the parameters of interest. Post hoc power analyses with an α-level of .05 yielded a larger power $(1\text{-}\beta) = .81$ for bound source memory (d) than for unbound source memory parameters. For sleep-wake differences of .10 in parameters $e^{\text{Horizontal}}$ and e^{Vertical}, the power is only $(1\text{-}\beta) = .51$ and $(1\text{-}\beta) = .38$, respectively. In a nutshell, while statistical power is satisfactory for detecting a sleep-wake difference of at least .10 in bound source memory d (i.e., $1\text{-}\beta = .81$ or larger) – the key effect in our current experiment –, it is weak for detecting the same difference in unbound source memory parameters (i.e., $1\text{-}\beta = .51$ or even less). Thus, the population parameter pattern underlying our results is not inconsistent with Berres et al. (2025), and a sleep benefit in unbound source memory cannot be ruled out given our current data.

Regarding item memory, our current data add to previous mixed results (e.g., Berres et al., 2025; Mawdsley et al., 2014; van der Helm et al., 2011). Specifically, we observed that *d'* and the model-based estimates of the item memory parameter *D* are descriptively higher for the sleep than wake condition. However, this descriptive benefit in recognition is small, and neither of these results proved to be statistically significant. This is in line with Berres et al. (2025), who observed similar patterns and reported a statistically significant sleep benefit in item recognition memory for complete pooling data only. Berres et al. (2025) also combined the data of their experiments ($N = 266$) and still did not find a significant sleep benefit in *d'*. They concluded that an even larger sample size of at least 362 participants would be necessary for a high-powered study of the relatively small sleep benefit in item recognition memory (i.e., Hedges' $g = 0.38$) that can be expected based on the meta-analysis of Berres and Erdfelder (2021). Thus, future studies with larger samples are required to address the question of a sleep-induced item recognition memory benefit more rigorously. The results of the present study, however, imply that sleep benefits in episodic memory are much larger for bound source memory of cross-dimensional context associations than for single items, a finding that is in line with the active systems consolidation hypothesis (cf. Inostroza & Born, 2013; Klinzing et al., 2019).

Although we cannot rule out additional sleep benefits on memory due to reduced retroactive interference, we focus on the active systems consolidation hypothesis to explain our results (for a review of interference and consolidation theories, see Berres & Erdfelder, 2021). We thereby follow the memory-system dependent forgetting hypothesis (Hardt et al., 2013; see also Sadeh et al., 2014), which predicts interference effects on hippocampal memory representations to be "minimal" (Hardt et al., 2013, p. 111). The rationale behind this prediction is the circuit architecture of the hippocampus, which allows efficient pattern separation. In line with this prediction, several studies on forgetting over short, interference-filled lags found no statistically significant interference-based forgetting for item-item and item-context associative memory (e.g., Kuhlmann et al., 2021; Yonelinas & Levy, 2002). Building on these results, sleep benefits for item-context and cross-dimensional context associations should depend more on memory consolidation than on reduced retroactive interference. Nevertheless, a detailed investigation of the mechanisms underlying sleep benefits in source memory is warranted. To investigate possible additional sleep benefits due to reduced retroactive interference, an early evening nap study comparing SWS-rich sleep with wakeful rest (e.g., rest quietly with eyes closed to reduce retroactive interference) and wakefulness (e.g., watching documentaries) can be conducted.

Moving forward, additional research should also check whether our findings generalise to three-dimensional (3D) space. In the present study, we presented pictures in a two-dimensional (2D) space by manipulating horizontal (x-axis, left vs. right) and vertical (y-axis, top vs. bottom) spatial locations. Moving into 3D space requires adding an additional dimension of depth (z-axis, front vs. back). According to the cognitive map theory, which was first proposed by Tolman (1948), geometric properties of space are represented as a cognitive map in the hippocampus (Eichenbaum et al., 1999). Put differently, it is assumed that the hippocampus binds geometric properties such as the horizontal, vertical and depth dimensions of spatial locations to a holistic representation of space during encoding. Crucially, it is well established that the hippocampus is involved in binding the content of memories to its unique context, applying the same mechanisms to spatial and non-spatial information (e.g., Dudai et al., 2015; Mitchell & Johnson, 2009; Xing & Saunders, 2022). As the underlying processes are likely the same, it is a plausible assumption that our findings in 2D space conceptually replicate for 3D. However, this remains to be tested.

Finally, additional research is also needed to address possible concerns regarding time-of-day effects in the classical 12-h sleep study design that compares natural nighttime sleep and daytime wakefulness. Although previous research showed that circadian effects are not a serious confound in this design (e.g., Abel & Bäuml, 2012, 2013a, 2013b, 2014; Bäuml et al., 2014; Fenn & Hambrick, 2013), we suggest conducting additional studies using other sleep-study designs such as nighttime naps to corroborate the current results.

To conclude, although further research is warranted and welcomed, this study extends previous research on sleep benefits in memory by showing, for the first time, that a period of sleep versus wakefulness within a 12-h retention interval also improves cross-dimensional binding. Hereby, the current work adds to the growing empirical evidence that memory consolidation as proposed by the active systems consolidation hypothesis might be a key mechanism underlying sleep benefits in episodic memory.

Notes

1. The definition of source in the source-monitoring framework (Johnson et al., 1993) encompasses context and internal features (e.g., spatial location and cognitive operations; Mitchell & Johnson, 2009). As we focus on spatial context dimensions, we use the terms source and context interchangeably. Both terms refer to a variety of dimensions that, taken together, make a memory representation unique by defining the specific conditions under which it was formed (Johnson et al., 1993; Mitchell & Johnson, 2009).
2. There are other theories that explain sleep benefits in episodic memory by memory consolidation, for example the sequential hypothesis (Ambrosini & Giuditta, 2001; Giuditta, 2014; Giuditta et al., 1995) or the synaptic homeostasis hypothesis (Tononi & Cirelli, 2003, 2014, 2020). We focus on the active systems consolidation hypothesis which integrates aspects of various consolidation theories, including the aforementioned hypotheses (for a review, see Berres & Erdfelder, 2021).

3. For analysis, there were 22 more participants in the sleep than the wake condition. This imbalanced sample size is due to a larger number of dropouts in the wake condition during online data collection. Further, more exclusions occurred in the wake condition (number of exclusions: $n_{wake} = 32$, $n_{sleep} = 23$).
4. Note that this significant result differs from the finding for response bias *c*, which showed no statistically significant difference between the wake and sleep condition. Parameter *b* and response bias *c* are two different measures based on different conceptualisations of recognition memory, that is, discrete states (MPT models, parameter *b*) versus continuous memory strength (SDT, response bias *c*). This appears to make a difference for the conclusion here.

Acknowledgements

We thank Mira Istvánffy and Alena Schmale for their help with data collection.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

This study was funded by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) – project numbers 392884168 (Emmy Noether Research Group "Source Forgetting in Younger and Older Adults"), 401384275, and 310365261 (GRK 2277, Research Training Group "Statistical Modeling in Psychology" [SMiP]).

Ethical approval

According to §6 of the statute of the Ethics Committee of the University of Mannheim dated 15.12.2016 (with changes dated 26.05.2021), no examination is required for this kind of study (https://www.uni-mannheim.de/universitaet/organisation/organe-und-gremien/kommissionen-und-ausschuesse/ethikkommission/). The procedures used in this study adhere to the tenets of the Declaration of Helsinki.

Consent to participate

Informed consent was obtained from all individual participants included in the study at the beginning of the registration session.

Consent for publication

All participants consented to data publication in anonymised form at the beginning of the registration session.

Availability of data and materials

The data, codebook and a list of the stimuli for the experiment are available at the Open Science Framework (OSF, https://osf.io/v78y5/?view_only=7fae4b70acc34741ac90d614342602bc). The experiment was not preregistered.

Code availability

The code for the analyses is available from the corresponding author on reasonable request.

CRediT authorship contribution statement

Sabrina Shakoor: Conceptualisation, Formal Analysis, Methodology, Software, Visualisation, Writing – original draft, Writing – review and editing. Edgar Erdfelder: Conceptualisation, Funding Acquisition, Methodology, Project Administration, Supervision, Writing – review and editing. Beatrice G. Kuhlmann: Conceptualisation, Funding Acquisition, Methodology, Project Administration, Supervision, Writing – review and editing.

ORCID

Sabrina Shakoor https://orcid.org/0000-0001-9868-8824
Edgar Erdfelder https://orcid.org/0000-0003-1032-3981
Beatrice G. Kuhlmann https://orcid.org/0000-0002-3235-5717

References

Abel, M., & Bäuml, K.-H. T. (2012). Retrieval-induced forgetting, delay, and sleep. *Memory*, *20*(5), 420–428. https://doi.org/10.1080/09658211.2012.671832

Abel, M., & Bäuml, K.-H. T. (2013a). Adaptive memory: The influence of sleep and wake delay on the survival-processing effect. *Journal of Cognitive Psychology*, *25*(8), 917–924. https://doi.org/10.1080/20445911.2013.825621

Abel, M., & Bäuml, K.-H. T. (2013b). Sleep can eliminate list-method directed forgetting. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *39*(3), 946–952. https://doi.org/10.1037/a0030529

Abel, M., & Bäuml, K.-H. T. (2014). Sleep can reduce proactive interference. *Memory*, *22*(4), 332–339. https://doi.org/10.1080/09658211.2013.785570

Ambrosini, M. V., & Giuditta, A. (2001). Learning and sleep: The sequential hypothesis. *Sleep Medicine Reviews*, *5*(6), 477–490. https://doi.org/10.1053/smrv.2001.0180

Batchelder, W. H., & Riefer, D. M. (1990). Multinomial processing models of source monitoring. *Psychological Review*, *97*(4), 548–564. https://doi.org/10.1037/0033-295X.97.4.548

Batchelder, W. H., & Riefer, D. M. (1999). Theoretical and empirical review of multinomial process tree modeling. *Psychonomic Bulletin & Review*, *6*(1), 57–86. https://doi.org/10.3758/BF03210812

Bäuml, K.-H. T., Holterman, C., & Abel, M. (2014). Sleep can reduce the testing effect: It enhances recall of restudied items but can leave recall of retrieved items unaffected. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *40*(6), 1568–1581. https://doi.org/10.1037/xlm0000025

Bayen, U. J., Murnane, K., & Erdfelder, E. (1996). Source discrimination, item detection, and multinomial models of source monitoring. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *22*(1), 197–215. https://doi.org/10.1037/0278-7393.22.1.197

Berres, S., & Erdfelder, E. (2021). The sleep benefit in episodic memory: An integrative review and a meta-analysis. *Psychological Bulletin*, *147*(12), 1309–1353. https://doi.org/10.1037/bul0000350

Berres, S., Erdfelder, E., & Kuhlmann, B. G. (2025). Does sleep benefit source memory? Investigating 12-h retention intervals with a multinomial modeling approach. *Memory & Cognition*, *53*, 467–493. https://doi.org/10.3758/s13421-024-01579-8

Bloch, K. E., Schoch, O. D., Zhang, J. N., & Russi, E. W. (1999). German version of the epworth sleepiness scale. *Respiration; International Review of Thoracic Diseases*, *66*(5), 440–447. https://doi.org/10.1159/000029408

Born, J., & Wilhelm, I. (2012). System consolidation of memory during sleep. *Psychological Research*, *76*(2), 192–203. https://doi.org/10.1007/s00426-011-0335-6

Boywitt, C. D., & Meiser, T. (2012). The role of attention for context-context binding of intrinsic and extrinsic features. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *38*(4), 1099–1107. https://doi.org/10.1037/a0026988

Bröder, A., & Meiser, T. (2007). Measuring source memory. *Zeitschrift für Psychologie / Journal of Psychology*, *215*(1), 52–60. https://doi.org/10.1027/0044-3409.215.1.52

Cansino, S., Maquet, P., Dolan, R. J., & Rugg, M. D. (2002). Brain activity underlying encoding and retrieval of source memory. *Cerebral Cortex*, *12*(10), 1048–1056. https://doi.org/10.1093/cercor/12.10.1048

Denis, D., Schapiro, A. C., Poskanzer, C., Bursal, V., Charon, L., Morgan, A., & Stickgold, R. (2020). The roles of item exposure and visualization success in the consolidation of memories across wake and sleep. *Learning & Memory*, *27*(11), 451–456. https://doi.org/10.1101/lm.051383.120

Diekelmann, S., & Born, J. (2010). The memory function of sleep. *Nature Reviews Neuroscience*, *11*, 114–126. https://doi.org/10.1038/nrn2762

Dudai, Y., Karni, A., & Born, J. (2015). The consolidation and transformation of memory. *Neuron*, *88*(1), 20–32. https://doi.org/10.1016/j.neuron.2015.09.004

Duñabeitia, J. A., Crepaldi, D., Meyer, A. S., New, B., Pliatsikas, C., Smolka, E., & Brysbaert, M. (2018). MultiPic: A standardized set of 750 drawings with norms for six European languages. *Quarterly Journal of Experimental Psychology*, *71*(4), 808–816. https://doi.org/10.1080/17470218.2017.1310261

Dzulkifli, M. A., & Mustafar, M. F. (2013). The influence of colour on memory performance: A review. *The Malaysian Journal of Medical Sciences*, *20*(2), 3–9.

Eichenbaum, H., Dudchenko, P., Wood, E., Shapiro, M., & Tanila, H. (1999). The hippocampus, memory, and place cells: Is it spatial memory or a memory space? *Neuron*, *23*(2), 209–226. https://doi.org/10.1016/S0896-6273(00)80773-4

Erdfelder, E., Auer, T.-S., Hilbig, B. E., Aßfalg, A., Moshagen, M., & Nadarevic, L. (2009). Multinomial processing tree models. *Zeitschrift für Psychologie / Journal of Psychology*, *217*(3), 108–124. https://doi.org/10.1027/0044-3409.217.3.108

Erdfelder, E., Quevedo Pütter, J., & Schnuerch, M. (2024). On aggregation invariance of multinomial processing tree models. *Behavior Research Methods*, *56*(8), 8677–8694. https://doi.org/10.3758/s13428-024-02497-y

Feld, G. B., & Born, J. (2017). Sculpting memory during sleep: Concurrent consolidation and forgetting. *Current Opinion in Neurobiology*, *44*, 20–27. https://doi.org/10.1016/j.conb.2017.02.012

Fenn, K. M., & Hambrick, D. Z. (2013). What drives sleep-dependent memory consolidation: Greater gain or less loss? *Psychonomic Bulletin & Review*, *20*(3), 501–506. https://doi.org/10.3758/s13423-012-0366-z

Garner, W. R. (1974). *The processing of information and structure*. Lawrence Erlbaum.

Garner, W. R., & Felfoldy, G. L. (1970). Integrality of stimulus dimensions in various types of information processing. *Cognitive Psychology*, *1*(3), 225–241. https://doi.org/10.1016/0010-0285(70)90016-2

Gelman, A., & Rubin, D. B. (1992). Inference from iterative simulation using multiple sequences. *Statistical Science*, *7*(4), 457–472. https://doi.org/10.1214/ss/1177011136

Giuditta, A. (2014). Sleep memory processing: The sequential hypothesis. *Frontiers in Systems Neuroscience*, *8*, Article 219. https://doi.org/10.3389/fnsys.2014.00219

Giuditta, A., Ambrosini, M. V., Montagnese, P., Mandile, P., Cotugno, M., Zucconi, G. G., & Vescia, S. (1995). The sequential hypothesis of the function of sleep. *Behavioural Brain Research*, *69*(1-2), 157–166. https://doi.org/10.1016/0166-4328(95)00012-I

Grau, J. W., & Kemler Nelson, D. G. (1988). The distinction between integral and separable dimensions: Evidence for the integrality of pitch and loudness. *Journal of Experimental Psychology: General*, *117*(4), 347–370. https://doi.org/10.1037/0096-3445.117.4.347

Groch, S., Zinke, K., Wilhelm, I., & Born, J. (2015). Dissociating the contributions of slow-wave sleep and rapid eye movement sleep to emotional item and source memory. *Neurobiology of Learning and Memory*, *122*, 122–130. https://doi.org/10.1016/j.nlm.2014.08.013

Hardt, O., Nader, K., & Nadel, L. (2013). Decay happens: The role of active forgetting in memory. *Trends in Cognitive Sciences*, *17*(3), 111–120. https://doi.org/10.1016/j.tics.2013.01.001

Hautus, M. J. (1995). Corrections for extreme proportions and their biasing effects on estimated values of d′. *Behavior Research Methods, Instruments, & Computers*, *27*(1), 46–51. https://doi.org/10.3758/BF03203619

Heck, D. W., Arnold, N. R., & Arnold, D. (2018). TreeBUGS: An R package for hierarchical multinomial-processing-tree modeling. *Behavior Research Methods*, *50*(1), 264–284. https://doi.org/10.3758/s13428-017-0869-7

Henninger, F., Shevchenko, Y., Mertens, U. K., Kieslich, P. J., & Hilbig, B. E. (2022). Lab.js: A free, open, online study builder. *Behavior Research Methods*, *54*(2), 556–573. https://doi.org/10.3758/s13428-019-01283-5

Inostroza, M., & Born, J. (2013). Sleep for preserving and transforming episodic memory. *Annual Review of Neuroscience*, *36*(1), 79–102. https://doi.org/10.1146/annurev-neuro-062012-170429

Johns, M. W. (1991). A new method for measuring daytime sleepiness: The epworth sleepiness scale. *Sleep*, *14*(6), 540–545. https://doi.org/10.1093/sleep/14.6.540

Johnson, M. K., Hashtroudi, S., & Lindsay, D. S. (1993). Source monitoring. *Psychological Bulletin*, *114*(1), 3–28. https://doi.org/10.1037/0033-2909.114.1.3

Klauer, K. C. (2010). Hierarchical multinomial processing tree models: A latent-trait approach. *Psychometrika*, *75*(1), 70–98. https://doi.org/10.1007/s11336-009-9141-0

Klinzing, J. G., Niethard, N., & Born, J. (2019). Mechanisms of systems memory consolidation during sleep. *Nature Neuroscience*, *22*(10), 1598–1610. https://doi.org/10.1038/s41593-019-0467-3

Köster, M., Finger, H., Kater, M.-J., Schenk, C., & Gruber, T. (2017). Neuronal oscillations indicate sleep-dependent changes in the cortical memory trace. *Journal of Cognitive Neuroscience*, *29*(4), 698–707. https://doi.org/10.1162/jocn_a_01071

Kuhlmann, B. G., Brubaker, M. S., Pfeiffer, T., & Naveh-Benjamin, M. (2021). Longer resistance of associative versus item memory to interference-based forgetting, even in older adults. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *47*(3), 422–438. https://doi.org/10.1037/xlm0000963

Leiner, D. J. (2020). *SoSci Survey* (Version 3.3.10) [Computer software]. https://www.soscisurvey.de.

Lewis, P. A., Cairney, S., Manning, L., & Critchley, H. D. (2011). The impact of overnight consolidation upon memory for emotional and neutral encoding contexts. *Neuropsychologia*, *49*(9), 2619–2629. https://doi.org/10.1016/j.neuropsychologia.2011.05.009

Lewis, P. A., & Durrant, S. J. (2011). Overlapping memory replay during sleep builds cognitive schemata. *Trends in Cognitive Sciences*, *15*(8), 343–351. https://doi.org/10.1016/j.tics.2011.06.004

Mawdsley, M., Grasby, K., & Talk, A. (2014). The effect of sleep on item recognition and source memory recollection among shift-workers and permanent day-workers. *Journal of Sleep Research*, *23*(5), 538–544. https://doi.org/10.1111/jsr.12149

Meiser, T. (2014). Analyzing stochastic dependence of cognitive processes in multidimensional source recognition. *Experimental*

Psychology, *61*(5), 402–415. https://doi.org/10.1027/1618-3169/a000261

Meiser, T., & Bröder, A. (2002). Memory for multidimensional source information. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *28*(1), 116–137. https://doi.org/10.1037/0278-7393.28.1.116

Mitchell, K. J., & Johnson, M. K. (2009). Source monitoring 15 years later: What have we learned from fMRI about the neural mechanisms of source memory? *Psychological Bulletin*, *135*(4), 638–677. https://doi.org/10.1037/a0015849

Moshagen, M. (2010). Multitree: A computer program for the analysis of multinomial processing tree models. *Behavior Research Methods*, *42*(1), 42–54. https://doi.org/10.3758/BRM.42.1.42

Muehlroth, B. E., Rasch, B., & Werkle-Bergner, M. (2020). Episodic memory consolidation during sleep in healthy aging. *Sleep Medicine Reviews*, *52*, 101304. https://doi.org/10.1016/j.smrv.2020.101304

Murnane, K., & Bayen, U. J. (1996). An evaluation of empirical measures of source identification. *Memory & Cognition*, *24*(4), 417–428. https://doi.org/10.3758/BF03200931

Nestler, S., & Erdfelder, E. (2023). Random effects multinomial processing tree models: A maximum likelihood approach. *Psychometrika*, *88*(3), 809–829. https://doi.org/10.1007/s11336-023-09921-w

O'Neill, J., Pleydell-Bouverie, B., Dupret, D., & Csicsvari, J. (2010). Play it again: Reactivation of waking experience and memory. *Trends in Neurosciences*, *33*(5), 220–229. https://doi.org/10.1016/j.tins.2010.01.006

Park, H., & Rugg, M. D. (2011). Neural correlates of encoding within- and across-domain inter-item associations. *Journal of Cognitive Neuroscience*, *23*(9), 2533–2543. https://doi.org/10.1162/jocn.2011.21611

Pfeiffer, B. E. (2020). The content of hippocampal "replay". *Hippocampus*, *30*(1), 6–18. https://doi.org/10.1002/hipo.22824

Rasch, B., & Born, J. (2013). About sleep's role in memory. *Physiological Reviews*, *93*(2), 681–766. https://doi.org/10.1152/physrev.00032.2012

Rauchs, G., Bertran, F., Guillery-Girard, B., Desgranges, B., Kerrouche, N., Denise, P., Foret, J., & Eustache, F. (2004). Consolidation of strictly episodic memories mainly requires rapid eye movement sleep. *Sleep*, *27*(3), 395–401. https://doi.org/10.1093/sleep/27.3.395

Rauchs, G., Feyers, D., Landeau, B., Bastin, C., Luxen, A., Maquet, P., & Collette, F. (2011). Sleep contributes to the strengthening of some memories over others, depending on hippocampal activity at learning. *The Journal of Neuroscience*, *31*(7), 2563–2568. https://doi.org/10.1523/JNEUROSCI.3972-10.2011

Riefer, D. M., & Batchelder, W. H. (1988). Multinomial modeling and the measurement of cognitive processes. *Psychological Review*, *95*(3), 318–339. https://doi.org/10.1037/0033-295X.95.3.318

Sadeh, T., Ozubko, J. D., Winocur, G., & Moscovitch, M. (2014). How we forget may depend on how we remember. *Trends in Cognitive Sciences*, *18*(1), 26–36. https://doi.org/10.1016/j.tics.2013.10.008

Schmidt, O., Erdfelder, E., & Heck, D. W. (2025). How to develop, test, and extend multinomial processing tree models: A tutorial. *Psychological Methods*, *30*(4), 720–743. https://doi.org/10.1037/met0000561

Simon, K. C. N. S., Gómez, R. L., & Nadel, L. (2018). Losing memories during sleep after targeted memory reactivation. *Neurobiology of Learning and Memory*, *151*, 10–17. https://doi.org/10.1016/j.nlm.2018.03.003

Singmann, H., Heck, D. W., Barth, M., Erdfelder, E., Arnold, N. R., Aust, F., Calanchini, J., Gümüsdagli, F. E., Horn, S. S., Kellen, D., Klauer, K. C., Matzke, D., Meissner, F., Michalkiewicz, M., Schaper, M. L., Stahl, C., Kuhlmann, B. G., & Groß, J. (2024). Evaluating the robustness of parameter estimates in cognitive models: A meta-analytic review of multinomial processing tree models across the multiverse of estimation methods. *Psychological Bulletin*, *150*(8), 965–1003. https://doi.org/10.1037/bul0000434

Sopp, M. R., Michael, T., Weeß, H.-G., & Mecklinger, A. (2017). Remembering specific features of emotional events across time: The role of REM sleep and prefrontal theta oscillations. *Cognitive, Affective, & Behavioral Neuroscience*, *17*(6), 1186–1209. https://doi.org/10.3758/s13415-017-0542-8

Spence, I., Wong, P., Rusan, M., & Rastegar, N. (2006). How color enhances visual memory for natural scenes. *Psychological Science*, *17*(1), 1–6. https://doi.org/10.1111/j.1467-9280.2005.01656.x

Spencer, W. D., & Raz, N. (1995). Differential effects of aging on memory for content and context: A meta-analysis. *Psychology and Aging*, *10*(4), 527–539. https://doi.org/10.1037/0882-7974.10.4.527

Stanislaw, H., & Todorov, N. (1999). Calculation of signal detection theory measures. *Behavior Research Methods, Instruments, & Computers*, *31*(1), 137–149. https://doi.org/10.3758/BF03207704

Tolman, E. C. (1948). Cognitive maps in rats and men. *Psychological Review*, *55*(4), 189–208. https://doi.org/10.1037/h0061626

Tononi, G., & Cirelli, C. (2003). Sleep and synaptic homeostasis: A hypothesis. *Brain Research Bulletin*, *62*(2), 143–150. https://doi.org/10.1016/j.brainresbull.2003.09.004

Tononi, G., & Cirelli, C. (2014). Sleep and the price of plasticity: From synaptic and cellular homeostasis to memory consolidation and integration. *Neuron*, *81*(1), 12–34. https://doi.org/10.1016/j.neuron.2013.12.025

Tononi, G., & Cirelli, C. (2020). Sleep and synaptic down-selection. *European Journal of Neuroscience*, *51*(1), 413–421. https://doi.org/10.1111/ejn.14335

Tulving, E. (2002). Episodic memory: From mind to brain. *Annual Review of Psychology*, *53*(1), 1–25. https://doi.org/10.1146/annurev.psych.53.100901.135114

van der Helm, E., Gujar, N., Nishida, M., & Walker, M. P. (2011). Sleep-dependent facilitation of episodic memory details. *PLoS One*, *6*(11), e27421. https://doi.org/10.1371/journal.pone.0027421

Wang, B., & Fu, X.-I. (2009). Gender difference in the effect of daytime sleep on declarative memory for pictures. *Journal of Zhejiang University SCIENCE B*, *10*(7), 536–546. https://doi.org/10.1631/jzus.B0820384

Wang, J.-Y., Weber, F. D., Zinke, K., Noack, H., & Born, J. (2017). Effects of sleep on word pair memory in children – Separating item and source memory aspects. *Frontiers in Psychology*, *8*, Article 1533. https://doi.org/10.3389/fpsyg.2017.01533

Wichmann, F. A., Sharpe, L. T., & Gegenfurtner, K. R. (2002). The contributions of color to recognition memory for natural scenes. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *28*(3), 509–520. https://doi.org/10.1037/0278-7393.28.3.509

Wilson, M. A., & McNaughton, B. L. (1994). Reactivation of hippocampal ensemble memories during sleep. *Science*, *265*(5172), 676–679. https://doi.org/10.1126/science.8036517

Xing, X., & Saunders, J. A. (2022). Non-spatial similarity can bias spatial distances in a cognitive map. *Cognition*, *229*, 105251. https://doi.org/10.1016/j.cognition.2022.105251

Yonelinas, A. P., & Levy, B. J. (2002). Dissociating familiarity from recollection in human recognition memory: Different rates of forgetting over short retention intervals. *Psychonomic Bulletin & Review*, *9*(3), 575–582. https://doi.org/10.3758/BF03196315

Zhao, C., & Vogel, E. K. (2025). Individual differences in working memory and attentional control continue to predict memory performance despite extensive learning. *Journal of Experimental Psychology: General*, *154*(5), 1268–1283. https://doi.org/10.1037/xge0001728