Revisiting Hebb: The Mechanisms of Repetition Learning

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All data and scripts related to the analyses presented in this manuscript have been made publicly available on the OSF and can be accessed at https://osf.io/p2xfe/.

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Abstract

Back in 1961, Donald Hebb established a classic paradigm for studying repetition learning: He asked participants to remember several memory sets for an immediate serial recall task and repeated one set multiple times throughout the experiment. Participants' ability to recall the repeated set improved gradually with repetitions, thereby demonstrating repetition learning. Explaining this effect has concerned researchers for decades, as it provides key insights into how we form durable memory representations through repeated exposure. In this review, we revisit the dominant views on the mechanisms underlying repetition learning, thereby challenging two central assumptions: The assumption that repetition learning is gradual, and the assumption that it is implicit. We show how these views have emerged from flawed analytical approaches, summarize recent evidence strongly contradicting these claims, and present a re-analysis of previously published data to illustrate how correcting implausible analytical assumptions leads to different theoretical conclusions. We propose an updated theoretical framework of the cognitive mechanisms underlying repetition learning in which we integrate elements from previous models of the Hebb repetition effect with established models of episodic memory, thereby joining two branches of the memory literature.

Keywords: Working Memory, Long-Term Memory, Repetition Learning, Hebb Effect

Revisiting Hebb: The Mechanisms Underlying Repetition Learning

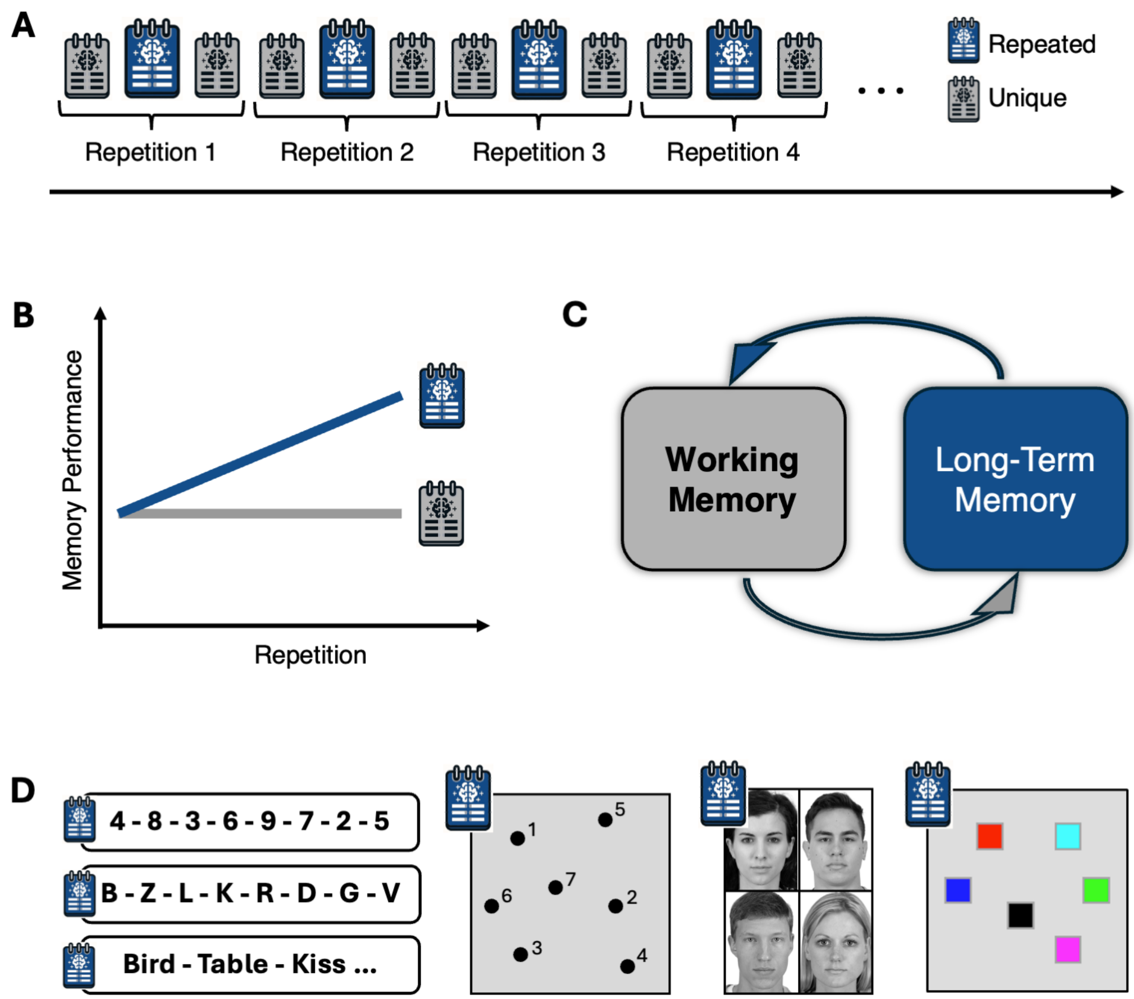
When we attempt to acquire new knowledge, we frequently engage in repeated practice. We study new words over and over when we learn the vocabulary of a new language, and we repeatedly rehearse what we want to say when preparing for a presentation. Learning from repetition is fundamental to human knowledge acquisition, and the cognitive mechanisms underlying this process have concerned researchers for more than 60 years.

Back in 1961, Donald Hebb established an experimental paradigm for the study of repetition learning. He presented participants with sequences of nine digits and asked them to recall a sequence immediately after the last digit had been presented. Unbeknownst to participants, he repeated one sequence multiple times throughout the experiment. Hebb observed that participants' ability to recall the repeated sequence improved steadily with the number of repetitions, whereas performance on interleaving unique sequences remained constant (Hebb, 1961; see Figure 1A and 1B for a schematic representation of the paradigm and findings). Hebb himself was surprised by this result. He had not expected to observe any learning effects when interrupting the repetition of a sequence by other unique filler sequences. He had hypothesized that the immediate serial recall of a memory sequence was solely based on an "activity trace", a reverberatory activation of the encoded information (Hebb, 1949). Once a new sequence is presented, this activity trace would get wiped out, leading to complete forgetting of the previous sequence. His results proved him wrong and had important implications for our understanding of memory and learning. Hebb showed that even a single presentation of a sequence must lead to a long-lasting structural change in the brain, allowing us to cumulatively learn from repeated experiences (Hebb, 1961).

Today, more than 60 years after Hebb's seminal paper, the *Hebb repetition effect* has been replicated numerous times and continues to inform our understanding of human memory and learning for various reasons. First, the Hebb repetition effect offers a model system for understanding the bi-directional interaction between working memory and long-term memory. It demonstrates 1) how repeatedly representing the same information in working memory can lead to the formation of long-lasting representations in long-term memory, and 2) how these representation in long-term memory can, in turn, support the maintenance of information in working memory (Burgess & Hitch, 2006; Page & Norris, 2009; Figure 1C). Second, the Hebb repetition effect has been proposed as an analogue of word form learning, and thus, can provide important insights into the mechanisms underlying language acquisition (Gupta, 2008; Norris et al., 2018; Page & Norris, 2008; Saint-Aubin & Guérard, 2018; Szmalec et al., 2009, 2012). Third, the Hebb repetition effect has been replicated across many different stimulus domains and presentation modalities, including sequences of letters (e.g., Araya et al., 2022; Page et al., 2006), words (e.g., Dutli et al., 2024; Page et al., 2013), spatial locations (e.g., Couture & Tremblay, 2006; Gagnon et al., 2005; Tremblay & Saint-Aubin, 2009; Turcotte et al., 2005), and faces (Horton et al., 2008; A. J. Johnson et al., 2017; A. J. Johnson & Miles, 2019), as well as simultaneously presented visual arrays (Musfeld et al., 2023; Musfeld, Souza, et al., 2024; Shimi & Logie, 2019; Souza & Oberauer, 2022), highlighting its universality as a very general form of learning.

Figure 1

A *Trial structure of a typical Hebb paradigm, in which one memory set is repeated amidst unique Filler sets.* **B** *Schematic visualization of the data pattern typically observed in the Hebb paradigm. Memory performance for the repeated memory set steadily increases with repetitions, whereas memory performance for unique, unrepeated Filler sets remains constant.* **C** *Schematic visualization of the bi-directional flow of information between working memory and long-term memory, used to explain the increase in memory performance observed in the Hebb repetition effect.* **D** *Examples of different stimulus materials for which the Hebb repetition effect has been demonstrated.*



Thus, understanding the cognitive mechanisms underlying the Hebb repetition effect is informative about many basic functionalities of our cognitive system.

In this review, we will revisit the prevailing assumptions that have been proposed to explain learning in Hebb's paradigm over the last decades and reevaluate their validity in light of recent findings and developments. We will demonstrate that some of these assumptions are flawed, and show how they have resulted from incorrect ways of analyzing data. Based on these new insights, we will propose a new theoretical framework of the mechanisms underlying repetition learning in the Hebb paradigm, thereby offering a new perspective on one of the most classical effects in cognitive psychology.

Prevailing Assumptions about the Mechanisms Underlying Repetition Learning

The question of how we learn from repeated exposure involves two theoretically relevant aspects. The first concerns the flow of information from working memory to long-term memory, that is: How does repeated exposure to the same information in a working memory task lead to a long-lasting representation in long-term memory? The second concerns the flow of information from long-term memory to working memory, that is: How can the representation in long-term memory be beneficial to performance in a test of working memory? Several attempts have been made to explicate these mechanisms in computational models of memory (Burgess & Hitch, 2005, 2006; Norris & Kalm, 2024; Page & Norris, 2009). Although these models show substantial differences in their general conception of short-term and working memory, they nevertheless share some common assumptions about the mechanisms underlying repetition learning.

The first of these common assumptions is the idea that repetition learning leads to the formation of new chunk representations in long-term memory. Chunk formation is a process by which multiple separate elements of information are integrated into one unified representation (i.e., a "chunk") of the elements and their structure (Cowan & Chen, 2008; Ericsson & Kintsch, 1995; Miller, 1956). Related to the Hebb repetition effect, this can be the integration of a sequence of digits into a phone number (Hebb, 1961; McKelvie, 1987), the integration of phonemes into a word (Szmalec et al., 2009, 2012), or the integration of multiple pieces on a chess board into a known pattern (Ericsson & Kintsch, 1995; Gobet & Simon, 1996b, 1996a). Chunk formation is a key feature for dealing with the limited capacity of our cognitive system, as it allows us to represent information in a more efficient or compressed way, thereby making room for other information to be processed (Awh & Vogel, 2025; Brady et al., 2009; Chekaf et al., 2016; Huang & Awh, 2018; Ngiam et al., 2019; Norris et al., 2020; Norris & Kalm, 2021; Thalmann et al., 2019).

A second assumption that can be identified is that repetition learning reflects a cumulative process, by which every repetition gradually strengthens a representation in memory (Burgess & Hitch, 2005; Norris & Kalm, 2024; Page & Norris, 2009). This learning process is initiated by the first presentation of a repeated memory set and is commonly assumed to be rather slow, with each repetition leading to a gain in recall accuracy of only some single-digit percentage.

The last assumption that has been proposed consistently over the last decades is the claim that the Hebb repetition effect is an example of implicit learning. This means that participants don't have to be aware of studying the same information over and over again for learning[1] to occur. Although this assumption is not inherently included in the computational models of the Hebb repetition effect, it is a widely accepted assumption that has been supported by several empirical findings (Couture & Tremblay, 2006; Guérard et al., 2011; Hebb, 1961; McKelvie, 1987; Seger, 1994; Smalle et al., 2018). In the following, we will revisit the evidence for these three assumptions and evaluate their validity in light of new findings and recent developments.

Assumption 1: Repetition Learning Forms Chunks

The assumption that Hebb repetition learning leads to the formation of chunked representations has evolved primarily from studies demonstrating conditions under which repetitions did *not* result in learning, thereby revealing key constraints on what is learned. For instance, Schwartz and Bryden (1971) reported no Hebb repetition effect when the first two items of an otherwise repeated sequence varied on each presentation, and Hitch et al. (2005) found that repeating only every other item (e.g., only odd or even positions) also did not result in any learning. Similarly, Cumming et al. (2003) observed no transfer of learning when only every other item of a once well-learned list was repeated. These results converge on the idea that learning in the Hebb paradigm is *not* operating at the level of single elements; rather, it seems to rely on integrating the elements of a memory set into a unified representation – a chunk that is

[1] When we speak of (repetition) learning, we refer to an improvement in memory test performance, as shown for instance by the Hebb repetition effect.

stored and retrieved as a single unit (Cumming et al., 2003; Hitch et al., 2005; Page & Norris, 2009).

Recent evidence points to the possibility that chunk formation might be more flexible than initially assumed. Mizrak and Oberauer (2022), for example, demonstrated that participants could selectively retrieve *subsets* of a previously learned list in isolation, suggesting that retrieval of the acquired long-term memory representation does not necessarily unfold in an all-or-nothing manner. This aligns with recall time patterns in visual repetition learning (Adam et al., 2024): After several repetitions of the same 6-item array, the times of successive recall responses peak after at the first and the fourth response, suggesting that elements of a learnt memory set are retrieved from long-term memory in two subsets of three items.

There is evidence that not only the retrieval but also the learning itself operates on smaller subsets of a memory set. For instance, early work by Bower and Winzenz (1969) and also Winzenz (1972) has shown that the Hebb effect is susceptible to grouping effects: When memory lists are grouped by temporal gaps, repetition learning only appears when the grouping structure remains consistent across trials. When the grouping structure was changed with every repetition, learning was absent, even though all list items were repeated. More recently, Musfeld, Dutli et al. (2024) demonstrated that a Hebb repetition effect can also be observed when only a contiguous subset of list items is repeated, provided that participants were able to identify the beginning and end of that subset. These results suggest that learning does not have to result in chunks that ingrate the entire memory set. The learning mechanism appears to be flexible enough to acquire smaller chunks integrating subsets of the memory set (see also Szmalec et al., 2009, 2012). These subsets are likely to be established already during initial encoding, and then continue to guide chunk learning over consecutive repetitions (Musfeld, Dutli, et al., 2024). This is consistent with inter-response time patterns observed in free recall, showing that participants spontaneously break down longer lists into smaller, more manageable, subsets (N. R. Greene et al., 2025).

A challenge for the chunking hypothesis comes from the Hebb repetition effect with complex span tasks (Araya et al., 2022, 2023; Oberauer et al., 2015). In a complex span task, the presentation of each memory item is interleaved with processing of one or more distractor stimuli, thereby potentially disrupting the integration of repeated items into a chunk (Hitch et al., 2005; Musfeld, Dutli, et al., 2024). This seems to contradict the idea that Hebb repetition learning relies on integrating contiguous sequences of items into chunks. However, distractor stimuli do not have to be memorized, and can be removed from working memory immediately after processing (Oberauer & Lewandowsky, 2016). In that way, they do not become part of the memory representation of the list. After distractors are removed from working memory, the list items are again represented as a list of contiguous items that can be chunked. This is consistent with the conclusions by Araya et al. (2022, 2023), who found that repetition learning in simple and complex span tasks is based on the same mechanism, which is likely to be chunking.

One benefit of chunking is that it allows us to represent information in a more efficient or compressed way, thereby freeing up capacity in working memory for other information to be maintained and processed (Bartsch & Shepherdson, 2022; Mızrak & Oberauer, 2022; Norris & Kalm, 2021; Thalmann et al., 2019). For example, when participants are asked to remember the sequence “PDF-KGW-HPN”, not only the pre-known chunk “PDF” but also the unfamiliar letter sequence following it are remembered better compared to a condition in which no chunk is present early in the sequence. Consistent with this characteristic of chunks, we demonstrated that representations learned through repetition can free up capacity in working memory as well (Musfeld, Dutli, et al., 2024). By using partially repeated memory lists, in which only a specific subset of a memory list contained repeating items, we observed that learning of the repeated subset not only improved memory for the repeated items, but also for other, not-repeated items within the same list. This finding shows that learning the repeated subset reduces the load on working-memory capacity, thereby freeing up capacity for remembering other information.

Taken together, the assumption that repetition learning leads to the formation of chunks is empirically well supported. Yet, what exactly constitutes a chunk remains surprisingly elusive (Gobet et al., 2016; Terrace, 2001). In the literature, the term “chunking” has been used with a wide range of meanings (Allen et al., 2021; Anderson, 1993; French et al., 2011; Gobet et al., 2016; Gobet & Simon, 1996b; Huang & Awh, 2018; N. F. Johnson, 1970, 1972; Jones et al., 2014; Norris & Kalm, 2021; Orbán et al., 2008; Thalmann et al., 2019), highlighting the need for a clearer and more consistent understanding of chunking to properly understand what kind of representation exactly is learned from repetition.

Assumption 2: Repetition Learning Reflects a Gradual Strengthening of Representations in Long-Term Memory

The assumption of repetition learning reflecting a gradual learning process is a conclusion inferred from the data pattern observed in almost every experiment conducted on the Hebb repetition effect: When data is aggregated over participants, the results show a gradual improvement in immediate memory performance on the repeated memory set as a function of repetitions (see Figure 1B). However, this does not guarantee that learning proceeds gradually, as the aggregated learning curve is not always a correct reflection of the individual learning curve (Estes, 1956; Gallistel et al., 2004; Hayes, 1953).

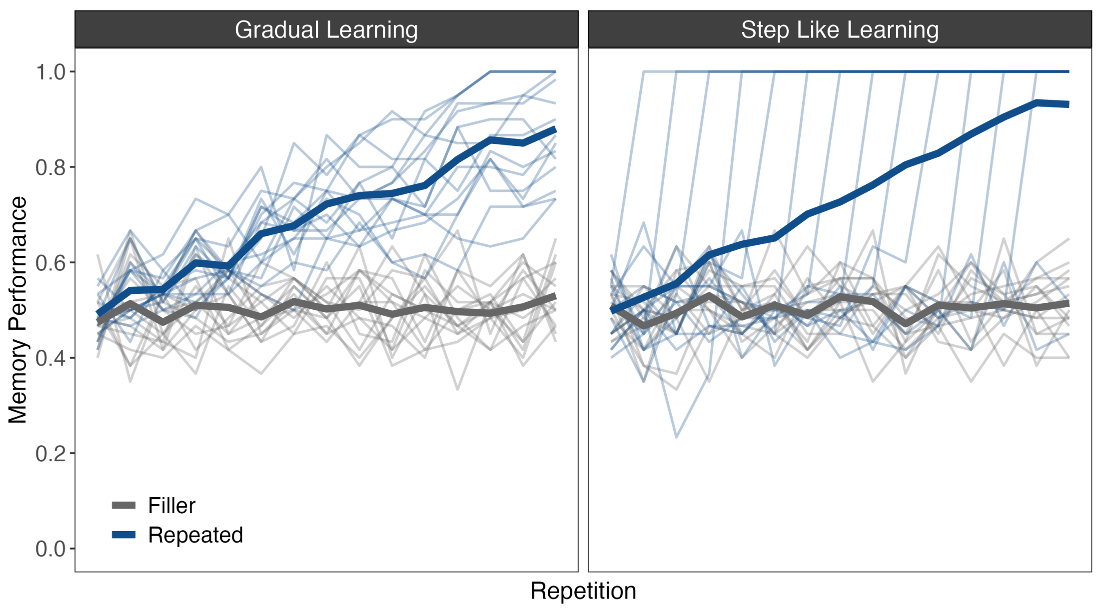
This problem is illustrated in Figure 2, by making use of two extreme scenarios: The left panel of the Figure shows data simulated based on the assumption of a gradual learning process[2]. The thin transparent lines show learning curves from individual participants, and the thick line represents their average. This is how one would usually imagine the individual learning curves to look like, when drawing conclusions from the aggregated curve: Participants differ in their rate of learning, but for everyone, performance improves gradually over repetitions. The right panel of Figure 2 shows data simulated based on a different data generating process. Here, all participants learn the repeated list within a single repetition, but they differ in their onset point of learning. Although this reflects a completely different assumption about learning, the resulting aggregated curve looks exactly the same: It suggests a gradual improvement in

[2]Detailed R-code for the simulation can be found at: https://osf.io/p2xfe/.

performance as a function of repetition. Hence, analyzing data aggregated over participants can be misleading, and individual data patterns should be considered for better understanding the processes underlying repetition learning.

Figure 2

Visualization of two almost identical aggregated learning curves, derived from completely different data generating processes. The thin lines represent individual participants, and the thick lines their average. In the left panel, data was simulated by assuming a gradual learning process, by which memory performance gradually improves as a function of repetition, and participants differ in their rate of learning. In the right panel, data was simulated by assuming a step-like learning process, by which a memory set is learned within a single repetition, but participants differ in their onset point of learning.



We recently addressed this issue by introducing a new Bayesian hierarchical measurement model that allowed us to analyze data on the level of individual participants, rather than the sample average, to determine the shape of the underlying learning curve more accurately (Musfeld et al., 2023). The model is built on two assumptions. First, it includes two main parameters that determine the shape of the learning curve: one parameter for the rate of learning, and an additional parameter for the onset of learning, which are freely estimated for every participant. This gives the model full flexibility in capturing the shape of the individual learning curves, from a slow but steady increase in performance starting from the first repetition to a rather steep increase in performance with varying onset points of learning, and everything in-between. Second, it involves a classification process, which determines if a participant showed a learning effect or not. This is based on the observation that within a sample of a typical Hebb study, many participants' performance on the repeated list never improves. By separating participants who show a learning effect from those who don't, it can be ensured that the estimation of learning related parameters is only informed by participants who show a learning effect. The result is a mixture model, in which learning and non-learning participants are described by different sub-models, and which estimates a parameter reflecting the proportion of learning participants within a sample.

Here, we applied this model to two large data sets to obtain an accurate estimation of the shape of the learning curves[3]. One data set contains data from ~300 participants performing a visual Hebb paradigm, in which a visual array of six colored squares was repeated 30 times amidst unrepeated Filler arrays (see Figure 1D for an example). The data was taken from Musfeld et al. (2023). The other data set contains

[3] The data sets, stan model and a detailed analysis script for fitting that model to the data can be found at: https://osf.io/p2xfe/.

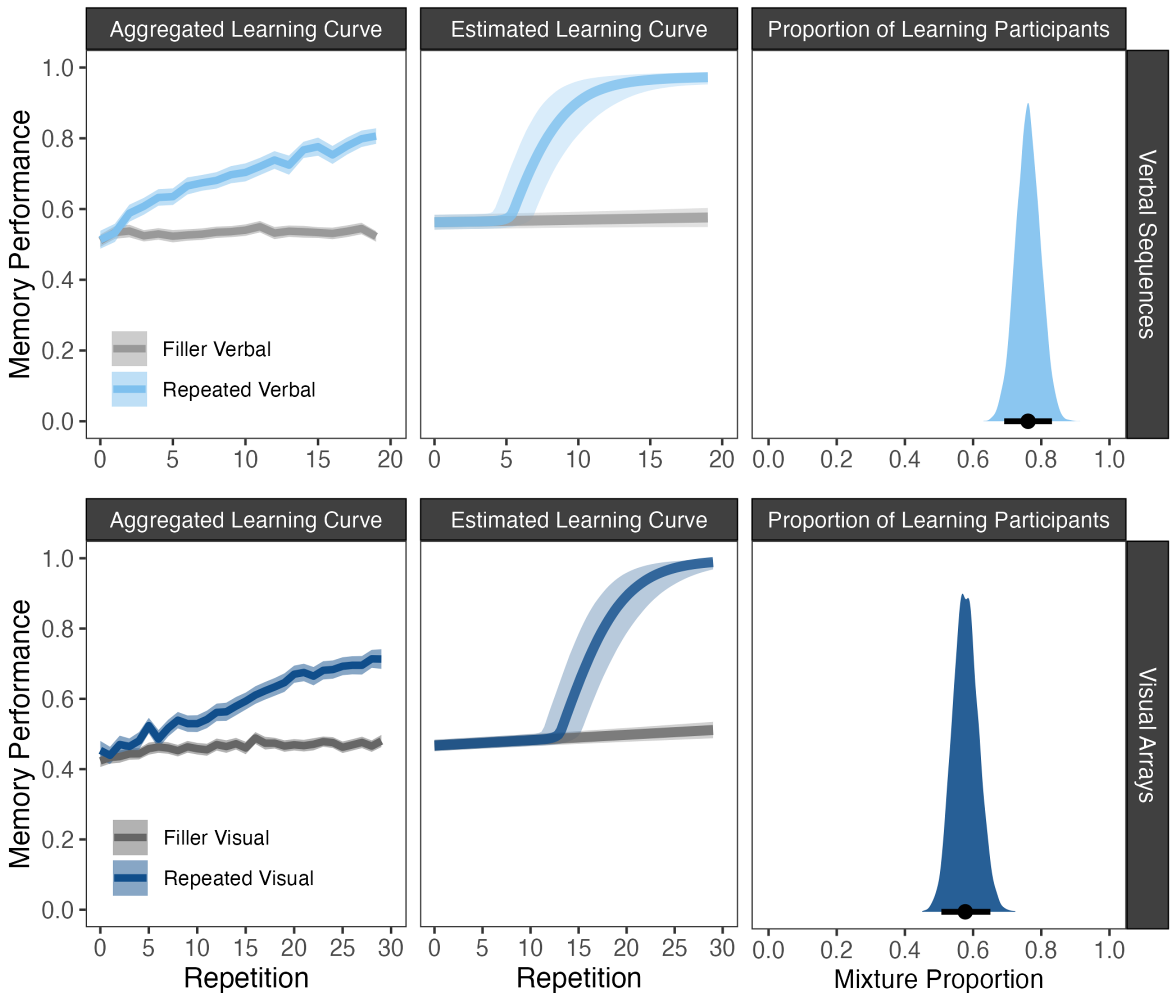
data from ~300 participants performing a typical verbal Hebb paradigm, in which a sequence of 9 consonants was repeated 20 times amidst unrepeated Filler lists for an immediate serial recall task. This data was collected for the purpose of this review[4].

The aggregated results from both experiments are presented in the left panels of Figure 3. Both show the typical data pattern of the Hebb repetition effect: memory performance gradually increases with repetitions. When looking at the results from the Bayesian hierarchical mixture model, however, a different picture emerges. The middle panels of Figure 3 show the shape of the estimated learning curve based on the underlying individual data patterns for both experiments (i.e., participants' average onset point of learning combined with participants' average rate of learning). The right panels of Figure 3 show the estimated proportion of learning participants in the two experiments. What becomes evident from these results is that immediate recall performance on the repeated memory set does not steadily improve with each repetition. Instead, the estimated learning curves show a delay in when the learning process begins and once initiated, are steeper than suggested from the aggregated data.

[4] We did not use the data from the verbal Hebb experiment in Musfeld et al. (2023) as the testing procedure deviates from a typical Hebb task by using a cued random order recall task instead of a serial recall task. To show that the same results generalize to the more typical scenario of the immediate serial recall task in the Hebb paradigm, we repeated the study using a serial recall procedure. Other than that, the design was the same as reported in Musfeld et al., 2023. The new data can be found at https://osf.io/p2xfe/ and a detailed description of the methods is provided in the supplementary materials.

Figure 3

Results from a verbal and a visual Hebb experiment, analyzed and plotted in two different ways. The plots in the left panels show memory performance as a function of repetitions, aggregated over participants. The plots in the middle and right panels show the results of the Bayesian hierarchical mixture model, fitted to the same data. The middle panels show the estimated learning curve for the two experiments based on the shape of the underlying individual learning curves (i.e., combining the average onset point of learning with the average rate of learning). The right panels show the estimated mixture proportion, which reflects the proportion of participants who showed a learning effect in the two samples. Shaded areas around the aggregated and estimated learning curves reflect 95% within-subject confidence intervals and 95% highest density intervals respectively.



When comparing learning effects between the two experiments, it also becomes clear that they mainly differ in two aspects: 1) the proportion of participants who learn the repeated memory set, and 2) the onset point of the learning effect. Once initiated, however, learning seems to proceed at similar rates.

These results contradict the commonly accepted assumption of repetition learning being a continuous process in which each repetition gradually improves memory. This assumption seems to rest upon the analysis of aggregated learning curves, which do not resemble the underlying individual curves. When describing learning effects on the level of individuals it becomes evident that repetitions do not always result in learning (i.e., improvement in immediate recall performance). Instead, there seems to be a precondition that must be met for learning to occur. Only once this condition is met, repetitions seem to improve immediate recall performance. However, this improvement is much faster than implied by the aggregated learning curve, and quickly results in perfect memorization of the entire memory set. If this condition is not met, however, learning can be delayed or does not occur at all. Overall, this implies that not every repetition has the same effect on long-term memory, and raises the question under which conditions repetitions strengthen existing memory representations. We propose an answer in the next section.

Assumption 3: Repetition Learning Occurs Implicitly

The assumption of repetition learning being an implicit process dates back to Hebb himself. Although he had not systematically tested if learning was affected by participants' awareness of the repetition, his account to explain the observed learning effect included the assumption that repetition awareness was not necessary for learning to occur (Hebb, 1961). Later, several empirical findings supported Hebb's claim by showing that a Hebb repetition effect can be observed regardless of whether participants reported awareness of a repetition or not (Couture & Tremblay, 2006; Guérard et al., 2011; McKelvie, 1987).

Other researchers have argued that repetition learning requires explicit recognition of what is being repeated (Bower & Winzenz, 1969; Cohen & Johansson, 1967; Cunningham et al., 1984; Winzenz, 1972). Although there have been several studies that supported this idea (e.g., Ngiam et al., 2019; Sechler & Watkins, 1991; Shimi & Logie, 2019; Sukegawa et al., 2019), the dominant view has remained that repetition learning in the Hebb paradigm does not require repetition awareness.

The learning curves observed for individual participants, however, raise questions that challenge this assumption once more: Why do some participants never learn to recall the repeated memory set better? Why can the onset of such learning be delayed but then still result in rapid improvements? One possibility is to assume that repetition awareness is indeed a necessary condition for memory representations to become stronger, and thus, for proper learning to occur. In this case, memory representations are not passively strengthened by every repetition of the repeated list, but only once participants explicitly identify a memory set as repeating. As long as the repetition goes unnoticed, no learning occurs, resulting in a delay in the onset, or even the complete absence of learning.

Based on these considerations, we will revisit the relationship between learning and awareness in the Hebb paradigm. We will start by re-evaluating previous empirical evidence claiming that repetition learning is not influenced by repetition awareness and then turn to the question if repetition awareness should be considered a necessary condition for repetition learning to occur.

Is repetition learning affected by repetition awareness? Several studies have claimed that the Hebb repetition effect is not affected by whether people are aware of the repetition or not. To our knowledge, there are three studies that came to this conclusion: One using sequences of digits (McKelvie, 1987) and two using sequences of spatial locations (Couture & Tremblay, 2006; Guérard et al., 2011). To assess the effect of repetition awareness on repetition learning, these researchers classified participants as either aware or unaware and compared the learning effect between the two awareness groups. The classification was based on a post-experimental assessment, in which participants were asked if they noticed anything special about the experiment. Participants were classified as "aware" if they mention something about a repetition, and as "unaware" if they didn't. Here we present a reanalysis of all three studies[5] by using two different analytical approaches: The one that has been used in the original

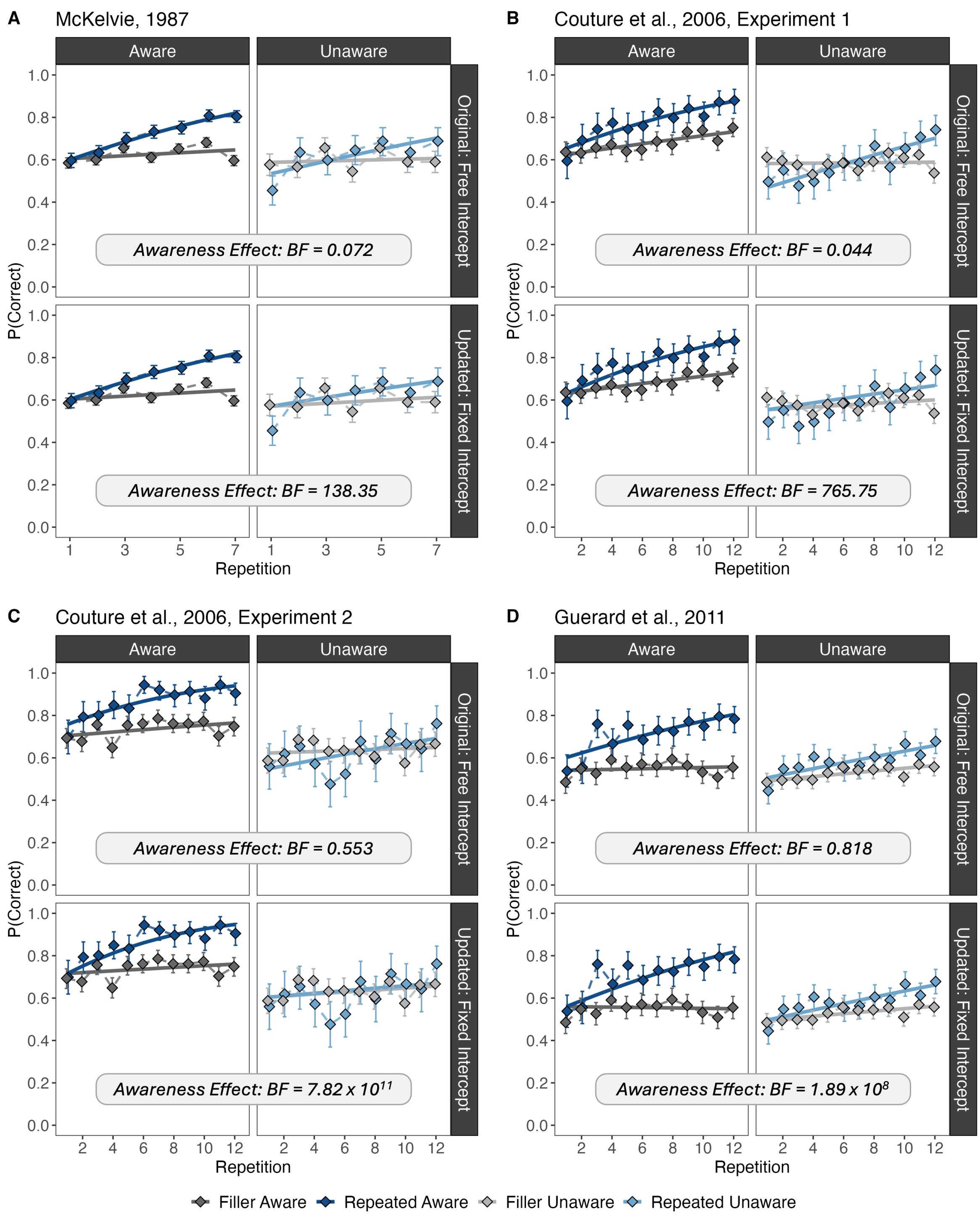
[5] As the original raw data were not available, we reconstructed the data from the information reported in the publications. We first extracted the mean proportion of correct responses within each design cell, together with the total number of responses this average was based on. This allowed us to calculate how many responses out of the total number of responses were correct within each design cell, and to feed that information into a binomial regression model. In this way, we were still able to take the number of participants and number of trials into account, although only averages were reported. While this provides only an approximation of the data, we were able to replicate all conclusions reported in the original publication, when using a similar analytical approach as reported there. Detailed analysis scripts for reconstruction and analysis of the data can be found at: https://osf.io/p2xfe/. A more detailed description of the fitted models is provided in the supplementary materials.

studies, and a slightly different approach, for which we will argue that it provides a more accurate way of analyzing the data.

Figure 4 shows the results for all three studies, with the data from the aware participants in the left panels of the plots, and the data from the unaware participants in the right panels. One thing that becomes evident just from visual inspection of the data is that there seems to be a substantial difference in the learning effect between the two awareness groups across all studies. Yet, all studies concluded that learning was not affected by repetition awareness. How does this align? The reason for this is related to the way the data was analyzed: In all three studies, the learning effect was not estimated in relation to a common baseline (i.e., the performance in non-repeated filler trials). The Hebb repetition effect, however, is defined as the selective improvement in immediate memory performance on a repeated memory set beyond any changes in immediate memory performance on unique Filler sets. Thus, the Filler sets serve as a critical baseline, which needs to be considered when estimating the learning effect.

Figure 4

Re-analysis of four experiments reporting evidence against an effect of repetition awareness on learning. The top panels of the plots show the results based on the original analysis; the bottom panels show the results based on an alternative re-analysis. Solid lines show the fit of the binomial regression models to the data. Error bars reflect 95% quantile intervals from the binomial distribution. Bayes Factors (BF) indicate the evidence in favor of a three-way interaction between trial-type (Filler vs. Repeated), repetition, and awareness, which reflects the difference between the slopes of the increase in memory performance over repetitions for aware and unaware repeated trials.



One consequence resulting from this consideration is that memory performance on repeated and unique memory sets should be equalized at the beginning of the experiment, because at the very first presentation of the repeated set it is not yet repeated. If this is not considered, the estimated slopes can be biased in two possible ways: In some experiments, the starting point of the regression line for repeated sets in the unaware group is estimated below the baseline performance in corresponding Filler sets (see the unaware groups in Figure 4A, 4B and 4C), which increases the slope for the unaware repeated sets, although performance never substantially improves above performance in Filler sets. In other experiments, the starting point of the regression line for repeated sets in the aware group already starts above the baseline performance in corresponding Filler sets (see the aware groups in Figure 4C and 4D), which decreases the slope for the repeated sets, although performance did substantially improve above performance in Filler sets. The result is that the estimated slopes for the two awareness groups might not differ, although performance on repeated sets improves to different degrees compared to the baseline.

To test this, we first conducted the analysis in the same way as it was done originally. The results of this analysis are presented in the upper panels of Figure 4 (labeled “Original: Free Intercept”). The reported Bayes Factors reflect the evidence for the three-way interaction between trial-type (Repeated vs. Filler), repetition, and awareness (aware vs. unaware), which is indicative of the difference in the Hebb repetition effect (i.e., the increase in immediate memory performance in repeated compared to Filler lists over repetitions) between the two awareness groups[6]. When analyzing the data in this way, the slope of the estimated learning effect does not credibly differ between the two awareness groups. Rather, all four experiments provide evidence against an effect of awareness, thereby replicating the original conclusions (although for two experiments, the evidence remains inconclusive). In an alternative statistical model, we set the intercept for repeated and unrepeated memory sets to be equal to represent the fact that these conditions are indistinguishable in the first trial. This change in the analysis changes the results completely: Now, all experiments reveal overwhelming evidence in favor of an effect of repetition awareness on learning (see lower panels of Figure 4 labeled “Updated: Fixed Intercept”).

The reanalysis demonstrates that the assumption of repetition learning not being affected by repetition awareness stands on shaky ground. When taking baseline performance into account, all three studies provide evidence that learning in the Hebb paradigm is strongly affected by participants’ awareness of the repetition.

Is repetition awareness a necessary condition for repetition learning? Showing that repetition learning correlates with participants’ repetition awareness still does not mean that awareness is required for learning to occur. To assert such a necessity, two criteria must be met: First, participants who report no repetition awareness should show no learning. Second, in those who report repetition awareness, awareness should precede any improvements in immediate recall performance and not just emerge as

[6] Further details about the analysis and the exact models that we fit are provided in the supplementary materials.

consequence of the latter. If either condition is not met, repetition learning could still occur implicitly.

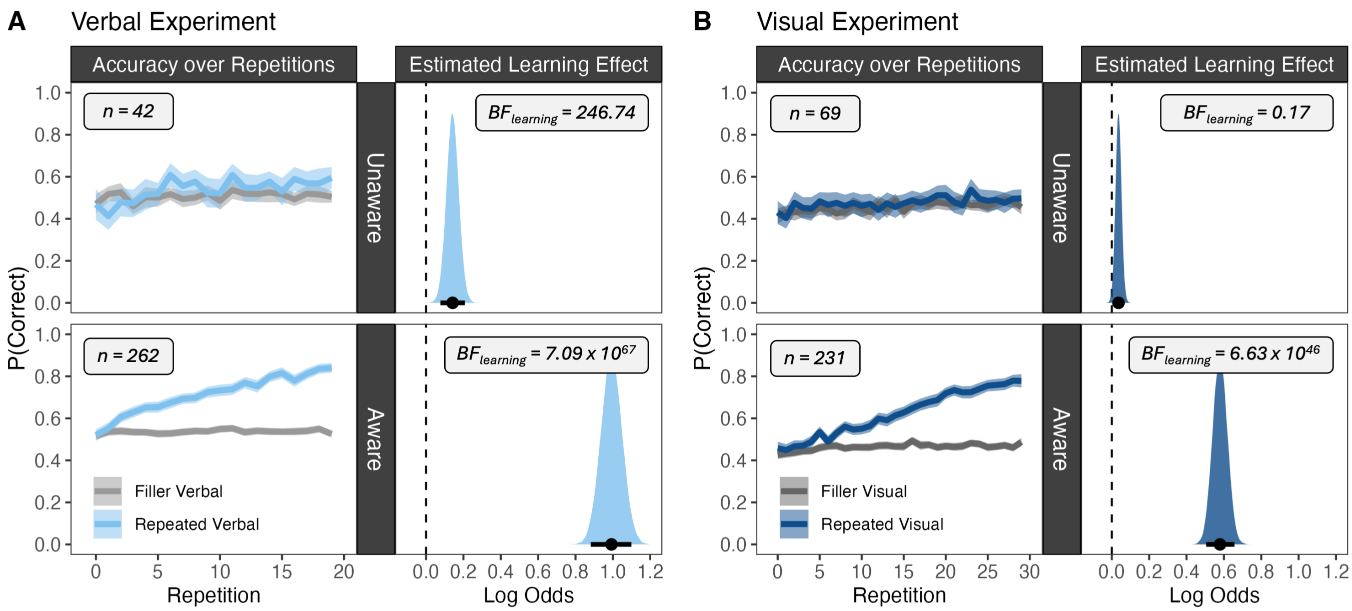
To test if learning is observable for participants who report no repetition awareness, we again made use of the two large data sets introduced earlier (~300 participants from a visual, and ~300 participants from a verbal Hebb experiment). In both studies, participants were asked at the end of the experiment if they noticed the repetition of a particular memory set. This allowed us to split the data by participants' repetition awareness and examine learning separately within the two awareness groups.

Figure 5 presents the data from both experiments split by participants' repetition awareness (left panels), alongside posterior estimates of the corresponding learning effects (i.e., the two-way interaction between trial-type and repetition; right panels)[7]. Regarding the evidence for learning in the unaware group, the results provide a somewhat mixed picture: For the visual experiment, we find evidence against the presence of a learning effect in the unaware group, showing that without participants being aware of the repetition, no learning effect is observed. This was different for the verbal experiment: here, the Bayes Factor supported the presence of a learning effect even in the absence of repetition awareness.

[7] See supplementary materials for further details on the conducted analysis.

Figure 5

Data from a large verbal (A) and a large visual (B) Hebb experiment, split by a post-experimental assessment of participants' repetition awareness. The left panels show the data plotted as a function of repetition, aggregated over participants. Shaded areas reflect 95%-within confidence intervals. The right panels show the posterior distributions of the two-way interaction of trial-type and repetition, which reflects an estimate of the learning effect. Points reflect the mean, bars the 95% highest density intervals. Parameters are estimated on the scale of log odds from a Bayesian hierarchical logistic regression model.



Does this imply that the Hebb repetition effect occurs implicitly? We consider this to be unlikely. While our analysis cannot fully rule out that some learning might still occur implicitly, two points should be considered. First, the size of the estimated learning effect in the absence of awareness is very small, resulting in an almost negligible gain in immediate recall performance, even over many repetitions. Instead, a substantial Hebb repetition effect in the form of learning a whole repeated memory set as a new chunk (see previous section), seems only to occur in combination with explicit awareness. Second, the reliability of assessing repetition awareness based on a post-experimental self-report can be questioned. For example, participants may misclassify themselves, by accident or due to different thresholds in reporting repetition awareness, which could potentially drive the observed small learning effect even in the group of unaware participants.

Assessing awareness based on a post-experiment questionnaire comes with another shortcoming: It does not allow to determine when in the experiment awareness arose. Concluding that awareness is a necessary condition for the Hebb repetition effect to occur, however, also requires to show that those participants who report awareness became aware of the repetition prior to any improvements in immediate recall performance, and not just in consequence. We recently addressed this issue by developing a new method that combines a Hebb paradigm with a trial-by-trial assessment of participants' repetition awareness: after each trial, participants have to indicate whether they think that a just presented memory set had been presented before (repeated) nor not (new). This allows to assess if and at which point in the experiment participants are able to distinguish between a repeated memory set and unrepeated Filler sets (see Musfeld et al., 2023 for further details)[8]. Combining this trial-by-trial assessment of participants' repetition awareness with the trial-by-trial assessment of immediate memory performance within a joint modeling approach then allows to estimate 1) the onset point of learning, 2) the onset point of repetition awareness, and 3) their temporal relation for each individual participant.

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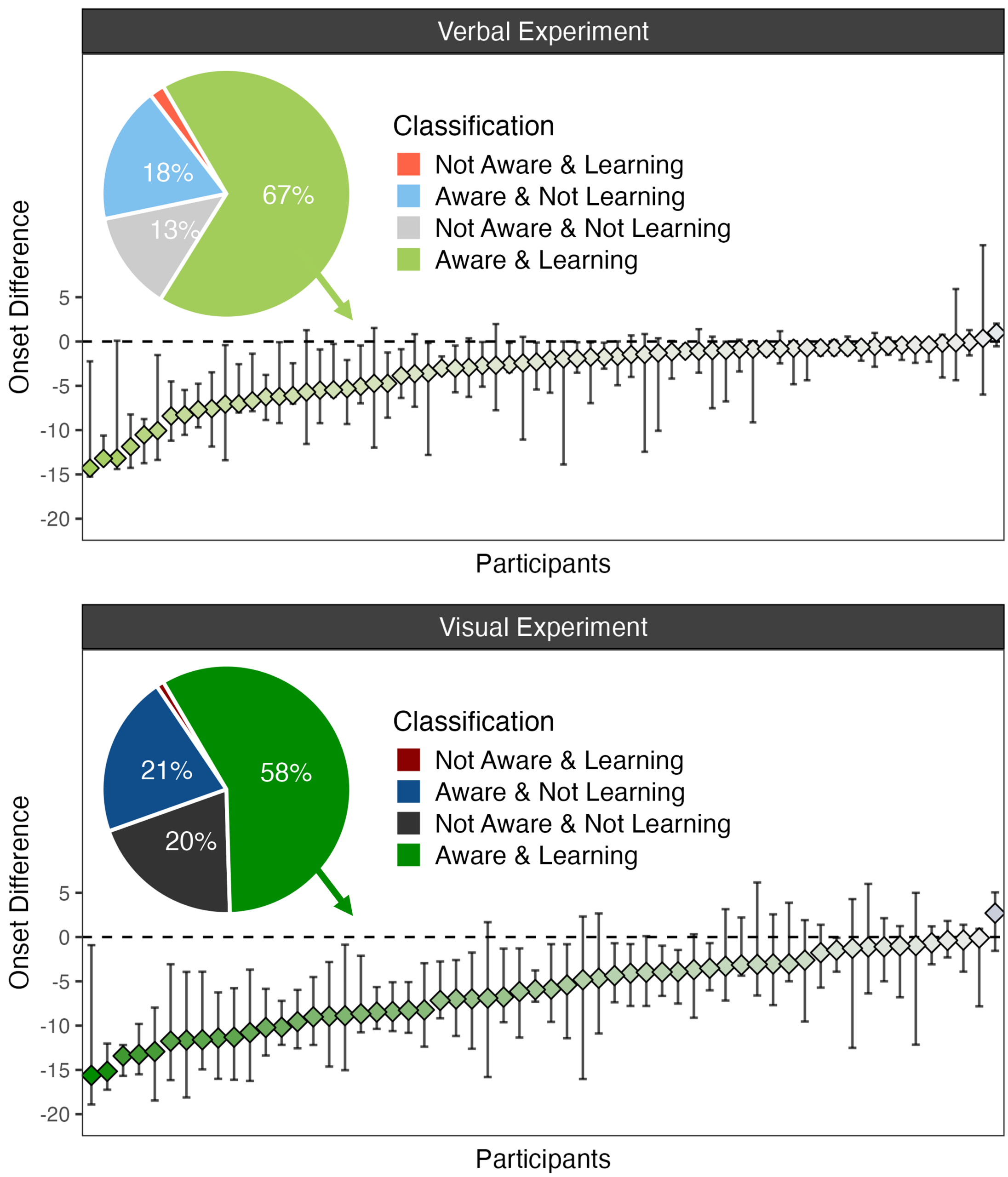
[8] Note that this method inevitable points participants to the fact that there is a repeating memory set. This is information that is typically not provided to participants in a Hebb paradigm. To account for this, all reported experiments included control conditions to ensure that the additional knowledge did not affect the observed learning (see also supplementary materials).

Figure 6

Results from jointly modelling a trial-by-trial assessment of participants' repetition awareness and immediate recall performance. The pie charts show the cross-classification from classifying participants as aware and as learning, with the percentages for each category. Data points show the estimated difference between the onset of awareness and the onset of learning for each participant who was classified as aware and learning. Bars represent 95% highest density intervals. Negative differences indicate awareness prior to the onset of learning; positive difference indicate awareness after the onset of learning.



To illustrate this point, we once more applied this approach to 1) the data from the visual Hebb experiment reported in Musfeld et al. (2023), and 2) the new data from the verbal Hebb experiment introduced here[9]. Figure 6 shows the estimated differences between the onset of awareness and the onset of learning for each participant who was classified as learning and as becoming aware of the repeated memory set at some point. Negative difference indicate that the onset of awareness occurred prior to the onset of learning, whereas positive differences indicate the opposite. The results provide a clear picture: Across both experiments, and for every participant, repetition awareness either preceded or coincided with the onset of learning, showing that participants only improved their recall performance once they had recognized what was being repeated.

Taken together, the presented results show three important points: 1) Previous studies seem to have underestimated the effect of repetition awareness on repetition learning; 2) learning effects are very small or absent altogether when no repetition awareness is reported; 3) when repetition awareness is measured more objectively on a trial-by-trial level, it shows that recall performance only improves once participants explicitly recognize the repetition. This renders it unlikely that the Hebb repetition effect occurs implicitly. Rather, it suggests that explicit recognition of what is repeated is a necessary precondition for robust learning to occur (see also Bower & Winzenz, 1969; Cunningham et al., 1984; Winzenz, 1972 for earlier mentions of this idea). This demands

[9] This only includes a subset of the two previously described data sets (~100 participants each), for which we had collected trial-by-trial ratings of participants' repetition awareness.

an update of the proposed mechanisms underlying repetition learning. In the following, we will sketch such an updated theoretical framework.

Rethinking the Mechanisms Underlying Repetition Learning in the Hebb Paradigm – The Role of Episodic Memory

The benefit of repetitions on memory has not only been studied within the Hebb paradigm, but has also motivated a large body of research within models of episodic memory (Benjamin & Tullis, 2010; Ensor et al., 2021; Hintzman, 2004, 2010; Hintzman & Block, 1971; Raaijmakers, 2003; Toppino & Gerbier, 2014). Episodic memory refers to our ability to store and recollect past experiences, including information about the temporal and spatial context an event has been experienced in (Renoult et al., 2019; Tulving, 1972, 1983). Most computational models of episodic memory are based on a form of instance theory (Jamieson et al., 2022; Logan, 1988, 2002), which postulates that every experienced event is stored as a separate record – or instance – within episodic memory, regardless of someone's intention to remember (Craik & Tulving, 1975; Henke, 2010; Popov & Dames, 2023). While this assumption closely aligns with what has been proposed in models of the Hebb repetition effect (Burgess & Hitch, 2006; Page & Norris, 2009), different proposals have been made regarding the representation of repeated experiences. Whereas some models have adopted the assumption that repeated experiences accumulate within a single trace in episodic memory (e.g., Gillund & Shiffrin, 1984; Murdock, 1995; Shiffrin & Steyvers, 1997; Wickelgren, 1972), an alternative approach has been formulated in the multiple-trace hypothesis (Hintzman &

Block, 1971; Morton, 1968; Underwood, 1963). This hypothesis assumes that each experience is stored in an independent memory trace, even if it is a repetition. This facilitates memory for repeated events because it provides multiple independent access routes to the same information during retrieval (Hintzman, 1984; Lansdale & Baguley, 2008; Logan, 1988).

Although both approaches can account for a general benefit of repetition on memory, they have been criticized for various reasons (see Greene, 2008 for a review). One the one hand, empirical findings show that participants have access to information about separate occurrences of repeated items. This indicates that some independent memory trace must have been stored during each repetition, which contradicts the idea of a cumulative strengthening account (Hintzman, 2004, 2010; Hintzman & Block, 1971; Morton, 1968). On the other hand, empirical findings show that repetition effects on memory can be superadditive, which means that memory performance for repeated events is typically superior to what one would expect from an additive effect of independent memory traces (Begg & Green, 1988; Hintzman, 2004; Johnston & Uhl, 1976). This violates the assumption of independence in the multiple-trace hypothesis and suggests that repeated experiences have to strengthen their representations in memory in some interactive way (Benjamin & Tullis, 2010; Hintzman, 2010).

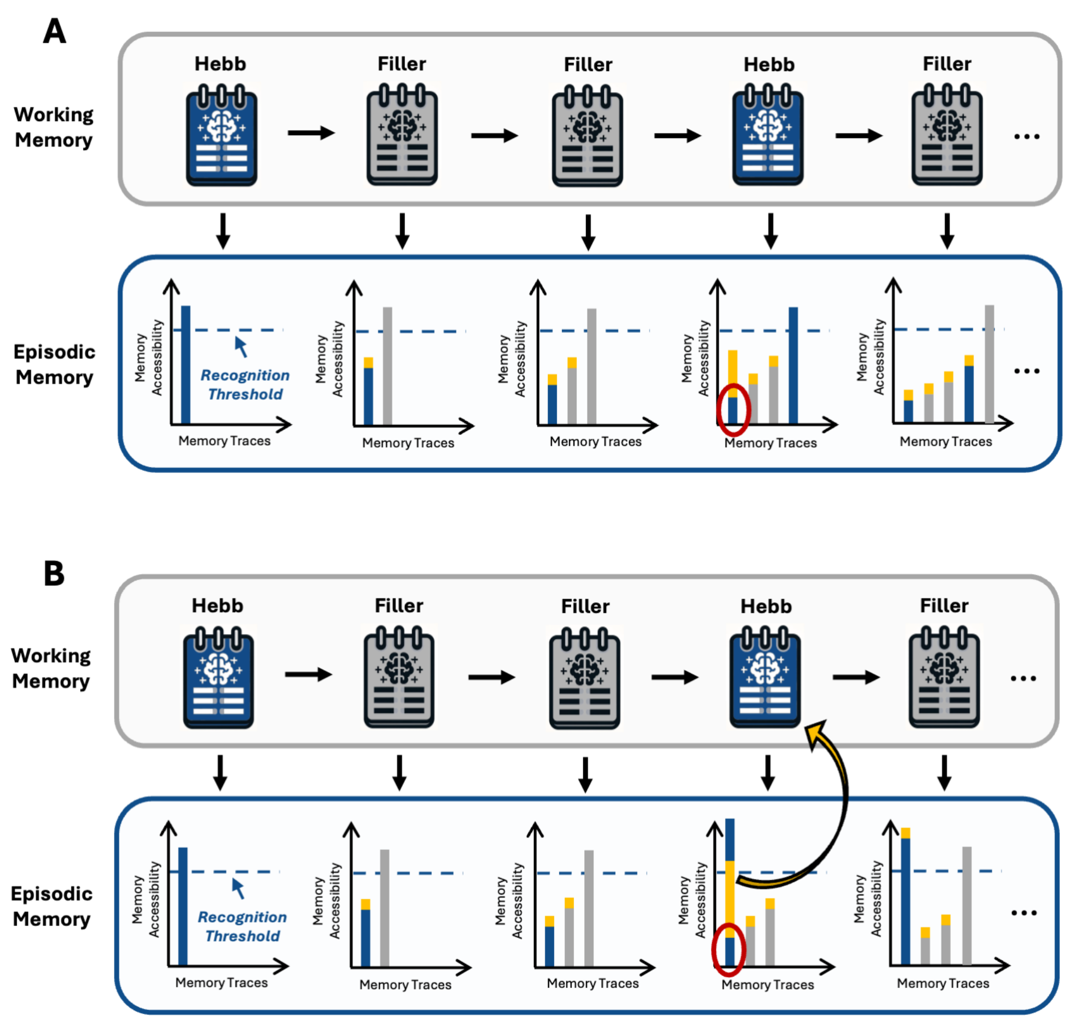
Based on the identified shortcomings, hybrid approaches have been proposed, which combine ideas from multiple-trace and cumulative strengthening accounts. These approaches are based on the idea of study-phase retrieval (Thios & D'Agostino, 1976), which has also been referred to as reminding (Benjamin & Tullis, 2010; Hintzman, 2004, 2010; Tullis et al., 2014). In reminding accounts, it is assumed that a repetition is only beneficial for memory if a repeated encounter of an event is recognized as such and leads to the retrieval of a previous encounter during encoding (i.e., It “reminds” of having seen this before). If reminding is successful, previous and current experiences can be integrated, thereby cumulating both experiences within a strengthened memory trace (Benjamin & Tullis, 2010; Hintzman, 2004). If a repetition does not remind of a previous encounter, however, the repetition will have no effect on memory traces of previous events and rather an independent memory trace is formed. We will next outline how such a reminding account offers a promising explanation for the Hebb repetition effect.

A Reminding Account of the Hebb Repetition Effect

The results reviewed above provide two crucial insights into the Hebb repetition effect: When data is analyzed on the level of individual participants, 1) learning curves follow a two-stage process, in which a phase without learning is followed by a rather rapid learning process with an onset that varies between people, and 2) the onset of learning is always preceded by or coincides with the moment at which participants explicitly recognize that a memory set is presented repeatedly. This suggests that explicit recognition of what is being repeated is a necessary condition for learning to occur and is consistent with the previously described idea of reminding. When applying this concept to the Hebb repetition effect, one could sketch the process as follows (see Figure 7 for a visualization).

Figure 7

Schematic visualization of the reminding account of learning in the Hebb paradigm. Each encoded memory set leaves a trace in episodic memory with a given accessibility. Accessibility of previous traces is reduced by encoding new memory sets into memory. When a new memory is encoded, it can cue previous encounters in episodic memory, thereby increasing their accessibility (indicated by the orange bars on top of the memory traces). When a memory set is repeated, two scenarios are possible: **A** *The repetition of a memory set could fail to re-activate a previous encounter sufficiently to cause its explicit retrieval. In this case, the repetition is not recognized, and an independent trace is laid down in episodic memory.* **B** *The repetition of a memory set could successfully cue the retrieval of a previous encounter, thereby allowing to integrate previous and recent encounters into a common trace and laying down a stronger trace instead of creating a new one.*



We first adopt the assumption from instance theory that every event, like the presentation of a memory set in a memory experiment, creates a trace of this event in (episodic) memory[10]. This idea has been consistently applied in both models of episodic memory and models of the Hebb repetition effect, and builds the most basic prerequisite for repetition learning (Benjamin & Tullis, 2010; Burgess & Hitch, 2006; Gillund & Shiffrin, 1984; Hintzman, 1984; Logan, 2002; Norris & Kalm, 2024; Shiffrin & Steyvers, 1997). Every time a new memory set is encoded, it will serve as a potential retrieval cue for previously encountered events stored in episodic memory. If the current event is a new memory set, it is unlikely to cue the retrieval of a previous event, and hence, a new independent trace is laid down in episodic memory. With that, multiple traces of similar memory episodes accumulate in episodic memory. When a memory set is repeated, two scenarios are possible.

First, encoding a repeated memory set could successfully cue the retrieval (or "remind") of a previous encounter of the same memory set. In that case, a person explicitly recognizes the repetition and – rather than generating a new trace – the current experience is integrated into the previous trace which has been retrieved from episodic memory (Benjamin & Tullis, 2010). This creates a stronger version of the original memory trace that is likely to be even more accessible upon future repetitions, and thereby enables a rapid cumulative learning process. In essence, this scenario

[10] For simplicity, we assume that each memory set is stored within a single episodic memory trace, but the same idea could be applied to storing multiple traces for different subsets of a memory set. Under some conditions, encoding longer lists within smaller subsets might even increase the chance for detecting repeated patterns (see, e.g., Musfeld, Dutli, et al., 2024).

closely resembles what has been incorporated as a default assumption into the models of Burgess and Hitch (2006) and Page and Norris (2009) for every trial of a Hebb experiment.

However, a second scenario is possible, which has not yet been considered for the Hebb repetition effect: Encoding a repeated memory set could fail to cue the retrieval of a previous encounter of the same memory set. In that case, the repetition is not recognized and will not result in learning. Instead, the episode is experienced as a new event and leaves an independent trace in episodic memory. If several repetitions of the same event remain unnoticed, multiple independent traces of this event accumulate in episodic memory. During this time, no performance improvements will be observed in the immediate memory task, because knowledge does not accumulate within a single memory trace. However, storing multiple traces of the same event increases the probability that at some point, at least one of these traces is retrieved during encoding of the repeated event, and eventually result in learning (Hintzman, 1976; Hintzman & Block, 1971). This is consistent with the observation that when the onset of learning is delayed, it is still followed by a strong learning effect (Musfeld et al., 2023).

In the presented proposal, the success of repetition learning depends on the accessibility of memory traces for previous events in episodic memory: If an existing memory trace of a specific event is not accessible upon its repeated encounter, memory representations are not strengthened. This leads to the prediction that the very same factors that have been identified to modulate the accessibility and strength of episodic memory traces should also modulate the success of repetition learning in the Hebb paradigm. Two of these factors that have been investigated extensively in research on episodic memory are the effects of retroactive interference and of retrieval practice, and we will discuss how the Hebb repetition effect is similarly affected by these variables.

The Role of Retroactive Interference for Repetition Learning in the Hebb Paradigm

Retroactive interference refers to the effect that newly memorized information can degrade the accessibility of previously memorized information, especially if those previous memories have not yet been properly consolidated (Müller & Pilzecker, 1900; Wixted, 2021). In the Hebb paradigm, this effect can occur when the accessibility of a repeated episode is impaired by the encoding of several unique Filler episodes in between two repetitions. In Figure 7, this is indicated by the decreasing accessibility of memory traces with the subsequent encoding of new memory episodes. This general idea was supported by an early finding by Melton (1963), who showed that learning effects in the Hebb paradigm can be impaired when more Filler episodes are added in between repetitions.

The pure encounter of new events between repetitions, however, might not be sufficient to account for a possible delay or absence of repetition learning effects in the Hebb paradigm. As we have established above, the occurrence of repetition learning effects depends on the successful recognition of a repeated memory set during its repeated presentation. In this process, the repeated presentation of a memory set serves as a (strong) retrieval cue, which might still be sufficient to re-activate an episode of its previous encounter, even if its accessibility has been degraded. Thus, another important factor to consider is the specificity of the repeated memory set to act as a retrieval cue for re-activating a memory trace of its previous occurrence (Nairne, 2002). If all memory episodes are relatively distinct from each other, the repeated presentation of a memory set should offer a relatively specific cue, and thus, the chance of recognizing a repetition should be high, even if several Filler episodes have been encoded in between repetitions. If, however, memory episodes are highly similar, repeating a memory set provides a less specific cue, and thus, might fail to reactivate its previous encounter. This has also been referred to as cue-overload and adds another form of interference to the retrieval stage of memories (Watkins & Watkins, 1975; Wixted, 2004). For the Hebb repetition effect, it leads to the prediction that learning should be harder with increasing similarity between lists.

Several studies have investigated the effect of list similarities on the Hebb repetition effect, typically by manipulating the degree of item overlap between repeated and filler lists (e.g., presenting the same items on every trial in a different order, or composing each list by different items; Dutli et al., 2024; Johnson & Miles, 2019; Melton, 1963; Page et al., 2013; Smalle et al., 2016). All of these studies align on the finding that higher list similarity / overlap resulted in a weaker Hebb repetition effect. This confirms the prediction described above and supports the assumption that repetitions have to be effective retrieval cues to re-activate memory traces of previous occurrences for repetition learning to occur. When this is not the case because many similar episodes have accumulated in episodic memory, repetitions can go unnoticed, leading to a delay or the absence of learning[11].

The Role of Testing and Retrieval Practice for Repetition Learning in the Hebb Paradigm

In research on episodic memory, testing has been found to be an effective way to enhance retention over the long-term: Successfully retrieving a memory representation during a test increases its chances to be retrieved again on a future test (Carpenter et al., 2008; Roediger & Karpicke, 2006). Moreover, this effect is stronger if memory retrieval is more demanding – for instance in a recall test compared to a recognition test (Carpenter & Delosh, 2006; Karpicke & Roediger, 2007). Thus, testing is one way to create more accessible representations in episodic memory. In the Hebb paradigm, testing is inherent, as typically each presented memory set is tested immediately after its presentation. Although this is primarily a test of working memory, it is still possible that representations in episodic memory contribute to this task, thereby practicing their retrieval and consolidating them in episodic memory (Bartsch & Oberauer, 2023; Oberauer et al., 2017; Oberauer & Awh, 2022; but see Oberauer & Bartsch, 2023 for evidence that episodic memory might contribute less to tasks typically used in the Hebb paradigm). This leads to the prediction that testing, and especially the

[11] Note that the model by Page and Norris (2009) incorporates a very similar mechanisms for explaining the effect of list similarities on repetition learning, while not relying on episodic memory or the assumption that repetitions have to be recognized.

retrieval demands of the test, should influence the success of learning in the Hebb paradigm, most probably by affecting the accessibility of previously encoded episodes.

Several studies have investigated the effects of testing on the Hebb repetition effect, mostly focusing on the learning of verbal sequences (Cohen & Johansson, 1967; Cunningham et al., 1984; Kalm & Norris, 2016; Oberauer & Meyer, 2009). These studies compared conditions in which the presentation of a memory list was followed by an immediate serial recall test to conditions in which memory lists were only encoded but not tested. The results converge on the finding that testing is not necessary (Kalm & Norris, 2016; Oberauer & Meyer, 2009), but strongly facilitates the occurrence of the Hebb repetition effect (Cohen & Johansson, 1967; Cunningham et al., 1984; Kalm & Norris, 2016; Oberauer & Meyer, 2009).

An even more critical role of testing has been identified for the Hebb effect in the visuospatial domain. Here, testing, and especially the need to recall the memory items, have been identified as a key factor for the Hebb repetition effect to occur (Musfeld, Souza, et al., 2024; Souza & Oberauer, 2022). Whereas many previous studies have failed to observe a Hebb repetition effect in the visuospatial domain when working memory was tested by a recognition task (Fukuda & Vogel, 2019; Logie et al., 2009; Olson & Jiang, 2004), it is observed reliably when a recall test is used (Musfeld, Souza, et al., 2024; Souza & Oberauer, 2022). Furthermore, Souza and Oberauer (2022) have shown that the strength of the Hebb repetition effect increases with the number of items that have to be recalled in each trial, thereby demonstrating a modulation of the effect by the retrieval demands at test.

Overall, these findings align with previous work on the testing effect (e.g., Carpenter et al., 2008; Carpenter & Delosh, 2006; Karpicke & Roediger, 2007; Roediger & Karpicke, 2006) in episodic memory. They imply that testing – and especially the retrieval demands of the test – provide an opportunity to practice the retrieval of the encoded information, which further consolidates that information in episodic memory and reduces its susceptibility to interference. This makes memory of the repeated sets more accessible and thereby more likely to be recognized and retrieved during a repeated encounter and hence, increases the probability of learning.

Challenges and Future Directions

In the last section, we have sketched a tentative framework for explaining recent findings on the Hebb repetition effect that incorporates a critical involvement of episodic memory in repetition learning. While we have shown the plausibility of this account by highlighting many parallels between the Hebb repetition effect and research on episodic memory, there are also a few challenges that arise from this perspective.

One of these challenges is the observation of a Hebb repetition effect in amnesic patients with damages in the medial temporal lobe (e.g., Gagnon et al., 2004). The medial temporal lobe, and especially the hippocampus, have been strongly associated with functions of episodic memory (like the recognition and retrieval of previously presented information), and damages in these brain areas have been found to result in related impairments (e.g., Eichenbaum et al., 2007; Kopelman et al., 2007; Manns et al., 2003; Squire et al., 2007; Wais et al., 2006). Thus, observing a Hebb repetition effect in patients with damages in the medial temporal lobe area questions the critical involvement of episodic memory in such learning. However, studies on this matter are rare, often rely on individual cases and have so far resulted in mixed results. Whereas some studies find that repetition learning is preserved in amnesic patients (Baddeley & Warrington, 1970; Gagnon et al., 2004; Rausch & Ary, 1990), others do observe related impairments (Charness et al., 1988; Drachman, 1966; Milberg et al., 1988). Thus, more direct tests of the involvement of episodic memory in the Hebb repetition effect will be required for testing the proposed account.

Another potential discrepancy lies in the relation between the Hebb repetition effect and the spacing effect in episodic memory. The spacing effect refers to the well-established finding that spaced repetitions (i.e., separating repeated study episodes by time and other content) leads to more successful learning than massed repetitions, without any separation of study opportunities (see, e.g., Cepeda et al., 2006; Delaney et al., 2010; Toppino & Gerbier, 2014 for overviews). The opposite, however, would be expected from the proposed framework: If the success of repetition learning depends on the accessibility of previous encounters of the same information in episodic memory, non-interleaved / massed repetition should result in more successful learning. Yet, these relations are likely more complex than sketched within this simplified framework. The reminding model by Benjamin and Tullis (2010) for example incorporates the assumption that a successful reminding is more beneficial for learning the more difficult it is to retrieve the associated information. This assumption could be easily integrated into the presented framework, as it is consistent with the finding that the strength of the Hebb repetition effect increases with the retrieval demands at test (e.g., Musfeld, Souza, et al., 2024; Souza & Oberauer, 2022). Thus, while massed repetitions in the Hebb paradigm might make the occurrence of successful remindings more likely, more spaced repetitions could still result in a stronger learning outcome, thereby accounting for the spacing effect. One difficulty for this assessment is that the Hebb repetition effect is typically studied over much shorter time intervals than the spacing effect. Although it has been demonstrated that representations learned in the Hebb paradigm are stable over extended periods of time (Page et al., 2013), it is yet to be shown how the robustness of such learning might be influenced by different repetition spacings during the initial learning.

A final open question is whether repetition learning leads to a strengthening of representations in episodic memory or to the creation of new representations in semantic memory. In the presented framework, we have adopted assumptions from reminding accounts, and more specifically, the assumption that repeated experiences are integrated into a previous episodic memory trace, which is retrieved if a reminding happens during encoding (Benjamin & Tullis, 2010). This allows this trace to become stronger over subsequent repetitions, but it keeps the locus of the learning effect within episodic memory. This also means that the retrieval of such representations remains dependent on episodic memory, which is an assumption that could be questioned. Learning from repetition is assumed to result in representations of knowledge, which is a kind of representation we typically associate with semantic rather than episodic memory (Renoult et al., 2019; Tulving, 1972). Thus, an alternative could be that - once some repeated pattern is recognized - a new representation is formed, which only integrates, or abstracts what is common among repeated study episodes. In this case, only the initial stage of the learning process (i.e., the recognition of what is repeated) depends on episodic memory, while the learned representation transitions into a state of semantic knowledge that is independent of specific contextual features an event has been experienced in. Future research will have to clarify to what extent a dependency on episodic memory remains throughout the learning process.

Conclusion

The Hebb repetition effect has been one of the most influential phenomena for studying the cognitive processes underlying repetition learning and the exchange of information between working memory and long-term memory. In this review, we have critically revisited the prevailing assumption that have been proposed to explain learning in Hebb's paradigm and reevaluated their validity in light of recent findings and developments. Contrary to long-standing assumptions, repetition learning in the Hebb paradigm does neither occur gradually nor implicitly. These assumptions are likely an artifact from analyzing data aggregated over participants and do not resonate with the data patterns observed for individual participants. Instead, learning repeated patterns seems to require the explicit recognition of what is being repeated. To account for these new insights, we have outlined a theoretical framework based on models of episodic memory, and especially the idea of reminding. Future research will be needed to test the predictions of our account more critically, and to develop a more formalized version of the account to derive more precise predictions. We believe that our proposal offers a new perspective that can explain many old findings and motivate new research on the topic.

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