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Repetition learning is neither a continuous nor an implicit process

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Learning advances through repetition. A classic paradigm for studying this process is the Hebb repetition effect: Immediate serial recall performance improves for lists presented repeatedly as compared to nonrepeated lists. Learning in the Hebb paradigm has been described as a slow but continuous accumulation of long-term memory traces over repetitions [e.g., Page & Norris, *Phil. Trans. R. Soc. B* 364, 3737–3753 (2009)]. Furthermore, it has been argued that Hebb repetition learning requires no awareness of the repetition, thereby being an instance of implicit learning [e.g., Guérard et al., *Mem. Cogn.* 39, 1012–1022 (2011); McKelvie, *J. Gen. Psychol.* 114, 75–88 (1987)]. While these assumptions match the data from a group-level perspective, another picture emerges when analyzing data on the individual level. We used a Bayesian hierarchical mixture modeling approach to describe individual learning curves. In two preregistered experiments, using a visual and a verbal Hebb repetition task, we demonstrate that 1) individual learning curves show an abrupt onset followed by rapid growth, with a variable time for the onset of learning across individuals, and that 2) learning onset was preceded by, or coincided with, participants becoming aware of the repetition. These results imply that repetition learning is not implicit and that the appearance of a slow and gradual accumulation of knowledge is an artifact of averaging over individual learning curves.

repetition learning | Hebb repetition effect | working memory | long-term memory | implicit learning

Significance

Learning from experience is ubiquitous: We get better the more we practice. Repetition learning has been studied using the Hebb repetition paradigm: Memory steadily improves for a repeated set appearing amid nonrepeated ones.
These data have been interpreted as showing a gradual accumulation of knowledge, assumed to occur without explicit awareness. Here, we show these conclusions are at fault.
First, individual data show variability in when people start learning and a fairly rapid performance increase afterward. This is inconsistent with a continuous accumulation of knowledge. Second, directly measuring repetition awareness revealed that awareness almost invariably preceded or co-occurred with learning. Our findings demand a reformulation of current theories: Recognition of the repetition triggers a swift boost on knowledge formation.

Learning from repetition is ubiquitous; we get better, the more we practice. We learn to ride a bike through repeated practice; we learn the words of a foreign language by studying them over and over again. The benefit of repetition has been found to be one of the most general properties of memory, and decades of research have been put into understanding the cognitive mechanisms behind this effect (see, e.g., refs. 1–3 for overviews).

Back in 1961, Donald Hebb introduced a paradigm to study repetition learning: Participants were presented with several nine-digit lists for an immediate memory test. Unbeknownst to participants, one of these lists was repeated every third trial. Immediate memory performance for the repeated memory list improved steadily with the number of repetitions, whereas memory performance for the nonrepeated filler lists remained constant (4).

This so-called Hebb repetition effect has been studied extensively and replicated with various kinds of materials, including letters (5, 6), words (7), spatial locations (8, 9), visuospatial configurations (10, 11), and faces (12, 13). Some researchers have proposed that the Hebb repetition effect can be used as a model for human language acquisition, in particular the learning of new word forms (2, 14–17), stressing the universality of the effect as an example of very general human learning processes. This general process is the acquisition of chunks (18), that is, of unified representations of repeatedly encountered configurations of elements, such as the sequence of phonemes that form a word or the constellations of chess pieces that form a recognizable pattern for experienced players (2, 19–21).

Chunk formation is key to the efficient interplay between working memory and long-term memory (20). Working memory is a capacity-limited system that holds mental representations temporarily available for use in thought and action (22, 23). Long-term memory, in contrast, is a capacity-unlimited system that stores our knowledge and experiences (24). The immediate memory test in Hebb's paradigm is a common test of working memory. The improvement through repetition of a memory set reflects the formation of new long-term memory traces, which are then used to support working memory in the immediate memory test (2, 25, 26). Thus, the Hebb repetition paradigm can serve as a model system for the interaction between working memory and long-term memory in the acquisition of new knowledge (2, 19, 27).

Current cognitive and computational models of the Hebb repetition effect have proposed that repetition learning constitutes a slow, continuous process. It is initialized by the first occurrence of a repeated memory set and reflects the accumulation of new long-term memory traces, which gradually gain in strength over repetitions (2, 19, 25).

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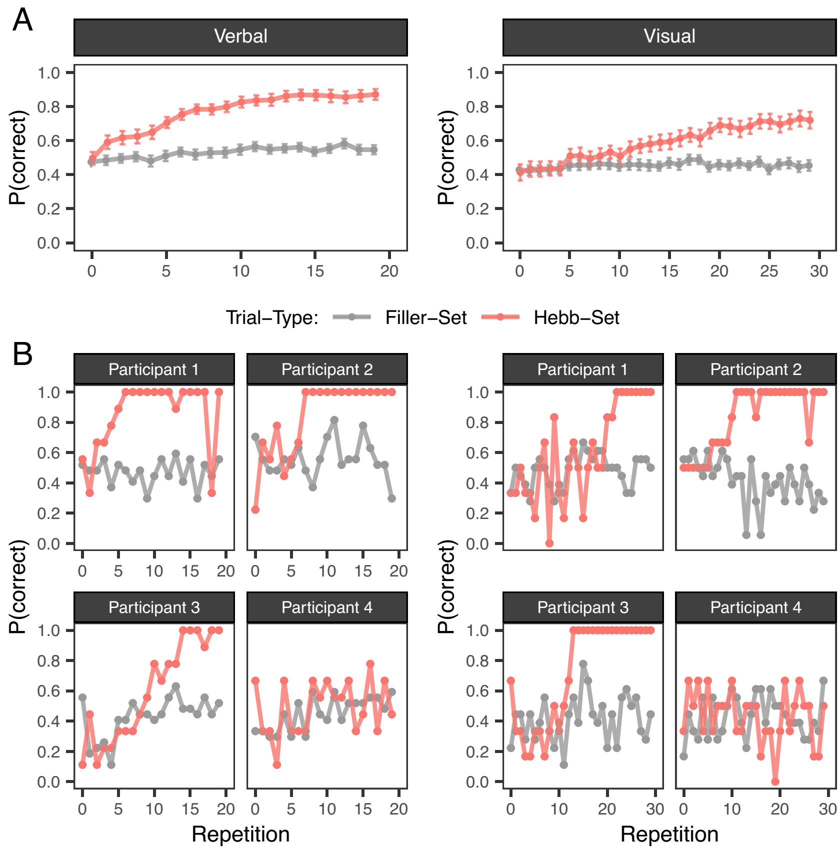

Fig. 1. (*A*) Examples of aggregated learning curves typically observed in Hebb repetition experiments. The data are from the "Awareness Rating Condition" of the verbal and visual Hebb experiments conducted in this study. (*B*) Examples of individual learning curves of four participants each, drawn from the aggregated samples shown on top. Note: P(correct) = proportion of correct responses. The x-axes in panels *A* and *B* show the repetition number for the Hebb set. For the filler sets, this corresponds to the average performance in each mini-block.

Furthermore, some authors have argued that the Hebb repetition effect is an instance of implicit learning (4, 8, 28–30). This means that people do not need to be aware of the memory set repetition to gradually build a long-term representation of it. However, other studies have questioned this claim (31–33). The role of repetition awareness for the Hebb repetition effect remains an open question.

A common problem underlying all existing studies on the Hebb repetition effect is that data of all participants are aggregated and analyzed on the group level. This has led to the typical observation of gradually increasing memory performance for the repeated memory set above nonrepeated sets (see Fig. 1*A* for typical examples). However, as Estes has already noted in 1956, drawing inference about cognitive processes from aggregated curves can be problematic because the aggregated curve does not necessarily reflect the shape of the curve on the individual level (34, 35). This problem becomes evident for the Hebb repetition effect. Fig. 1*B* shows examples of individual learning curves, which were drawn from the same sample displayed on the aggregated level in Fig. 1*A*. The individual learning curves do not resemble the aggregated learning curve. Instead, individual data suggest a two-stage process in which an initial phase of no learning is followed by a rather sudden onset of the learning process. The data show variability in the onset of the learning process and that for some participants, no learning effect is observed at all.*

*A collection of individual learning curves from every participant in the samples of the two present studies can be found in our online repository at https://osf.io/dpkyb/, showing that this pattern generalizes for all participants, not only for the selected ones.

This observation challenges the assumption that learning occurs gradually over repetitions and demands a reevaluation of the learning process on the individual level instead. One general characteristic of the individual learning curves shown in Fig. 1*B* is a variable onset of the learning effect, followed by a substantial improvement in immediate performance within just a few trials. This raises the question of what enables participants to suddenly improve on the repeated memory set. One possibility is that learning onset is caused by participants becoming aware of the repetition. This hypothesis contradicts the idea of repetition learning as an implicit process, but it is consistent with theoretical considerations about the repetition benefit in episodic long-term memory. Here, many findings have stressed the importance of study-phase retrieval or reminding as a crucial factor for learning from repetition (36–41). One idea emerging from this work is that the repeated presentation of a stimulus needs to cue the retrieval of a previous encounter of the same stimulus for strengthening effects to occur. Transferred to the Hebb paradigm, participants might need to explicitly retrieve a previous encounter of the repeated memory set before being able to benefit from the repetition.

This assumption leads to two predictions: First, the time at which people start to learn should correlate with the time at which they become aware of the repetition. Second, the time of awareness should precede, or coincide with, the onset time of learning. In contrast, if people become aware of the repetition only after the learning process had already started, learning would still reflect an implicit process, which leads to awareness in its wake. So far, no study has looked at the relationship between learning onset and awareness in the Hebb repetition paradigm at the level of individuals or at their temporal relation.

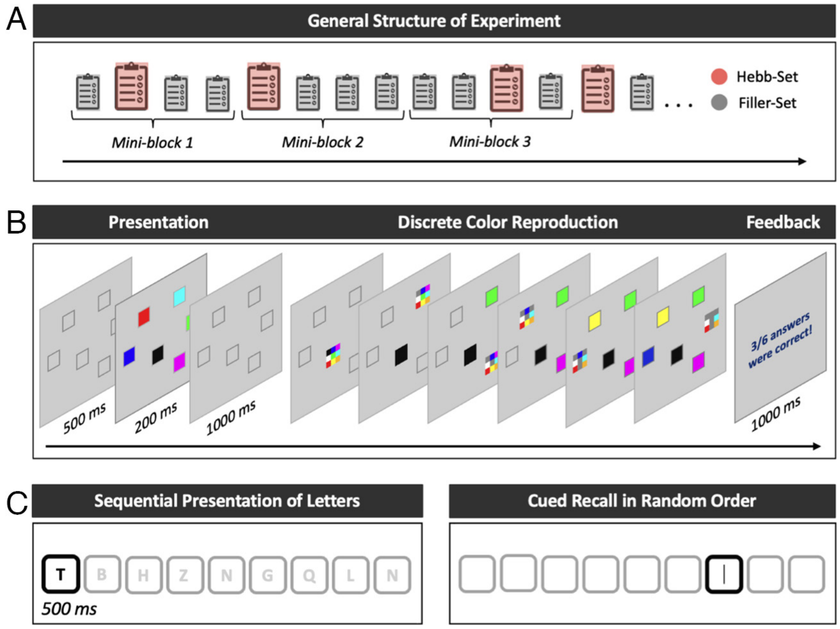

Fig. 2. Overview of the experimental design. (*A*) General structure of the Hebb paradigm as used in this study. One memory set, the Hebb set, is presented repeatedly among nonrepeated filler sets. The Hebb set appeared, on average, every fourth trial. (*B*) Flow of a trial in the visual Hebb experiment. (*C*) Flow of a trial in the verbal Hebb experiment. Note that in the actual experiment, the upcoming memory-list boxes were empty.

Here, we introduce a modeling approach which allowed us to do both: to analyze data on the level of individual participants and examine the temporal relation between the onset of the individual learning process and the onset of repetition awareness. In two typical Hebb experiments, one using verbal memory lists and one using visuospatial arrays, we combined the measurement of participants' immediate memory performance with a trial-by-trial assessment of their awareness of the repeated memory set (see Fig. 2 for an overview). Repetition awareness was assessed after each trial by asking participants whether or not they had seen the just-presented memory set before. Participants gave their response by adjusting a slider scale ranging from "very certain new" to "very certain repeated". This allowed us to measure if, and at which point in the experiment, a participant was able to distinguish between repeated and nonrepeated memory sets, thereby indicating awareness of the repetition. By relating this estimated onset of awareness to an estimate of the onset of learning, we identified the temporal relation between awareness and learning for each participant.

Asking participants about their awareness of a repeated memory set could affect the learning process itself, limiting the generality of our conclusions. To rule this out, we tested two control groups in which 1) participants did not perform the awareness rating task but were informed about the possibility of repeating memory sets (Information Only condition), or 2) participants did not perform the awareness rating task and received no additional information about the possibility of repeating memory sets (No Information condition). For all conditions, large samples of about 100 participants were collected.

Results

Modeling of Individual Learning Curves and Model Comparisons. To describe the learning process on the individual level, we developed a Bayesian hierarchical mixture model. We assumed each sample to be a mixture of learning and not learning participants (Fig. 1*B*). Accordingly, the model first classified participants into learning and not learning and includes a parameter for the proportion of learners. Next, the model predicted the number of correctly recalled items on each trial through a logistic function of a latent variable θ reflecting a person's ability to recall the current memory set.

For participants classified as not learning, we modeled θ as a linear function of mini-blocks of trials without distinguishing between repeated and unrepeated memory sets. Each mini-block included one presentation of the repeated Hebb set and three unrepeated filler sets (Fig. 2*A*). For learning participants, we assumed that participants, at some point, start to improve on the repeated memory set. To describe learning, we modeled θ for the repeated set by a growth curve with a variable onset point, whereas the filler sets were modeled as for the not learning participants. The learning curve was governed by three parameters: the onset point of the learning curve, the rate of learning, and an upper asymptote. Fig. 3*A* shows an example of the model fitted to a learning and a not learning participant. Further information on the model can be found in *SI Appendix*, *SI Methods*.

The modeling approach described here incorporates the assumption that the individual learning process should be described with a variable but instantaneous onset of the learning curve. This contrasts with the common assumption of repetition learning as a continuous process which starts with the first repetition. Therefore, we specified an alternative continuous model in which the onset of the learning process was fixed to the first occurrence of the repeated memory list and gradually accumulated over repetitions. Model comparisons using leave-one-out cross-validation (42) showed that our variable onset model outperformed the alternative continuous learning model for all collected samples. The exact results of the model comparison are presented in *SI Appendix*, Table S2.

Effect of the Awareness Rating Task on the Learning Effect. To track the onset of awareness, we assessed participants' awareness of the repeated memory list by asking about it after every trial in the Awareness Rating condition. This could have influenced participants' ability to learn the repeated list, thereby biasing the observed relation of interest. To control for this possibility, we included two control groups that were not requested to perform

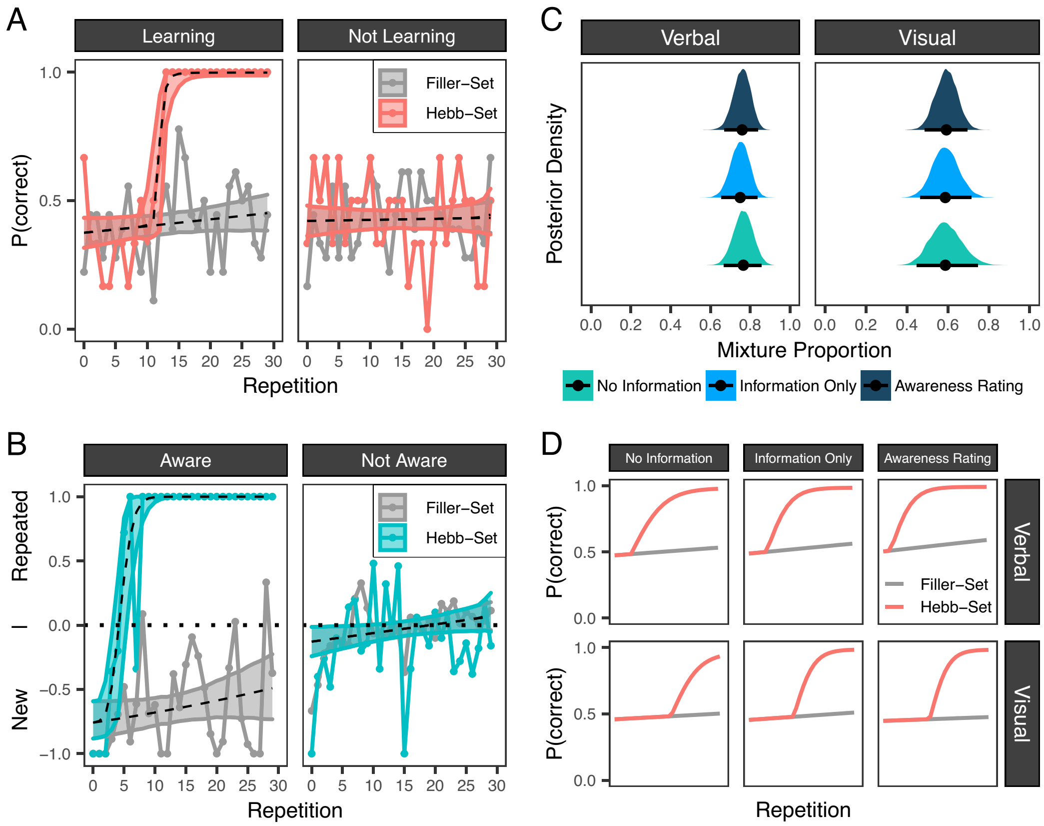

Fig. 3. Examples of learning (*A*) and awareness rating (*B*) data from two participants together with the fit of our model. The example shows the classification of participants into learning/not learning and aware/not aware. The dashed line indicates the predictions of the model with the best-fitting parameters. The colored areas indicate the range of model predictions with parameters sampled from their 95% highest density interval. (*C*) Estimated mixture proportions from the three experimental conditions in both experiments. The mixture proportion indicates the proportion of participants who were classified as learning. (*D*) Visualization of the estimated learning curves for the three experimental conditions in both experiments. Learning curves are generated with the medians of the posterior population-level parameters from the fitted model. Note: P(correct) = proportion of correct responses. The *x*-axes in panels *A* and *B* show the repetition number for the Hebb set. For the filler sets, this corresponds to the average performance in each mini-block.

the awareness rating task, and we fitted our measurement model separately to each group in both experiments. Comparing the estimated population-level learning parameters between the three groups allowed us to identify the putative impact of our awareness manipulations. Most important for this is the estimate of the mixture proportion, which indicates the proportion of participants who were able to learn the repeated set. Fig. 3*C* shows that there was no group difference in the proportion of participants learning the repeated set in both experiments. Fig. 3*D* displays the learning curves computed for each group from its population-level parameter estimates of the onset, rate, and asymptote of the learning curve. The three experimental groups did not show any substantial difference in any of these parameters. Hence, informing participants of the repetition, and testing their awareness of the repeated memory set, did not lead to a measurable effect on learning.

Awareness Rating Group: Temporal Relation between Awareness and Learning. In the Awareness Rating group, we fitted our measurement model not only to the learning data but also to the data from the awareness rating task to describe participants' awareness curves. This was possible because of the continuous assessment of awareness using a visual slider scale. Again, our model 1) classified participants into aware and unaware participants and 2) estimated the onset, the rate, and the upper asymptote of the awareness curves. This allowed us to estimate whether and when a participant became aware of the repetition. An example for the model fit to an aware and a not aware participant is presented in Fig. 3*B*. Awareness ratings were jointly modeled with the data from the working memory task in a multivariate model which allowed to estimate correlations between the parameters of the learning and the awareness process. We next assessed the relation between learning and awareness in three steps.

First, we cross-tabulated the classification of participants with regard to learning and awareness (Fig. 4*A*). In both experiments, the majority of participants were classified consistently as either aware and learning, or unaware and not learning, showing a close relation between the two processes. Critically, overall, only three participants were found who were classified as learning without showing indications of awareness. This combination is diagnostic for the presence of an implicit learning effect, but almost no participant met this condition. Additionally, none of these participants provided convincing evidence for the presence of an implicit learning effect because their performance was noisy: Either their awareness ratings were variable (verbal participants) or their learning effect was weak (visual experiment; *SI Appendix*, *SI Results*). Instead, a larger subset of participants was classified as being aware but without showing a learning effect (*SI Appendix*, *SI Results*), which indicates that awareness is a required but not sufficient condition for learning.

Second, we analyzed the correlations between parameters in the learning and awareness models. For both experiments, strong correlations were found between the onset points (verbal: r = 0.74 [0.46; 0.97]; visual: r = 0.82 [0.63; 0.94]), the learning rates (verbal: r = 0.83 [0.67; 0.95]; visual: r = 0.43 [0.05; 0.73]), and the upper asymptotes (verbal: r = 0.75 [0.52; 0.92]; visual: r = 0.67 [0.31; 0.91]) describing the learning and the awareness data, emphasizing that both processes were closely related (for a full posterior of all correlations, see *SI Appendix*, Fig. S1 in *SI Appendix*, *SI Results*).

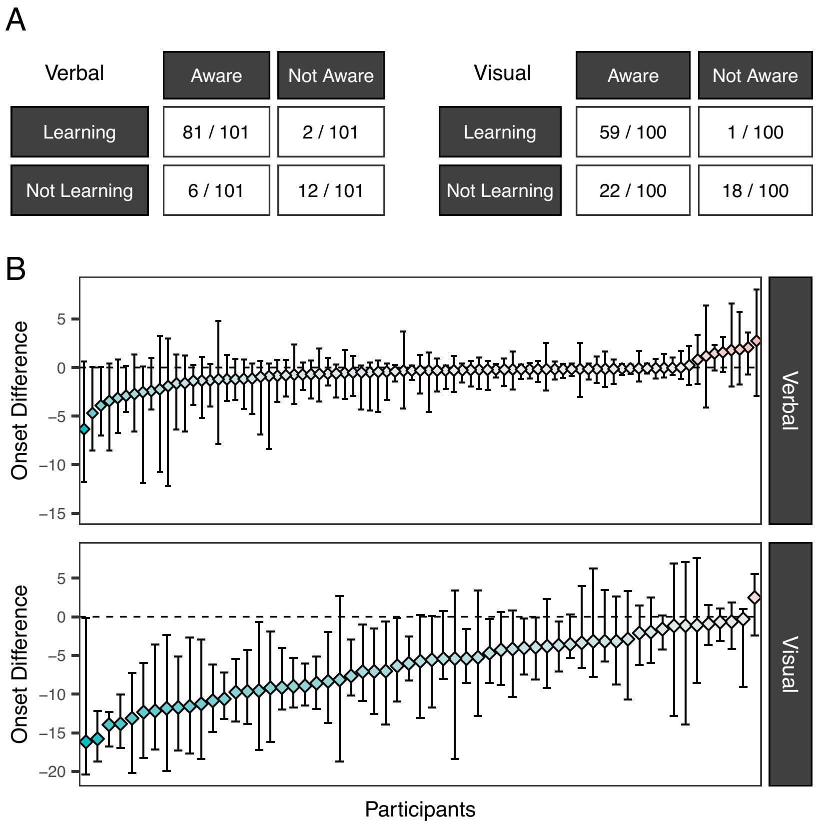

Fig. 4. Results for both experiments on the relation between awareness and learning in the "Awareness Rating" condition. (*A*) Cross-classification of participants into aware/not aware and learning/not learning. (*B*) Differences between the estimated onset of learning and estimated onset of awareness for each participant who was classified as aware and learning. Negative values indicate that the onset of awareness happened before onset of learning; positive values indicate that the onset of awareness happened after the onset of learning. Points reflect the median of the estimated onset difference. Error bars reflect the 95% highest density interval.

Third, we analyzed the temporal relation between the onset of awareness and the onset of learning within the subset of participants who had been classified as both aware and learning. For these participants, our model provided individual estimates of the onset point of repetition awareness and the onset point of learning. To evaluate how these onset points were related, we subtracted the posterior samples of the individual learning onset time from the posterior samples of the individual awareness onset. Because both onset points are estimated on the same temporal scale, the estimate of their difference tells us for each participant, which onset happened earlier. Negative onset differences show that repetition awareness occurred prior to learning, whereas positive onset differences show that learning commenced prior to repetition awareness. Fig. 4*B* presents the onset differences for each participant in the two experiments. Almost no participant showed an onset of the learning effect before becoming aware of the repetition. Instead, for almost every participant, the onset of the learning effect was either accompanied (verbal experiment) or preceded (visual experiment) by the onset of repetition awareness. This is further evidence against the idea that learning can occur implicitly without the person's awareness of the repetition. In contrast, it suggests that learning can only occur explicitly, when participants are also aware of the repetition.

Discussion

The present study investigated the mechanisms underlying repetition learning using the Hebb paradigm as an experimental model. Researchers have described this learning process as an accumulation of new long-term representations, which gradually gain in strength over repetitions. Furthermore, some—including Hebb himself—have claimed that this learning process could happen implicitly, without repetition awareness. However, these assumptions have been reached from looking at data aggregated over participants. As we have demonstrated here, the aggregated curves do not resemble the learning curves on the individual level, thereby inviting a misconception about the cognitive processes underlying repetition learning. With a hierarchical mixture model, we have shown that individual learning curves were instead better described by a two-stage process in which a phase of no learning is followed by a rather rapid learning process with variable onset points over repetitions. Our finding that individual learning curves differ qualitatively from those aggregated over individuals resonates with earlier work pointing toward potential artifacts of aggregation (34, 35, 43–47). The hierarchical mixture modeling approach introduced in this study offers a flexible and powerful tool for analyzing learning data on the level of individuals.

Our modeling approach also allowed us to investigate how the onset of learning is related to participants' awareness of the repetition. We found almost no participant who our model classified as learning without awareness, and for almost every participant who acquired awareness and learned, the learning effect was either preceded or accompanied by becoming aware of the repetition.

Our results are inconsistent with both the assumption of memory traces gaining in strength incrementally over repetitions and the assumption that this process could happen implicitly. Instead, our findings provide strong evidence for a two-stage process in which repetition awareness seems to be a necessary precursor for learning. This challenges existing explanations of the Hebb repetition effect and demands a reformulation of current theories and models.

We propose that during the first stage of learning, every episode—for instance, every trial of an immediate memory task—leaves a separate trace in episodic memory. This is an assumption based on the instance theory and forms the basis of several successful models of episodic memory (41, 48–53). Across multiple trials of a Hebb learning experiment, multiple traces of similar memory sets accumulate in episodic memory. Every time a newly presented memory set is encoded, its current representation in working memory acts as a potential retrieval cue for similar experiences in episodic memory. In this way, repeated memory sets in a Hebb experiment could elicit the retrieval of a previous encounter with the same memory set. However, weak encoding of individual episodes, as well as interference between representations in episodic memory, often renders memory traces of such previous encounters inaccessible (54–56). In that case, the person does not become aware of the repetition, and the current experience is not integrated with the episodic traces of previous experiences with the same memory set. Instead, a new episodic memory trace is created for every trial.

Over several repetitions, multiple independent traces of the same memory set are laid down, increasing the chance that at least one of them is accessed when the repeated set is encountered again (1, 57, 58). When a previous memory trace of the repeated memory set is accessed successfully, the current experience is integrated with the retrieved representation, thereby creating a stronger episodic trace that is more accessible upon future experiences of the repeated memory set. This assumption builds on work on the importance of study-phase retrieval, or reminding, which suggests that repetition is only beneficial to memory, if the repeated presentation of some information cues the retrieval of (i.e., "reminds of") a previous encounter with the same information (36–40, 59). Our results strongly support this assumption by showing that beneficial effects of repetition on immediate memory performance can only be observed when participants are able to explicitly recognize the repeated memory set.

Once a previous instance of the repeated memory set is retrieved from episodic memory, two processes are enabled. One is that the person becomes aware of the repetition (i.e., is able to report it). The other is that the representation of the current memory set in working memory can be integrated with the retrieved episodic memory trace rather than generating a new trace in episodic memory. This integration of repeated experiences of the same memory set averages out idiosyncrasies of individual experiences and strengthens what they have in common, thereby transforming an episodic memory trace into a representation of knowledge that is independent of individual experiences. As has been suggested in previous models of the Hebb effect (e.g., ref. 2), this knowledge can be characterized as a chunk that represents a repeated pattern in a compact, unified form (14, 27, 60). Our data suggest that this process, once initiated by explicit recognition, operates much faster than assumed in previous models as participants are often able to reach perfect performance on the repeated list or array within a few trials.

One finding in our data which deserves notice is the time lag between the onset of repetition awareness and the onset of the learning process in the visual experiment, which was largely absent in the verbal experiment. At this point, we can only speculate about causes of this lag. For verbal memory lists, list repetition can only be recognized by retrieving a memory trace of the same letter sequence in an earlier trial. This memory trace already contains information needed for recalling the list. By contrast, for visuospatial arrays, recognition of a repetition can rely on retrieval of the same spatial configuration of squares in a previous trial, without already retrieving which colors have been associated with each square location. This possibility is supported by evidence that people can remember the spatial locations of objects in an array but fail to remember which objects have been in which locations (61, 62). When that happens, recognition of the repeated array by its spatial configuration precedes retrieval of the color–location conjunction needed to improve task performance.

Is awareness of the repetition causally responsible for the onset of learning? In light of our proposed explanation of the two-stage learning process, we should expect not—rather, awareness and the onset of learning are both caused by the successful recognition and retrieval of a memory representation of a prior encounter with the same memory set. On that basis, purely informing people about a repetition should not accelerate learning. This is consistent with what we observe in this study: The between-group comparisons showed no evidence that informing participants of the repetition, and even asking them to watch out for it, accelerates learning. To accelerate learning, we predict that improving participants' ability to access episodic memory traces of previous instances of the same memory set will be more helpful than making them aware of the repetition.

Methods

Both experiments were preregistered prior to data collection, including the models which were used to analyze the data. Preregistrations, data, analysis scripts, model codes, and experimental software are available at https://osf.io/dpkyb/ (63). The experiments were part of a research project which received general ethics approval by the Ethics Committee of the Faculty of Arts and Social Sciences of the University of Zurich (approval no. 20.4.7). Both experiments were carried out in accordance with the regulations of that committee and did not require individual approval.

Experiments were programmed using the online study builder lab.js (64). The analytical models were programmed in Stan (65), and all analyses were carried out using *R v4.2.1* (66) and the R package *rstan v2.26.13* (67). A more extensive description of the experimental design, including a detailed description of the modeling approach, is provided in *SI Appendix*, *SI Methods*.

Participants. Data were collected online via the participant platform Prolific. We recruited a total of N = 301 participants for the visual ($n_{no\ information}$ = 99, $n_{information\ only}$ = 102, and $n_{awareness\ rating}$ = 100) and a total of N = 308 participants for the verbal experiment ($n_{no\ information}$ = 107, $n_{information\ only}$ = 100, and $n_{awareness\ rating}$ = 101). All participants were between 18 and 35 y old, were English speaking, and provided online informed consent prior to participation.

Stimuli. In the verbal experiment, memory lists consisted of nine consonants which were sampled without replacement from the set of all consonants except W and Y. In the visual experiment, memory arrays consisted of six colors which were selected from a set of nine discrete colors (white, black, blue, cyan, green, yellow, orange, red, and magenta). For each memory set, the spatial locations for presenting the colors were selected at random from an invisible 7×7 grid centered in the middle of the screen.

Design. Both experiments employed the same general design and differed only in their type of stimulus material and the number of trials performed.

Upon starting the experiment, participants were randomly assigned to one of three between-subject conditions. The conditions differed in the instruction participants received at the beginning of the study: Participants in the No Information condition received no information about the possibility that memory sets can repeat; participants in the Information Only group were informed about this possibility; participants in the Awareness Rating condition were informed about the possibility of repetition and additionally asked to rate their awareness of a repetition after each trial. To assure instructions were read carefully, participants answered a short questionnaire about the experiment before proceeding to the main task. For the Information Only and the Awareness Rating groups, this questionnaire contained a critical question about the possibility of repeating memory sets. Participants were only allowed to participate if all questions were answered correctly.

In both experiments, memory sets were randomly created anew for each participant. For the verbal experiment, 80 memory lists were created; for the visual experiment, 120 visual arrays were created. For each participant, one memory set was randomly selected as the repeated Hebb set, which was then repeated, on average, every fourth trial. For this, both experiments were divided into mini-blocks of four trials each. Within each mini-block, the Hebb set was shown once at a random trial position, with the only constraint that two Hebb trials were not allowed to follow immediately after another. There was a total of 20 repetitions in the verbal and 30 repetitions in the visual experiment. The remaining trials involved the presentation of nonrepeated filler sets.

Procedure. The Fig. 2 *B* and *C* shows the flow of a trial in the visual experiment and the verbal experiment, respectively.

In the visual experiment, each trial started with the presentation of six unfilled squares at random screen locations for 500 ms. These served as placeholders to indicate the positions of the presented items. The squares were simultaneously filled with six colors for 200 ms, followed by a retention interval of 1,000 ms. Position placeholders remained on-screen throughout the trial. For the working memory test, participants were cued with a random location of the array and asked to select the color which was presented at the cued location by choosing from a 3×3 matrix of nine possible colors. Each response option could only be used once within each trial. After being tested on all colors of the array in a random order, participants received a short text message about how many items they had recalled correctly. In the No Information and the Information Only conditions, the experiment moved on to the next trial. In the Awareness Rating condition, participants were asked if they had seen the just-presented memory list before (repeated) or not (new). Participants responded by adjusting a visual slider scale, ranging from "very certain new" to "very certain repeated". The center of the scale was labeled as "uncertain".

In the verbal experiment, each trial started with the presentation of a row of nine unfilled boxes for 500 ms. Afterward, boxes were sequentially filled from left to right with the nine consonants of a list. Each consonant remained visible for 500 ms, followed by a short interstimulus interval of 100 ms between consonants. Immediately after presentation of the last consonant, the working memory test started. Here, participants were cued with a random position of the list by highlighting one of the boxes on the screen and asked to type the consonant presented at the cued location. After being tested on all letters of a list in a random order, participants received a short information on how many items they had recalled correctly. Participants in the No Information and the Information Only groups moved on to the next trial, whereas participants in the Awareness Rating group performed the awareness rating task described above.

Data, Materials, and Software Availability. Anonymized CSV, TXT, analysis scripts, model codes, and experimental software data have been deposited in the Open Science Framework (https://doi.org/10.17605/OSF.IO/DPKYB) (63).

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1. M. J. Kahana, N. B. Diamond, A. Aka, Laws of human memory (2022). PsyArXiv [Preprint], 10.31234/osf.io/aczu9 (20 January 2023).
2. M. P. A. Page, D. Norris, A model linking immediate serial recall, the Hebb repetition effect and the learning of phonological word forms. *Phil. Trans. R. Soc. B* **364**, 3737–3753 (2009).
3. T. C. Toppino, E. Gerbier, "About Practice" in *Psychology of Learning and Motivation* (Elsevier, 2014), pp. 113–189.
4. D. O. Hebb, "Distinctive features of learning in the higher animal" in *Brain Mechanisms and Learning*, J. F. Delafresnaye, Ed. (Blackwell, 1961), pp. 37–46.
5. K. Oberauer, T. Jones, S. Lewandowsky, The Hebb repetition effect in simple and complex memory span. *Mem. Cogn.* **43**, 852–865 (2015).
6. M. P. A. Page, N. Cumming, D. Norris, G. J. Hitch, A. M. McNeil, Repetition learning in the immediate serial recall of visual and auditory materials. *J. Exp. Psychol. Learn. Memory Cogn.* **32**, 716–733 (2006).
7. M. P. A. Page, N. Cumming, D. Norris, A. M. McNeil, G. J. Hitch, Repetition-spacing and item-overlap effects in the Hebb repetition task. *J. Mem. Lang.* **69**, 506–526 (2013).
8. M. Couture, S. Tremblay, Exploring the characteristics of the visuospatial hebb repetition effect. *Memory Cogn.* **34**, 1720–1729 (2006).
9. M. Sukegawa, Y. Ueda, S. Saito, The effects of Hebb repetition learning and temporal grouping in immediate serial recall of spatial location. *Mem Cogn.* **47**, 643–657 (2019).
10. A. S. Souza, K. Oberauer, Promoting visual long-term memories: When do we learn from repetitions of visuospatial arrays? *J. Experiment. Psychol.* **151**, 3114–3133 (2022), 10.1037/xge0001236.
11. P. Musfeld, A. S. Souza, K. Oberauer, Testing expectations and retrieval practice modulate repetition learning of visuo-spatial arrays (2022). PsyArXiv [Preprint], 10.31234/osf.io/fsvkt (29 November 2022).
12. N. Horton, D. C. Hay, M. M. Smyth, Hebb repetition effects in visual memory: The roles of verbal rehearsal and distinctiveness. *Q. J. Exp. Psychol.* **61**, 1769–1777 (2008).
13. A. J. Johnson, C. Miles, Visual hebb repetition effects: The role of psychological distinctiveness revisited. *Front. Psychol.* **10**, 17 (2019).
14. D. Norris, M. P. A. Page, J. Hall, Learning nonwords: The Hebb repetition effect as a model of word learning. *Memory* **26**, 852–857 (2018).
15. A. Szmalec, M. P. A. Page, W. Duyck, The development of long-term lexical representations through Hebb repetition learning. *J. Memory and Language* **67**, 342–354 (2012).
16. J. Saint-Aubin, K. Guérard, The Hebb repetition effect as a laboratory analogue of language acquisition: Learning three lists at no cost. *Can. J. Exp. Psychol.* **72**, 2–8 (2018).
17. A. Szmalec, W. Duyck, A. Vandierendonck, A. B. Mata, M. P. A. Page, Short Article: The Hebb repetition effect as a laboratory analogue of novel word learning. *Q. J. Exp. Psychol.* **62**, 435–443 (2009).
18. G. A. Miller, The magical number seven, plus or minus two: Some limits on our capacity for processing information. *Psychol. Rev.* **63**, 81–97 (1956).
19. N. Burgess, G. J. Hitch, A revised model of short-term memory and long-term learning of verbal sequences. *J. Memory and Language* **55**, 627–652 (2006).
20. K. A. Ericsson, W. Kintsch, Long-term working memory. *Psychol. Rev.* **102**, 211–245 (1995).
21. F. Gobet, H. A. Simon, Templates in chess memory: A mechanism for recalling several boards. *Cognit. Psychol.* **31**, 1–40 (1996).
22. N. Cowan, The many faces of working memory and short-term storage. *Psychon. Bull. Rev.* **24**, 1158–1170 (2017).
23. K. Oberauer, "Design for a working memory" in *Psychology of Learning an Motivation* (Elsevier, 2009), pp. 45–100.
24. E. Tulving, "Episodic and semantic memory" in *Organization of Memory*, E. Tulving, W. Donaldson, Eds. (Academic Press, 1972).
25. N. Burgess, G. Hitch, Computational models of working memory: Putting long-term memory into context. *Trends Cognit. Sci.* **9**, 535–541 (2005).
26. N. Cumming, M. Page, D. Norris, Testing a positional model of the Hebb effect. *Memory* **11**, 43–63 (2003).
27. E. Mızrak,K. Oberauer,Working memory recruits long-term memory when it is beneficial: Evidence from the Hebb effect. *Journal of Experimental Psychology: General* **151**, 763–780 (2022).
28. K. Guérard, J. Saint-Aubin, P. Boucher, S. Tremblay, The role of awareness in anticipation and recall performance in the Hebb repetition paradigm: Implications for sequence learning. *Mem. Cogn.* **39**, 1012–1022 (2011).
29. S. J. McKelvie, Learning and awareness in the hebb digits task. *J. General Psychol.* **114**, 75–88 (1987).
30. L. Attout, L. Ordonez Magro, A. Szmalec, S. Majerus, The developmental neural substrates of Hebb repetition learning and their link with reading ability. *Hum. Brain. Mapp.* **41**, 3956–3969 (2020).
31. S. Gagnon, M.-J. Bédard, J. Turcotte, The effect of old age on supra-span learning of visuo-spatial sequences under incidental and intentional encoding instructions. *Brain and Cognition* **59**, 225–235 (2005).
32. W. X. Q. Ngiam, J. A. Brissenden, E. Awh, "Memory compression" effects in visual working memory are contingent on explicit long-term memory. *J. Exp. Psychol. General* **148**, 1373–1385 (2019).
33. A. Shimi, R. H. Logie, Feature binding in short-term memory and long-term learning. *Q. J. Exp. Psychol.* **72**, 1387–1400 (2019).
34. W. K. Estes, The problem of inference from curves based on group data. *Psychol. Bull.* **53**, 134–140 (1956).
35. C. R. Gallistel, S. Fairhurst, P. Balsam, The learning curve: Implications of a quantitative analysis. *Proc. Natl. Acad. Sci. U.S.A.* **101**, 13124–13131 (2004).
36. F. S. Bellezza, H. B. Winkler, F. Andrasik, Encoding processes and the spacing effect. *Memory Cognit.* **3**, 451–457 (1975).
37. A. S. Benjamin, J. Tullis, What makes distributed practice effective? *Cognit. Psychol.* **61**, 228–247 (2010).
38. D. L. Hintzman, Judgment of frequency versus recognition confidence: Repetition and recursive reminding. *Memory Cognit.* **32**, 336–350 (2004).
39. W. A. Johnston, C. N. Uhl, The contributions of encoding effort and variability to the spacing effect on free recall. *J. Exp. Psychol. Hum. Learn. Memory* **2**, 153–160 (1976).
40. A. W. Melton, Repetition and retrieval from memory. *Science* **158**, 532–532 (1967).
41. J. G. W. Raaijmakers, Spacing and repetition effects in human memory: Application of the SAM model. *Cognit. Sci.* **27**, 431–452 (2003).
42. A. Vehtari, A. Gelman, J. Gabry, Practical Bayesian model evaluation using leave-one-out cross-validation and WAIC. *Stat. Comput.* **27**, 1413–1432 (2017).
43. A. Cochrane, C. S. Green, Assessing the functions underlying learning using by-trial and by-participant models: Evidence from two visual perceptual learning paradigms. *J. Vis.* **21**, 5 (2021).
44. B. A. Dosher, Z.-L. Lu, The functional form of performance improvements in perceptual learning: Learning rates and transfer. *Psychol. Sci.* **18**, 531–539 (2007).
45. A. Heathcote, S. Brown, D. J. K. Mewhort, The power law repealed: The case for an exponential law of practice. *Psychonomic Bull. Rev.* **7**, 185–207 (2000).
46. S. M. Stratton, Y.-T. Liu, S. L. Hong, G. Mayer-Kress, K. M. Newell, Snoddy (1926) revisited: Time scales of motor learning. *J. Motor Behav.* **39**, 503–515 (2007).
47. P. Zhang, Y. Zhao, B. A. Dosher, Z.-L. Lu, Assessing the detailed time course of perceptual sensitivity change in perceptual learning. *J. Vis.* **19**, 9 (2019).
48. D. L. Hintzman, MINERVA 2: A simulation model of human memory. *Behav. Res. Methods Instrument. Comput.* **16**, 96–101 (1984).

49. R. K. Jamieson, B. T. Johns, J. R. Vokey, M. N. Jones, Instance theory as a domain-general framework for cognitive psychology. *Nat. Rev. Psychol.* **1**, 174–183 (2022).
50. G. D. Logan, Toward an instance theory of automatization. *Psychol. Rev.* **95**, 492–527 (1988).
51. G. D. Logan, An instance theory of attention and memory. *Psychol. Rev.* **109**, 376–400 (2002).
52. R. M. Nosofsky, "The generalized context model: An exemplar model of classification" in *Formal Approaches in Categorization*, E. M. Pothos, A. J. Wills, Eds. (Cambridge University Press, ed. 1, 2011), pp. 18–39.
53. R. M. Shiffrin, M. Steyvers, A model for recognition memory: REM—retrieving effectively from memory. *Psychon. Bull. Rev.* **4**, 145–166 (1997).
54. R. G. Crowder, *Principles of Learning and Memory* (Lawrence Erlbaum Associates; distributed by the Halsted Press, 1976).
55. O. C. Watkins, M. J. Watkins, Buildup of proactive inhibition as a cue-overload effect. *J. Exp. Psychol. Hum. Learn. Memory* **1**, 442–452 (1975).
56. J. T. Wixted "The role of retroactive interference and consolidation in everyday forgetting *" in *Current Issues in Memory*, J. Rummel, Ed. (Routledge, ed. 1, 2021), pp. 117–143.
57. D. L. Hintzman, "Repetition and Memory" in *Psychology of Learning and Motivation* (Elsevier, 1976), pp. 47–91.
58. D. L. Hintzman, R. A. Block, Repetition and memory: Evidence for a multiple-trace hypothesis. *J. Exp. Psychol.* **88**, 297–306 (1971).
59. T. M. Ensor, A. M. Surprenant, I. Neath, Modeling list-strength and spacing effects using version 3 of the retrieving effectively from memory (REM.3) model and its superimposition-of-similar-images assumption. *Behav. Res.* **53**, 4–21 (2021).
60. D. Norris, K. Kalm, J. Hall, Chunking and redintegration in verbal short-term memory. *J. Exp. Psychol. Learn. Memory Cognit.* **46**, 872–893 (2020).
61. Y. A. Markov, I. S. Utochkin, T. F. Brady, Real-world objects are not stored in holistic representations in visual working memory. *J. Vis.* **21**, 18 (2021).
62. Y. Pertzov, M. Y. Dong, M.-C. Peich, M. Husain, Forgetting what was where: The fragility of object-location binding. *PLoS One* **7**, e48214 (2012).
63. P. Musfeld, A. Souza, K. Oberauer, Data, materials, and code for: Repetition learning: Neither a continuous nor an implicit process. *Open Science Framewrok*. 10.17605/OSF.IO/DPKYB. Deposited 23 October 2022.
64. F. Henninger, Y. Shevchenko, U. Mertens, P. J. Kieslich, B. E. Hilbig, lab.js: A free, open, online experiment builder. *Zenodo*. 10.5281/ZENODO.597045. Deposited 5 March 2021.
65. Stan Development Team, Stan modeling language users guide and reference manual (Version 2.30, R Package, 2022).
66. R Core Team, R: A language and environment for statistical computing (Version 4.2.2, R Foundation for Statistical Computing, Vienna, Austria, 2022).
67. Stan Development Team, RStan: The R interface to Stan (Version 2.26.13, R Package, 2022).