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Cognition and Behavior

Manipulating the Rapid Consolidation Periods in a Learning Task Affects General Skills More than Statistical Learning and Changes the Dynamics of Learning

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Abstract

Memory consolidation processes have traditionally been investigated from the perspective of hours or days. However, recent developments in memory research have shown that memory consolidation processes could occur even within seconds, possibly because of the neural replay of just practiced memory traces during short breaks. Here, we investigate this rapid form of consolidation during statistical learning. We aim to answer (1) whether this rapid consolidation occurs in implicit statistical learning and general skill learning, and (2) whether the duration of rest periods affects these two learning types differently. Human participants performed a widely used statistical learning task—the alternating serial reaction time (ASRT) task—that enables us to measure implicit statistical and general skill learning separately. The ASRT task consisted of 25 learning blocks with a rest period between the blocks. In a between-subjects design, the length of the rest periods was fixed at 15 or 30 s, or the participants could control the length themselves. We found that the duration of rest periods does not affect the amount of statistical knowledge acquired but does change the dynamics of learning. Shorter rest periods led to better learning during the learning blocks, whereas longer rest periods promoted learning also in the between-block rest periods, possibly because of the higher amount of replay. Moreover, we found weaker general skill learning in the self-paced group than in the fixed rest period groups. These results suggest that distinct learning processes are differently affected by the duration of short rest periods.

Key words: general skill learning; rapid consolidation; statistical learning

Significance Statement

Results of this study suggest that short rest periods affect general skill learning and the dynamics of statistical learning. Shorter rest periods could lead to online learning, while longer rest periods promote offline improvement. Our results can be explained by the different number of neural replays during the different lengths of short rest periods.

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Introduction

Learning is the process of gaining knowledge or skills by studying, practicing, or experiencing events repeatedly. The development of knowledge is not limited to the duration of the practice, as it continues to develop between training sessions, either during awake or sleep periods. This phenomenon is known as memory consolidation (Robertson et al., 2004b). Consolidation was previously thought to occur during an extended period, from hours to days (Squire et al., 2015). Recent studies suggest that memory consolidation can occur within shorter periods, even in seconds (Bönstrup et al., 2019). It has been suggested that this phenomenon is because of the neural replay of just practiced memory traces during short breaks (Buch et al., 2021). However, previous research has investigated the effect of short rest periods—when replays occur—on learning only with one predetermined fixed rest period (Du et al., 2016; Bönstrup et al., 2019) or multiple self-paced rest periods (Quentin et al., 2021; Fanuel et al., 2022). Their results do not allow us to determine the causal role of short rests in the learning process, or whether more replay leads to better learning performance. To fill this gap, in the present study, we manipulated the duration of rest periods—indirectly the possible amount of replay—to test whether rest durations affect differently (1) the general speedup on a statistical learning task independent of the statistical probabilities in the task (general skill learning) and (2) the learning of statistical probabilities (statistical learning).

Rest periods inserted in a learning process may facilitate the acquisition of new skills (Walker et al., 2002). In the study of Bönstrup et al. (2019), the performance on an explicit motor skill learning task improved during short, 10 s rest periods. In their study, frontoparietal β oscillatory activity during rest periods was associated with learning gains from rapid consolidation. A reanalysis of these data suggested that such rapid consolidation is driven by the replay of just practiced memory traces during short breaks (Buch et al., 2021). As the awareness of learning determines how knowledge acquisition gains from offline periods (Robertson et al., 2004a, b), this rapid consolidation may manifest differently or even be absent during implicit learning of statistical

regularities. Implicit statistical learning implies the process of unintentional acquisition of probabilistic regularities embedded in the environment (Cleeremans and Jimenez, 1998; Howard et al., 2004). So far, two studies have examined the rapid consolidation in implicit statistical learning. On one hand, they have found that implicit acquisition of statistical knowledge does not improve during short breaks but deteriorates, and this effect is not associated with the length of rest periods (Fanuel et al., 2022). On the other hand, statistical learning was found to develop during practice (online), indicating that it benefits from evidence accumulation during practice and the information learned does not consolidate during short rest periods (Quentin et al., 2021).

Based on previous results, implicit statistical learning occurs only online and does not benefit from rapid consolidation. However, previous studies have a crucial limitation: the length of the rest periods was not controlled experimentally. In the present study, to grasp a causal relationship between the length of breaks and the learning performance, we varied the rest period duration between participants. We aimed to test whether shorter and longer rest durations affect the performance of implicit statistical learning (i.e., the learning of probabilistic regularities) and general skill learning (i.e., the general speedup on a learning task independent of the statistical probabilities). To tackle this question, we used the alternating serial reaction time (ASRT; Fig. 1A,B) task (Howard et al., 2004), which enables us to measure these two aspects of learning separately. Healthy adults performed 25 blocks of the ASRT task (one block = 80 trials) and were offered to rest after each block. The rest period was (1) a shorter 15 s break, (2) a 30 s break, or (3) a self-paced duration (Fig. 1C). As rapid consolidation is related to neural replay (Buch et al., 2021), we expected that the extended rest periods would benefit implicit statistical learning more than the shorter rest periods because of the higher amounts of replays. Moreover, we aimed to test whether there is dissociation in the temporal dynamics of general skill learning and statistical learning regarding online and offline changes and how it is affected by the length of the rest periods.

Materials and Methods

Participants

There were 361 participants in this preregistered, online study (<https://osf.io/pfy7r>). Participants were university students and gained course credits for their participation. Following careful quality control of participant data (see below in the section Quality control of data), the final sample consisted of 268 participants (age: mean = 21.46 years; SD = 2.20 years; 77.61% female, 22.39% male). Participants were randomly divided into three groups (15 s break, 30 s break, and self-paced). Participants in the three groups did not differ in age, education, sex, handedness, or working memory performance (Table 1). All participants had normal or corrected-to-normal vision, and none of them reported a history of any neurologic or psychiatric condition. Participants provided informed consent, and all study procedures were approved by the

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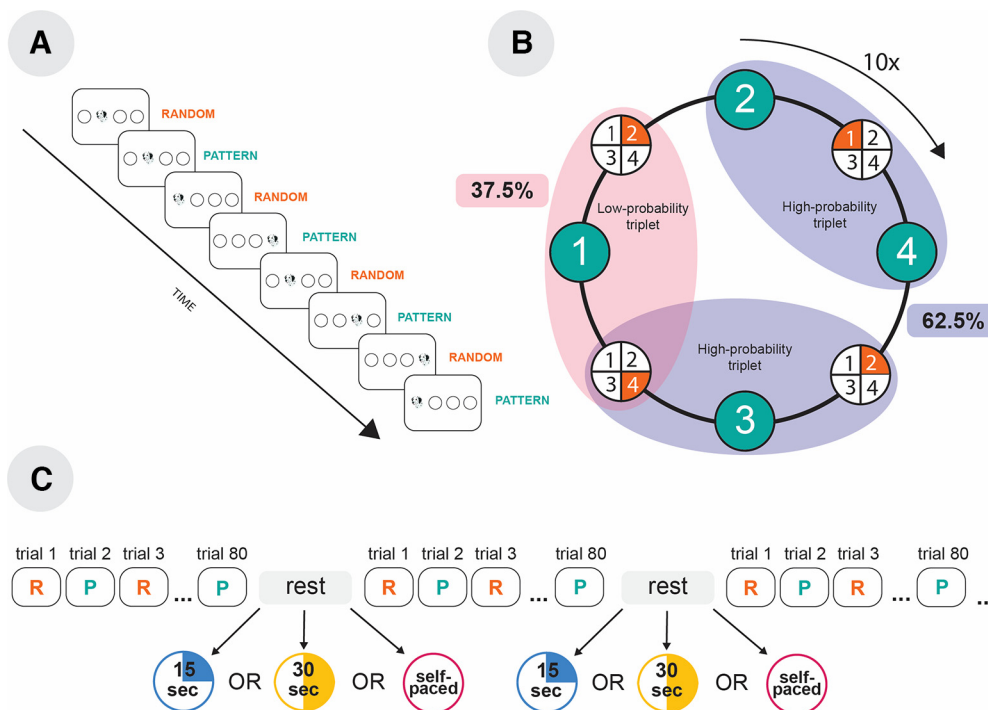


Figure 1. The ASRT task and the study design. **A**, The temporal progress of the task. A drawing of the head of a dog appeared as a target stimulus in one of four horizontally arranged locations. The stimuli followed a probabilistic sequence, where every other trial was a part of a four-element fixed sequence (pattern elements) interspersed with random elements. **B**, The formation of triplets in the task. In the eight-element probabilistic sequence, pattern (green) and random (orange) trials alternated. Numbers 1–4 represent the location of the four circles from left to right. Every trial was categorized as the third element of three consecutive trials (i.e., a triplet). Because of the probabilistic sequence structure, some triplets appeared with higher probability (high-probability triplets) than others (low-probability triplets). The ratio of high-probability triplets was higher (62.5% of all trials) than that of low-probability triplets (37.5% of all trials). The eight-element alternating sequence was repeated 10 times in a learning block. **C**, Study design. Each block contained 80 trials. The between-blocks rest period was 30 s (30 s group), 15 s (15 s group), or a self-paced duration (self-paced group).

Research Ethics Committee of the Eötvös Loránd University (Budapest, Hungary) and was conducted in accordance with the Declaration of Helsinki.

Alternating serial reaction time task

We used the ASRT task to measure implicit statistical and general skill learning separately. The ASRT task was programmed in JavaScript using the jsPsych framework [de Leeuw, 2015; code is openly available on GitHub: https://github.com/vekteo/ASRT_rapid_consolidation (see also <https://doi.org/10.5281/zenodo.7124730>)]. During the ASRT task, a visual stimulus appeared on the screen (a drawing of the head of a dog) in one of four horizontal

locations. Participants must have indicated the location of the target stimulus by pressing the corresponding key on the keyboard (from left to right, the S, F, J, and L keys on a computer keyboard). Participants were instructed to use their left and right middle and index fingers to respond to the targets. Unknown to the participants, the stimuli followed a probabilistic eight-element sequence, where pattern and random elements alternated with each other (e.g., 2 - r - 4 - r - 3 - r - 1 - r, where *r* indicates a random location, and the numbers represent the predetermined positions from left to right). Each participant was randomly assigned to 1 of 24 possible sequences (as the permutation of the 8-element sequence structure allowed 24 different sequences) and then was exposed to

Table 1: Descriptive statistics of the three experimental groups

	Self-paced group (<i>n</i> = 88)	15 s group (<i>n</i> = 90)	30 s group (<i>n</i> = 90)	Comparison
Age (years)	21.89 ± 2.07	21.24 ± 2.23	21.27 ± 2.26	<i>p</i> = 0.09, BF ₀₁ = 2.76
Education (sec/BA/MA)	68/17/3	67/22/1	73/16/1	<i>p</i> = 0.56, BF ₀₁ = 16.37
Gender (M/F)	18/70	20/70	22/68	<i>p</i> = 0.82, BF ₀₁ = 16.43
Handedness (l/r/a)	8/80/0	8/80/2	10/78/2	<i>p</i> = 0.68, BF ₀₁ = 10.02
2-back task (<i>d'</i>)	1.57 ± 0.95	1.49 ± 0.87	1.52 ± 0.89	<i>p</i> = 0.82, BF ₀₁ = 21.03

Mean and SD values for age and 2-back task are presented. For education (sec, secondary education or lower; BA, bachelor’s level or equivalent; MA, master’s level or equivalent), gender (M, male; F, female), and handedness (l, left, r, right, a, ambidextrous), case numbers are presented. To compare age and 2-back task scores, one-way ANOVAs were conducted. To compare education, gender, and handedness ratios, χ^2 tests were conducted.

that one sequence throughout the task. Because of the probabilistic sequence structure, some runs of three consecutive stimuli (triplet) appeared with higher probability (high-probability triplets) because the third element of such triplets can be predicted by the first trial with a greater probability (62.5% of all trials) compared with third elements of other triplets that can be predicted by the first trial with a lower probability (low-probability triplets, 37.5% of all trials). We can sort every item according to whether they are the third element of a high-probability or a low-probability triplet. Statistical learning was defined as the increase of reaction time (RT) difference between trials that were the third element of a high-probability triplet or low-probability triplet. General skill learning was defined as the overall speeding up on the task (i.e., smaller RTs in later blocks), regardless of the probability of the occurrence of items.

Process dissociation procedures task

To determine whether the learning of statistical regularities occurred implicitly, we administered a task based on the process dissociation procedure (PDP; Jacoby, 1991), which is a widely used method to disentangle the explicit-implicit processes in memory tasks (Destrebecqz and Cleeremans, 2001; Destrebecqz et al., 2005; Jiménez et al., 2006; Fu et al., 2010). In the first part of the task, we asked participants to try to create a sequence with the help of the same four response keys as used in the ASRT task (inclusion instruction). After that, we asked participants to generate new sequences that differed from the learned sequence (exclusion condition). Both parts consisted of four runs, and each run lasted up to 24 button presses, equivalent to three rounds of the eight-element alternating sequence (Kóbor et al., 2017; Horváth et al., 2020). The runs where >50% of participants' key presses were either repetitions or trills were removed from the analysis. As a result, seven participants from the self-paced group, three participants from the 15 s group, and three participants from the 30 s group were removed entirely from the analysis, as their answers only contained trills and repetitions in the exclusion condition.

We assessed the implicitness of the participants' knowledge by calculating the ratio of high-probability triplets in the sequence of responses. The chance level of generating high-probability triplets was considered 25% because, after two consecutive button presses, the chance for the third button press to form a high-probability triplet with the two preceding button presses is $1/4 = 25\%$. We also compared the percentages of the high-probability triplets across conditions (inclusion and exclusion condition) and groups (self-paced, 15 s, 30 s) (see also <https://doi.org/10.5281/zenodo.7253644>).

Procedure

We used the Gorilla Experiment Builder (<https://www.gorilla.sc>) to host our experiment (Anwyl-Irvine et al., 2020), which allows accurate stimulus and response timing in online experiments (Anwyl-Irvine et al., 2021). Data

were collected between April 13, 2021, and October 31, 2021 (experiment material is available on Gorilla Open Materials, <https://app.gorilla.sc/openmaterials/397611>). Participants were randomly assigned to one of three versions of the task, which differed only in the duration of between-block rest periods. The between-block rest periods were either (1) 15 s breaks, (2) 30 s breaks, or (3) self-paced (i.e., participants were allowed to continue the task with the next block whenever they were ready). The participants performed two practice blocks, then continued with 25 learning blocks, which took ~25 min to complete. Each block consisted of 80 trials, corresponding to the eight-element sequence repeated 10 times. Accuracy and RT were recorded for each trial. After accomplishing the ASRT task we tested the participants' awareness of the hidden structure with a short questionnaire and a task based on the process dissociation procedure, which enables us to differentiate explicit and implicit processes in memory tasks (Jacoby, 1991). Finally, they performed 0-back and 2-back tasks (Kirchner, 1958) to assess their working memory capacity (see <https://doi.org/10.5281/zenodo.7100178>). Data are available on OSF (<https://osf.io/ukbfz/>).

Quality control of data

We have set up exclusion criteria before the analysis of the data. Participants were deemed unreliable and were excluded if (1) they did not reach 80% accuracy on the ASRT task (34 participants were excluded for this reason), as in laboratory experiments the general accuracy on the ASRT task is typically >90% (Janacsek et al., 2012); or (2) they performed the 0-back task with <60% accuracy (8 participants), (3) did not complete the *n*-back tasks correctly (i.e., did not press response keys during the task; 16 participants), or (4) had quit the experiment and restarted later (4 participants); or (5) indicated that they had already taken part in an ASRT experiment (8 participants); and (6) had not started blocks on time after the rest period expired (21 participants). We fixed this limit at 1500 ms after the end of the rest period in at least five blocks, and we also excluded the participants whose average RT for the first trials of blocks was >1000 ms (9 participants in the 15 s group; 12 participants in the 30 s group). In addition to the participants excluded according to the predetermined exclusion criteria, as the age range was wide and unequal among the groups, outlying participants (age >35 years) were also excluded (11 participants).

Quantification of statistical learning and general skill

Inaccurate responses, trills (e.g., 1-2-1) and repetitions (e.g., 1-1-1), and trials with an RT of >1000 ms were excluded from the analysis. There was a total of 535,994 trials, from which a total of 49,927 (9.31%) incorrect trials were excluded. Regarding triplets, 48,715 (9.09%) were trills (e.g., 1-2-1), and 16,302 (3.04%) were repetitions (e.g., 1-1-1). Furthermore, there were 1304 trials (0.24% of all trials) with RTs >1000 ms. As there were overlaps between the trials with different exclusion criteria (e.g.,

from the 48,715 trials, 7544 were also incorrect trials), the total number of excluded trials is not the sum of the numbers of the different types of excluded trials. We excluded a total amount of 108,344 trials (20.22% of all trials).

To facilitate data processing and filter out noise, the blocks of ASRT were organized into units of five consecutive blocks (Bennett et al., 2007; Barnes et al., 2008; Nemeth et al., 2010), for which we calculated statistical learning and general skill learning scores. Each task trial was categorized as the third element of a low-probability or a high-probability triplet (except the first two trials of each block that could not have been categorized as the third element of a high-probability or low-probability triplet). To measure the degree of implicit statistical learning, we calculated a statistical learning score by subtracting the median RT of the high-probability triplets from the median RT of the low-probability triplets. Then, to control the difference in base RTs between groups, we divided this learning score by the mean RT (standardized statistical learning scores). To measure general skill learning, the median RTs of each unit of five blocks were calculated regardless of the probability of the occurrence of items.

Quantification of online and offline changes

Further scores were calculated to compare the online and offline general skill learning and statistical learning changes. Each block of 80 trials was divided into five bins (each containing 16 consecutive trials). For each bin, we calculated the difference between high-probability and low-probability triplets, resulting in a single learning score for each bin for each block. To calculate the online change in statistical learning, we subtracted the learning score of the first bin from that of the last bin of the same block (the change from the beginning to the end of the block). Twenty-five scores were obtained corresponding to the online changes of learning in the 25 blocks. We averaged the 25 online learning scores to obtain a single online learning score for each participant. To calculate the offline change of statistical learning, we subtracted the learning score of the last bin from the first bin of the next block (the change from the end of the block and the beginning of the next block). Twenty-four scores were obtained corresponding to the offline changes of learning in the 25 blocks (henceforth referred to as “change scores”). We averaged over the 24 offline learning scores to obtain a single offline learning score for each participant. The same procedure was repeated to obtain the online and offline changes for general skill learning, except that scores were obtained from median RTs independent of the probability of items.

Statistical analysis

Statistical analysis was performed in JASP 0.16. Before conducting the statistical analyses of the main hypotheses, we calculated the mean and median rest duration of the self-paced group. The mean rest period in the self-paced group was 16.67 s (SD = 25.48), and the median rest period was 10.58 s. One-sample t tests revealed that the mean rest duration of the self-

paced group did not differ significantly from the rest duration of the 15 s group ($t_{(87)} = 0.62$, $p = 0.54$) but significantly differed from the rest duration of the 30 s group ($t_{(87)} = -4.91$, $p < 0.001$).

The learning blocks of the ASRT task were grouped into five larger units of analysis (blocks 1–5, blocks 6–10, blocks 11–15, blocks 16–20, and blocks 21–25). Mixed-design ANOVAs on median RTs and statistical learning scores were performed to compare general skill learning and implicit statistical learning between groups, respectively. Offline and online changes were also compared with mixed-design ANOVAs separately for statistical learning and general skill learning. To evaluate the PDP task, we used one-sample t tests to compare the proportion of high-probability triplets in the inclusion and exclusion condition to the chance level and conducted mixed-design ANOVA to compare the proportions between groups and conditions. Greenhouse–Geisser corrections were applied if necessary. For ANOVAs, significant main effects and interactions were further analyzed using Bonferroni-corrected *post hoc* comparisons and/or one-sample t tests.

In addition to the classical frequentist approach, Bayesian ANOVAs were also performed with the same factors as described above. Here, we report the exclusion Bayes factors (BFs) of Bayesian model averaging across all matched models. $BF_{\text{exclusion}}$ indicates the amount of evidence for the exclusion of a given factor. Accordingly, the higher the $BF_{\text{exclusion}}$ value (>1), the more it supports the exclusion of the given factor, and, vice versa, the smaller the $BF_{\text{exclusion}}$ value (<1), the more evidence for inclusion.

Results

Did rest period duration influence statistical learning?

To test whether the duration of rest periods between learning blocks affected statistical learning, we conducted a mixed-design ANOVA with the within-subjects factor of Blocks (blocks 1–5 vs blocks 6–10 vs blocks 11–15 vs blocks 16–20 vs blocks 21–25) and the between-subjects factor of Group (self-paced, 15 s breaks, 30 s breaks) on the learning scores. The analyses revealed a gradual increase of learning scores in each group, regardless of the rest period duration (main effect of Blocks: $F_{(4,1060)} = 25.68$, $p < 0.001$, $\eta_p^2 = 0.09$, $BF_{\text{exclusion}} < 0.001$). According to pairwise comparisons, there was no significant increase in learning between blocks 6–10 and blocks 11–15 ($p = 0.82$), between blocks 6–10 and blocks 16–20 ($p = 0.06$), between blocks 11–15 and blocks 16–20 ($p < 0.99$), and between blocks 16–20 and blocks 21–25 ($p = 0.19$). All other paired comparisons of block arrays were significant (all $p < 0.01$). Thus, the consecutive learning units did not significantly differ from each other but learning could be discovered between temporally more distant parts of the task. Importantly, the three experimental groups did not differ in statistical learning (main effect of Group: $F_{(2,265)} = 0.65$, $p = 0.53$, $\eta_p^2 < 0.01$, $BF_{\text{exclusion}} = 31.39$). The Blocks \times Group interaction was also nonsignificant ($F_{(8,1060)} = 0.28$, $p = 0.97$, $\eta_p^2 < 0.01$, $BF_{\text{exclusion}} = 3262.88$); thus, the three groups did not differ in the time course of statistical learning either (Fig. 2A,C). To

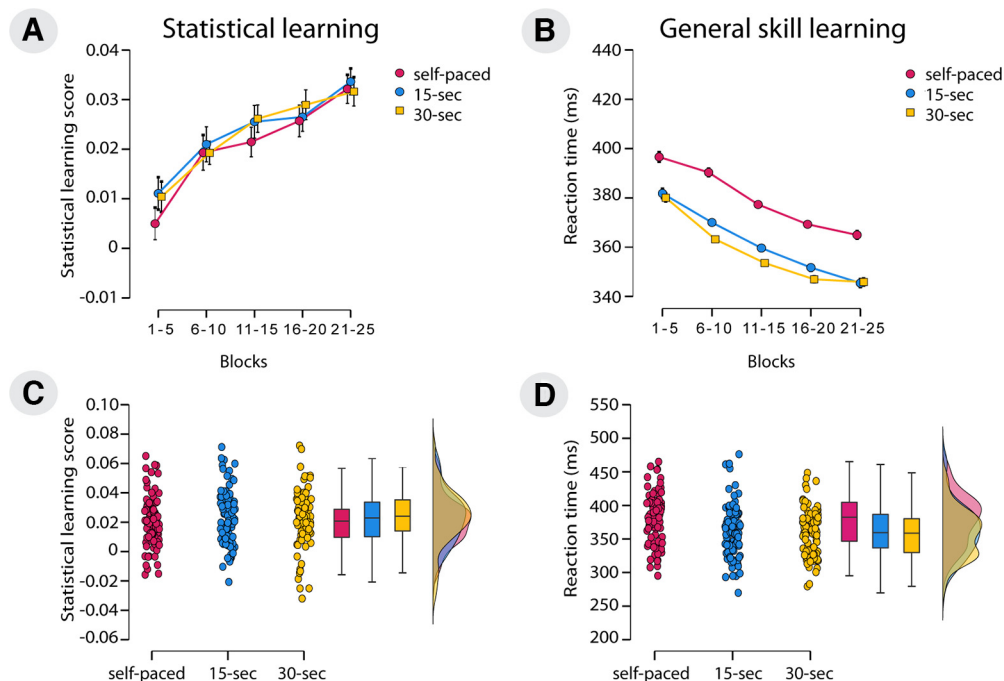


Figure 2. The effect of manipulating rest period duration on statistical learning and general skill learning. Error bars represent the SEM. The x-axes indicate the blocks of experiment/experimental groups; the y-axes represent the statistical learning score/reaction time. **A**, The temporal dynamics of statistical learning scores in the three groups. All groups showed a significant increase in statistical learning throughout the experiment, but the learning of the three groups did not differ. To see the original variables that statistical learning score were calculated from, see Extended Data Figure 2-3. **B**, The temporal dynamics of general skill learning in the three groups. All groups showed a decrease in RT over the course of the experiment, suggesting the learning of general skills. The self-paced group showed slower RTs compared with the 15 and 30 s groups. **C**, Individual data of the overall statistical learning scores (one dot represents the mean statistical learning score for one participant). Boxplots and violin plots visualize the distribution of statistical learning scores in the three groups. **D**, Individual data of the general RT scores (one dot represents the mean general RT for one participant). Boxplots and violin plots visualize the distribution of general RTs in the three groups. These results stayed intact without age-based exclusion (Extended Data Figs. 2-1, 2-2).

see Results without age-based exclusion, check Extended Data Figure 2-1. Original high-probability and low-probability variables can be seen in Extended Data Figure 2-3.

Did rest period duration influence the performance of general skill learning?

To test whether the overall speedup on the task differed between groups (i.e., whether the duration of rest periods between learning blocks affected general skill learning), we conducted a mixed-design ANOVA with the within-subjects factor of Blocks (blocks 1–5 vs blocks 6–10 vs blocks 11–15 vs blocks 16–20 vs blocks 21–25) and the between-subjects factor of Group (self-paced, 15 s breaks, 30 s breaks) with median RT as the dependent variable. We found a gradual decrease in RTs throughout the task (main effect of Blocks: $F_{(2,73,723,72)} = 275.21$, $p < 0.001$, $\eta_p^2 = 0.51$, $BF_{\text{exclusion}} < 0.001$). Based on pairwise comparisons, each epoch significantly differed from each other (all $p < 0.01$), with increasing learning through all blocks. The three groups significantly differed in response times (main effect of Group: $F_{(2,265)} = 8.69$, $p < 0.001$, $\eta_p^2 = 0.06$, $BF_{\text{exclusion}} = 0.01$), with the self-paced group being slower than the 15 and 30 s groups. The Blocks \times Group interaction was also significant ($F_{(8,1060)} = 2.33$, $p = 0.04$, $\eta_p^2 =$

0.02, $BF_{\text{exclusion}} = 5.25$). Pairwise comparisons revealed significantly higher RTs in the self-paced compared with the 30 s group in blocks 6–10, blocks 11–15, blocks 16–20, and blocks 21–25 (all $p < 0.01$). The self-paced group also showed significantly higher RTs compared with the 15 s group in blocks 6–10, blocks 11–15, blocks 16–20, and blocks 21–25 (all $p < 0.01$). Thus, the three groups showed a similar speed in the first learning unit, but the self-paced group began to slow down compared with the other two groups starting from the second learning unit (Fig. 2B,D). However, the $BF_{\text{exclusion}}$ score of the interaction is >3 , which indicates moderate evidence for the lack of interaction; thus, the interaction is deemed unreliable. For results without age-based exclusion, see Extended Data Figure 2-2.

How did break duration affect offline and online statistical learning?

A mixed-design ANOVA was run with the within-subjects factor of Learning Phase (offline vs online) and the between-subject factor of Group (self-paced, 15 s breaks, and 30 s breaks) on the change scores of statistical learning. The ANOVA revealed an interaction between Learning Phase and Group factors ($F_{(2,265)} = 3.51$, $p = 0.03$, $\eta_p^2 = 0.03$, $BF_{\text{exclusion}} = 0.05$). Bonferroni-corrected *post*

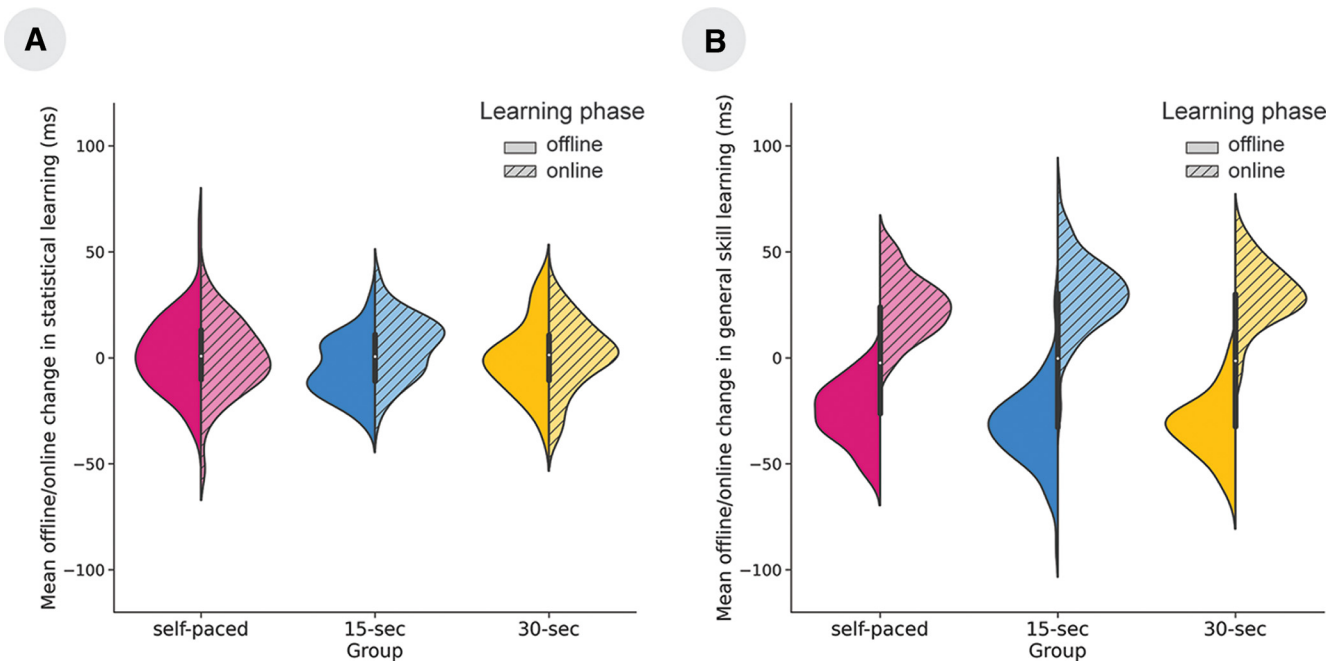


Figure 3. The offline versus online changes in statistical learning/general skill. The x-axes indicate the three groups, and the y-axes represent the mean offline/online changes in milliseconds. The filled halves of the violin plots indicate offline changes, whereas the striped halves show the online changes. **A**, In the 15 s group, the offline and online changes differed from each other in statistical learning: the online changes were significantly higher than the offline changes. The group-level online changes were positive (indicating online improvement in statistical learning), whereas the offline changes were negative (indicating forgetting; for dynamic change of the original variables, see Extended Data Fig. 3-3). **B**, Changes in general skills were similar in the three groups: acceleration after the offline periods and deceleration during the online period. These results stayed intact without age-based exclusion (Extended Data Figs. 3-1, 3-2).

hoc comparisons revealed that online and offline changes differed in the 15 s break group ($p=0.04$): the offline changes were significantly smaller than the online changes. No main effect of Group ($F_{(2,265)} = 1.60, p=0.20, \eta_p^2 = 0.01, BF_{\text{exclusion}} = 42.28$) or Learning Phase ($F_{(2,265)} = 2.50, p=0.12, \eta_p^2 < 0.001, BF_{\text{exclusion}} = 0.97$) was found (Fig. 3). For results without aged-based exclusion, check Extended Data Figure 3-1. To see how offline and online learning scores dynamically change across blocks, check Extended Data Figure 3-3.

To clarify whether offline and online learning occurred in the whole sample as well as in the three groups, one-sample t tests were conducted. We have found that on the whole sample, the online learning scores were significantly different from zero ($t_{(267)} = 2.05, p < 0.05$), while the offline learning score was not ($t_{(267)} = 1.11, p = 0.27$). In the self-paced group, neither the online learning score ($t_{(87)} = -0.17, p = 0.86$) nor the offline learning scores ($t_{(87)} = 0.92, p = 0.36$) differed from zero. Similarly, in the 30 s group, neither the online learning scores ($t_{(89)} = 0.61, p = 0.55$) nor the offline learning scores ($t_{(89)} = -0.05, p = 0.96$) differed from zero. However, both learning scores differed from zero in the 15 s group: the online learning scores were higher than zero ($t_{(89)} = 3.50, p < 0.001$), while the offline learning scores were below zero ($t_{(89)} = -3.39, p < 0.01$). We can conclude that in this group, participants learned online and forgot offline. We suggest that the reason behind the lack of online and offline learning in the other two groups can be explained by the balanced ratio of positive

and negative learning scores within the groups (Fig. 4A–C). The distribution of high positive (≥ 5) and high negative (≤ -5) offline and online learning scores can be seen in Extended Data Figures 4-1 and 4-2.

How did break duration affect offline and online general skill learning?

A mixed-design ANOVA was run on the change scores of general skill learning, with the within-subjects factor of Learning Phase (offline vs online) and the between-subject factor of Group (self-paced, 15 s breaks, 30 s breaks). We found the main effect of Learning Phase ($F_{(2,265)} = 920.49, p < 0.001, \eta_p^2 = 0.77, BF_{\text{exclusion}} < 0.001$), with a slowing down of RT during the blocks, while an acceleration of RTs occurred after the rests. No main effect of Group was found ($F_{(2,265)} = 0.02, p = 0.98, \eta_p^2 < 0.001, BF_{\text{exclusion}} = 45.61$). The interaction between the Learning Phase and Group factors was significant ($F_{(2,265)} = 4.38, p = 0.01, \eta_p^2 < 0.03, BF_{\text{exclusion}} = 0.01$). However, no differences survived Bonferroni-corrected between-group comparisons for online and offline changes (all comparisons between groups revealed $p > 0.17$; Fig. 3). For results without age-based exclusion, see Extended Data Figure 3-2.

One-sample t tests revealed that participants learned online ($t_{(267)} = 29.14, p < 0.001$) and forgot offline ($t_{(267)} = -30.60, p < 0.001$) the general skill in the whole sample. This pattern was observed in all three groups. Online learning of the general skill took place in the self-paced group

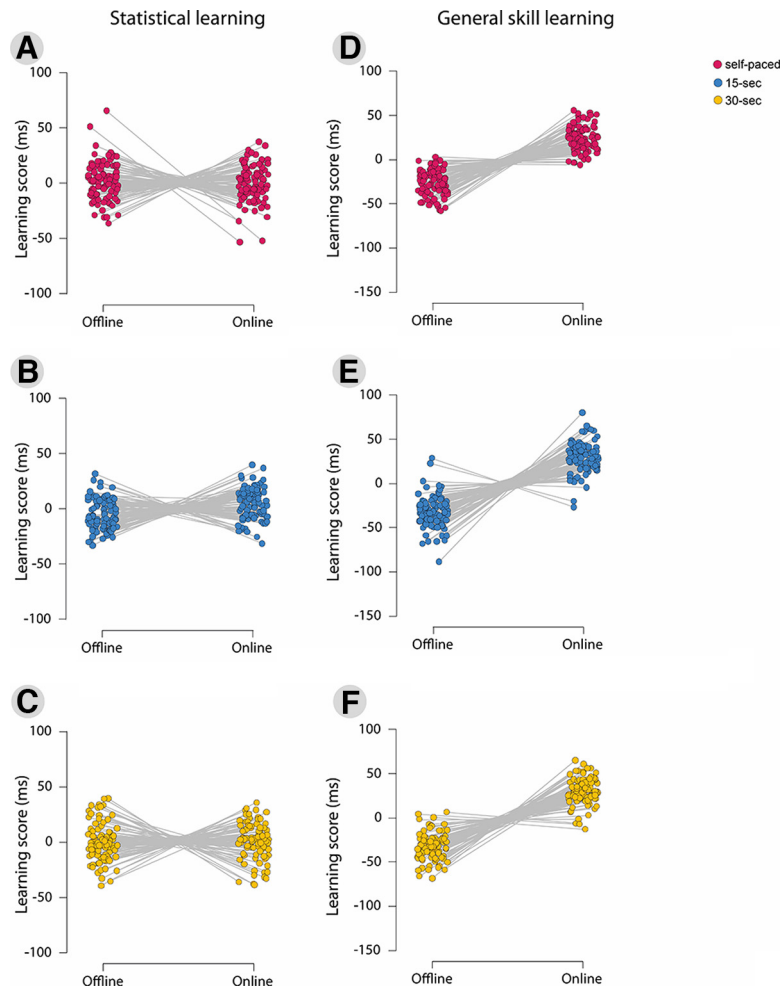


Figure 4. Dynamics of offline/online statistical learning/general skills and forgetting in the different groups. The y-axes indicate offline and online learning in milliseconds; the x-axes show the mean offline/online learning score of each participant. **A–F**, The different figures depict the individual data of offline and online statistical learning scores in the self-paced group (**A**), the 15 s group (**B**), and the 30 s group (**C**), and the individual data of offline and online general skill learning scores in the self-paced group (**D**), the 15 s group (**E**), and the 30 s group (**F**). The exact distribution of positive and negative offline and online learning scores can be seen in Extended Data Figures 4-1 and 4-2.

($t_{(87)} = 15.87$, $p < 0.001$), in the 15 s group ($t_{(89)} = 16.35$, $p < 0.001$), as well as in the 30 s group ($t_{(89)} = 19.18$, $p < 0.001$). During the offline periods, participants' general skill performance decreased in the self-paced group ($t_{(87)} = -17.16$, $p < 0.001$), the 15 s group ($t_{(89)} = -16.78$, $p < 0.001$), and the 30 s group ($t_{(89)} = -20.21$, $p < 0.001$; Fig. 4D–F).

Was statistical learning implicit in the three groups?

Last, we tested whether learning occurred implicitly in the three experimental groups. We compared the percentage of high-probability triplets generated in the PDP task to the chance level (25%) in the three groups. Participants in the self-paced group generated more high-probability triplets both in the inclusion and exclusion conditions than would occur at chance level (inclusion condition: mean \pm SD = $31.5 \pm 0.8\%$, $t_{(80)} = 7.79$, $p < 0.001$, $BF_{01} = 0.001$; exclusion condition: mean \pm SD = $29.2 \pm 1\%$, $t_{(80)} = 3.06$, $p < 0.001$, $BF_{01} < 0.001$). It was the same in the 15 s group (inclusion condition:

mean \pm SD = $31.1 \pm 0.8\%$, $t_{(86)} = 7.54$, $p = 0.001$, $BF_{01} < 0.001$; exclusion condition: mean \pm SD = $27.5 \pm 1\%$, $t_{(86)} = 2.62$, $p = 0.001$, $BF_{01} < 0.001$), and in the 30 s group (inclusion condition: mean \pm SD = $30.3 \pm 0.7\%$, $t_{(86)} = 6.57$, $p < 0.001$, $BF_{01} < 0.001$; exclusion condition: mean \pm SD = $29.0 \pm 1\%$, $t_{(86)} = 3.30$, $p = 0.001$, $BF_{01} < 0.001$). Thus, we can conclude that learning can be considered implicit in all groups.

Furthermore, we explored the potential differences between groups with a 2 (condition: inclusion vs exclusion) \times 3 (group: self-paced vs 15 s vs 30 s) ANOVA. The main effect of the condition was significant ($F_{(1,252)} = 15.027$, $p = 0.001$, $\eta_p^2 = 0.06$, $BF_{\text{exclusion}} = 0.01$), indicating that participants performed better in the inclusion condition. The group main effect did not reach significance ($F_{(2,252)} = 0.13$, $p = 0.88$, $\eta_p^2 = 0.001$, $BF_{\text{exclusion}} = 28.02$), indicating that the three groups performed equally on the tasks. The interaction of the condition and group factors was also nonsignificant ($F_{(2,252)} = 1.03$, $p = 0.36$, $\eta_p^2 = 0.01$, $BF_{\text{exclusion}} = 9.35$), revealing that the lack of difference between groups was

not influenced by the task condition. Together, the results indicate that the knowledge of the three groups remained equally implicit.

Discussion

Our study aimed at testing whether the duration of short rest periods, when neural replay occurs, influences statistical learning and general skill learning. To measure these two aspects of learning independently, we used an implicit sequence-learning task, the ASRT task (Howard et al., 2004). We varied the lengths of rest periods across participants: 15 s (15 s group) or 30 s (30 s group) between the learning blocks or participants could decide when to resume the task (self-paced group). We wondered (1) whether the three groups differed in the extent of general skill learning and statistical learning and (2) whether rapid consolidation emerged during between-block rest periods in general skill learning and statistical learning. Break duration affected general skills and statistical learning differently. We observed that the self-paced group was generally slower than the other two groups. However, all groups showed a similar degree of statistical learning. Because of the same proportion of those who learned or forgot offline/online, group-level offline and online learning could not be detected in the self-paced and 30 s groups, while the 15 s group showed mainly online improvement and offline forgetting.

Our results suggest that the duration of rest periods is not necessarily decisive in statistical learning over the entire task. This result seems to be inconsistent with the results of the study by Bönstrup et al. (2019). They showed that short, 10 s rest periods could facilitate motor skill learning, and this improvement could continue with even shorter rest periods (Bönstrup et al., 2020). In contrast, previous studies that also measured pure statistical learning are consistent with our results (Fanuel et al., 2022). The task used in the study of Bönstrup et al. (2020) does not allow the differentiation of subprocesses of learning and mixes general skill learning with statistical learning; therefore, it is difficult to decide which was the determining factor in this result.

According to the results of Buch et al. (2021), we expected that the longer rest period (i.e., 30 s) would result in better learning compared with the shorter rest period (i.e., 15 s), because it may contain more replays, which is the neural basis of rapid consolidation. However, we measured only one learning session, and it is conceivable that the beneficial effect of an expanded rest period would appear instead in the longer run. On the other hand, the length of rest periods used in our study might not have been suitable to capture the critical period when rapid consolidation is beneficial in statistical learning. These questions should be further explored using a much more comprehensive range of rest periods and introducing delayed testing of implicit statistical learning.

In general skill learning, participants showed longer RTs in the self-paced condition where they were allowed to decide about the rest period duration, compared with those conditions where rest period duration was fixed (i.e., 15 and 30 s). How could we interpret the longer RTs in the

self-paced group? On the one hand, this difference could be because of a difference in the rest period duration in the self-paced group compared with the two fixed rest period groups. On the other hand, it could be because of the specificity of the self-paced condition. The mean rest period in the self-paced group was similar to the rest period duration of the 15 s group, but the two groups still significantly differed in overall speed. However, the high SD shows considerable variability in the time the participants decided to rest between blocks. We suggest that it is not the duration of the rest period that is critical in the performance of general skill learning, but the nature of the expiry of the rest period (voluntary or compulsory). The knowledge that the rest period will be limited might have urged participants to complete the task as soon as possible, which resulted in faster RTs.

Our results about the offline and online changes in general skill learning are in accordance with previous studies with the same sequence-learning task (Quentin et al., 2021; Fanuel et al., 2022): during practice, the speed decreases, and between blocks, it increases. However, our results only partially replicated previous findings on statistical learning. Previously, it was shown that statistical learning mainly occurs during blocks, and forgetting occurs between blocks. In our study, this pattern was only detectable for the 15 s group: in the 30 s and self-paced groups, such strong dissociation could not be seen in the online versus offline changes. It is possible that the 30 s and the self-paced groups took enough break time to benefit from both online learning and rapid consolidation (potentially allowing more replay to occur in the offline periods), but the fixed 15 s length was not enough for the latter. This hypothesis could be supported by the results of the study by Prashad et al. (2021), who found offline improvement in probabilistic sequence learning with 2-min-long breaks between the learning blocks. However, as the differences in break durations are relatively large between these two studies, it is still a pending question to establish the minimum length of a between-block break for rapid consolidation. Studies that directly manipulate the number of neural replays between block periods are warranted.

Another possible explanation might be that our study was completed online: participants completed the task in their environment, where the stress level is possibly smaller than in laboratory settings. The limited rest period could have increased the stress level during the experiments, creating similar circumstances that participants experienced in the laboratory. As statistical learning is affected by stress levels (Tóth-Fáber et al., 2021), this could have prompted participants to maximize their performance during practice and benefit more from rest periods. However, no difference in learning outcomes was found between the groups, suggesting that different lengths of the rest periods only change the learning dynamics; they do not affect the outcomes of statistical learning.

Together, we observed that the manipulation of the length of the rest periods—indirectly the neural replay—affects general speed on a sequence-learning task. In contrast, statistical learning seems to be independent of the length of the rest period. The length of rest periods did not

affect the outcome of statistical learning, but did affect the dynamics of learning (i.e., whether learning occurs online or offline): if we do not have enough time during breaks for offline consolidation, we might compensate by increasing online learning performance. Thus, our results suggest that the length of short rest periods has a different effect on separate learning and consolidation processes. Also, from a methodological perspective, our results show the importance of measuring the temporal dynamics of learning, and do not provide only a general measure of the overall learning across the task.

References

- Anwyl-Irvine AL, Massonnié J, Flitton A, Kirkham N, Evershed JK (2020) Gorilla in our midst: an online behavioral experiment builder. *Behav Res* 52:388–407.
- Anwyl-Irvine A, Dalmaijer ES, Hodges N, Evershed JK (2021) Realistic precision and accuracy of online experiment platforms, web browsers, and devices. *Behav Res* 53:1407–1425.
- Barnes KA, Howard JH, Howard DV, Gilotty L, Kenworthy L, Gaillard WD, Vaidya CJ (2008) Intact implicit learning of spatial context and temporal sequences in childhood autism spectrum disorder. *Neuropsychology* 22:563–570.
- Bennett J, Howard JH, Howard DV (2007) Age-related differences in implicit learning of subtle third-order sequential structure. *J Gerontol B Psychol Sci Soc Sci* 62:P98–P103.
- Bönstrup M, Iturrate I, Thompson R, Cruciani G, Censor N, Cohen LG (2019) A rapid form of offline consolidation in skill learning. *Curr Biol* 29:1346–1351.e4.
- Bönstrup M, Iturrate I, Hebart MN, Censor N, Cohen LG (2020) Mechanisms of offline motor learning at a microscale of seconds in large-scale crowdsourced data. *NPJ Sci Learn* 5:7.
- Buch ER, Claudino L, Quentin R, Bönstrup M, Cohen LG (2021) Consolidation of human skill linked to waking hippocampo-neocortical replay. *Cell Rep* 35:109193.
- Cleeremans A, Jimenez L (1998) Implicit sequence learning: the truth is in the details. In: *Handbook of implicit learning* (Frensch PA, Stadler M, eds), pp 323–364. Thousand Oaks, CA: Sage Publications.
- de Leeuw JR (2015) jsPsych: a JavaScript library for creating behavioral experiments in a Web browser. *Behav Res* 47:1–12.
- Destrebecqz A, Cleeremans A (2001) Can sequence learning be implicit? New evidence with the process dissociation procedure. *Psychon Bull Rev* 8:343–350.
- Destrebecqz A, Peigneux P, Laureys S, Degueldre C, Del Fiore G, Aerts J, Luxen A, Van Der Linden M, Cleeremans A, Maquet P, Del Fiore G, Aerts J, Luxen A, Van Der Linden M, Cleeremans A, Maquet P (2005) Neural correlates of implicit and explicit sequence learning: interacting networks revealed. *Learn Mem* 12:480–490.
- Du Y, Prashad S, Schoenbrun L, Clark JE (2016) Probabilistic motor sequence yields greater offline and less online learning than fixed sequence. *Front Hum Neurosci* 10:87.
- Fanuel L, Pleche C, Vékony T, Janacsek K, Nemeth D, Quentin R (2022) How does the length of short rest periods affect implicit probabilistic learning? *Neuroimage* 2:100078.
- Fu Q, Dienes Z, Fu X (2010) Can unconscious knowledge allow control in sequence learning? *Conscious Cogn* 19:462–474.
- Horváth K, Török C, Pesthy O, Nemeth D, Janacsek K (2020) Divided attention does not affect the acquisition and consolidation of transitional probabilities. *Sci Rep* 10:22450.
- Howard DV, Howard JH, Japikse K, DiYanni C, Thompson A, Somberg R (2004) Implicit sequence learning: effects of level of structure, adult age, and extended practice. *Psychol Aging* 19:79–92.
- Jacoby LL (1991) A process dissociation framework: separating automatic from intentional uses of memory. *J Mem Lang* 30:513–541.
- Janacsek K, Fiser J, Nemeth D (2012) The best time to acquire new skills: age-related differences in implicit sequence learning across the human lifespan. *Dev Sci* 15:496–505.
- Jiménez L, Vaquero JMM, Lupiáñez J (2006) Qualitative differences between implicit and explicit sequence learning. *J Exp Psychol Learn Mem Cogn* 32:475–490.
- Kirchner WK (1958) Age differences in short-term retention of rapidly changing information. *J Exp Psychol* 55:352–358.
- Kóbor A, Janacsek K, Takács A, Nemeth D, Kóbor A, Janacsek K, Takács A, Nemeth D (2017) Statistical learning leads to persistent memory: evidence for one-year consolidation. *Sci Rep* 7:760.
- Nemeth D, Janacsek K, Londe Z, Ullman MT, Howard DV, Howard JH (2010) Sleep has no critical role in implicit motor sequence learning in young and old adults. *Exp Brain Res* 201:351–358.
- Prashad S, Du Y, Clark JE (2021) Sequence structure has a differential effect on underlying motor learning processes. *J Mot Learn Dev* 9:38–57.
- Quentin R, Fanuel L, Kiss M, Vernet M, Vékony T, Janacsek K, Cohen LG, Nemeth D (2021) Statistical learning occurs during practice while high-order rule learning during rest period. *NPJ Sci Learn* 6:14.
- Robertson EM, Pascual-Leone A, Press DZ (2004a) Awareness modifies the skill-learning benefits of sleep. *Curr Biol* 14:208–212.
- Robertson EM, Pascual-Leone A, Miall RC (2004b) Current concepts in procedural consolidation. *Nat Rev Neurosci* 5:576–582.
- Squire LR, Genzel L, Wixted JT, Morris RG (2015) Memory consolidation. *Cold Spring Harb Perspect Biol* 7:a021766.
- Tóth-Fáber E, Janacsek K, Szóllósi Á, Kéri S, Nemeth D (2021) Regularity detection under stress: faster extraction of probability-based regularities. *PLoS One* 16:e0253123.
- Walker MP, Brakefield T, Morgan A, Hobson JA, Stickgold R (2002) Practice with sleep makes perfect: sleep-dependent motor skill learning. *Neuron* 35:205–211.