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How does the length of short rest periods affect implicit probabilistic learning?

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ABSTRACT

Memory consolidation has been mainly investigated for extended periods, from hours to days. Recent studies focused on memory consolidation occurring within shorter periods, from seconds to minutes. Yet, these studies focused on explicit sequence learning with fixed rest periods. Our study aimed at determining whether short rest periods enhance implicit probabilistic sequence learning and whether the length of rest duration influences such offline changes. Participants performed an implicit probabilistic sequence learning task throughout 45 blocks. Between blocks, participants were allowed to rest and then to continue the task at their pace. The results show that probabilistic sequence knowledge decreased from pre-to post-rest periods, and this decrement was not related to the length of rest duration. These results suggest that probabilistic sequence knowledge decays during short rest periods and that such forgetting is not time-dependent. Overall, our findings highlight that ultra-fast consolidation differently affects distinct cognitive processes.

1. Introduction

Taking a break during a learning period may facilitate the acquisition of new perceptual and motor skills (e.g., perceptual discrimination or finger tapping) and also benefit more complex cognitive skills, such as solving mathematical problems (e.g., Fischer et al., 2002; Stickgold et al., 2000; Stickgold and Walker, 2004; Walker et al., 2002). During rest periods (i.e., between two learning sessions), our brain strengthens memories through consolidation, potentially leading to performance improvements (e.g., Robertson, Pascual-Leone and Miall, 2004). So far, consolidation processes have been mainly investigated on extended periods following learning, such as days or hours (Squire et al., 2015 for a review). Recent studies showed that shorter rest periods, within a single learning session, also benefit performance (Bönstrup et al., 2019; Du et al., 2016; Hotermans et al., 2006, Quentin et al., 2021). This phenomenon was referred to as ultra-fast offline improvement (Robertson, 2019). These studies focused on the acquisition of new motor skills. In the present study, we aimed to test whether and how short rest periods affect implicit probabilistic sequence learning.

Empirical evidence for ultra-fast offline improvements was provided for explicit sequence learning of deterministic sequences during10 s rest periods (Bönstrup et al., 2019). In that study, participants learned a finger-tapping sequence, alternating between 10 s of practice and 10 s of rest. Performance improvements over practice and rest periods were separately measured. Increases in performance over rest periods considerably contributed to the overall learning of the sequence, suggesting the strengthening of just-practiced skills during rest periods. Concomitant magnetoencephalographic measures further highlighted

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modulation in beta-band frequency during rest periods. Beta-band oscillations are associated with reactivation of previous practice-related activity (Maquet et al., 2000; Ramanathan et al., 2015; see also Spitzer and Haegens, 2017 for a review), also referred to as memory replay (Cohen et al., 2015). It has since been confirmed that neural replay of the learned sequence occurred during short rest periods (Buch et al., 2021).

As consolidation processes seem to vary depending on the awareness of learning (Robertson, Pascual-Leone and Press, 2004), it is not clear whether ultra-fast offline improvements could extend to implicit probabilistic sequence learning. This type of learning can be described as the development of knowledge about regularities embedded in the environment without awareness nor intention of learning (e.g., Cleeremans and Jiménez, 1998; Howard et al., 2004). This sort of learning is involved in the acquisition of motor, cognitive and social skills (Lieberman, 2000; Nemeth et al., 2011; Romano Bergstrom et al., 2012; Ullman, 2016). Recently, it has been shown that probabilistic knowledge, measured with reaction times, was acquired online during the practice itself and not during short breaks (Quentin et al., 2021).

In the present study, we aimed to test whether the length of rest duration influences ultra-fast offline changes in implicit acquisition of probabilistic sequence knowledge. To address this question, we used the Alternating Serial Reaction Time (ASRT) task (e.g., Howard et al., 2004; Song et al., 2007). In this paradigm, an array of four positions was presented on the screen, and each position was mapped to a specific response key. On each trial, one of the positions was filled, and the participant had to press the corresponding key as fast and accurately as they could. Importantly, without the participant's awareness, the sequence of events followed a predictable pattern that was embedded in noise (i.e., presented among random positions). Participants were offered to rest after each block (corresponding to 85 trials) and resumed the task whenever ready. So far, previous studies have used fixed rest periods of either 10 s (Bönstrup et al., 2019) or 2 min (Du et al., 2016). Our experimental design with self-paced rest periods granted more spontaneous and natural rest duration, thus allowing us to directly measure how the length of rest periods affected learning performance. A previous study by Du et al. (2016) investigated general reaction times in deterministic and probabilistic sequences to differentiate the two types of learning. However, solely the average reaction times of high transitional probabilities were used, without using information from low transitional probabilities, which is required to disentangle general skill learning from probabilistic learning. In contrast, in our study, probabilistic sequence knowledge was evaluated by comparing the speed and accuracy of responses depending on the items' probability of occurrence (high-probability or low-probability) and was measured before and after each rest period. We investigated whether rest duration could influence ultra-fast offline improvements. If ultra-fast offline improvements occur over rest periods, then longer rest periods could lead to greater offline improvement. On the contrary, if memory decay occurs during rest periods, we expected rest periods to impact the amount of memory decay.

2. Methods

2.1. Participants

One hundred and eighty healthy young adults participated in this study (M_{age} = 21.64 years, SD_{age} = 4.11, $M_{education}$ = 14.69 years, $SD_{education}$ = 2.16, 152 females). All participants had normal or corrected-to-normal vision, and none of them reported a history of any neurological and/or psychiatric condition. Participants provided informed consent to the procedure before enrollment as approved by the institutional review board of the local research ethics committee. The study was approved by the United Ethical Review Committee for Research in Psychology (EPKEB) in Hungary (Approval number: 30/2012) and by the research ethics committee of Eötvös Loránd University, Budapest, Hungary. The study was conducted in accordance with the Declaration of Helsinki. Participants received course credits for taking part in the experiment. The dataset was previously used in Kóbor et al. (2017), Török et al. (2017) and Quentin et al. (2021). Results constituting the present paper were not tested nor reported before.

2.2. Alternating Serial Reaction Time task

The Alternating Serial Reaction Time (ASRT) task was used to induce implicit probabilistic sequence learning (Howard et al., 2004; Song et al., 2007). Four empty circles were horizontally arranged on the screen. A stimulus (a drawing of a dog's head) appeared in one of four circles (Fig. 1A) (Nemeth et al., 2013). Participants were instructed to press the corresponding key (Z, C, B, or M on a QWERTY keyboard) as quickly and accurately as possible after the appearance of the stimulus. Participants used their left and right middle and index fingers to respond to the targets. The serial order of the four possible positions (coded as 1, 2, 3, and 4 in a horizontal arrangement from left to right) in which target stimuli could appear was determined by an eight-element sequence. In this sequence, every second element appeared in the same order as the task progressed, while the other elements' position was randomly chosen (e.g., 2 – *r* – 1 – *r* – 3 – *r* – 4 – *r*; where numbers refer to a predetermined location in one of the four locations and *r*'s refer to randomly chosen locations out of the four possible, Fig. 1A). Six different sequences of predetermined elements were created, and one sequence was assigned to each subject in a permutated order.

Due to the alternating sequence structure, some patterns of three consecutive elements (henceforth referred to as triplets) occurred with a greater probability than other ones (Fig. 1A). *Each element* was categorized as either the third element of a high- or a low-probability triplet. High-probability triplets could be either formed by predetermined (P) elements or random (r) ones. For instance, 2 – r – 1, if the item 2 was the first triplet element, the item 1 had a 50% probability of occurring because it was a predetermined element (i.e., the third element of the triplet 2 – r – 1) plus 12.5% of chances to occur as a random element (i.e., the third element of the triplet 2 – P – 1). The third element of less probable triplets (e.g., 1 – P – 3 and 4 – P – 2) could have only been random and was thus less predictable (e.g., if the first triplet element was the item 1, item 3 had 12.5% of chances to occur). Low-probability triplets forming repetitions (e.g., 222) or trills (e.g., 232) were discarded from analyses as participants often show preexisting response tendencies to them. By eliminating these triplets, we could ascertain that any high-versus low-probability differences were due to learning and not to preexisting tendencies.

During the task, participants usually become faster and more accurate for the high-probability triplets compared to the low-probability ones. Therefore, the task allows us to separate pure *implicit probabilistic sequence learning* (i.e., the difference between high- and low-probability triplets) from *general skill learning* (Song et al., 2007). General skill learning refers to changes in accuracy and response times independently from the probability of occurrence of the events (Hallgató et al., 2013).

2.3. Procedure

The ASRT task was administered in three sessions, each containing 15 blocks (45 blocks in total). Each block consisted of 85 trials, corresponding to five warm-ups, i.e., random trials followed by the eight-element sequence repeated ten times (Fig. 1B). Accuracy and response time (RT) were recorded for each element. Between each block, a rest was proposed, and participants resumed the task whenever they were ready. Between sessions, participants filled questionnaires. Because (1) between-sessions breaks were not self-paced, in the sense that participants would start after filling questionnaires instead of deciding when they felt rested enough, and (2) the present study focused on ultra-fast consolidation, only very short breaks and task-free breaks (i.e., between-block rest periods) were included in the following analyses.

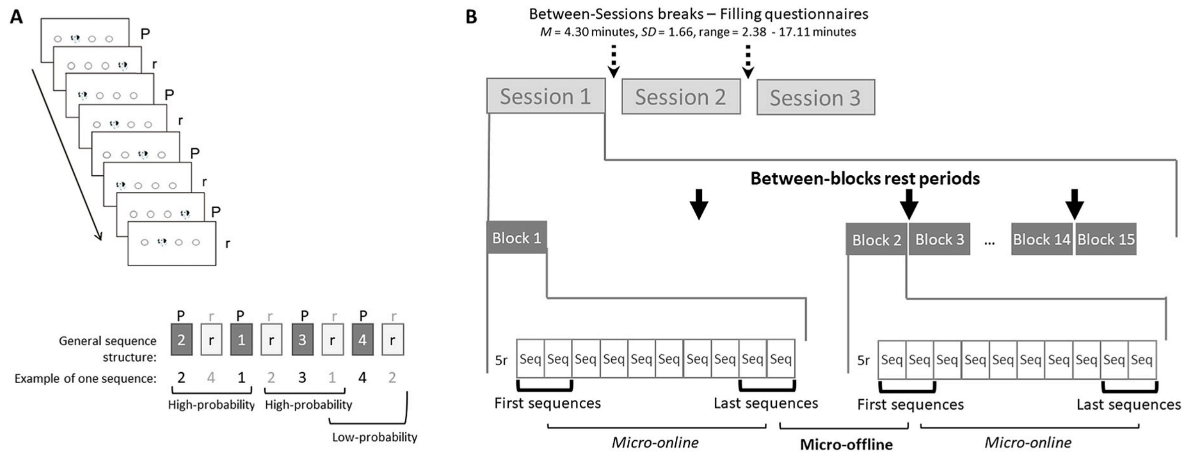

Fig. 1. Schematic representation of (A) an ASRT sequence and (B) the overall structure of the task. Each sequence was composed of eight elements alternating between predetermined (P) and random (r) elements. The experiment was divided into three sessions, each composed of 15 blocks. A rest period was offered after each block (arrows). Between-sessions breaks (dotted arrows) were discarded from analyses because participants filled questionnaires during this time. Only self-paced between-blocks rest periods (bold arrows) were included in the analyses. Each block was composed of five warm-up random trials (5r), followed by ten eight-element sequences (Seq). Brackets flag the two first and the two last sequences from which micro-offline improvement scores were computed.

2.4. Quantification and statistical analyses

To assess the impact of rest duration on probabilistic sequence learning, we measured the length of between-blocks rest periods as well as various indices of learning. We measured probabilistic sequence knowledge acquired across the whole experiment as well as at the beginning and the end of each block. We further provided a measure of micro-offline gain in probabilistic sequence knowledge during each rest period.

Between-blocks rest periods measure. The amount of time elapsed between the last response of block N and the key-press that started block N+1 was computed for each between-block rest period (M = 18.75 s, SD = 10.70 s, range = 15.39–507 s). This procedure resulted in 42 measures of between-blocks rest durations for each participant. Median between-blocks rest durations were computed for each participant. To account for possibly erroneous procedures (e.g., participant had to leave the room during a break), participants whose median between-blocks rest durations that were below or above the conventional exclusion threshold of 2

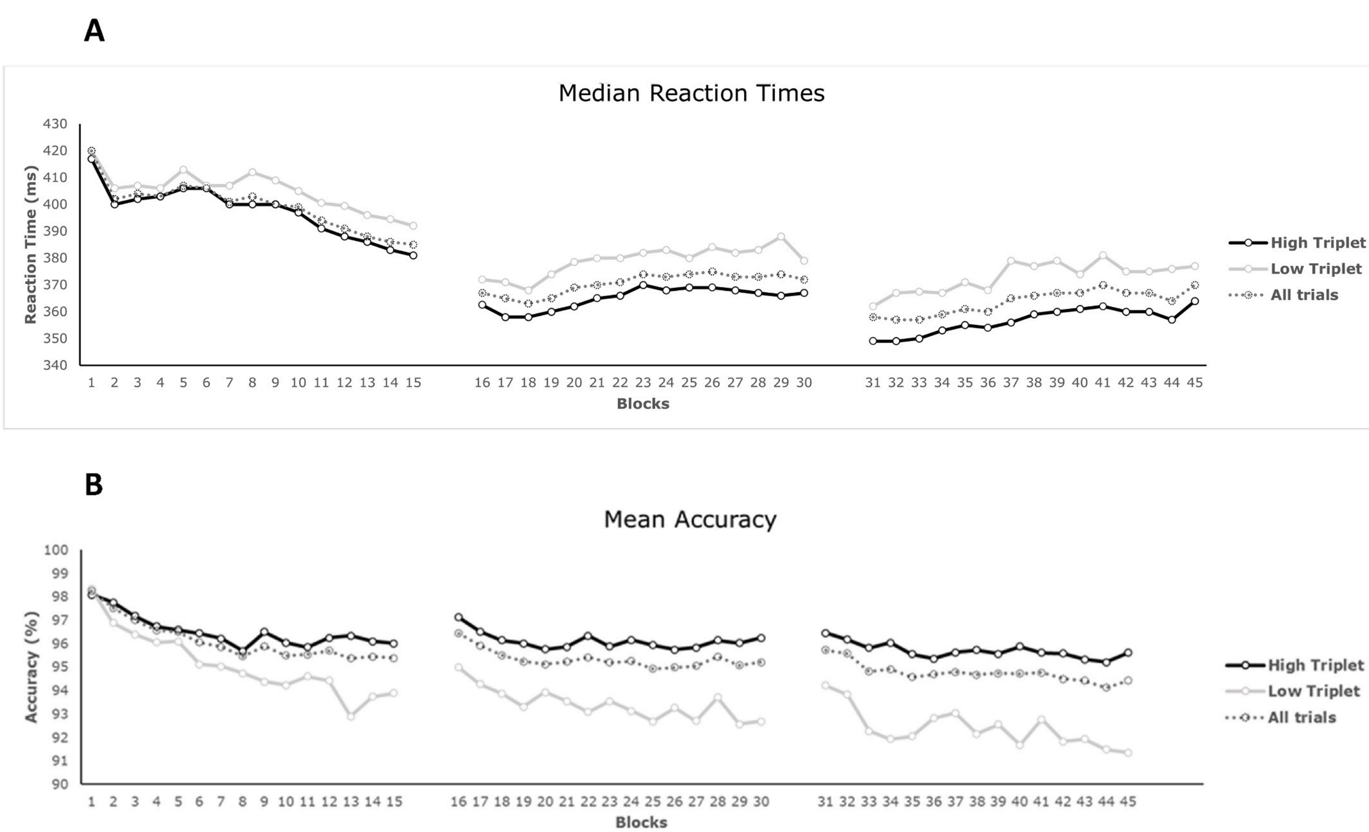

Fig. 2. Raw measures for reaction times (A) accuracy (B), for all trials including the beginning random elements and separately for high- and low- probability triplets. See Supplementary Figs. 2 and 3 for the within-block learning dynamics.

SD above the mean were removed from the sample. We decided to exclude these participants because we considered that unusual long breaks could affect not only the following block but also the next ones. Nevertheless, all conclusions of this study are unchanged without this exclusion procedure. Therefore, the following statistical analyses included 173 participants aged between 17 and 48 years ($M_{age} = 21.65$ years, $SD_{age} = 4.16$, $M_{education} = 14.70$ years, $SD_{education} = 2.17$, 147 females).

Probabilistic sequence knowledge. Probabilistic sequence knowledge was considered as the difference in performance depending on triplets' probability of occurrence. To compute an index of probabilistic sequence knowledge, we first calculated mean accuracy and median RT for low- and high-probability triplets separately (Fig. 2). Probabilistic sequence knowledge score consisted of the difference between the score for low-probability triplets and the score for high-probability triplets for RT measures and the difference between the score for high-probability triplets and the score for low-probability triplets for accuracy measures. For both measures, higher scores indicated larger probabilistic sequence knowledge. Following this procedure, we measured (1) the *probabilistic sequence knowledge* acquired at the beginning and the end of each block and (2) the probabilistic sequence knowledge acquired at the end of the experiment, further referred to as *final probabilistic sequence knowledge.* To measure the probabilistic sequence knowledge at the beginning and the end of each block, we first computed mean accuracy and median RT for correct responses for the two first sequences (i.e., the first 14 trials after the five warm-up trials) and the two last sequences (i.e., last 16 trials) of each block and each triplet probability. For the first two sequences, 14 and not 16 trials were used because the first 2 elements on each sequence cannot be predicted using preceding trials. This method resulted in eight scores for each block: median RT and mean accuracy for the low-probability triplets and high-probability triplets of the first two sequences and the last two sequences. Four scores of probabilistic sequence knowledge were computed for each block: accuracy and RT indices for the first two sequences of each block and the last two sequences of each block. Then, probabilistic sequence knowledge for both RT and accuracy was separately averaged for all first and last sequences of the block for each participant. To measure the final probabilistic sequence knowledge, we first computed median RT and mean accuracy of the last five blocks of the experiment for each triplet probability. The difference between the score for high-probability triplets and the score for low-probability triplets provided a measure of the final probabilistic sequence knowledge.

Micro-offline modulations. Offline modulations in probabilistic sequence knowledge consisted of the difference of RT or accuracy indices of probabilistic knowledge (i.e., the difference between high- and low-probability triplets) between the first two sequences of a block (after warm-up trials) and the last two sequences of the previous block. For offline modulations, a negative difference shows a decrease of probabilistic sequence knowledge. The calculation of offline modulations resulted in 42 offline scores that were averaged for each participant.

Linear relationship between offline modulations and rest duration. We assessed the relationship between the ultra-fast offline modulations in probabilistic sequence knowledge and the duration of the between-blocks rest periods. For *between-participants analyses*, mean offline modulations in probabilistic sequence knowledge were calculated for both RT and accuracy for each participant. We tested their correlation with median rest duration using frequentist Pearson's and Bayesian correlations. To account for the intra-individual variability, we also conducted *within-participant analyses*. Beforehand, outlier data points were removed: between-block rest durations that were 2 SD above the participant's median rest duration were excluded from the sample. We removed 2 ± 0.81 between-block rest duration (range: 0–4) for each participant (i.e., 4.76% of the total amount of data points). For both RT and accuracy measures, we computed Pearson's correlations between between-blocks rest duration and offline modulation in probabilistic sequence knowledge separately for each participant. The resulting correlation coefficients (Pearson's r) were considered as an individual measure of the relationship between between-blocks rest duration and offline modulation in probabilistic sequence knowledge for RT and accuracy. Frequentists and Bayesian one-sample t-tests contrasting correlation coefficients to zero were conducted separately for RT and accuracy measures.

Bayesian statistical analyses and guidelines for interpretation. In addition to classical frequentist statistics, Bayesian factors were computed. A Bayes factor can give evidence towards the alternative hypothesis (H1) or the null hypothesis (H0). BF_{10} between 3 and 10 and above 10 is considered as moderate support and strong support for the alternative hypothesis, respectively (Lee and Wagenmakers, 2014). BF_{10} values between 1/3 and 1/10 and below 1/10 are considered as moderate support and strong support for the null hypothesis, respectively. BF_{10} values between 1/3 and 3 are regarded as ambiguous information (Etz et al., 2017; Lee and Wagenmakers, 2014; Wagenmakers, 2007). All statistical analyses were performed using JASP 0.11.1 (JASP Team, 2019) with the default settings.

3. Results

3.1. Did between-block rest periods influence probabilistic sequence knowledge?

As the task progressed, participants became faster (blocks x element probability interaction in repeated measure ANOVA $F(44, 7876) = 12.9$, $p < .001$) and more accurate ($F(44, 7876) = 5.1$, $p < .001$) for high-*vs.* low-probability elements. To test whether ultra-fast offline improvements in implicit probabilistic sequence knowledge occurred during between-block rest periods, one-way repeated-measures ANOVAs were run with Block (Last sequences of block n vs. First sequences of block n+1) as a within-participants factor. Frequentists and Bayesian ANOVAs were conducted on RT and accuracy measures (Fig. 3).

The main effect of Block was significant and associated with strong evidence in favor of the effect for RT and accuracy, $F(1, 172) = 41.36$, $p < .001$, $\eta^2 p = .19$, $BF_{10} = 1.30 \times 10^7$ and $F(1, 172) = 13.86$, $p < .001$, $\eta^2 p = .08$, $BF_{10} = 87.15$, respectively. RT and accuracy measures decreased over between-block rest periods, suggesting an offline decay in probabilistic sequence knowledge. Follow-up analyses were performed to investigate whether the duration of rest periods influenced offline decay of probabilistic sequence knowledge.

3.2. Is there a linear relationship between between-block rest durations and offline modulations of probabilistic sequence knowledge?

Between-participant analysis of offline modulations. For RT, correlation was not significant and associated with moderate evidence in favor of the null hypothesis, $r(171) = 0.04$, $p = .57$, $BF_{10} = 0.11$ (Fig. 4A). For accuracy, correlation was significant and positive but associated with ambiguous information, $r(171) = 0.15$, $p = .04$, $BF_{10} = 0.76$ (Fig. 4B). These results suggest no linear relationship between median between-blocks rest duration and offline decay in probabilistic sequence knowledge.

Within-participant analysis of offline modulations. The absence of a relationship between ultra-fast offline modulations and between-blocks rest duration at the group level could be due to high intra-participants variability that would be hindered by the averaging of break durations. To account for this variability, we further inspected the strength of the relationship between offline modulation of probabilistic sequence knowledge and between-blocks rest duration for each participant. Correlation coefficients did not significantly differ from zero, and BF_{10} showed strong evidence for the null hypothesis for RT measures, $t(172) = 0.167$, $p = .87$, $BF_{10} = 0.09$ (Fig. 4C) and moderate evidence for the null hypothesis for accuracy measures, $t(172) = 1.61$, $p = .11$, $BF_{10} = 0.30$ (Fig. 4D). These results strengthen the lack of a linear relationship

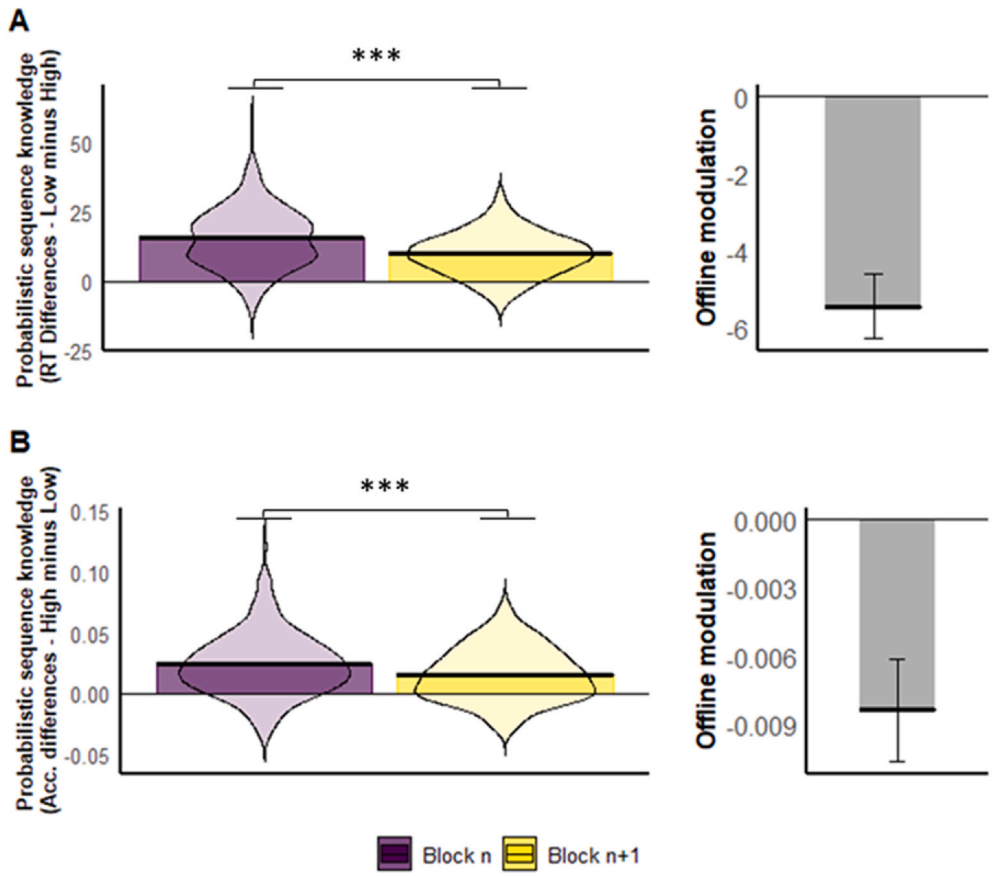

Fig. 3. Offline modulations in probabilistic sequence knowledge for RT (A) and accuracy (B) measures. In each panel, the plot on the left corresponds to measures of probabilistic sequence knowledge as a function of Block (Block n: Last sequences of block n, Block n+1: First sequences of block n+1). The plot on the right corresponds to offline modulation measures, that is the difference in probabilistic sequence knowledge measures (RT or accuracy) between the first sequences of block n+1 and the last sequences of block n. To visualize learning in the same direction for RTs and accuracy, offline modulation in RTs was computed as low minus high-probability triplets and offline modulation in accuracy was computed as high- minus low-probability triplets. Thus, negative offline modulations over between-block rest periods for both RT and accuracy represent an offline decay in probabilistic sequence knowledge. Violin plots represent data distribution; black horizontal lines represent the mean across participants. Vertical error bars represent the standard error of the mean (SEM). *** stands for $p <$ .001.

between offline decay in probabilistic sequence knowledge and between-blocks rest duration, even at an individual level.

Between-blocks rest durations and probabilistic sequence knowledge acquired at the end of the experiment. To test whether between-blocks rest duration had a more general influence on probabilistic sequence learning throughout the course of the experiment, we investigated the relationship between between-blocks rest duration and probabilistic sequence knowledge acquired at the end of the experiment. Probabilistic sequence learning acquired by the end of the experiment, further referred to as *final probabilistic sequence knowledge*, was computed based on the mean accuracy difference and median RT difference between high- and low-probability triplets for correct responses during the last five blocks for each participant (see the Methods section).

Beforehand, we ran one-sample frequentists and Bayesian t-tests comparing probabilistic sequence learning to zero to ensure that participants indeed learned probabilistic properties of the sequences during the experiment. Both RT and accuracy scores for final probabilistic sequence knowledge showed significant knowledge at the end of the experiment and were associated with strong evidence in favor of the alternative hypothesis (for RT: $t(172) = 19.91$, $p < .001$, Cohen's $d = 1.51$, $BF_{10} = 1.26 \times 10^{43}$; for accuracy: $t(172) = 13.02$, $p < .001$, Cohen's $d = 0.99$, $BF_{10} = 1.67 \times 10^{24}$).

Then, frequentist Pearson's correlations and Bayesian correlations between the median between-blocks rest duration over the task and the final probabilistic sequence knowledge scores were computed. Correlations were not significant for RT nor for accuracy and were associated with strong evidence for the null hypothesis for RT, $r(171) = -0.02$, $p = .77$, $BF_{10} = 0.10$, and moderate evidence for null hypothesis for accuracy, $r(171) = 0.07$, $p = .34$, $BF_{10} = 0.15$. These results show that while participants have learned the probabilistic structure of the sequences during the experiment, the amount of probabilistic sequence knowledge at the end of the task was not related to between-blocks rest duration.

To sum up, our results showed decrements in probabilistic sequence knowledge over between-blocks rest periods. Between-block rest duration was not related to offline decrements in probabilistic sequence knowledge, neither at group nor individual level. No relationship between rest duration and probabilistic sequence knowledge was observed despite the fact that probabilistic sequence knowledge was acquired during the experiment.

4. Discussion

The present study investigated whether short rest periods influence implicit probabilistic learning (also referred to as statistical learning). Participants were allowed to rest after each block before triggering the next block by pressing a button, producing a self-paced fluctuation in the duration of rest periods. The performance was assessed before and after each rest period, granting measures of ultra-fast offline modulation in probabilistic sequence knowledge. We wondered (1) whether ultra-fast offline improvements in probabilistic sequence learning can emerge during between-block rest periods and (2) whether the *duration* of between-block rest period affects offline modulations in implicit probabilistic sequence knowledge. In other words, can longer rest periods lead to better (or worse) learning performance? We observed that rest periods led to a between-block decrease in probabilistic sequence knowledge. Decrements in probabilistic sequence knowledge were not linked to rest duration, neither at the group nor at the individual level.

First of all, our results highlight a decrement in probabilistic sequence knowledge during rest periods. This result seems to oppose a previous study suggesting that memory consolidation of probabilistic information benefit from 2-min rest periods (Du et al., 2016). Du et al. (2016) showed that offline learning drove the fast acquisition of probabilistic sequences, whereas online learning did not contribute to probabilistic sequence acquisition. This suggested that implicit

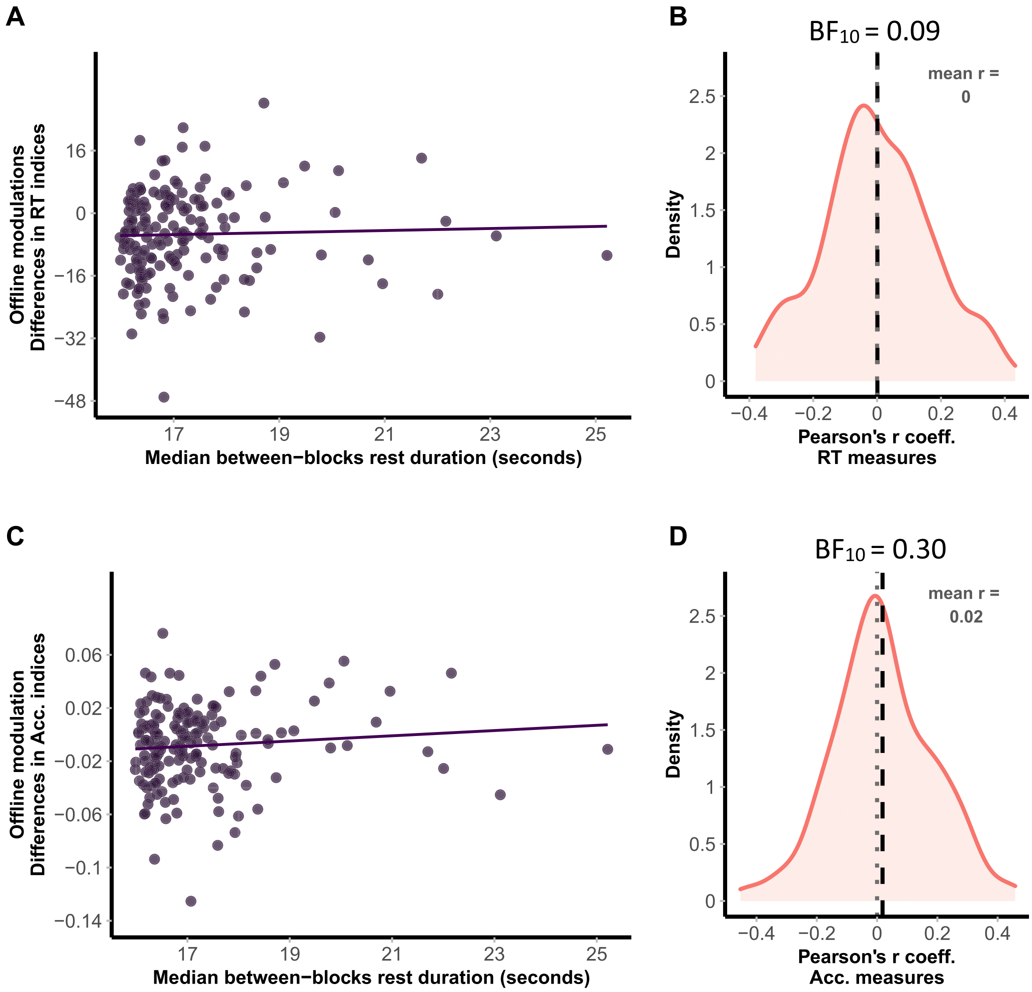

Fig. 4. Offline modulation in probabilistic sequence knowledge as a function of between-blocks rest duration. Distribution on mean offline modulation depending on mean between-blocks rest duration is represented for RT (A) and accuracy (B) measures. Solid black lines represent linear trends. The density of Pearson's r coefficients resulting from the correlation between between-blocks rest duration and offline modulation for each participant are represented for RT (C) and accuracy (D) measures. Dashed lines represent the mean of Pearson's r coefficients across participants. Dotted lines mark the value to which Pearson's r coefficients are compared (i.e., zero). No linear relationship between offline modulation in probabilistic sequence knowledge and between-blocks rest duration emerged, neither at the between-participants level nor at the within-participant level. This was true for both RT and accuracy measures. Bayes factors are reported for non-significant effects. BF10 < $^{1}/_{3}$ shows evidence for the null hypothesis (see the Methods section for more details).

probabilistic sequence learning could not develop without offline learning. Yet, in our study, probabilistic sequence knowledge was acquired over the experiment despite any evidence for ultra-fast offline improvements, suggesting that implicit probabilistic sequence knowledge *can* develop without offline learning. Several aspects differed between our study and the Du et al.'s (2016): the implementation of probabilistic sequences (a predetermined sequence hidden in random elements in ours, a sequence based on a Markov chain transitional matrix in Du et al.'s), the number of blocks of trials containing the to-be-learned probabilistic events (45 blocks in our study, four blocks in Du et al.'s study), the duration of rest periods (self-paced and lasting 18.35 ± 9.40 s in ours, fixed at 2 min in Du et al.'s), and the assessment of the probabilistic sequence knowledge (difference between high- and low-probability events in ours, RT measures for the more probable events without comparing them to the less probable ones in Du et al.'s). The latter aspect can plausibly explain the discrepant results between our and Du et al.'s study. In Du et al. offline improvements in probabilistic knowledge were not completely distinguished from improvements in general skills. An offline improvement in general skills (as observed in our study, see Supplementary materials, and in Bönstrup et al., 2019) might have influenced the measure of offline learning in probabilistic sequence knowledge. In our ASRT task, the measure of probabilistic sequence learning (i.e., difference score between high- and low-probability events) enabled us to disentangle probabilistic knowledge from general skills (Hallgató et al., 2013; Nemeth et al., 2010; Song et al., 2007). Measures of probabilistic sequence knowledge used in our study thus reflected processes involved in *pure* probabilistic learning, distinct from those underlying general skill learning.

Differences in the duration of rest periods between the Du et al. (2016) study and our studymight suggest that (1) a crucial parameter might be the duration of rest periods, and (2) a minimum amount of time might be necessary for memory consolidation to take place. Fortunately, our design allowed us to test this hypothesis directly. Beyond the between-blocks rest periods, the experimental design contained two between-session rest periods (mean = 4.30 min, SD = 1.66, range = 2.38–17.11 min) during which participants filled questionnaires. Even though these rest periods were longer, no significant offline learning in probabilistic sequence knowledge emerged following these rest periods (see Supplementary materials). Thus, overall, the duration of rest periods does not seem crucial for offline improvements in probabilistic sequence knowledge. To determine in which conditions do offline learning during implicit probabilistic sequence learning emerge and test the hypothesis of a critical period that is essential for offline learning to emerge, future studies should directly manipulate the duration of rest periods, from seconds to a few minutes.

Secondly, we tested whether offline decrements in probabilistic sequence knowledge depend on the duration of between-block rest periods. Consistently at the between-participants and within-participants level, ultra-fast offline decrements were not related to the between-block rest duration. In other words, longer averaged offline periods did not lead to more pronounced forgetting. This result raises the question of what causes forgetting in probabilistic knowledge during short rest periods. Forgetting can be due to two processes: time-based decay and interference. Decay theory posits that memory traces fade away with the mere passage of time (Brown, 1958), but this theory is still widely debated (Ricker et al., 2014). Other studies suggest that in implicit probabilistic learning studies, interference contributes to forgetting to a great extent because events are typically generated by recombining a small number of features, thus strongly interfering with each other (Perruchet and Pacton, 2006). In ASRT tasks, random elements are based on the same features as pattern elements (i.e., spatial location and its mapping to the response keys) and are likely to interfere with pattern elements. Forgetting over the rest periods observed in the present study thus seems more likely to come from interference, which might explain the absence of time-based decay. Future studies will need to disentangle the contribution of time and interference in forgetting during implicit probabilistic learning. To do so, we suggest to orthogonally manipulate the rest period duration and the amount of interference between target and not-target event.

Previous studies suggested that explicit sequence learning improves over a short period (Bönstrup et al., 2019). Our present study shows that implicit probabilistic sequence knowledge, however, is prone to forgetting rather than offline learning over short periods within a single training session. Forgetting of probabilistic sequence knowledge does not seem to depend on time and might rather be due to interference. Because of the shortness of rest periods, our results raise the question of a critical time period for consolidation to occur and compensate or overcome forgetting of implicit probabilistic knowledge. Our present study explored the time-dependency of offline processes in a passive way, and future studies should investigate this question by manipulating the duration of rest periods. Future studies should carefully distinguish processes underlying general visuomotor learning, task adaptation, and fatigue/inhibition release from those specifically linked to the acquisition of probabilistic sequence knowledge.

Contributions

DN, LF, RQ conceived the presented idea, KJ and DN designed the study and organized the data collection. LF and CP analyzed the data. LF wrote the first draft of the manuscript. TV, KJ, DN and RQ reviewed and critically edited the previous versions of the manuscript. All authors read and approved the final version of the manuscript.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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