Explicit instruction differentially affects subcomponents of procedural learning and consolidation

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Abstract

Procedural learning facilitates the efficient processing of complex environmental stimuli and contributes to the acquisition of automatic behaviour. In the present study, we investigated two sub-components of procedural learning: *statistical learning* and *sequence learning*. The former one refers to the acquisition of frequency-based associations between stimuli, while the latter one refers to the acquisition of order-based relationship of a series of events. It is still unclear whether these sub-processes are differentially affected by explicit awareness during learning and consolidation. Our goal was to compare explicit and implicit procedural memory formation and consolidation in the same task to directly test the effect of the explicit instruction on procedural learning. Second, we aimed to distinguish sequence learning and statistical learning *within* procedural learning and measured the two processes in parallel. Seventy-four young adults performed either the original implicit (N = 37) or the modified cued (N = 37) version of the Alternating Serial Reaction Time (ASRT) task. To test the effect of delay on retention, performance was retested after a 12-hour offline period. Statistical learning performance was similar in the two groups, while the explicit cues boosted sequence learning performance. Nevertheless, awareness had no effect on consolidation: both statistical and sequence knowledge was preserved over the 12-hour delay and retention was comparable in the two experimental groups. Our findings could provide a better insight into the role of awareness in procedural learning and consolidation.

Keywords: implicit learning, sequence learning, statistical learning, awareness

Introduction

The classic theory of learning and memory supports the existence of multiple memory systems that rely on separate brain structures: non-declarative or implicit memory relies primarily on the basal ganglia, and declarative or explicit memory relies primarily on the medial temporal lobe (Squire, 2004). Recent studies suggest that this distinction might not be precise and memory functions could not be strictly separated based on merely the level of awareness concerning the learning situation and the ability of recollection of the learnt material (Henke, 2010; Sanchez & Reber, 2013). There is growing evidence that, contrary to Squire's division of memory systems, the hippocampus also plays a role in implicit learning (Albouy, King, Maquet, & Doyon, 2013; Cleeremans & Jiménez, 2002; Keele, Ivry, Mayr, Hazeltine, & Heuer, 2003; Poldrack & Rodriguez, 2004). Although a large number of studies have investigated the differences of implicit and explicit memory, the vast majority compared tasks requiring different learning mechanisms (e.g. story recall vs. sequence learning: Csábi, Benedek, Janacsek, Katona, & Nemeth, 2013; Wilhelm, Diekelmann, & Born, 2008) and a very few manipulated only the level of consciousness within the same task (Robertson, Pascual-Leone, & Press, 2004; Sanchez & Reber, 2013). Comparison of different tasks can easily lead to false dissociations that emerge from the type of tasks rather than from the level of awareness. Our goal was to overcome these limitations and directly contrast implicit and explicit memory from memory formation to consolidation in a unified paradigm.

The concept of procedural learning is an umbrella term covering several sub-processes that should be clearly distinguished both on conceptual and methodological level. The contradictory findings often observed in procedural learning research may at least partly result from the lack of such differentiation. Our second goal was to differentiate between at least two sub-processes of procedural learning, namely sequence learning and statistical learning (Nemeth, Janacsek, & Fiser, 2013) and assess these processes in parallel. Sequence learning refers to the acquisition of a series of repeating elements occurring in the same *order* without or with some embedded noise (deterministic vs. probabilistic sequences) (Brawn, Fenn, Nusbaum, & Margoliash, 2010; Rickard, Cai, Rieth, Jones, & Ard, 2008), while statistical learning refers to the recognition and acquisition of *frequency or probability* based shorter-range associations among stimuli (i.e., differentiating between more frequent and less frequent stimulus chunks, such as pairs or triplets of stimuli) (Fiser & Aslin, 2002; Siegelman, Bogaerts, Christiansen, & Frost, 2017; Thiessen, Kronstein, & Hufnagle, 2013; Turk-Browne, Scholl, Johnson, & Chun, 2010). In the current study, we define statistical learning as introduced by Kóbor et al. (2018). Here we used a probabilistic sequence learning task, which is a unique tool to measure both statistical learning and sequence learning in parallel due to the noise embedded into the sequential order (Nemeth, Janacsek, & Fiser, 2013). Recent studies revealed that these two parallel learning processes can be differentiated in the ASRT task on developmental and neurocognitive level. Findings on procedural learning indicate that statistical and sequence learning follow different developmental trajectories (Nemeth, Janacsek, & Fiser, 2013) and they also show different electrophysiological patterns measured by event-related brain potentials (Kóbor et al., 2018) and time-frequency-analysis (Simor, Zavecz, Horváth, et al., 2017).

To the best of our knowledge, there is only one study that compared statistical learning with sequence learning in the same task and tested the effect of explicit instruction on learning (Nemeth, Janacsek, & Fiser, 2013). They found that explicit instructions improved performance on both measures in healthy young adults. Nevertheless, this performance improvement may have resulted from the fact that participants had as much time as they wanted to process the stimuli and respond, which may have favoured the explicit instruction group as they spent more time on the task compared to the implicit group. Moreover, Nemeth and colleagues (2013) did not investigate the changes in learning performance after a delay period (i.e., how statistical and sequence learning consolidate over time). Here, we aimed to investigate not only memory formation but also consolidation on relatively process-level by contrasting statistical and sequence learning in the same experimental paradigm and testing how explicit instruction alters these processes.

Previous studies have shown that memories can undergo significant changes during practice, in the so-called 'online' periods, as well as between practice sessions, in the so-called 'offline' periods (Meier & Cock, 2014; Robertson, 2009; Robertson, Pascual-Leone, & Miall, 2004). These offline periods contribute to changes in the acquired knowledge referred to as consolidation (Krakauer & Shadmehr, 2006). Usually, implicitly learnt material remains retained during the offline period (Nemeth et al., 2010; Robertson, 2009; Song, 2009). In contrast, previous studies led to mixed findings in the case of explicitly acquired knowledge: while in some cases successful consolidation of explicitly acquired knowledge means lower degree of forgetting (Mednick, Mednick, Cai, Kanady, & Drummond, 2008), in other cases retention or even improvement in performance occurred after the delay period (Pan & Rickard, 2015; Robertson, Pascual-Leone, & Press, 2004). Studies that investigated the consolidation of implicit procedural learning usually found retained knowledge over the offline period (Hallgato, Győri-Dani, Pekár, Janacsek, & Nemeth, 2013; Janacsek & Nemeth, 2012; Nemeth & Janacsek, 2011; Song, Howard, & Howard, 2007b). Nevertheless, they did not separate the sub-processes of procedural learning. Consequently, the question remains what changes the sub-processes of procedural learning, i.e., statistical knowledge and sequential information, undergo during an offline period and what is the role of consciousness in their consolidation.

The aim of the present study was twofold. First, our goal was to compare the explicit and implicit procedural memory formation and consolidation in the same task to directly test the effect of the explicit instruction on procedural learning. Second, we aimed to distinguish sequence learning and statistical learning *within* procedural learning and measured the two processes in parallel. Here, we used the Alternating Serial Reaction Times task (J. H. Howard, Jr. & Howard, 1997) to assess these processes. We went beyond the study of Nemeth et al. (2013) by controlling the timing of the task with a fixed interstimulus interval instead of the self-paced timing used in the original study since the latter enables the explicit group to spend more time on task. With this modification, we aimed to eliminate any potential confounds that could have affected the comparison of the explicit vs. implicit groups' performance measures in the original study. Furthermore, we tested not only how statistical and sequential knowledge emerges during the learning phase but also how the acquired knowledge consolidates over a delay period. We hypothesized that the controlled timing of the task reduces or even eliminates the benefit of the explicit instruction on learning. In the case of consolidation, we can directly test whether the level of awareness (explicit vs. implicit) or the type of acquired knowledge (statistical vs. sequential) affects the outcomes of consolidation primarily, or these two dimensions interact with one another during consolidation.

Methods

Participants

Ninety-three healthy young adults participated in the experiment. We matched the implicit and explicit groups based on age, education, gender, handedness, working memory and attention performance. Six participants were excluded due to matching and another thirteen participants due to outlier performance on the ASRT task (overall accuracy and/or raw reaction time separately for each trial types fall outside three SDs in at least two epochs out of five in the Learning Phase). Outliers were defined as three standard deviations from group average. Thus, the final sample consisted of seventy-four adults, thirty-seven in each group (Table 1).

All participants had normal or corrected-to-normal vision, none of them reported a history of any neurological and/or psychiatric condition and drug-use. Prior to their inclusion in the study, participants provided informed consent to the procedure as approved by the research ethics committee of Eötvös Loránd University, Budapest, Hungary. The study was conducted in accordance with the Declaration of Helsinki and participants received course credits for taking part in the experiment.

Table 1. Demographic data of the implicit and explicit groups. Mean (SD) shown for age, education and standard neuropsychology tests. Ratio is presented for handedness, gender and delay activity.

Variable	Implicit group (N = 37)	Explicit group (N = 37)
Age (year)	21.2 (2.04)	20.7 (1.35)
Education (year)	14.1 (1.91)	14.05 (1.31)
Handedness	32 right / 5 left	31 right / 6 left
Gender	11 male / 26 female	8 male / 29 female
Delay activity	20 sleep / 17 no-sleep	19 sleep / 18 no-sleep
Digit Span	6.4 (1.06)	6.2 (0.99)
Counting Span	3.5 (1.12)	3.4 (0.70)
ANT Alerting Attention (ms)	41.2 (26.14)	40.4 (21.20)
ANT Orienting Attention (ms)	31.9 (21.72)	39.6 (21.25)
ANT Executive Attention (ms)	85.5 (33.93)	86.8 (27.58)

***Note* ANT – Attention Network Test**

Task

Alternating Serial Reaction Time (ASRT) task - The ASRT task was used to measure statistical and sequence learning in parallel. In this task, the target stimulus appeared in one of the four horizontally arranged circles on the screen. Participants were instructed to respond with the corresponding key (Z, C, B or M on a QWERTY keyboard) when the stimulus occurred. One block of the ASRT task contained 85 trials (stimuli). The presentation of the stimuli was determined by an eight-element sequence, in which pattern (P) and random (r) elements were alternating. In each block, the eight-element alternating sequence repeated 10 times after five warm-up trials consisting only of random stimuli. One example of the sequence is 2-r-3-r-1-r-4-r, where numbers represent predetermined locations on the screen and r indicate randomly chosen locations out of the four possible ones. This alternating structure resulted in some of three consecutive trials (*triplets*) occurring more frequently than others (*frequency property* of the task). If a triplet appeared frequently, its first two elements predicted the third element with a greater certainty (called *high-frequency triplets*, taking up 62.5% of all trials), while the third element of infrequent triplets was less predictable (called *low-frequency triplets*, taking up 37.5% of all trials). This frequency information defined the statistical property of the triplets. However, triplets could also be defined based on their structure: the last element of a triplet could occur in a pattern position (P-r-P structure) or in a random one (r-P-r structure; *sequential property* of the task). Based on the frequency and sequential properties of triplets, the last element of each triplet could be divided into three categories: pattern-high, random-high and random-low elements (Figure 1A).

The ASRT task is a unique tool that enables us to assess several learning processes within the same task (Nemeth, Janacsek, & Fiser, 2013). The most common analysis so far has solely focused on *triplet learning*. Triplet learning, however, is not a pure measure, and at least two separate learning processes contribute to this learning measure, namely, the so-called *pure statistical learning* and *higher-order sequence learning* (Nemeth, Janacsek, & Fiser, 2013). Pure statistical learning is defined as the difference in responses between high-frequency and low-frequency triplets analyzed only in random elements. In this case, the sequential properties of the stimuli are controlled, and the only difference between the two stimulus types is frequency-based, that is statistical in nature. In contrast, higher-order sequence learning is defined as the differences in responses between pattern (always high-frequency) and high-frequency random elements. Here, the statistical properties of the stimuli are controlled (both types are high-frequency), and the only differentiation of the two elements is based on sequence properties (pattern vs. random; Figure 1B). Importantly, both learning measures - expressed as difference scores - can be separated from the so called *general skill learning* that is related to general performance improvement as the task progresses (mainly due to improved visuomotor coordination) and affects the different trial types similarly. Here we focus only on pure statistical learning and higher-order sequence learning.

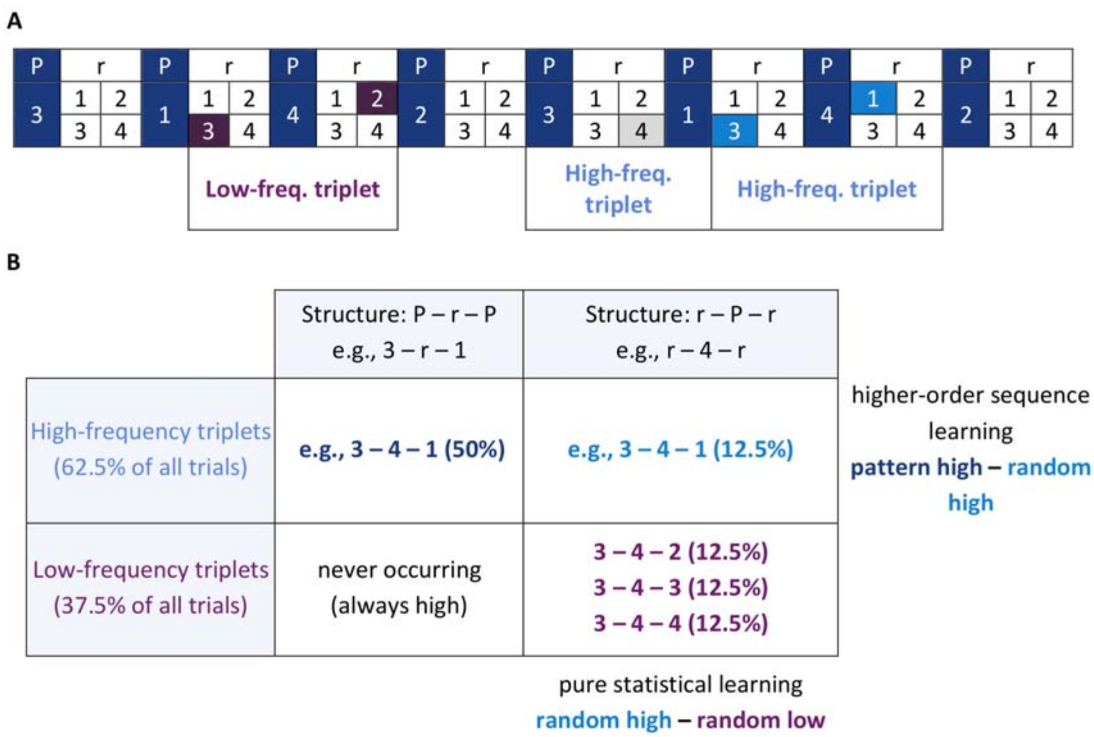

Figure 1. Stimulus structure and learning processes in the ASRT task (P – pattern, r – random). **(A)** As the ASRT task contains an alternating sequence structure (e.g., 2r3r1r4r, where numbers correspond to the four locations on the screen and the r represents randomly chosen locations), some runs of three consecutive elements (called triplets) occur more frequently (blue) than others (purple). In the example above 2-_-4, 4-_-3, 3-_-1, and 1-_-2 occur often. In contrast, 2-_-3 or 1-_-4 would occur less frequently. **(B)** We determined for each pattern and random stimulus whether it was the last element of a high- or a low-frequency triplet, thus three different elements could occur: pattern (dark blue, always high-frequency), random-high (light blue) and random-low (purple). Pure statistical learning is computed as the difference in responses between random-high and random low-elements. Higher-order sequence learning is defined as the difference in responses between pattern and random-high elements.

It has been well documented that participants do not become aware of the underlying sequence/statistical structure embedded in the ASRT task even after extended practice (e.g., ten days; (D. V. Howard et al., 2004) and when examined with more sensitive recognition tests (Song, Howard, & Howard, 2007a), thus it indeed measures implicit learning. Nevertheless, to ascertain that the sequence structure of the ASRT task and the learning situation itself remained implicit in the implicit group in the current study, a short **questionnaire** was administered after the Testing Phase, similar to previous studies (Nemeth et al., 2010; Song et al., 2007a; Unoka et al., 2017). Participants were asked whether they observed any regularity in the task. None of them reported anything regarding the sequence embedded in the ASRT task, and moreover, none of them was aware of that any kind of learning occurred during the task. To test whether the explicit group successfully learned the cued alternating sequence structure of the task (order information), we asked them to report the sequence of the pattern stimuli after each block: they had to type the four-digit order of the sequential elements three times. However, participants were not informed about the length of the sequence, thus they had to figure out not only the order but the length of the sequence as well. We expected this sequence report to be more sensitive and avoid ceiling effects as seen in Nemeth et al. (2013) where information about the length was provided. Note that sequence reports after each block were not required in the implicit group as those would have undermined the implicit nature of the task in this group.

Inclusion-Exclusion Task – Whereas sequence reports after each block in the explicit group was administered to reveal how consciously accessible sequence knowledge (order information) became during learning, the Inclusion-Exclusion task (Destrebecqz & Cleeremans, 2001; Destrebecqz et al., 2005; Fu, Dienes, & Fu, 2010; Jiménez, Vaquero, & Lupiá ez, 2006) was administered to reveal how consciously accessible triplet knowledge (frequency-based information) became in both the implicit and explicit groups. This task is based on the well-established "Process Dissociation Procedure" (Jacoby, 1991) and consists of two parts: first, participants are asked to report in what order the stimuli (both pattern and random elements) appeared in the task (*Inclusion condition)*, then they have to generate a new sequence of stimuli (both pattern and random elements) that is different from the learned one (*Exclusion condition*). Both parts contain four runs and the participants use the same response buttons as in the ASRT task. Each run finishes after 24 button presses, which is equal to three rounds of the eight-element alternating sequence. Since participants are asked to produce a stimulus stream including both pattern and random stimuli, this task enables to measure how consciously accessible their knowledge about the statistical regularities (i.e., triplets) is. Following the standard analysis and interpretation of the task outlined in previous studies, successful performance in the inclusion part can be achieved by solely implicit knowledge (i.e., without conscious access to their knowledge), while good performance in the exclusion part requires accessible explicit knowledge to exert control over their responses and generate a stimulus stream that is indeed different from what they learned. Consequently, to test whether participants gained conscious knowledge of the statistical regularities, we calculated the percentage of high-frequency triplets in the inclusion and exclusion conditions separately, and tested whether participants produced more high-frequency triplets than it is expected by chance and whether the percentage of high-frequency triplets differs across (inclusion/exclusion) conditions or across groups (for more details see: Kóbor, Janacsek, Takács, & Nemeth, 2017).

Procedure

The experiment consisted of two sessions to assess both learning and consolidation of the acquired knowledge. The Learning Phase contained 25 blocks. Half of the participants received the uncued version of ASRT (*implicit group*), while the other half performed a cued version of the task (*explicit group*). The implicit group was informed that the aim of the experiment was to measure the effect of extended practice on motor performance, thus they were unaware of the sequential structure embedded in the task. In contrast, participants in the explicit group were informed about the sequence structure of the task and were instructed to learn the sequence of the pattern elements. In this case, pattern and random stimuli were marked with different target pictures (dogs for pattern and penguins for random stimuli) similarly to the original study of Nemeth et al. (2013). This type of cuing was necessary to ensure that participants in the explicit group can identify the pattern trials that follow a predetermined sequence but it does not warrant that participants can find and learn the sequential pattern itself (D. V. Howard & Howard, 2001; Song, 2009; Song et al., 2007a). Consequently, the implicit and explicit groups were named after the lack or presence of explicit information provided to them (about the existence of a predetermined sequence that can be learned in the task), irrespective of whether or not they gained consciously accessible (explicit) knowledge about the sequential regularities in the task.

The Learning Phase was followed by a 12-hour delay, thereafter the Testing Phase was administered, which contained five blocks. In order to counterbalance potential time of day effect, during the delay, half of both implicit and explicit groups slept (PM-AM design) and the other half had normal daily activity (AM-PM design) (Nemeth et al., 2010; Song et al., 2007b). Since previous ASRT studies did not find sleep-dependent behavioural changes in learning performance (Hallgato et al., 2013; Nemeth et al., 2010; Song et al., 2007b), we did not expect groups differences here either. Nevertheless, we conducted all our analyses including the time-of-day condition as well and summarize the relevant findings in the Results section. All participants were aware that they perform the same task in the second experimental session (Figure 2). We used fixed inter-stimulus interval (ISI) to equalize the time spent on each stimulus between the two groups. The duration of stimulus presentation was 580 ms, then a white screen was presented for 120 m before the next stimulus appeared, thus, total ISI was 700 ms. These values are defined based on previous studies investigating healthy young adults, where participants had an average response time under 450 ms at the beginning of the task and 430 ms by the end of the learning phase (Nemeth et al., 2010; Nemeth, Janacsek, Polner, & Kovacs, 2013; Tóth et al., 2017; Unoka et al., 2017).

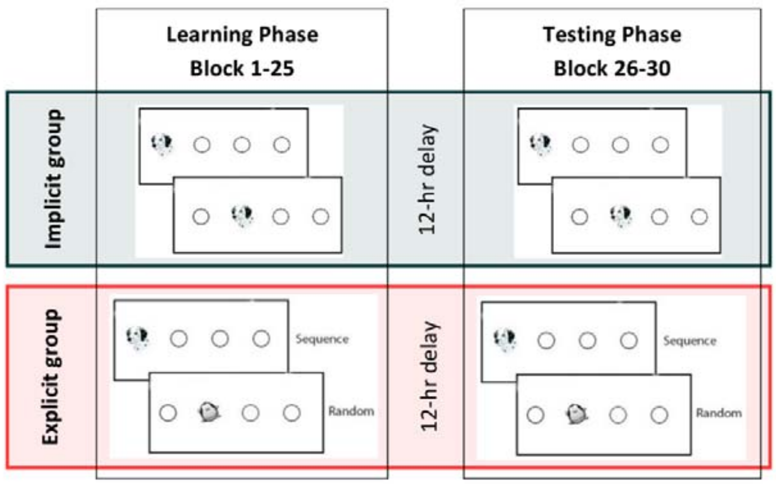

Figure 2. Design and procedure of the experiment. The original implicit and the modified cued version of the ASRT task were administered in the experiment. In the cued (explicit) version of the task (red panel), the regularity was marked by using different stimuli for sequence elements (a dog's head) and for random ones (penguin). In the implicit version of the task (green panel), sequence and random elements were not marked differently (a dog's head was used always). The Learning Phase (right column) consisted of 25 blocks, while the Testing Phase (left column) contained five blocks. The two sessions were separated by a 12-hour delay. All participants performed the same task in the Testing Phase as in the Learning Phase.

Following the Testing Phase, the implicit group was asked whether they noticed any regularities in the task, then received information about the hidden sequence structure of the task. Then both the implicit and the explicit group performed the Inclusion-Exclusion Task.

For additional information about the general cognitive performance (i.e., short-term and working memory and attention), three neuropsychological tests were administered after the ASRT task (see Table 1). Participants performed a digit span task (Isaacs & Vargha-Khadem, 1989; Racsmány, Lukács, Németh, & Pléh, 2005), a counting span task (Case, Kurland, & Goldberg, 1982; Conway et al., 2005; Engle, Tuholski, Laughlin, & Conway, 1999) and an attentional network test (Fan, McCandliss, Sommer, Raz, & Posner, 2002) in a randomly permuted order.

Statistical analysis

Statistical analysis was based on previous studies (e.g. J. H. Howard, Jr. & Howard, 1997; Nemeth, Janacsek, & Fiser, 2013) and were carried out by SPSS version 22.0 software (SPSS, IBM). Epochs of five blocks were analyzed instead of single blocks. The Learning Phase consisted of five epochs, while the Testing Phase consisted of one epoch. The explicit group showed - on average - lower reaction times (RTs) and accuracy compared to the implicit group. To ensure that potential between-group differences in statistical and sequence learning are not due to these general performance differences, we transformed the data by dividing each participants' raw RT/accuracy values with the their own average performance of the first epoch of the Learning Phase (for a similar approach see: Nitsche et al., 2003). In the next step, we multiplied all data by 100 for easier interpretability and presentation. This way each participants performance at the beginning of the Learning Phase was around 100 and changed as the task progressed (see Figure 3 for RTs, separately for the implicit and explicit groups). Following the transformation, the implicit and explicit groups showed similar RTs and accuracy GROUP effect, RTs: $F(1, 72) = 0.012$, $\eta_p^2 = .000$, $p = .911$, accuracy: $F(1, 72) = 0.618$, $\eta_p^2 = .00092$, $p = .434$. We did not find any significant interactions among the type of activity during the delay (i.e. sleep vs. no-sleep) and the offline changes (comparisons including SLEEP x EPOCH interaction, RT: all ps > .406: the AM-PM and PM-AM groups showed similar consolidation effects, henceforth their data were combined in all further analyses.

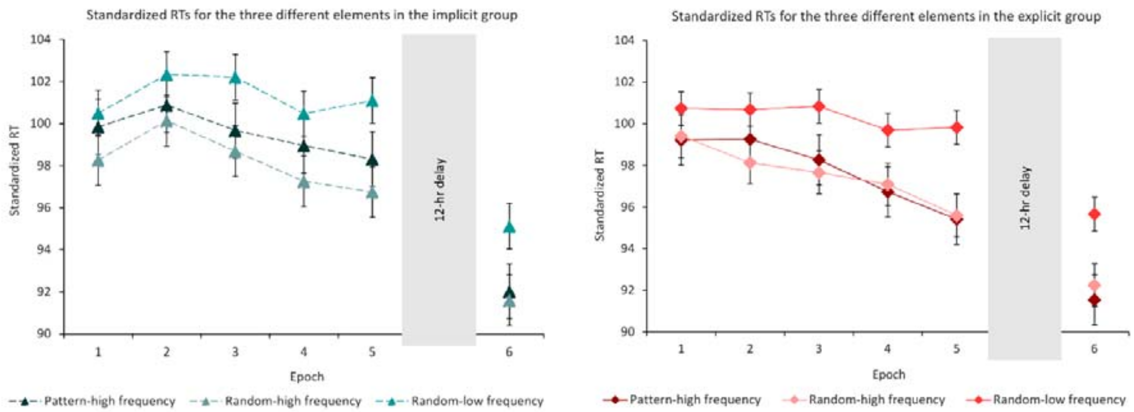

Figure 3. Reaction times (RTs) over the time course of learning for the pattern-high, random-high and random-low elements, separately for the implicit (greens) and the explicit (reds) group. Error bars represent Standard Error of Mean (SEM).

We calculated median RTs for correct responses only for each participant and each epoch, separately for the pattern, random-high and random-low elements. Then we calculated learning scores as a difference between RTs (higher-order sequence learning: random-high minus pattern, pure statistical learning: random-low minus random-high). Larger scores indicate better learning performance. Due to the transformation procedure, these learning score can be interpreted as percentages showing how much faster participants responded to the pattern trials compared to the random-high ones (higher-order sequence learning) or to the random-high trials compared to the random-low ones (pure statistical learning). These learning scores were submitted to mixed design ANOVAs to evaluate learning and retention of the acquired statistical knowledge, respectively. Greenhouse-Geisser epsilon (ε) correction was used when necessary. Original *df* values and corrected *p* values (if applicable) are reported together with partial eta-squared (η_p^2) as the measure of effect size. Results concerning raw reaction times and accuracy can be found in the Supplementary Materials (Table S1, Table S2 respectively). We also report the analysis for triplet learning (i.e., all high frequency triplets compared to the low frequency triplets) to promote comparability with previous ASRT studies that did not separate statistical and sequential learning measures (see Table S3) (Song et al., 2007b).

Based on the previous (especially implicit) consolidation studies, it is plausible to expect retention of the acquired knowledge over the delay period (Janacsek & Nemeth, 2012; Nemeth et al., 2010; Song et al., 2007b), which would results in *no* significant difference in performance between the end of the Learning Phase and the beginning of the Testing Phase. No difference between conditions or groups, however, cannot be conclusively proved by frequentist statistics (null hypothesis significance testing - NHST, (Dienes, 2011, 2014; Kóbor et al., 2017; Unoka et al., 2017). To overcome the limitations of NHST, we conducted Bayesian ANOVAs and calculated the Bayes Factors (BF) for the relevant comparisons using JASP (version 0.8.1.1, JASP Team, 2017). BFs assess the amount of evidence whether our data favor the null-hypothesis (H_0, no difference between the two measures) or the alternative hypothesis (H_1, difference between the two measures exists) (Dienes, 2011, 2014; Wagenmakers, 2007). If the value of BF_{01} is between 1 and 3, it indicates that we have weak evidence for H_0, and strong evidence, if it is between 3 and 10. Similarly, if BF_{01} is between 1/3 and 1, it means we have weak evidence for H_1 and strong evidence, if it is between 1/3 and 1/10 (Wagenmakers, Wetzels, Borsboom, & van der Maas, 2011). In the case of Bayesian ANOVAs, BF values reflect how well a model behaves compared to the null-model. The smaller the BF_{01} value is, the better the model predicts the data. BF_{01} value of the null-model is always 0 (Jarosz & Wiley, 2014). Here, we report BF_{01} values for all the models and the ratio of the best model to the null-model.

Results

Do the implicit and explicit groups show different pure statistical learning performance in the Learning Phase?

We tested potential group differences in pure statistical learning between the two groups by conducting a mixed design ANOVA on standardized RT data of the statistical learning scores (i.e., difference between random low-frequency and random high-frequency elements) with EPOCH (1-5) as a within-subject factor and GROUP (Implicit vs. Explicit) as a between-subject factor. The ANOVA revealed pure statistical learning (significant INTERCEPT: $F(1, 72) = 184.149$, $p < .001$, $\eta_p^2 = .719$), that is, participants responded faster to random-high frequency elements compared to the random-low frequency ones. The implicit and explicit group did not differ significantly in the degree of pure statistical learning (main effect of GROUP: $F(1, 72) = 0.558$, $p = .457$, $\eta_p^2 = .008$), indicating that the explicit instruction did not affect this type of learning. Irrespective of the group instruction, pure statistical knowledge was increasing as the task progressed (significant main effect of EPOCH: $F(4, 288) = 5.784$, $p < 0.001$, $\eta_p^2 = .074$). The EPOCH x GROUP interaction did not reach significance ($F(4, 288) = 0.357$, $p = .836$, $\eta_p^2 = .005$), suggesting that the temporal pattern of pure statistical learning was also independent of the explicit instruction (see Figure 4). The Bayesian mixed design ANOVA provides further support for our results: it revealed that the model including only the EPOCH - i.e., increasing statistical learning as the task progresses - fits the data best ($BF_{01} = 0.011$, $BF_{null\text{-}model}/BF_{EPOCH} = 90.901$). The Bayesian ANOVA also confirmed that there is no considerable effect of GROUP ($BF_{01} = 7.016$) or EPOCH x GROUP interaction ($BF_{01} = 2.030$), thus the explicit instruction did not affect the amount of pure statistical learning or its time course either.

Do the implicit and explicit groups show different pure statistical performance over the 12-hr offline period?

A similar mixed design ANOVA on statistical learning scores was conducted to assess retention after the offline period on with TYPE EPOCH (the last epoch of the Learning Phase and the first epoch of the Testing Phase; thus, Epoch 5 vs. Epoch 6) as a within-subject factor and GROUP (Implicit vs. Explicit) as a between-subject factor. Overall, participants showed knowledge of the statistical regularities as they responded faster on random-high elements compared to random-low elements (significant INTERCEPT: $F(1, 72) = 178.231$, $p < .001$, $\eta_p^2 = .712$). Similarly to the Learning Phase, the implicit and explicit groups did not differ significantly in the amount of statistical knowledge (main effect of GROUP: $F(1, 72) = 0.040$, $p = .842$, $\eta_p^2 = .001$). Statistical knowledge was retained over the offline period (main effect of EPOCH: $F(1, 72) = 2.190$, $p = .143$, $\eta_p^2 = .030$). The EPOCH x GROUP interaction was not significant ($F(1, 74) = 0.017$, $p = .898$, $\eta_p^2 < 0.001$), suggesting that the pattern of offline retention was also independent of the explicit instruction. To further elaborate these results, a Bayesian mixed design ANOVA and BF_{01} values were calculated for learning scores in Epoch 5 and 6. This analysis provided further support for our results: our data favored the null-model ($BF_{01} = 1$; EPOCH: $BF_{01} = 1.572$, GROUP: $BF_{01} = 5.281$, EPOCH x GROUP interaction: $BF_{01} = 48.358$), suggesting retention in pure statistical knowledge over the offline period and similar performance across the two groups (see Figure 4).

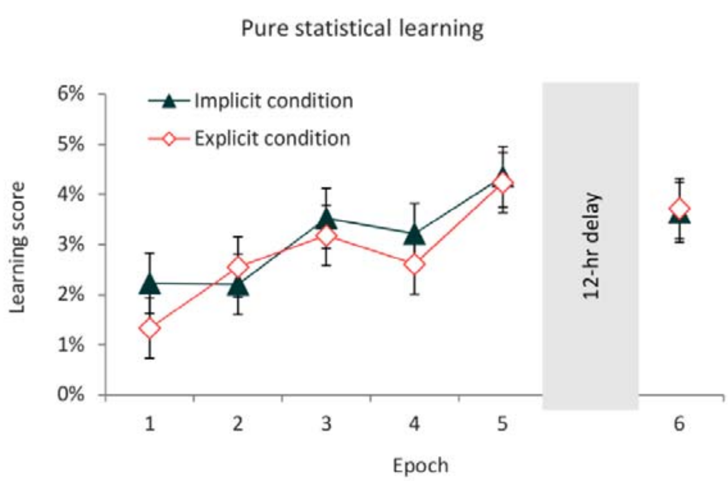

Figure 4. Pure statistical learning scores (the difference between RTs for random-low vs. random-high predictability triplets) over the Learning and Testing Phases. The implicit and explicit groups showed similar learning performance in the first session. Over the 12-hour delay period, both the implicit and explicit groups retained the acquired knowledge. Error bars represent Standard Error of Mean (SEM).

Do the implicit and explicit groups show different higher-order sequence learning performance in the Learning Phase?

To measure higher-order sequence learning performance in the Learning Phase, we conducted a mixed design ANOVA similar to the one reported above on higher-order sequence learning scores (i.e., difference between pattern and. random-high trials) with EPOCH (1-5) as a within-subject factor and GROUP (implicit vs. explicit) as a between-subject factor. Overall, the ANOVA revealed a significant INTERCEPT ($F(1, 72) = 17.357$, $p < .001$, $\eta_p^2 = .122$), indicating that participants responded differently to pattern and random-high elements. Moreover, the main effect of GROUP was also significant ($F(1, 72) = 9.986$, $p = .002$, $\eta_p^2 = .122$): the explicit group showed a higher degree of higher-order sequence learning compared to the implicit group. This finding confirms that participants followed the explicit instruction to improve their learning performance. The main effect of EPOCH and the EPOCH x GROUP interaction were not significant ($F(4, 288) = 0.307$, $p = .867$, $\eta_p^2 = .004$; $F(4, 288) = 1.422$, $p = .228$, $\eta_p^2 = .019$, respectively), suggesting that the advantage of the explicit instruction did not change over the task (see Figure 5). In accordance with previous studies that used a similar amount of practice (e.g., Nemeth, Janacsek, Király, et al., 2013; Song et al., 2007a), the implicit group showed "negative learning" in that reaction times were faster for the random-high frequency elements compared to the pattern-high frequency ones. In contrast to statistical learning that occurs quite early during practice, this result suggests that higher-order sequence learning develops gradually across a longer practice period (e.g., 4-6 days, D. V. Howard et al., 2004; J. H. Howard, Jr. & Howard, 1997) but can be accelerated with explicit instruction. The Bayesian mixed design ANOVA conducted on the learning scores proved that the best model is the one including only the GROUP factor (BF_{01} = 0.015, $BF_{null-model}$ $/BF_{GROUP}$ = 66.667): thus, the amount of evidence provided by the data supports better higher-order learning performance in the explicit group compared to the implicit one. The EPOCH (BF_{01} = 101.514) and EPOCH x GROUP interaction (BF_{01} = 1.548) models failed to predict the data better than the null-model, suggesting that the advantage of the explicit instruction did not change over the task.

Do the implicit and explicit groups consolidate higher-order sequence knowledge differently over the 12-hr offline period?

Offline changes of higher-order sequence knowledge over the 12-hr delay were analyzed by comparing higher-order sequence learning scores from the last epoch of the Learning Phase and the first epoch of the Testing Phase. These variables were submitted to a mixed design ANOVA with EPOCH (Epoch 5 vs. Epoch 6) as a within-subjects factor and GROUP (Explicit vs. Implicit) as a between-subjects factor. The overall higher-order sequence learning score did not reach significance (main effect of INTERCEPT: $F(1, 72) = 0.955$, $p = .322$, $\eta_p^2 = .014$). However, the main effect of GROUP was significant ($F(1, 72) = 6.926$, $p < .001$, $\eta_p^2 = .088$) as the explicit groups showed higher scores compared to the implicit one, similarly to the Learning Phase. Regardless of group, there was a trend for a slight increase in higher-order sequence knowledge over the 12-hour offline period (main effect of EPOCH: $F(1, 72) = 3.199$, $p = .078$, $\eta_p^2 = .043$). Finally, the EPOCH x GROUP interaction failed to reach significance ($F(1, 72) = 0.413$, $p = .523$, $\eta_p^2 = .006$) suggesting a similar pattern of offline changes in higher-order sequence knowledge in the explicit and implicit groups (see Figure 5). The Bayesian mixed design ANOVA and BF_{01} values for learning scores revealed that the best fitting model contained the GROUP factor solely (BF_{01} = 0.045, $BF_{null-model}$ $/BF_{GROUP}$ = 22.222), the other models had only weaker predictive power (model with EPOCH factor: BF_{01} = 1.410; model with the EPOCH x GROUP interaction: BF_{01} = 0.217). These results provide support for the advantage of the explicit group in higher-order sequence knowledge that seems to be retained over the offline period.

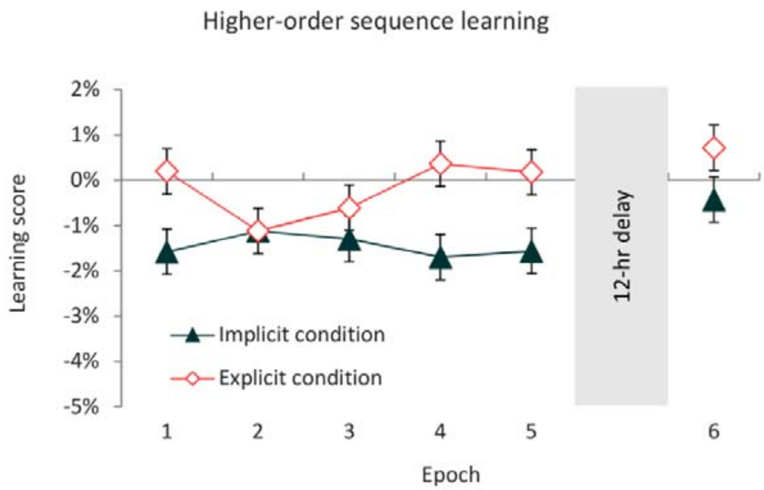

Figure 5. Higher-order sequence learning scores (the difference between RTs for pattern vs. random-high predictability triplets) over the Learning and Testing Phases. The explicit group showed better learning performance in the Learning Phase. Over the 12-hour delay period, both the implicit and explicit groups showed retention of the previously acquired knowledge. Error bars represent Standard Error of Mean (SEM).

How explicit/implicit was the acquired knowledge?

Explicit sequence reports - To test whether the explicit group gained consciously accessible knowledge about the sequence, participants were asked to type in the exact order of the pattern stimuli after each block of the cued ASRT. To avoid giving extra cues about the sequence (e.g., about the length), we asked them to type in 12 items after each block, which corresponds to three repetitions of the 4-item pattern sequence. Performance was defined as percentage of reporting the sequence correctly after a given block (12 items in correct order corresponding to 100% performance), and average performance was calculated for each epoch to facilitate comparison with the ASRT learning performance measures. Data from one participant is missing due to technical issues during data collection.

First, we tested the relationship of explicit sequence report performance and sequence learning performance on the ASRT task. Average percentage of correctly reported sequence elements significantly correlated with the average sequence learning score in the whole Learning Phase ($r(35) = .49$, $p = .002$), that is better sequence learning performance is associated with better sequence report performance. Similar relationship was found in the Testing Phase ($r(35) = .35$, $p = .046$), thus the positive association remained present after the offline delay.

Second, we tested whether the sequence report performance changed over the 12-hr offline period by comparing performance on Epoch 5 (last epoch of the Learning Phase) vs. Epoch 6 (Testing Phase) using paired sample t-test. Here we found no significant effect of time ($t(35) = -1.49$, $p = .146$, $d = 0.096$, $BF_{01} = 2.039$), thus, on the group level, sequence report performance did not change significantly over the 12-hr delay ($M_{Epoch\ 5} = 73.7\%$ vs. $M_{Epoch\ 6} = 76.6\%$). Nevertheless, to further test the possibility that individual differences emerged beyond the average group performance, we also tested the relationship between the difference in sequence report performance over the 12-hr delay and the ASRT sequence learning performance in the Testing Phase (i.e., whether increase in explicit knowledge over the offline period was related to better performance in the Testing Phase). We found no significant relationship between the two measures ($r = -.07$, $p = .681$).

Finally, we also compared the sequence report performance of the sleep and no-sleep groups to reveal whether the offline activity affected their explicit knowledge. Here we found that they performed on a similar level both in the Learning Phase (main effect of SLEEP: $F(1, 34) = 0.01$, $p = .944$, $\eta_p^2 < .001$, $BF_{01} = 2.850$; SLEEP x EPOCH interaction: $F(4, 136) = 0.55$, $p = .621$, $\eta_p^2 = .02$, $BF_{01} = 1.580$) and the Testing Phase (change in percentage of correctly reported elements from Epoch 5 to Epoch 6, SLEEP x EPOCH interaction: $F(1, 34)$

$= 0.03$, $p = .870$, $\eta_p^2 = .001$, $BF_{01} = 2.495$; performance in Epoch 6: $t(34) = 0.38$, $p = .761$, $d = 0.128$, $BF_{01} = 2.934$). These results further support the unification of the two groups.

Inclusion/Exclusion task – To test whether the acquired frequency-based information remained implicit or became explicitly accessible, the Inclusion/Exclusion task was administered in both groups (see Methods). In the implicit group, two participants' data is missing, and three participants were excluded as they did not follow the instructions in the exclusion condition. Participants in the implicit group generated 6% more high-frequency triplets than chance level (25%) in the inclusion condition ($t(34) = 3.19$, $p = .003$, $d = 0.539$, $BF_{01} = 0.085$). Interestingly, they generated 7.5% more high-frequency triplets in the exclusion condition ($t(31) = 5.75$, $p < .001$, $d = 1.016$, $BF_{01} = 0.0001$) indicating that they could not exclude (consciously control) this knowledge. Performance in the two conditions did not differ ($t(31) = -.56$, $p = .580$, $d = -0.099$, $BF_{01} = 4.582$), thus the participants' triplet knowledge can be regarded as implicit memory. In the explicit group, data from three participants is missing and further five participants were excluded as they did not follow the instructions in the exclusion condition. Participants of the explicit group generated 8.5% more high-frequency triplets in the inclusion condition than it would have been expected by chance ($t(33) = 4.32$, $p < .001$, $d = 0.730$, $BF_{01} = 0.005$). Similarly to the implicit group, they also generated more high-frequency triplets than expected by chance in the exclusion task (5.4%; $t(28) = 4.08$, $p < .001$, $d = 0.690$, $BF_{01} = 0.011$). Comparing the inclusion and the exclusion conditions, they generated similar rate of high-frequency triplets ($t(28) = 1.37$, $p = .182$, $d = 0.250$, $BF_{01} = 2.184$), thus triplet knowledge remained implicit for participants in the explicit group as well. Altogether, the implicit and the explicit groups showed similar performance both in the inclusion ($t(67) = -.91$, $p = .745$, $d = -0.110$, $BF_{01} = 2.310$) and in the exclusion conditions ($t(59) = 1.10$, $p = .276$, $d = 0.141$, $BF_{01} = 2.831$).

Discussion

The present study investigated the effect of explicit cues on the subcomponents of procedural learning to compare implicit and explicit memory formation and consolidation. Performance was measured by a probabilistic sequence learning task (ASRT), which enabled us to clearly distinguish between statistical learning and sequence learning. To the best of our knowledge, this is the first study focusing on the role of awareness in the consolidation of these two subcomponents of procedural learning in the same experimental design. Our results revealed that the degree of statistical learning was not sensitive to the explicit instruction: the implicit and explicit groups showed similar learning scores. After the 12-hour offline period, both groups showed retained pure statistical knowledge, suggesting that the consolidation was independent of the level of awareness and was resistant to the delay. In contrast, sequence learning performance was improved by the explicit instruction, the experimental manipulation helped to acquire the exact order of the stimuli. This benefit remained present after the offline delay compared to the implicit group. Interestingly, performance slightly increased by the testing phase independently of whether participants received explicit instruction or not. These results suggest that while the emergence of sequence knowledge is sensitive to the explicitness of the task, retention is not affected by the instruction. Importantly, our findings of statistical and sequence learning are supported by Bayes factors, corroborating the classical statistical approach (Dienes, Coulton, & Heather, 2018).

The main experimental manipulation in our study was whether or not participants were given explicit instructions about the task. In the explicit group, we informed the participants that a sequence was repeating in the task, which could have affected their performance in two ways. First, they intentionally searched for the sequence and gained explicit knowledge about that. Second, they became aware about the learning situation itself, which may have created a different mind-set compared to the implicit group, where participants were informed that they perform a simple reaction time task. This might have had beneficial effects on the acquisition of statistical information even though the explicit instruction did not carry information about the frequency-based associations in the task. Contrary to this possibility, we found no difference between the statistical learning performance of the implicit and the explicit groups: both groups learned the statistical regularities similarly and this knowledge remained implicit in both cases. Nonetheless, improved statistical learning has been previously reported in the explicit compared to the implicit group in the study of Nemeth et al. (2013). The main difference between the two studies is that here we used fix paced timing (fix inter stimulus interval), while they used self-paced timing (fix response to stimulus interval). The self-paced timing enabled the explicit group to spend as much time on stimulus processing as they needed, which may have caused additional benefit compared to the implicit group not only for the sequential knowledge but also for the acquisition of statistical regularities. As we aimed to control the processing time in the implicit and explicit groups, we used fix-paced stimulus presentation. It is possible that the current timing parameters were perceived by the participants as too fast, potentially creating a more stressful situation which may have interfered with some aspects of learning. On the other hand, longer stimulus presentation may elicit other potential issues such as increased boredom, task-irrelevant thoughts, lack of motivation and/or lower involvement as the task progresses. Future studies should test the potential effect of various timing parameters and their interactions with explicit instruction on the acquisition of statistical regularities.

Another possible explanation is that despite the similar results, statistical learning is actually better in the explicit task, however, behavioural performance is decreased due to the increased level of required cognitive resources. Participants are instructed to pay attention to the cued stimuli, try to explicitly learn (and report) the exact order of these stimuli and respond fast and accurately, while the implicit group is instructed only to the latter one. Thus, the explicit ASRT can be regarded as a dual-task situation. Assuming that the cued (explicit) version requires more cognitive resources, while performance is comparable to the implicit version, the explicit instruction might have boosted statistical learning performance, which was reduced by the dual task and the fix paced nature of the task. This explanation is in line with the results of Nemeth et al. (2013): despite the dual-task situation the boosting effect of explicit instruction could emerge on the behavioural level as a consequence of self-paced timing. Jimenez and Mendez (2001) showed that participants under dual-task situation could not use the explicit cues to boost implicit procedural learning performance, which supports our interpretation. This possible explanation can be tested in future experiments by comparing the performance of an explicitly instructed group with the performance of an implicit, dual-tasking group, using the same stimulus timing parameters.

One of our main aims was to test the consolidation of statistical information, which has received little empirical attention so far (S. J. Durrant, Cairney, & Lewis, 2013; S. J. Durrant, Taylor, Cairney, & Lewis, 2011; Kim, Seitz, Feenstra, & Shams, 2009). Previous studies that used the implicit ASRT task only focused on the so-called triplet learning (see the Task section), which is closely related to statistical learning performance but is somewhat contaminated with sequential information (Hallgato et al., 2013; Janacsek & Nemeth, 2012; Kóbor et al., 2017; Nemeth et al., 2010; Simor, Zavecz, Csábi, et al., 2017; Song et al., 2007b). The acquired knowledge in these studies seemed to be robustly stable (e.g., neither forgetting, nor improvement occurred) during the offline delay, whether it is short or long, such as 12 hours (Hallgato et al., 2013; Nemeth et al., 2010; Simor, Zavecz, Csábi, et al., 2017; Song et al., 2007b), 24 hours (Janacsek, Ambrus, Paulus, Antal, & Nemeth, 2015; Janacsek & Nemeth, 2012), one week (Janacsek & Nemeth, 2012) or even one year (Kóbor et al., 2017). Consolidation in the cued (explicit) version of the ASRT task has been investigated only in one study: Simor, Zavecz, Horváth et al. (2017) showed that statistical learning performance did not change over a 1.5-hour long offline delay. Our findings are consistent with these previous studies, showing reliably retained pure statistical knowledge during consolidation.

Besides statistical learning, we also measured the acquisition and consolidation of higher-order sequential information. Regarding the learning phase, we found that the explicit instruction on the structure of the task (i.e., alternating sequence) successfully improved sequence learning performance: the explicit group outperformed the implicit group from the beginning of the task. This result is consistent with Nemeth et al.'s findings (2013), nevertheless, here we measured poorer learning performance, meaning that despite the explicit instruction and cued stimuli, the explicit group showed near zero-level learning performance in the first three epochs of the task. This finding may be explained by the degrading effect of the fix-paced timing. As discussed above, compared to the self-paced timing, where participants could use as much time as they needed to process the stimuli, find the alternating sequence and use that information to improve their performance, the fix-paced timing may have interfered with one of these processes. The implicit group showed negative learning performance: they performed better on the high-frequency random elements than the sequence elements. Previous studies have also reported this pattern (Nemeth, Janacsek, & Fiser, 2013; Song, Howard, & Howard, 2008), however the underlying processes have not yet been identified. Better performance on high-frequency random elements may suggest that statistical learning is primary compared to sequence learning. In line with this interpretation, Howard & Howard (1997) showed that triplet/statistical learning already occurs after one day of practice, while at least four days of consecutive practice is needed to learn the higher-order sequential information in the task if no explicit instructions are given (i.e., implicitly).

Our other main goal was to test the consolidation of the sequential information. Here we found that the explicit group, similarly to the learning phase, outperformed the implicit group after the 12-hour delay. Independently of instruction, the two groups showed a slight offline improvement, which was revealed by a trend in the classical statistical analysis and by anecdotal evidence in the Bayesian analysis. Only one study tested the consolidation of probabilistic sequential information but did not contrast implicit and cued versions of the ASRT task (Simor, Zavecz, Horváth, et al., 2017). In that study, all participants received explicit instruction and consolidation of sequential knowledge was tested after a 1.5-hour delay. They found no immediate improvement after the offline period. It is possible that the shorter offline period was not enough to promote improvement of sequential knowledge, while a longer period, such as 12 hours as in the current study may be sufficient to reveal small performance improvements. On the other hand, even the Bayesian analysis yielded anecdotal evidence for this improvement, which calls for further studies testing under what circumstances offline improvement can occur.

Although with deterministic sequence learning, Robertson et al. (2004) compared the effect of sleep in 12-hour consolidation of the implicit and explicit SRT task. They found that offline improvement occurred in the case of implicit learning regardless of sleep, while this improvement was present in the case of explicit learning only when the offline delay contained sleep. These results are in contrast with the present findings, however the classical SRT task uses second-order deterministic sequence, while the ASRT task has probabilistic structure. To conclude, both learning and consolidation processes of statistical learning and sequence learning dissociate in the ASRT task.

Considering the effect of sleep on consolidation, we did not find any effect of sleep on the offline changes either in the case of statistical learning or sequence learning. These negative results are in line with previous studies investigating the role of sleep in the consolidation of the ASRT task. These studies reported that neither sleep disorders (Csabi et al., 2015; Csabi, Varszegi-Schulz, Janacsek, Malecek, & Nemeth, 2014; Simor, Zavecz, Csábi, et al., 2017), nor overnight sleep compared to daily activity in the offline period (Nemeth et al., 2010) affected the retention of triplet knowledge. Simor, Zavecz, Horváth et al. (2017) showed that a 1.5-hour daytime nap had no effect either on the consolidation of explicit sequential or implicit statistical knowledge. These results altogether suggest that various aspects of procedural learning, regardless of awareness, do not benefit from sleep, at least on the behavioural level (see also: Mantua, 2018; Pan & Rickard, 2015).

Our findings show that awareness differentially affects memory formation in the domain of sequence learning and statistical learning. A potential limitation of our study may be the timing of the stimulus presentation. We intentionally chose fix ISI to fully control the timing of the presentation making comparable the explicit and implicit conditions. Here we conclude that although 500 ms is enough to process information, this ISI still might have been too fast to reach optimal performance. The optimal parameters of the ISI are not clear yet (and may depend on other experimental factors as well), hence further studies are needed to test slower but fix ISI parameters. On the other hand, the present study is uniquely high-powered in the field of comparing explicit and implicit learning as we had 37 participants per group compared to the typical group size of 15-20 in previous studies. Moreover, previous studies mostly used tasks with deterministic sequence, such as the SRT task. It has been showed that the test-retest reliability of the SRT is relatively weak (Stark-Inbar, Raza, Taylor, & Ivry, 2016; West, Vadillo, Shanks, & Hulme, 2017), while the probabilistic sequence structure appears to make the ASRT task a more reliable tool to test procedural learning (Stark-Inbar et al., 2016). Altogether, whereas the present study could be improved with more optimal timing parameters, the main strengths of the study are the relatively large sample size and using a task that showed better reliability compared to other, widely used tasks.

In summary, our study showed that awareness differently affects parallel formation of two sub-processes of procedural learning, namely statistical learning and sequence learning: while sequence learning can be boosted with explicit instruction, statistical learning seems to be independent of awareness. However, the consolidation of these two types of information is comparable: both the statistical knowledge and the sequential knowledge are retained during a 12-hour delay period regardless of the explicitness of the learning process. Overall, these findings provide a deeper insight into the role of awareness in procedural learning, moreover they highlight that the explicitness of a task does not necessarily affect all sub-processes of procedural memory formation.

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