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## Research Report

# Do temporal factors affect whether our performance accurately reflects our underlying knowledge? The effects of stimulus presentation rates on the performance versus competence dissociation



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## ABSTRACT

Ample evidence shows that the momentary performance can dissociate from the underlying knowledge (competence). Under what circumstances such dissociation occurs, however, remains unclear. Here we tested how temporal factors, and more specifically, the elapsed time between subsequent events affects the dissociation between performance and competence by systematically manipulating the stimulus presentation rates during and after learning. Participants completed a probabilistic sequence learning task with a fast (120 msec) or a slow (850 msec) response-to-stimulus-interval (RSI) during the Learning phase and they were tested with both RSIs 24 h later (Testing phase). We also tested whether they gained explicit knowledge about the sequence or their knowledge remained implicit. Our results revealed higher reaction time learning scores when tested with the fast RSI, irrespective of the RSI during learning, suggesting that faster presentation rates can help better express the acquired knowledge, leading to increased performance measures. For accuracy, participants showed higher learning scores when tested with the same presentation rate as the one that they encountered during learning. The acquired knowledge remained implicit in both groups, suggesting that the observed findings were not confounded by differences in awareness gained in the two groups. Overall, our study

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highlights that the momentary performance does not always accurately reflect the underlying knowledge, and temporal factors seem to influence this dissociation. Our findings have theoretical, methodological, and translational implications that likely extend beyond learning and memory to other functions and domains as well, including aspects of decision-making, perception, theory of mind, and language.

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## 1. Introduction

Ample evidence shows that learning can occur in the absence of any performance gain, and vice versa, momentary performance often fails to accurately reflect the underlying knowledge (Kantak & Winstein, 2012; Schmidt & Bjork, 1992; Soderstrom & Bjork, 2015). It is a common experience to perform weaker in a task in which we previously showed good performance; for example, we may experience a temporary drop in performance when playing sports or speaking a foreign language. These examples illustrate that there is a temporary fluctuation in behavior, and performance in a given moment may not accurately reflect the underlying knowledge (competence) (Soderstrom & Bjork, 2015). This phenomenon has been highlighted by previous theoretical work in language (Chomsky, 1965) as well as in learning and memory, with experimental evidence coming from latent learning in animals, and verbal learning and motor skill learning in humans (Kantak & Winstein, 2012; Schmidt & Bjork, 1992; Soderstrom & Bjork, 2015). Although experimentally this dissociation has been demonstrated mainly within learning and memory, its importance likely extends to other cognitive domains and more complex abilities that rely on learning and memory as well, including aspects of decision-making, perception, theory of mind, and language performance (Mutter, Alcorn, & Welsh, 2006; Rieskamp & Otto, 2006; Turk-Browne, Scholl, Johnson, & Chun, 2010; Ullman, Earle, Walenski, & Janacsek, 2020). While there are many examples for a dissociation between the momentary performance and the underlying competence in research as well as in our daily lives, it has remained elusive under what circumstances such dissociation occurs.

Here we aimed to test how temporal factors, and more specifically, the elapsed time between subsequent events, may contribute to this dissociation. We focused on this factor because previous research has shown that the elapsed time between subsequent events (items) can determine how our mind processes those events and whether it discovers potential relationships among them (Davachi & DuBrow, 2015; Destrebecqz & Cleeremans, 2003; Karlsen, Allen, Baddeley, & Hitch, 2010; Wlotko & Federmeier, 2015). Elapsed time also affects whether the formed memories of those events and relationships are retained for a longer period or become forgotten (Barrouillet, Bernardin, & Camos, 2004; Brown, Neath, & Chater, 2007; Cornelissen & Greenlee, 2000; Zhang & Luck, 2009). Moreover, elapsed time between subsequent events can alter our neural responses as well and shift the reliance from one neural network to another (e.g., Buhusi & Meck, 2005; Foerde & Shohamy, 2011; Schultz, Tremblay, &

Hollerman, 2003). Therefore, here we aimed to systematically test, by manipulating the stimulus presentation rates, to what extent the elapsed time between subsequent items affect the momentary performance versus the acquired knowledge (competence) itself. We chose a learning task that involves sequentially presented perceptual stimuli, which participants are required to process, respond to, and learn predictable inter-stimulus relationships, serving as an ideal model task for testing the effect of presentation rate on these processes.

Extracting sequential regularities embedded in the environment is a fundamental cognitive function that is involved in aspects of perception, predictive processing and procedural learning (Armstrong, Frost, & Christiansen, 2017; Bar, 2007; Fiser & Aslin, 2002; Turk-Browne et al., 2010; Ullman et al., 2020). Learning such regularities typically occurs implicitly (i.e., without conscious access either to what was learned or to the fact that learning occurred), although explicit (conscious) knowledge about the regularities can also emerge in certain cases (Cleeremans & Jiménez, 2002; Conway, 2020; Reber, 1993). Sequence learning tasks, such as the variants of the Serial Reaction Time (SRT) task, are the most commonly used paradigms to assess learning of sequential regularities (Janacsek & Nemeth, 2012; Nissen & Bullemer, 1987; Ullman et al., 2020).

The stimulus presentation rate can be manipulated by setting the Response-to-Stimulus Interval (RSI), that is, the time interval between a response and the next stimulus (Willingham, Greenberg, & Thomas, 1997). Previous studies using different RSIs in sequence learning tasks such as the SRT task have yielded mixed findings. Most studies found that shorter or more congruent RSIs led to better learning, particularly when measured by reaction time (RT) indices (Destrebecqz & Cleeremans, 2003; Dominey, 1998; Frensch & Miner, 1994; Howard, Howard, Dennis, & Yankovich, 2007; Nissen & Bullemer, 1987; Soetens, Melis, & Notebaert, 2004; Stadler, 1995). Others however reported an opposite pattern, with longer RSIs leading to better learning, at least in accuracy and judgment-based measures of performance (Arciuli & Simpson, 2011; Emberson, Conway, & Christiansen, 2011). These mixed findings may be explained by differences in the performance measures used in the task (e.g., accuracy or RT), while others suggested that differences in the level of awareness about the relevant task characteristics (e.g., whether the acquired knowledge remained implicit or explicit knowledge about the sequence structure also emerged during the task) could also affect the observed effects (Destrebecqz & Cleeremans, 2003; Frensch & Miner, 1994). Importantly, these

studies did not distinguish momentary performance from the underlying knowledge (i.e., competence), therefore how the elapsed time between subsequent items affects these processes remains unclear. Here we systematically tested the effect of the elapsed time on performance versus competence by manipulating the stimulus presentation rates (more specifically, the RSI) during learning, by analyzing both accuracy and RT measures, and by testing whether participants' knowledge remained implicit during the task or they also gained explicit knowledge about the sequence structure.

It has been suggested that a transfer condition could be employed to differentiate between performance and competence (Willingham et al., 1997). Using such transfer conditions, Willingham et al. (1997) showed that those who learned with longer RSIs showed higher learning scores when tested with shorter RSIs, suggesting that the participants' momentary performance in the former conditions did not accurately reflect their acquired knowledge that could better expressed when tested in the latter conditions. However, in that study, learning scores were measured only at the end of the learning phase due to the characteristics of the deterministic SRT task (for a review see Janacsek & Nemeth, 2012); therefore, how the RSI affects the time course of learning remains unclear. Moreover, only RT measures were used due to ceiling effects in accuracy, and the effect of RSI on whether participants gained explicit knowledge during the task was not tested, potentially leading to confounded effects. In the current study, we used a probabilistic sequence learning task, namely the Alternating Serial Reaction Time (ASRT) task (Howard & Howard, 1997; Kóbor, Janacsek, Takács, & Nemeth, 2017; Nemeth et al., 2010). In contrast to the deterministic SRT (Nissen & Bullemer, 1987), in the ASRT task, repeating sequence elements alternate with random ones throughout the task (see Fig. 1AB). This enables to track the time course of learning and provides reliable measures of learning both in accuracy and RT (Farkas, Krajcsi, Janacsek, & Nemeth, 2022; Stark-Inbar, Raza, Taylor, & Ivry, 2016; West, Vadillo, Shanks, & Hulme, 2017). Due to the probabilistic nature of the sequences, knowledge in the ASRT task remains implicit in most cases, minimizing the potential confounds of gaining explicit knowledge by some participants but not others.

Overall, the aim of our study was to test how the elapsed time between subsequent items, as manipulated by the stimulus presentation rate, affects the momentary performance versus the underlying competence. To this end, two versions of the ASRT task were compared in healthy young adults: the fast RSI group performed the task with 120 msec RSI and the slow RSI group performed the task with 850 msec RSI in the Learning phase. The RSI lengths were determined based on previous studies (Howard & Howard, 1997; Kóbor et al., 2017; Nemeth et al., 2010; Willingham et al., 1997). To test how the fast versus. slow RSI affected the momentary performance versus the acquired knowledge (competence), the two groups performed both RSI versions of the task 24 h later in the Testing phase. This retention period was chosen to ensure that well-consolidated knowledge is tested, thus the effect of RSI change is not confounded with further learning effects in the Testing phase (Kóbor et al., 2017; Nemeth & Janacsek, 2011). At the end of the Testing phase, participants also completed the so-called Inclusion-Exclusion task, in

which they were asked to generate responses based on the sequence that they learned in the ASRT task (Inclusion condition) or based on a different sequence (Exclusion condition). This additional task enabled us to test the effect of RSI on whether participants gained explicit knowledge about the underlying sequence of the ASRT task or their knowledge remained implicit. Overall, our study addresses three questions: (1) Does the stimulus presentation rate affect the learning scores in the Learning phase? (2) Do the learning scores accurately reflect the acquired knowledge (i.e., competence) or do they reflect momentary performance instead? (3) Does the stimulus presentation rate affect whether explicit knowledge is gained in the task or the knowledge remains implicit, irrespective of the presentation rate encountered during learning?

First, based on previous research described above (Frensch & Miner, 1994; Soetens et al., 2004; Willingham et al., 1997), we expected the slow RSI group to show lower learning scores compared to the fast RSI group in the Learning phase of the ASRT task. However, based solely on the Learning phase, it is unclear to what extent these learning scores reflect their acquired knowledge versus momentary performance. That is, if the slow RSI group showed lower learning scores in this phase, they either learned less than the fast RSI group (i.e., the level of competence is lower), or the characteristics of the task/learning situation (such as timing) influenced how much they could express what they learned (i.e., their learning scores might have not reflected accurately their acquired knowledge). Second, to clarify this, we looked at the Testing phase of the ASRT task, in which both groups were tested with both RSIs. Following from the prediction above, if presentation rates lead to a dissociation between the momentary performance and the underlying knowledge, then two effects could be observed. The fast RSI group (i.e., the group that learned with fast RSI) would exhibit lower learning scores when they are tested with the slow RSI (*vs* when tested with the fast RSI). Additionally, the slow RSI group would exhibit higher learning scores when they are tested with the fast RSI (*vs* when tested with the slow RSI). These observations would suggest that the learning scores measured in the slow RSI condition do not accurately reflect the underlying knowledge but their momentary performance, and the acquired knowledge could be better expressed in the fast RSI condition (Willingham et al., 1997). Third, compared to the fast RSI group, we hypothesized that the slow RSI group would exhibit greater explicit sequence knowledge as measured by the Inclusion-Exclusion task if the presentation rate affected the level of awareness about the relevant task characteristics as suggested by Destrebecqz and Cleeremans (2003).

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## 2. Materials and methods

### 2.1. Participants

Seventy-nine individuals (68 females and 11 males) aged between 19 and 30 ( $M_{\text{Age}} = 22.01$  years,  $SD_{\text{Age}} = 1.87$  years) took part in the experiment (for details on how required sample size was calculated, see [Supplementary methods](#)). All participants were university students ( $M_{\text{Years of education}} = 14.67$

years,  $SD_{\text{education}} = 1.62$  years) from Budapest, Hungary. None of them reported history of developmental, psychiatric, neurological or sleep disorders, and they had normal or corrected-to-normal vision. They performed in the normal range on standard neuropsychological tests of short-term and working memory (Digit span task:  $M = 6.06$ ,  $SD = 1.04$ ; Counting span task:  $M = 3.76$ ,  $SD = .84$ ; 1 missing data) (Case, Kurland, & Goldberg, 1982; Fekete et al., 2010; Janacsek & Nemeth, 2013; Racsomány, Lukács, Németh, & Pléh, 2005). Handedness was measured by the Edinburgh Handedness Inventory (Oldfield, 1971); the Laterality Quotient of the sample varied between  $-80$  and  $100$  (where  $-100$  means complete left-handedness, and  $100$  means complete right-handedness;  $M_{LQ} = 47.31$ ,  $SD_{LQ} = 47.54$ ; 1 missing data; 82% of participants were right-handed).

All recruited participants were included in the study. Participants were randomly assigned to one of two groups based on the RSI of the Learning phase, and they were further divided into two subgroups each in the Testing phase in order to counterbalance the testing order of the RSIs (see Procedure and Fig. 1C). Before the assessment, all participants gave signed informed consent and received course credit for participation. The study was approved by the Institutional Review Board of Eötvös Loránd University, Hungary.

## 2.2. Tasks

### 2.2.1. ASRT task

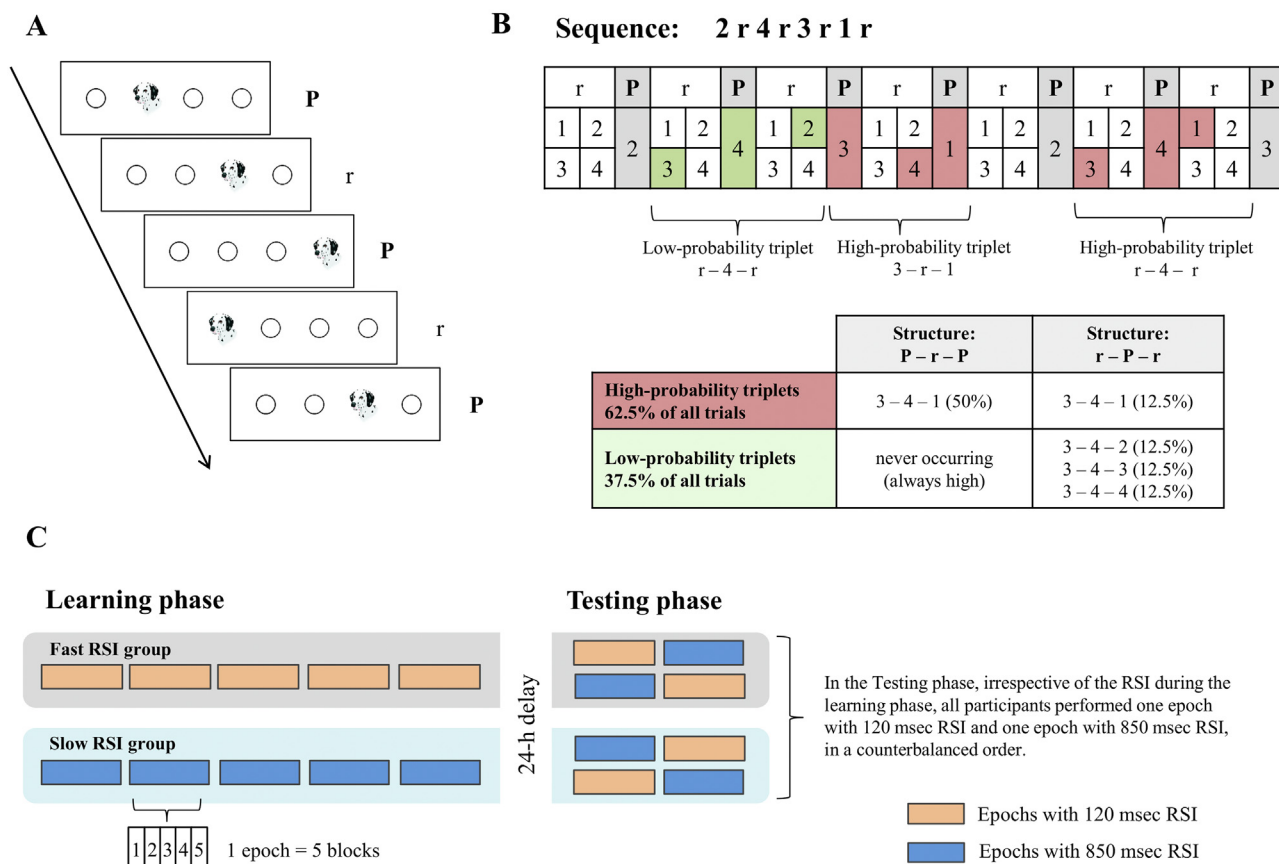
Learning was measured by the ASRT task (Howard & Howard, 1997; Nemeth et al., 2010). In this task, a stimulus (a dog's head) appeared in one of four horizontally arranged empty circles on the screen and participants were asked to press the corresponding button as quickly and accurately as they could when the stimulus occurred. The computer was equipped with a keyboard with four heightened keys (Z, C, B, M on a QWERTY keyboard), each corresponding to a circle in a horizontal arrangement. Participants were asked to respond to the stimuli using their middle- and index fingers bimanually. The stimulus remained on the screen until the participant pressed the correct button. The next stimulus appeared after a 120 or 850 msec response-to-stimulus-interval (RSI) (for more details on the presentation rates see Procedure). The task was presented in blocks of 80 trials: unbeknownst to the participants, an eight-element alternating sequence was presented ten times (e.g., 2r4r3r1r, where each number represents one of the four circles on the screen and r represents a randomly selected circle out of the four possible ones) (Fig. 1A). Due to the alternating sequence structure, some triplets (i.e., runs of three consecutive events) were more probable to occur than others. Following previous studies, we refer to the former as high-probability triplets and the latter as low-probability triplets (Fig. 1B). Note that due to the higher occurrence probability, the final event of high-probability triplets was more predictable from the initial event of the triplet compared to the low-probability triplets (Howard & Howard, 1997; Nemeth et al., 2010). For each trial, we determined whether it was the last event of a high- or low-probability triplet.

### 2.2.2. Inclusion-Exclusion task

To test whether the participants gained explicit knowledge about the regularities of the ASRT task, we administered the widely used Inclusion-Exclusion task (Buchner, Steffens, & Rothkegel, 1998; Destrebecqz & Cleeremans, 2001; Dienes & Scott, 2005; Jiménez, Vaquero, & Lupiáñez, 2006; Kóbor et al., 2017), which is based on the Process Dissociation Procedure (PDP; Jacoby, 1991). Before performing this task, participants were informed that the order of the stimulus appearance in the ASRT task followed a hidden sequence. First, they were asked to generate this sequence (Inclusion condition) using the same response buttons as the ones they used during the ASRT task. They were told to rely on their intuitions if they were unsure about the sequence. They performed four runs of this Inclusion condition. Then they were asked to generate a sequence of responses that was different from the learned ASRT sequence (Exclusion condition). They were instructed to try generating realistic sequences that could have occurred in the task, and therefore, use all response buttons equally and try to avoid simple repetitive sequences such as 12341234 or 11112222. Since participants were explicitly told that such sequences would have never occurred in the task, if they still generated such sequences, it clearly indicated that they did not follow the instructions. They performed four runs of this condition as well. In both conditions, each run was finished after 24 key presses (for more details see Horváth, Török, Pesthy, Nemeth, & Janacsek, 2020; Kóbor et al., 2017).

First, we removed runs in which participants did not follow the instructions. This was determined as follows: a run was removed from the analysis if the same response button was pressed for 50% or more of a run, or if simple repetitive sequences such as in the example above were generated consecutively for 50% or more of a run. We chose these thresholds to find a right balance between including as much data in the analysis as possible, while at the same time excluding those runs in which instruction was clearly not followed. These exclusion criteria were determined during the revision process of the paper and constitute a more lenient approach than the one used originally (notably, the pattern of results and conclusions remained unchanged during this process, suggesting a certain level of robustness in the data, irrespective of the different exclusion strategies). All data, including the runs removed from the analyses reported in the paper, are available on OSF for transparency (<https://osf.io/cy5j6>).

After removing those runs in which participants did not follow the instructions, we calculated the percentage of producing high-probability triplets in the Inclusion and Exclusion conditions separately. Then, we compared these scores to chance level, which was 25%. According to PDP, producing high-probability triplets above chance in the Inclusion condition could be achieved by relying on either implicit or explicit knowledge about the learned sequence. In contrast, producing high-probability triplets above chance in the Exclusion condition would indicate that participants' responses were primarily driven by implicit knowledge as they lacked sufficient explicit/conscious control to exclude their sequence knowledge and generate a different sequence than the learned one (Destrebecqz et al., 2005; Fu, Dienes, & Fu,



**Fig. 1 – Design of the experiment. (A)** In the Alternating Serial Reaction Time (ASRT) task participants were asked to respond to the stimuli (a dog's head) appearing in one of four locations, and press the corresponding key as fast and as accurately as they could. Unbeknownst to them, every second stimulus was part of a repeated alternating sequence (P – pattern) and every second stimulus was random (r – random). **(B)** As a result of the alternation of pattern and random trials, there were more probable and less probable combinations of three consecutive stimuli (high- and low-probability triplets, respectively). Learning was measured as differences in responses to high- versus low-probability triplets, both in reaction time and accuracy. An example of a possible sequence is shown in this panel. **(C)** The experiment consisted of two sessions, separated by a 24-h delay. On Day 1 (Learning phase) participants were randomly assigned to one of two groups: the fast RSI group performed 25 blocks (5 epochs) of the ASRT task with 120 msec response-to-stimulus interval (RSI), the slow RSI group performed 25 blocks (5 epochs) of the task with 850 msec RSI. On Day 2 (Testing phase), all participants performed 10 blocks (2 epochs) of the task: 5 blocks with the fast (120 msec) and 5 blocks with the slow (850 msec) RSI version of the task, in counterbalanced order.

2010; Jiménez et al., 2006; Kóbor et al., 2017). Consequently, producing a similar percentage of high-probability triplets above chance both in the Inclusion and Exclusion conditions would indicate that participants relied on implicit knowledge in both conditions. Contrary, a combination of producing high-probability triplets above chance in the Inclusion condition and (closer to or) at chance level in the Exclusion condition would indicate that participants gained (at least some) explicit knowledge about the task.

### 2.3. Procedure

There were two sessions in the experiment: a Learning phase and a Testing phase separated by a 24-h delay (Fig. 1C). On Day 1, the Learning phase of the ASRT task took place. Participants were not given any information about the regularity that was embedded in the task (Nemeth et al., 2010). They were

informed that the main aim of the study was to test how extended practice affected performance on a simple reaction time task. Therefore, we emphasized performing the task as accurately and as fast as they could. Between blocks, the participants received feedback about their average accuracy and reaction time presented on the screen, and then they had a rest period of between 10 and 20 sec before starting the next block.

Participants were randomly assigned to one of two groups on Day 1: 40 participants performed the fast RSI version, and 39 performed the slow RSI version of the ASRT task. In the fast version of the task, the RSI was 120 msec, while in the slow version, the RSI was 850 msec. The ASRT consisted of 25 blocks on Day 1. Thus, participants completed 2000 trials of the alternating sequence ( $25 \times 80$  trials/block) in this phase. Previous studies have shown that this amount of practice is sufficient to acquire the regularities embedded in the task (Janacsek, Ambrus, Paulus, Antal, & Nemeth, 2015; Nemeth

et al., 2010; Unoka et al., 2017). In the fast version of the task, one block took about 1–1.5 min, and in the slow version of the task, one block took about 1.5–2.5 min, therefore the fast version of the task took approximately 30 min, and the slow one approximately 45 min.

On Day 2, all participants performed 10 blocks of the ASRT task: 5 blocks with the fast and 5 blocks with the slow version of the task, in counterbalanced order (see Fig. 1B). For testing the potential order effects, see [Supplementary results I](#). The fast blocks took about 5–8 min, and the slow ones approximately 10–13 min, therefore, the Testing phase was 15–22 min long in total.

For each participant, one of the six unique permutations of the four possible ASRT sequence stimuli was selected in a pseudorandom manner (Howard & Howard, 1997; Kóbor et al., 2017; Nemeth et al., 2010). On Day 2, participants were tested with the same ASRT sequence as the one they learned on Day 1.

After performing the ASRT task on Day 2, we tested the amount of explicit knowledge the participants acquired about the task with a short questionnaire and the Inclusion-Exclusion task (see task description in Section 2.2.2 above). The short questionnaire (Nemeth et al., 2010; Song, Howard, & Howard, 2007a) included two questions: „Have you noticed anything special regarding the task?” and „Have you noticed some regularity in the sequence of stimuli?”. None of the participants reported noticing the hidden regularity in the task. The results of the Inclusion-Exclusion task are discussed in the Results section.

## 2.4. Statistical analysis

We followed the standard data processing and analysis protocols of previous ASRT studies (Janacsek, Borbély-Ipkovich, Nemeth, & Gonda, 2018; Kóbor et al., 2017; Nemeth et al., 2010; Nemeth, Janacsek, Király, et al., 2013; Song, Howard, & Howard, 2007b). Based on these protocols, epochs of five blocks were analyzed instead of single blocks (thus, Epoch 1 corresponds to Blocks 1–5, Epoch 2 corresponds to Blocks 6–10, etc.). We calculated mean accuracy for all trials and median RTs for correct responses only for each participant and each epoch, separately for high- and low-probability triplets. Accumulating evidence indicates that participants respond increasingly accurately and faster to high-probability triplets compared with low-probability ones as the ASRT task progresses, revealing learning of the regularities embedded in the task (e.g. Howard & Howard, 1997; Nemeth, Janacsek, & Fiser, 2013; Song et al., 2007b; Takács et al., 2018). Therefore, triplet learning scores were calculated as a difference in accuracy/RT for high- versus low-probability triplets (for accuracy: high- minus low-probability; for RTs: low- minus high-probability). Higher learning scores indicate better learning/performance in the task. These triplet learning scores were submitted to a series of mixed-design analyses of variance (ANOVAs) on Day 1 and Day 2 (for details see the Results section).

To probe whether participants gained explicit knowledge of the ASRT regularities or their knowledge remained implicit, performance in the Inclusion-Exclusion task was analyzed following the procedures described in previous ASRT studies (Horváth et al., 2020; Kóbor et al., 2017). To ensure that the data

accurately reflect the instructions given to participants in the two conditions, we excluded those runs in which participants did not follow the instructions and generated systematic combinations of stimuli (see the task description in Section 2.2.2). From the total of 632 runs, we excluded 39; thus, the analysis reported in the Results section contained 93.9% of the answers. For two participants, all four runs had to be removed from the Exclusion condition; for the remaining participants, the average number of runs remaining in this condition was 3.61 out of 4. No runs were excluded from the Inclusion condition since the specific instructions described in Section 2.2.2 were given only for the Exclusion condition. The percentage of the high-probability triplets produced by participants was calculated separately for the runs of the Inclusion and Exclusion conditions, and then it was averaged across runs to obtain one measure per condition. These measures were submitted to one-sample t-tests to see whether participants generated high-probability triplets above chance level in either condition. To test any potential differences across conditions or groups, the percentage of high-probability triplets generated by participants in the two conditions were also submitted to a mixed design ANOVA.

We also conducted Bayesian analyses to overcome the limitations of the frequentist approach (i.e., null-hypothesis significance testing) and gain statistical evidence for null-results where relevant (Dienes, 2011; Wagenmakers, 2007). For example, if participants' knowledge of regularities remained implicit in both the fast and slow RSI groups, the frequentist ANOVA on the Inclusion-Exclusion task data would yield non-significant results for group differences; in such a case, a Bayesian ANOVA could provide evidence for no difference. In Bayesian ANOVA, the evidence provided by the data for including a factor (e.g., condition or group) or an interaction in a model is quantified by  $BF_{\text{Exclusion}}$  values.  $BF_{\text{Exclusion}}$  values reflect the change from prior inclusion odds to posterior inclusion odds. The null model, which contains the grand mean only, always has a value of 1 (Jarosz & Wiley, 2014; Wagenmakers et al., 2018).  $BF_{\text{Exclusion}}$  values above 1 support the exclusion and values below 1 the inclusion of a given factor or interaction in the model that best predicts the data. Thus, the  $BF_{\text{Exclusion}}$  values show if the data provides evidence for similar ( $BF_{\text{Exclusion}} > 1$ ) or different performance ( $BF_{\text{Exclusion}} < 1$ ) across groups and/or conditions.

In addition to Bayesian ANOVA, Bayesian t-tests were also performed for pair-wise comparisons of ASRT data where evidence for no difference between conditions or groups was important to establish for the interpretation of non-significant results. For these Bayesian t-tests,  $BF_{01}$  values are reported, where values above 1 support the null hypothesis (i.e., no difference between conditions or groups) and values below 1 support the alternative hypothesis. Values around 1 do not support either hypothesis. For a more detailed interpretation, see Wagenmakers, Wetzels, Borsboom, and van der Maas (2011).

Frequentist analyses were conducted using IBM SPSS Statistics version 22 and Bayesian analyses were performed using JASP version 0.13.1. In all frequentist ANOVAs, the Greenhouse-Geisser epsilon ( $\epsilon$ ) correction (Greenhouse & Geisser, 1959) was used when necessary. Original  $df$  values and corrected  $p$  values are reported (if applicable) together

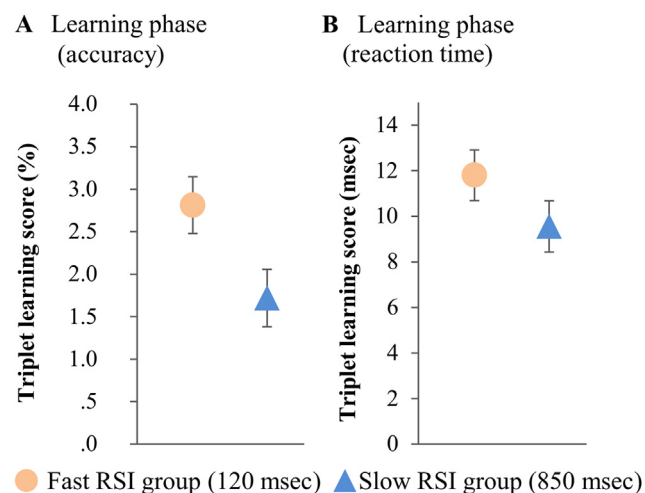
with partial eta-squared ( $\eta_p^2$ ) as the measure of effect size. LSD (Least Significant Difference) tests were used for pair-wise comparisons. For all Bayesian analyses, Cauchy prior distribution was used, with a fixed-effects scale factor of  $r = .5$  and a random-effects scale factor of  $r = 1$  for Bayesian ANOVA.

The tasks used in the experiment, the data and the analysis code are publicly available at <https://osf.io/cy5j6>. The study procedures and analyses were not preregistered prior to the research being conducted. We report how we determined our sample size, all data exclusions, all inclusion/exclusion criteria, whether inclusion/exclusion criteria were established prior to data analysis, all manipulations, and all measures in the study.

### 3. Results

#### 3.1. Does the RSI length affect the performance in the Learning phase?

To test whether the length of the RSI affected performance in the Learning phase of the ASRT task, we compared the performance of the fast (120 msec) versus slow (850 msec) RSI groups on Day 1. The triplet learning scores, separately for accuracy and RTs, were analyzed using a mixed design ANOVA with EPOCH (1–5) as a within-subject factor, and LEARNING RSI (fast vs slow RSI) as a between-subject factor. These results are shown on Fig. 2. The same analyses were performed on the raw accuracy and RT data (see Fig. 3) to explore to what extent the responses to high- or low-probability triplets accounted for the effects reported below; for conciseness, the analyses involving the raw accuracy and



**Fig. 2 – Triplet learning scores in the Learning phase, measured by accuracy (A) and reaction time (B). The fast RSI group showed overall higher triplet learning scores compared to the slow RSI group, that was significant in terms of the accuracy measures of learning. A similar trend was observed for reaction time learning scores, with significant group differences in the second part of the Learning phase (for details see the Results section). The error bars represent the standard error of the mean (SEM).**

RT data are reported in [Supplementary results III](#) and discussed where relevant in the [Discussion](#).

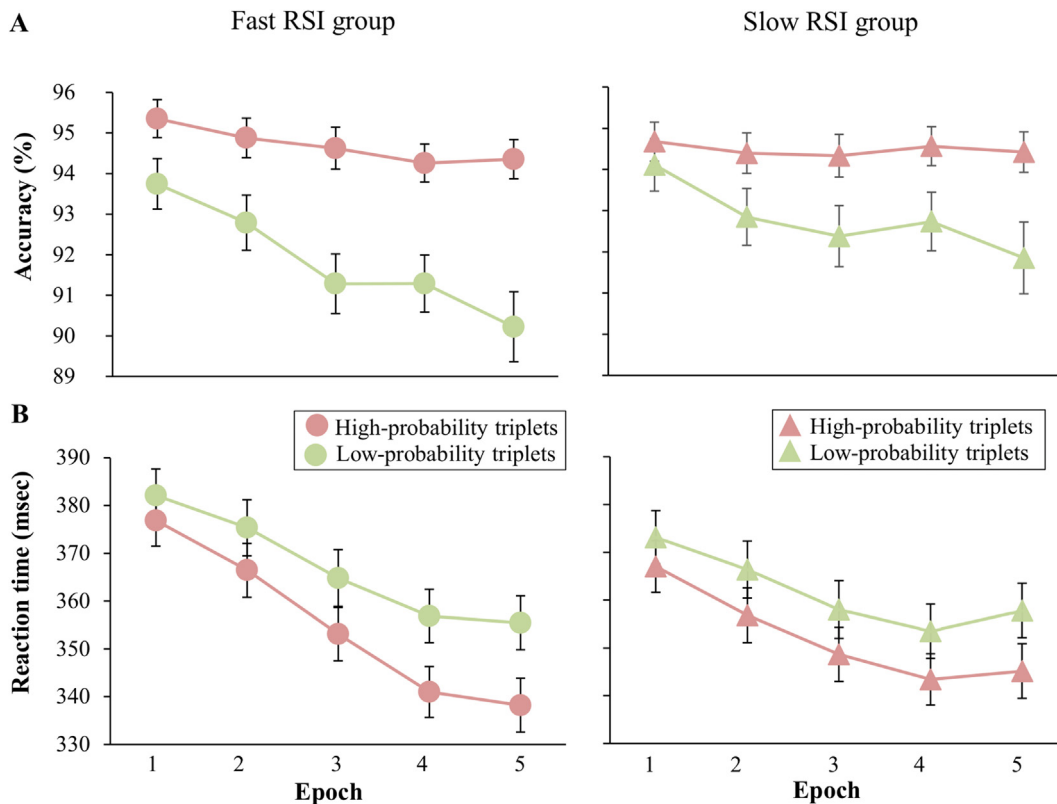
**Accuracy.** The ANOVA revealed significant triplet learning [indicated by the significant INTERCEPT:  $F_{(1, 77)} = 90.113$ ,  $p < .001$ ,  $\eta_p^2 = .539$ ], such that participants were more accurate on high- than on low-probability triplets. As the task progressed, the triplet learning scores increased [indicated by the significant main effect of EPOCH:  $F_{(4, 308)} = 5.265$ ,  $p < .001$ ,  $\eta_p^2 = .064$ ]. The two groups showed different triplet learning scores overall [significant main effect of LEARNING RSI:  $F_{(1, 77)} = 5.660$ ,  $p = .020$ ,  $\eta_p^2 = .068$ ]: the fast RSI group showed higher triplet learning scores than the slow RSI group [2.8% vs 1.7%, respectively] (Fig. 2A), suggesting that the length of the RSI affected triplet learning scores on Day 1. The time course of learning did not differ significantly between the two groups [EPOCH  $\times$  LEARNING RSI:  $F_{(4, 308)} = .271$ ,  $p = .897$ ,  $\eta_p^2 = .004$ ].

**Reaction Time.** A similar ANOVA was conducted for the RT data. The ANOVA revealed significant triplet learning [shown by the significant INTERCEPT:  $F_{(1, 77)} = 174.124$ ,  $p < .001$ ,  $\eta_p^2 = .693$ ], such that RTs were faster on high- than on low-probability triplets. As the task progressed, the participants' triplet learning scores increased [indicated by the significant main effect of EPOCH:  $F_{(4, 308)} = 11.563$ ,  $p < .001$ ,  $\eta_p^2 = .131$ ]. The two groups did not differ significantly in overall triplet learning [main effect of LEARNING RSI:  $F_{(1, 77)} = 1.935$ ,  $p = .168$ ,  $\eta_p^2 = .025$ ] (Fig. 2B), however, the time course of learning was significantly different between the groups [EPOCH  $\times$  LEARNING RSI interaction:  $F_{(4, 308)} = 2.424$ ,  $p = .048$ ,  $\eta_p^2 = .031$ ]. The post-hoc test revealed no significant difference in learning scores between the two groups in the first 3 epochs [all  $ps > .365$ ], while the fast RSI group showed significantly higher triplet learning scores than the slow RSI group in Epoch 4 and 5 [all  $ps < .033$ ].

#### 3.2. How does the RSI length affect the acquired knowledge (competence) versus the momentary performance? Results of the Testing phase

To test how the RSI length affected the acquired knowledge versus the momentary performance, we analyzed the accuracy and RT learning scores in the Testing phase of the ASRT task. Irrespective of the RSI during the Learning phase, here all participants were tested with both RSIs (120 and 850 msec), in a counterbalanced order. We conducted a mixed design ANOVA with TEST RSI (tested with 120 vs 850 msec RSI, irrespective of whether it was the first or the second epoch) as a within-subject factor, and LEARNING RSI (fast vs slow RSI) as a between-subject factor. These results are shown on Fig. 4. The same analyses were performed on the raw accuracy and RT data (see Fig. 5) to explore to what extent the responses to high- or low-probability triplets accounted for the effects reported below; for conciseness, these analyses are reported in [Supplementary results IV](#), and discussed where relevant in the [Discussion](#).

**Accuracy.** The ANOVA on the accuracy learning scores shown in Fig. 4A revealed no significant main effect of TEST RSI [ $F_{(1, 77)} = 1.774$ ,  $p = .187$ ,  $\eta_p^2 = .023$ ], nor LEARNING RSI

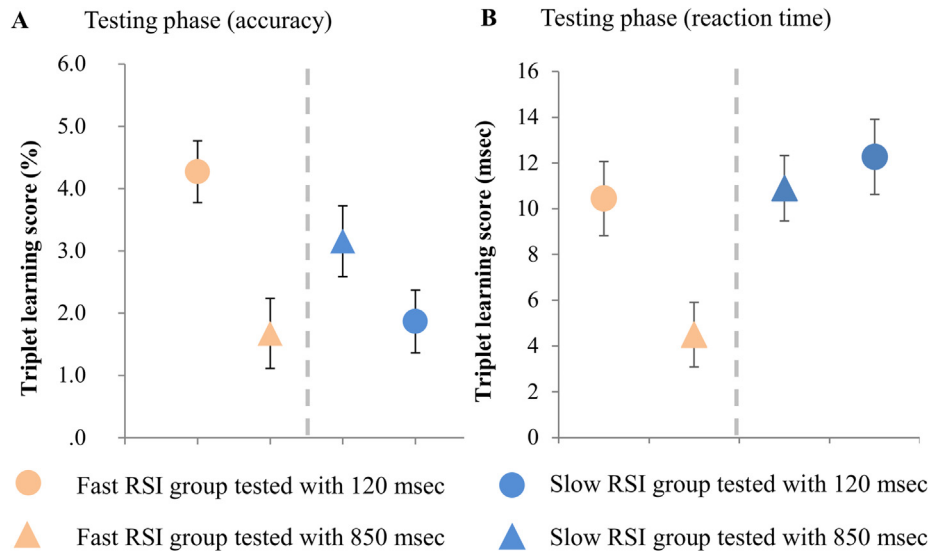


**Fig. 3** – Average accuracy (A) and reaction times (B) separately for high- and low-probability triplets for the fast and slow RSI groups in the Learning phase. The two groups did not differ significantly in average accuracy or reaction time in the Learning phase. (A) As learning progressed, accuracy decreased on low-probability triplets to a greater extent than on high-probability triplets, indicating triplet learning, confirming the interpretation of the ANOVA performed on the learning scores. The difference in accuracy for low- versus high-probability triplets was larger in the fast RSI group compared to the slow RSI group. (B) Reaction times decreased for high-probability triplets to a greater extent than for low-probability triplets, indicating triplet learning (again, confirming the interpretation of the ANOVA performed on the learning scores). The difference between high- and low-probability triplets was greater for the fast RSI group in Epochs 4 and 5 than for the slow RSI group. For further details, see [Supplementary results III](#). The error bars represent the SEM.

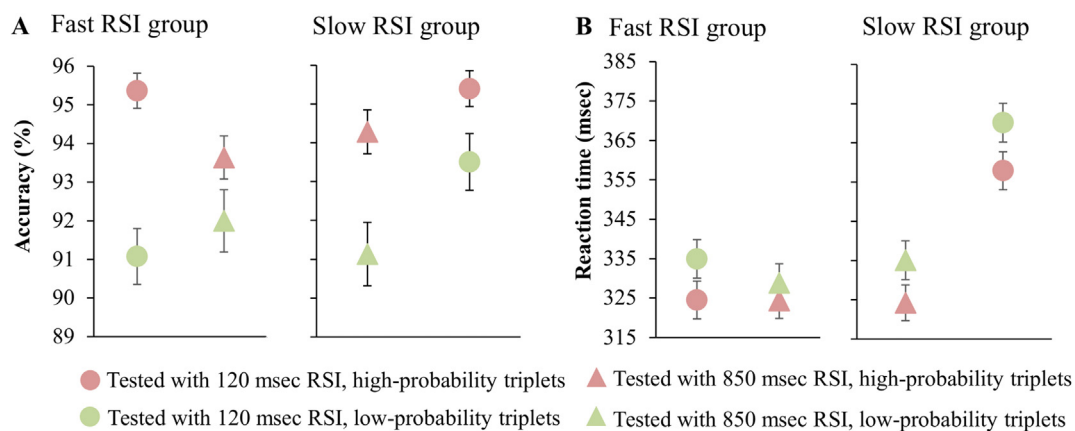
[ $F_{(1, 77)} = .670, p = .416, \eta_p^2 = .009$ ]. The TEST RSI  $\times$  LEARNING RSI interaction was, however, significant [ $F_{(1, 77)} = 14.086, p < .001, \eta_p^2 = .155$ ], suggesting that the performance in the Testing phase depended on both the RSIs during learning and during testing. From a between-group perspective, the post hoc tests revealed that, when tested with the 120 msec RSI, the group that learned with 120 msec (i.e., the fast RSI group) showed significantly higher learning scores than the group that learned with 850 msec [i.e., the slow RSI group; orange vs blue circles in Fig. 4A, 4.3% vs 1.9%, respectively;  $p = .001$ ]. When tested with the 850 msec RSI, the fast RSI group demonstrated marginally lower learning scores than the slow RSI group [orange vs blue triangles, 1.6% vs 3.1%, respectively;  $p = .062$ ]. Importantly, from a within-group perspective, the fast RSI group showed significantly lower learning scores when tested with the 850 msec versus 120 msec RSI [orange triangle vs circle, respectively;  $p = .001$ ]. This finding suggests that, in the slow RSI condition, their momentary performance did not accurately reflect the underlying knowledge that they could readily express when tested with the fast RSI. The group slow RSI group showed marginally lower learning scores when tested with the 120 versus 850 msec RSI [blue circle

vs triangle, respectively;  $p = .093$ ], suggesting a minor disturbance of the performance in the former testing condition.

**Reaction Time.** The ANOVA on the RT learning scores shown in Fig. 4B revealed a significant main effect of TEST RSI [ $F_{(1, 77)} = 5.798, p = .018, \eta_p^2 = .070$ ]: participants, irrespective of the RSI during learning, showed higher learning scores when tested with 120 than with the 850 msec RSI [11.4 vs 7.7 msec, respectively]. This suggests that a faster presentation rate generally results in better performance. Consequently, this result also suggests that the higher learning score of the fast RSI group in the Learning phase more accurately reflected their acquired knowledge than that of the slow RSI group. The main effect of LEARNING RSI was also significant [ $F_{(1, 77)} = 7.155, p = .009, \eta_p^2 = .085$ ]: the fast RSI group showed on average lower learning scores, which was likely driven by the lower learning scores of the fast RSI group when tested with the 850 msec RSI (see Fig. 4B). Although the TEST RSI  $\times$  LEARNING RSI interaction did not reach significance [ $F_{(1, 77)} = 2.267, p = .136, \eta_p^2 = .029$ ], an exploratory post hoc analysis suggests that this is indeed the case: the learning scores in the 120 and 850 msec testing conditions significantly



**Fig. 4 – Triplet learning scores in the Testing phase, measured by accuracy (A) and reaction time (B). The colors represent the groups that learned with different presentation rates (orange – fast RSI group, blue – slow RSI group), and the shapes represent different presentation rates during testing (circle – tested with the 120 msec RSI, triangle – tested with the 850 msec RSI). (A) In terms of the triplet learning scores measured by accuracy, both groups showed higher learning scores when tested with the same presentation rate as the one they encountered during learning. (B) In terms of the triplet learning scores measured by reaction time, the groups showed generally higher learning scores when tested with the faster presentation rate. For further details, see the Results section. The error bars represent SEM.**



**Fig. 5 – Average accuracy (A) and reaction times (B) separately for high- and low-probability triplets for the fast and slow RSI groups in the Testing phase. Both groups showed more accurate (A) and faster (B) responses on the high-probability triplets compared to the low-probability ones, indicating triplet learning in all conditions. For further details regarding group and condition differences, see Supplementary results IV. The error bars represent the SEM.**

differed in the fast RSI group (orange circle vs triangle, 10.4 vs 4.5 msec, respectively,  $p = .007$ ) but not in the slow RSI group (blue circle vs triangle, 12.3 vs 10.9 msec, respectively,  $p = .528$ ,  $BF_{01} = 5.029$ ). The fast RSI group's learning score was also significantly lower than that of the slow RSI group's score when tested with the 850 msec RSI (orange vs blue triangle, respectively,  $p = .002$ ), while there was no significant difference between the two groups' scores when tested with the 120 msec RSI (orange vs blue circles, respectively,  $p = .433$ ,  $BF_{01} = 3.267$ ).

### 3.3. Does the RSI affect whether participants gained implicit or explicit knowledge about the hidden ASRT regularities? Results of the Inclusion-Exclusion task

Overall, the percentage of high-probability triplets generated in the Inclusion-Exclusion task were significantly above chance level both in the Inclusion and Exclusion conditions [one-sample t-tests, Inclusion condition: 7.6%,  $t_{(78)} = 9.595$ ,  $p < .001$ ; Exclusion condition: 6.1%,  $t_{(76)} = 7.266$ ,  $p < .001$ ].

To test potential differences across conditions or groups, a mixed design ANOVA on the generated percentage of high-probability triplets was performed with CONDITION (Inclusion vs Exclusion) as a within-subject factor, and LEARNING RSI (fast vs slow) and TESTING ORDER (congruent-first vs incongruent-first) as between-subject factors. (Note that the TEST RSI factor used in the previous analyses was a within-subject factor of the ASRT task, and therefore it could not be used here. Instead, only the TESTING ORDER could be included in this ANOVA because participants were tested with the two RSIs in a counterbalanced order, forming two sub-groups based on which RSI was presented in Session 2 first; for details, see the procedure in Section 2.3, Fig. 1C, and Supplementary results I). The ANOVA revealed no significant main effects or interactions [all  $p$ s  $\geq .109$ ], suggesting no significant differences across conditions or groups. This interpretation was supported by the Bayesian ANOVA results, providing evidence that none of the main effects or interactions predicted the data better than the null model, which included the grand mean only (for further details see Section 2.4 above and Supplementary results V). In other words, based on the Bayesian ANOVA, we can conclude that the percentage of high-probability triplets generated by participants was similar across conditions and across groups.

According to the PDP, generating high-probability triplets above chance in the Inclusion condition could indicate either implicit or explicit knowledge about the ASRT regularities. In contrast, generating high-probability triplets above chance in the Exclusion condition would indicate a lack of/insufficient conscious control over the acquired knowledge (for more details on PDP see the task description in Section 2.2.2). Our results of generating high-probability triplets above chance in both conditions, together with the similar performance across conditions and groups, suggest that participants' knowledge about the regularities remained implicit in the ASRT task, irrespective of the presentation rate during learning or the testing order in Session 2.

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## 4. Discussion

### 4.1. Summary of the results

In our study, we systemically tested how the elapsed time between subsequent items, as manipulated by the stimulus presentation rate, affected momentary performance versus the underlying competence using a probabilistic sequence learning task. Our findings revealed a partially different effect of the presentation rates on performance versus competence depending on whether learning took place with the faster or slower presentation rate and whether accuracy or RT measures were analyzed.

The slower presentation rate led to lower learning scores in the Learning phase, consistent with our hypothesis. This was the case for the whole Learning phase for the accuracy learning scores, while this pattern emerged only around the end of the Learning phase for the RT learning scores. Importantly, based on the Learning phase alone, it is unclear whether the measured performance accurately reflects the acquired knowledge or not. For example, the lower learning

scores may result from a suboptimal context in which the acquired knowledge cannot be fully expressed. To test this possibility, performance was probed with another presentation rate as well that was different from the one encountered during learning.

The Testing phase revealed different patterns of results for accuracy and RT measures. For RTs, participants showed generally higher learning scores when tested with the faster presentation rate. For accuracy, participants showed higher learning scores when tested with the same (fast or slow) presentation rate as the one that they encountered during learning. Thus, RT results are consistent with the prediction that a faster presentation rate can help better express the acquired knowledge (i.e., performance  $\sim$  competence), while with slower presentation rates, performance might be poorer than the acquired knowledge (performance  $<$  competence). The accuracy results are inconsistent with this prediction; instead, they suggest that the presentation rate during learning may become part of acquired knowledge, leading to a better expression of that knowledge when tested with the same presentation rate as the one encountered during learning (performance  $\sim$  competence) and weaker performance when tested with a different presentation rate (performance  $<$  competence). Thus, dissociation between performance and competence seemed to occur both in RT and accuracy measures but under different circumstances (different testing conditions). Based on the results of the Inclusion-Exclusion task, the acquired knowledge remained implicit in both groups, suggesting that the level of awareness about the learned ASRT regularities did not have a confounding effect on the observed patterns.

### 4.2. Interpretation of the findings

As outlined in the Introduction, the phenomenon that the momentary performance does not necessarily reflect the underlying knowledge (competence) has been highlighted by previous theoretical work in language (Chomsky, 1965) as well as in learning and memory, with experimental evidence coming from latent learning in animals, and verbal learning and motor skill learning in humans (Kantak & Winstein, 2012; Schmidt & Bjork, 1992; Soderstrom & Bjork, 2015). While there are many examples for a dissociation between momentary performance and the underlying competence in research as well as in our daily lives, it has remained elusive under what circumstances such dissociation occurs.

Here we tested how the elapsed time between subsequent events may contribute to this dissociation. We focused on this factor because a great body of research has shown that the elapsed time between subsequent events (items) can determine how our mind processes those events and whether it discovers potential relationships among them (Destrebecqz & Cleeremans, 2003; Staresina & Davachi, 2009; Wlotko & Federmeier, 2015). Overall, our findings suggest that the elapsed time between subsequent items, as manipulated by stimulus presentation rates, can affect the acquired knowledge (competence) as well as whether that knowledge is accurately reflected in momentary performance. In the following subsections, we will focus on three channels by which the elapsed time between subsequent items could have

contributed to the observed pattern of findings. Namely, we will discuss how the elapsed time could affect implicit versus explicit knowledge acquisition (i.e., awareness of the acquired knowledge), binding, and response facilitation, and which aspects of the observed findings support the role of these channels in the competence versus performance dissociation. The channels considered here are based, at least partly, on previous theories developed in the field of learning and memory, and interpretations of behavioral patterns that emerged in previous studies. Importantly, the purpose of our study was to *empirically test* how the elapsed time between subsequent items (as manipulated by the stimulus presentation rate) affects the momentary performance versus the underlying competence, and not to contrast different theories. Nevertheless, we believe that exploring how these channels could explain aspects of the observed behavioral pattern can help better understand the effect of elapsed time on performance versus competence.

#### 4.2.1. *The effect of elapsed time on implicit versus explicit knowledge acquisition*

The elapsed time between subsequent items can affect how we extract information from the task at hand. For example, as presented in the Introduction, learning regularities typically occurs implicitly, although explicit, consciously accessible knowledge about the regularities can also emerge in certain cases (Cleeremans & Jiménez, 2002; Conway, 2020; Reber, 1993). It has been previously theorized that the longer the interval between subsequent events, the more time is available to consciously elaborate on those events, potentially leading to greater awareness (explicit knowledge) about the relevant task features (Destrebecqz & Cleeremans, 2003). In this view, the elapsed time between subsequent events would affect the level of awareness about the relevant task characteristics (and consequently, the acquired knowledge), and if this is not considered when dissociation between performance and competence is evaluated, it could lead to confounding effects.

We tested whether the different presentation rates affected implicit versus explicit knowledge acquisition by administering an additional task, the Inclusion-Exclusion task, at the end of the Testing phase. With this task, we found that knowledge about the regularities embedded in the ASRT task remained implicit in both groups, regardless of the presentation rate during learning. Based on this finding, it seems unlikely that the effect of presentation rates on the performance versus competence dissociation was driven or confounded by the level of awareness about the regularities. Nevertheless, it is possible that in other tasks or other domains of cognition (e.g., perception, decision-making) elapsed time between subsequent events could have a differential effect on the level of awareness about the relevant task features and consequently on the dissociation between performance and competence. Therefore, this possibility should be considered in future studies as well.

#### 4.2.2. *The effect of elapsed time on the binding of subsequent items*

The elapsed time between subsequent events could also affect whether our mind discovers potential relationships among

them, for instance, by binding them together (Davachi & DuBrow, 2015; Karlsen et al., 2010). The more time elapses since the previous event, the more likely the memory trace of that event fades away, consistent with the temporal decay theory of forgetting (Altmann, 2009; Barrouillet, De Paepe, & Langerock, 2012; Brown, 1958; Mercer & McKeown, 2014; Ricker & Cowan, 2010). This, in turn, decreases the likelihood of subsequent items to be represented and bound together in a local short-term storage or cache (Janacsek & Nemeth, 2013, 2015). Consequently, during learning, a slower presentation rate may decrease the number of consecutive items that can be simultaneously maintained, potentially hindering the learning of the regularities; and vice versa, a faster presentation rate may increase the number of simultaneously maintained items, leading to better learning as it was observed in several previous studies (Destrebecqz & Cleeremans, 2003; Dominey, 1998; Frensch & Miner, 1994; Soetens et al., 2004; Stadler, 1995). Thus, in this view, the elapsed time between subsequent items could affect the acquired knowledge itself by either limiting or enabling the binding of subsequent items.

As outlined in Section 4.1, the results of the Testing phase can reveal whether the presentation rates indeed affect the amount of the acquired knowledge, or instead they affect whether that knowledge is accurately expressed in the momentary performance. Based on the results of the Testing phase, both may be true. Interestingly, the effect of presentation rates revealed a different pattern for accuracy and RT measures. The finding that participants showed generally higher RT learning scores when tested with the faster presentation rate suggests that a faster presentation rate can help better express the acquired knowledge (performance ~ competence), while a dissociation occurs between performance and competence with slower presentation rates (performance < competence). Thus, this finding suggests that the elapsed time between subsequent items primarily affects the momentary performance instead of the acquired knowledge.

At the same time, participants showed higher accuracy learning scores when tested with the *same* (fast or slow) presentation rate as during learning. This finding can be explained by assuming that the temporal properties (elapsed time between subsequent events) became part of the acquired knowledge. Then, when participants were tested with a different presentation rate in the Testing phase, they showed a weaker performance because their knowledge was disrupted by this change in the task. This interpretation is consistent with the theory proposed by Dominey (1998) who showed that the temporal properties can be learned (together with the regularities embedded in the task), and the measured performance can deteriorate if a change occurs in those properties.

Overall, this pattern of findings suggests that the temporal properties (elapsed time between subsequent events) can become part of the acquired knowledge as well as affect whether momentary performance accurately reflects the underlying competence in a given condition. These findings also highlight that different behavioral (e.g., RT and accuracy) measures should be considered simultaneously to provide a more detailed characterization of the acquired knowledge and performance.

#### 4.2.3. The effect of elapsed time on response facilitation

In contrast to the previous interpretations that focus on the possible effects of the elapsed time on the acquired knowledge (competence), the time window in which consecutive events are simultaneously represented could affect the momentary performance as well (Burle, van den Wildenberg, & Ridderinkhof, 2005; Scharlau, 2007; Wlotko & Federmeier, 2015). Specifically, we suggest that if consecutive events are closer to one another, the representation of the previous events may be still active in the time window when response is made to the current event, potentially leading to response facilitation. Since the previous events predict the current event with a certain probability in the ASRT task, their activation in this time window may facilitate the response to the current event, which may be reflected in higher accuracy and/or faster RTs (Janacsek et al., 2018; Takács et al., 2018). This response facilitation may be greater for more predictable event combinations (such as the high-probability triplets) compared to the less predictable ones. As more time elapses between subsequent events, response facilitation may be weaker for slower presentation rates, resulting in smaller differences in the responses to more versus less predictable events (i.e., lower triplet learning scores).

Our findings revealed that, while the presentation rate did not have a significant overall effect on average accuracy or RTs during learning (see [Supplementary results III](#)), it differentially affected the responses to more versus less-predictable items under certain testing conditions, which could at least partly explain why the momentary performance did not accurately reflect the acquired knowledge in one condition but did in the other. For example, the group that learned with the faster presentation rate showed lower learning scores when tested with the slower presentation rate, suggesting that the performance in this testing condition did not accurately reflect the participants' knowledge that they could better express when tested with the faster presentation rate. This effect was present both in accuracy and RT measures. The more fine-grained analyses presented in [Supplementary results IV](#) revealed the following pattern.

While accuracy on low-probability triplets did not differ significantly when tested with the slower versus the faster presentation rate, the group that learned with the faster presentation rate exhibited lower accuracy on high-probability triplets in the former condition (see [Fig. 5A](#)), resulting in the lower triplet learning scores discussed above. This finding suggests that the slower presentation rate affected response facilitation on high-probability triplets to a greater extent than on low-probability triplets, consistent with the argument above. In terms of RTs, they were faster on low-probability triplets but did not differ significantly on high-probability triplets when tested with the slower presentation rate compared to the faster one ([Fig. 5B](#)). This suggests that the lower learning score in the former condition was primarily driven by the slower presentation rate speeding up the responses on low-probability triplets in this group, which seems to be at odds with the response facilitation account.

For the group that learned with the slower presentation rate, the more fine-grained analyses revealed that the presentation rates did not have a significantly different effect on the

responses to either the high- or the low-probability triplets, either in accuracy or RT measures. However, the analyses revealed more accurate and slower responses on both triplet types when tested with the faster presentation rate compared to the slower one (see [Fig. 5AB](#)). These differences in average accuracy and RTs suggest that the presentation rates affect some aspects of the momentary performance in this group as well.

Thus, overall, the pattern of our findings suggests that multiple channels may be simultaneously at play since presentation rates did not affect implicit versus explicit knowledge acquisition (Section 4.2.1) but seemed to affect both aspects of the acquired knowledge (possibly through binding; Section 4.2.2) and the momentary performance (possibly through response facilitation presented in this section).

#### 4.3. Open questions

We used a within-participant design in which all participants were tested with both the fast and slow presentation rates in a counterbalanced order. This design enabled us to probe if the testing order (congruent or incongruent presentation rate used first) affected the results, and if so, was this different for the two groups depending on the presentation rate encountered during learning (see [Supplementary results I](#)). Our results revealed that the group that learned with the faster presentation rate was significantly affected by the testing order (overall higher learning scores when tested with the congruent versus the incongruent presentation rate first) while there was no significant difference in the testing order for the group that learned with the slower presentation rate. These findings suggest that when learning takes place with faster temporal settings, performance may be more susceptible to later changes in those settings (e.g., a subsequent test under slower conditions, without a warm-up in the original, fast condition first). At the same time, when learning takes place with slower temporal settings, later temporal changes may have a smaller effect on performance, perhaps by developing a larger window of tolerance in timing (i.e., one tolerates a greater range of possible time windows in which subsequent events might occur). Since it was not the purpose of the current study, future research is needed to systematically probe and clarify the details of such a possible effect.

To obtain a more fine-grained picture about the performance versus competence dissociation, an exploratory analysis was performed on the so-called 'within block position effect' (see [Methods](#) and [Supplementary results II](#)). This effect relates to the phenomenon that during a longer reaction time task arranged into blocks (spanning several seconds or minutes) participants show different performance when the earlier versus later parts of each block are compared (Nemeth, Janacsek, Király, et al., 2013; Pan & Rickard, 2015; Török, Janacsek, Nagy, Orban, & Nemeth, 2017). The analysis on this within block position effect revealed that the group that learned with the slower presentation rate exhibited lower learning scores in the second halves of the blocks of the Learning phase compared to the first halves, while the learning scores of the group that learned with the faster presentation rate did not differ significantly in the two halves of the blocks. Additionally, the learning scores in the first versus second halves of the blocks did not differ significantly as

a function of the presentation rate of the Testing phase. Nevertheless, for the sake of completeness and potential comparisons with future studies, we reported these results in the [Supplementary materials](#).

In the present study, we used two presentation rates (120 and 850 msec RSI) that are considered as relatively fast and slow, respectively, based on previous studies of sequence learning (Destrebecqz & Cleeremans, 2003; Frensch & Miner, 1994; Howard et al., 2007; Howard & Howard, 1997; Soetens et al., 2004). These studies have typically found differences in learning measures when contrasting presentation rates of 0–500 versus 500–2000 msec, suggesting that values below versus above ~500 msec could lead to differential effects. Importantly, however, these studies did not directly test the role of presentation rates in the dissociation between performance and competence. Therefore, how other presentation rates would affect this dissociation remains to be tested.

Finally, it seems reasonable to assume that how the elapsed time between subsequent events (as measured with different presentation rates) affect the dissociation between performance and competence likely depends on other factors, such as the domain of the task (e.g., visual or auditory; verbal or nonverbal) and task/stimulus complexity as well. The role of elapsed time has received much attention in studies focusing on forgetting, particularly in short-term and working memory (Barrouillet et al., 2004; Brown et al., 2007; Cornelissen & Greenlee, 2000; Oberauer, Farrell, Jarrold, & Lewandowsky, 2016; Zhang & Luck, 2009). Although the elapsed time that led to forgetting varied greatly across domains and tasks, ranging from 50–100 msec up to 10–30 sec (Horoufchin, Philipp, & Koch, 2011; Mercer & McKeown, 2014; Schweickert & Boruff, 1986; Zhang & Luck, 2009), these results together with the findings of the present study highlight that the elapsed time has a fundamental role in multiple aspects of learning and memory. Our study contributes to this literature by showing that the elapsed time between subsequent events can affect not only the competence (e.g., the acquired knowledge or memory of items) but also whether that competence is accurately reflected in the momentary performance. Further studies seem warranted to systematically test this dissociation, including how the length of the elapsed time between subsequent events affects it, across a wide range of cognitive functions, domains and tasks.

#### 4.4. Implications

Our findings have theoretical, methodological as well as translational implications. From a theoretical perspective, our study highlights that performance in a given moment may not accurately reflect the underlying knowledge (competence), and temporal factors such as the elapsed time between subsequent events seem to influence this dissociation. As learning and memory support a wide range of functions and abilities (e.g., decision-making, perception, theory of mind, and language performance) (Mutter et al., 2006; Rieskamp & Otto, 2006; Turk-Browne et al., 2010; Ullman et al., 2020), the importance of the dissociation between performance and competence likely extends beyond the cognitive domains of learning and memory. Therefore, our findings can open new avenues of research in a wide range of cognitive functions and domains.

From a methodological perspective, we propose that experimental designs should be used that are able to reveal possible dissociations between momentary performance and the underlying knowledge. A key element of such designs is to test performance in multiple contexts, which could be created, for example, by different stimulus presentation settings (such as in the present study) or by changes in instructions given to the participants (Vékony et al., 2020). Such designs could help find optimal experimental settings that could be used in research to accurately measure a given cognitive function or mental representation, including both its behavioral and neural aspects. Moreover, the different pattern of findings in accuracy versus RT measures highlight that both measures should be assessed in future studies as they may be related to at least partially distinct cognitive processes (Burgess, Gilbert, & Dumontheil, 2007; Janacsek, Fiser, & Nemeth, 2012; Prinzmetal, McCool, & Park, 2005; Takács et al., 2018; Vékony et al., 2020). This could further enrich our understanding of participants' competence in a given task and whether that competence is accurately reflected in the momentary performance.

From a translational perspective, our findings could have implications for applied fields such as education, language learning, and sports, as well as for clinical diagnosis and rehabilitation. For instance, when learning a foreign language or mastering sports, students might show better performance if speeded processing and responding is required. In clinical settings, some patient populations may show generally slower responses in self-paced tasks compared to healthy participants, which can mask their competence (knowledge, understanding, or mental representation of the relevant task features), potentially leading to incorrect interpretations. Therefore, the temporal parameters of the tasks should be considered in these settings; for example, multiple testing sessions with different temporal parameters could be employed to precisely characterize the cognitive deficits in these patient populations.

#### 4.5. Conclusions

In summary, we systemically tested how the elapsed time between subsequent events, as manipulated by the stimulus presentation rate, affected the momentary performance versus the underlying competence using a probabilistic sequence learning task. Our study revealed that the presentation rate differentially affected whether the momentary performance accurately reflected the acquired knowledge depending on whether learning took place with the faster or slower presentation rate. We discussed three channels by which the elapsed time between subsequent events could have contributed to the observed pattern of findings: the role of awareness, binding and response facilitation. Altogether, our study contributes to a better understanding of the dissociation between performance and competence by showing how temporal factors can affect it and calls for further theoretical and empirical research as such dissociations are likely to be present not only in learning and memory but also in other functions and domains, including aspects of decision-making, perception, and language.

## CRediT author contributions

**Mariann Kiss:** Data curation; Formal analysis; Investigation; Project administration; Visualization; Writing - original draft; Writing - review & editing. **Dezso Nemeth:** Conceptualization; Funding acquisition; Resources; Supervision; Writing - review & editing. **Karolina Janacsek:** Conceptualization; Data curation; Formal analysis; Funding acquisition; Methodology; Project administration; Resources; Software; Supervision; Validation; Writing - review & editing.

## Open practices

The study in this article earned Open Data and Open Materials badges for transparent practices. Materials and data for the study are available at <https://osf.io/cy5j6/>.

## Declaration of competing interest

The authors report no conflict of interest.

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## Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.cortex.2022.09.003>.

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