Disentangling competence from performance in behavioral measures of learning: A lesson for cognitive neuroscience

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Abstract

In cognitive neuroscience, the momentary learning performance and the underlying competence on a behavioral task are typically not distinguished, which can lead to unreliable measures of brain-behavior relationships. Here we aimed to disentangle competence from performance by examining two groups with different (speed or accuracy) instructions in the learning phase and with the same instruction (focusing on both) in the testing phase. Healthy young adults performed an implicit probabilistic learning task in two sessions. In the learning phase, the two groups showed similar learning measured by reaction times; however, only the group with speed instruction showed learning measured by accuracy. In the testing phase, a similar level of knowledge was found in both measures. Overall, multiple sessions with different instructions enabled the separation of competence from performance. Additionally, reaction time measures seemed to be more resistant to speed/accuracy instructions. These findings can help create better experimental designs for cognitive neuroscience studies.

Keywords: performance, competence, probabilistic learning, reaction times, accuracy, implicit learning, statistical learning

Introduction

In cognitive neuroscience, the behavioral expression of learning is often determined by a measurement at a single session. Yet it is unclear whether this measurement reflects momentary *performance* on the task or the underlying *competence* itself. Typically, these two processes are not distinguished within a single session. Either only the performance is used to draw conclusions about the established knowledge, or inversely, the competence measured after performing the task is used to make assumptions about the initial performance. Subsequently, these measurements often serve as a basis for establishing brain-behavior relationships in combination with neuroimaging data from fMRI (e.g. Rose, Haider, Salari, & Buchel, 2011; Thomas et al., 2004; N. B. Turk-Browne, Scholl, Johnson, & Chun, 2010; Nicholas B Turk-Browne, Scholl, Chun, & Johnson, 2009), EEG (e.g. Kóbor et al., 2018; Tóth et al., 2017) or MEG (e.g. Heideman, van Ede, & Nobre, 2018). However, does the behavioral measure truly represent what we aim to assess? One aspect that may influence this measurement is whether participants focus on their speed at the expense of accuracy, or vice versa. This focus may depend on many things: the circumstances of the experiment, the fatigue or the boredom of the participant (Healy, Kole, Buck-Gengler, & Bourne, 2004; Kole, Healy, & Bourne Jr., 2008), or the explicit instructions given (Aasen & Brunner, 2016; Endrass, Schreiber, & Kathmann, 2012). To date, there is no evidence whether focusing on speed or accuracy affects only the performance during a learning task or the degree of acquired knowledge (competence) itself. If focusing either on speed or accuracy differently affects the performance and the competence in a task, then even slight differences in this can lead to altered conclusions. Here we present a study that shows how focusing on speed or accuracy dissociates performance from competence (acquired knowledge) using a probabilistic learning task.

What do we know about the effects of instructions on learning so far? In real-life skill learning, different instructions can lead to altered performance. For example, the performance of novice golfers is better under accuracy instructions, while experts profit more from speed instruction (Beilock, Bertenthal, McCoy, & Carr, 2004), at least when a well-known skill is tested (Beilock, Bertenthal, Hoerger, & Carr, 2008). Controlled learning experiments on the effects of instructions mainly focused on the characteristics of speed-accuracy trade-off during learning, and not on how successful it is with different strategies during task completion (Zhang & Rowe, 2014). Hoyndorf et al (2009) have tested the effect of instruction on implicit learning, which is a robust, unconscious form of learning (Cleeremans,

Destrebecqz, & Boyer, 1998; Janacsek & Nemeth, 2012; Perruchet & Pacton, 2006; Reber, 1993). Implicit learning occurs when predictive relationships in the form of statistical regularities or sequences of events are extracted from the environment without putting conscious e□ort into the process or realizing the learning process at all (Janacsek, Borbély-Ipkovich, Nemeth, & Gonda, 2018; Reber, 1993; Unoka et al., 2017). In Hoyndorf et al (2009), accuracy instruction was found to impair implicit learning compared to speed instruction; however, signs of learning were still detected under accuracy instruction compared to a non-learning control group. Yet in this experiment, the degree of the accumulated knowledge was not compared following the initial learning phase between learning with different instructions. If a similar instruction phase would be included *after* the learning phase then we could explore whether the instructions affect the performance only or the amount of learned information, i.e. the competence.

In the current study, we aimed to test whether performance and competence can be disentangled by altering the instructions (focusing on speed/accuracy or both) in the learning and the testing phase. In order to reach this aim, we used an implicit probabilistic learning task, the Alternating Serial Reaction Time task (ASRT) (J. H. Howard & Howard, 1997; Nemeth, Janacsek, Londe, et al., 2010) (Figure 1A). In this four-choice visuomotor reaction time task, some runs of consecutive visual stimuli (called *triplets*) occur with a greater probability than others (Figure 1B and 1C, for more details, see Methods). As participants are practicing on the task, apart from becoming generally faster and accurate due to practice (called *general skill learning*), they become increasingly faster and more accurate responding to high-probability triplets compared to the low-probability ones, reflecting *statistical learning* of probabilistic regularities (Janacsek et al., 2018; Juhasz, Nemeth, & Janacsek, 2019; Kobor, Janacsek, Takacs, & Nemeth, 2017; Unoka et al., 2017). We chose this particular task for several reasons. First, it enables the separate assessment of the instructions on general skill learning and statistical learning. Second, it allows us to monitor the accumulation of novel knowledge throughout a longer period. Third, as the statistical pattern is hidden in noise, it mimics real-life skill learning situations which also occur under uncertainty, in a noisy environment (Fiser, Berkes, Orbán, & Lengyel, 2010). Fourth, as implicit statistical learning is thought to be a relatively robust form of learning (Kobor et al., 2017), we assumed that if we find differences in this type of learning, then it would be more likely that similar effects are present also in more conscious learning processes. In our study, the ASRT task was completed in two different phases: In the first session, the participants

were told to focus either on the accuracy or the speed while performing the task (Accuracy vs. Speed Group). After the learning phase (Different Instruction Phase), both groups of participants were tested with the same instruction (i.e., focusing *both* on the accuracy and speed, Similar Instruction Phase) (Figure 1D). This design enabled us to differentiate between the performance of the participants (when different instructions were given) and their acquired knowledge, i.e. their competence (when tested with the same instructions).

Methods

Participants

Sixty-six healthy young adults took part in the study. Five of them were excluded from the experiment, because of the possibility of misunderstanding the instructions (their performance were more than 2 standard deviations away from the average of their group in more than 50% of the epochs, which was not observable during the practice session). Therefore, 61 participants remained in the final sample (40 females). They were between 19 and 27 years of age (M_{age} = 21.18 years, SD_{age} = 2.13 years). All of them were undergraduate students from Budapest, Hungary ($M_{years\ of\ education}$ = 14.14 years, $SD_{years\ of\ education}$ = 1.64 years). Participants had a normal or corrected-to-normal vision, none of them reported a history of any neurological and/or psychiatric disorders, and none of them was taking any psychoactive medication at the time of the experiment. Handedness was measured by the Edinburgh Handedness Inventory (Oldfield R.C., 1971). The Laterality Quotient (LQ) of the sample varied between −84.62 and 100 (−100 means complete left-handedness, 100 means complete right-handedness; M_{LQ}=62.25, SD_{LQ}=53.73). They performed in the normal range on the Counting Span Task ($M_{Counting\ Span}$ = 3.66, $SD_{Counting\ Span}$ = 0.81) All of the participants gave written informed consent before enrollment and received course credit for participating. They were randomly assigned to the Accuracy Group (n = 31) or to the Speed Group (n = 30). No groups differences were observed in terms of age, years of education, handedness, and neuropsychological performance (see Table 1). The study was approved by the Research Ethics Committee of the Eötvös Loránd University, Budapest, Hungary and it was conducted in accordance with the Declaration of Helsinki.

Table 1. Comparison of the two groups on age, years of education, handedness and neuropsychological performance

	Accuracy Group	*Speed Group*	*t-test*
	M(SD)	*M(SD)*	
Age (years)	21.29 (2.28)	21.07 (2.00)	$t(59) = 0.407$, $p = 0.686$
Education (years)	14.31 (1.60)	13.97 (1.71)	$t(59) = 0.802$, $p = 0.426$
Handedness (LQ)	54.88 (55)	69.86 (52.2)	$t(59) = -1.090$, $p = 0.280$
Counting Span Score	3.69 (0.75)	3.64 (0.88)	$t(59) = 0.211$, $p = 0.834$

Alternating Serial Reaction Time task

In this study, we used the implicit version of the Alternating Serial Reaction Time (ASRT) task (J. H. Howard & Howard, 1997; Nemeth, Janacsek, Londe, et al., 2010). In the ASRT task, four empty circles, 300 pixels each) were presented continuously on a white background in a horizontal arrangement in the middle of the screen. A target stimulus (a drawing of a dog's head, 300 pixels) was presented sequentially in one of the four empty circles (Figure 1A). A keyboard with four heightened keys (Z, C, B, and M on a QWERTY keyboard) was used as a response device, each of the four keys corresponding to the circles in a horizontal arrangement. Participants were asked to respond with their middle and index fingers of both hands by pressing the button corresponding to the target position.

The serial order of the four possible positions (coded as 1, 2, 3, and 4) in which target stimuli could appear was determined by an eight-element probabilistic sequence. In this sequence, every second element appeared in the same order as the task progressed, while the other elements' positions were randomly chosen out of the four possible locations (e.g., 2r4r3r1r; where r indicates a random position). Therefore, some combinations of three consecutive trials (*triplets*) occur with a greater probability than others. For example, 2_**4**, 4_**3**, 3_**1**, and 1_**2** (where ''_" indicates any possible middle element of the triplet) would occur often because the third element (bold numbers) could be derived from the sequence or occasionally could be a random element as well. In contrast, 1_**3** or 4_**2** would occur less frequently because the third element could only be random (Figure 1B). Therefore, the third element of a high-probability triplet is more predictable from the first event when compared to a low-probability triplet. There were 64 possible triplets in the task (four stimuli combined for three consecutive trials). Sixteen of them were high-probability triplets, each of them occurring in approximately 4% of the trials, about five times more often than the low-probability triplets. Overall, high-probability triplets occur with approximately 62.5%

probability during the task, while low-probability triplets only occur with 37.5% probability (Figure 1C). As participants practice the ASRT task, their responses become faster and more accurate to the high-probability triplets compared to the low-probability ones, revealing statistical learning throughout the task (J. H. Howard & Howard, 1997; Kobor et al., 2017; Song, Howard, & Howard, 2007; Unoka et al., 2017).

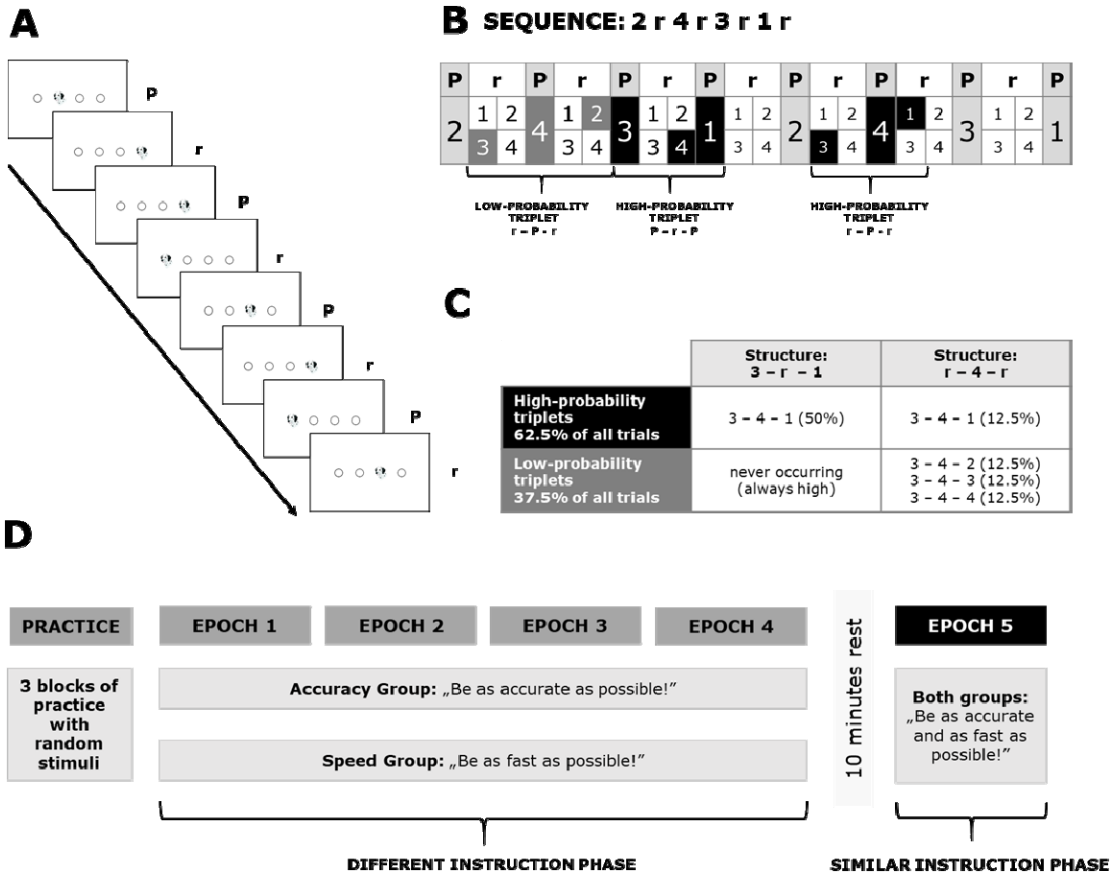

Figure 1. Task and design of the experiment. (A) Stimulus presentation in the ASRT task. A dog's head appeared on one of the four positions. Stimuli appeared either in a pattern (P) or a random (r) position, creating an eight-item long alternating sequence structure. (B) High- and low-probability triplets. Due to the alternating sequence structure, some runs of consecutive visual stimuli (called *triplets*) occurred with a greater probability than others. Every trial was defined as the third trial of a high- or a low-probability triplet, based on the two preceding trials. High-probability triplets can be formed by two pattern and one random elements, but also by two random and one pattern elements. (C) The proportion of high- and low-probability triplets. High-probability triplets occurred in 62.5% of all trials (of which 50% came from pattern trials, i.e., from P-r-P structure, and 12.5% came from random trials, i.e., from r-P-r structure, by chance). Low-probability triplets occurred in the remaining 37.5% of all trials (of which each individual low-probability triplet occurred with a 12.5% probability by chance, originating only from r-P-r structure). (D) The design of the study. In the Different Instruction Phase, different instruction was told to the Accuracy and the Speed Group. After 4 epochs (each containg 5 blocks) of the ASRT task, and a 10-minute long rest period, the instruction changed: in the fifth epoch (containing 5 blocks of stimuli), the same instruction was given to all of the participants (Similar Instruction Phase).

Inclusion-Exclusion Task

We also administered the Inclusion-Exclusion Task (A Destrebecqz et al., 2005; Arnaud Destrebecqz & Cleeremans, 2001; Fu, Dienes, & Fu, 2010; Jiménez, Vaquero, & Lupiáñez, 2006), which is based on the "Process Dissociation Procedure" (Jacoby, 1991). In the first part of the task, we asked the participants to generate a sequence of button presses that follows the regularity of the ASRT task, using the same four response buttons the participants used during the ASRT task (inclusion instruction). After that, participants were asked to generate new sequences which are different from the learned one (exclusion condition). Both parts consisted of four runs, and each run finished after 24 button presses, which is equal to three rounds of the eight-element alternating sequence (Horvath, Torok, Pesthy, Nemeth, & Janacsek, 2018; Kiss, Nemeth, & Janacsek, 2019; Kobor et al., 2017). The successful performance in the inclusion condition can be achieved by solely implicit knowledge (however, explicit knowledge can also boost performance, but it is not necessary to the successful completion of the task). On the contrary, successful performance in the exclusion condition (i.e., generating a *new* sequence that is different from the learned one) can only occur if the participant has conscious knowledge about the learned statistical regularities. Generation of the learned statistical regularities above chance level even in the exclusion task indicates that the participants rely on their implicit knowledge, as it cannot be controlled consciously. To test whether the participants gained consciously accessible triplet knowledge, we calculated the percentage of the generated high-probability triplets in the inclusion and in the exclusion condition separately and tested whether it differs from the probability of generating them by chance. We also compared the percentages of the high-probability triplets across conditions (inclusion and exclusion task) and across groups (Accuracy Group and Speed Group) (for more details about the Inclusion-Exclusion task, see: Horvath et al., 2018; Kiss et al., 2019; Kobor et al., 2017).

Questionnaire

We used a questionnaire to check whether the participants prefer accuracy or speed and whether they are rather accurate or fast in everyday life. The questionnaire consisted of the following questions: "*In an everyday situation, what do you attend more: speed or accuracy (in a scale from 1 to 10, where 1 means that only the accuracy is important and 10 means that only the speed is important)*?", "*In an everyday situation, how important is for you to be accurate/fast in a scale from 1 to 10?*", "*According to your friends and family, how fast/accurate are you when you need to solve a problem (in a scale from 1 to 10)?*".

Procedure

At the beginning of each block of the task, the four empty circles appeared horizontally on the screen for 200 ms, and after that, the first target stimulus occurred. It remained on the screen until the first correct response. The response-to-stimulus interval was set to 120 ms. Each block contained 85 stimuli (5 random elements at the beginning of the block, then the 8-element alternating sequence was repeated 10 times).

First, the participants completed 3 × 85 trials of practice with only random elements to familiarize with the task. After that, two sessions of ASRT task were completed by the participants. In the first session (referred to as Different Instruction Phase), different instruction was told to the participants of the Accuracy Group and the Speed Group. For the Accuracy Group, the instruction was to try to be as accurate as possible during the task. Contrary, the instruction for the Speed Group was to be as quick as possible. By this, we were able to investigate the performance on the task in the light of the different instructions. During the Different Instruction Phase, a total of 20 blocks (organized into 4 epochs, each containing 5 blocks) was presented to the participants. Participants could rest a bit after each block. Before the beginning of the second ASRT session, a 10 minutes rest period was inserted. During this, participants were not involved in any demanding cognitive activity. The second session of ASRT (referred as Similar Instruction Phase) contained 5 more blocks (1 epoch). This time, both the Accuracy Group and the Speed Group were instructed to respond to the target position as quickly and as accurately as they could (Figure 1D). As the instruction changed and there were no further restrictions for the performance in the Similar Instruction Phase, we were able to compare the acquired competence on the task between groups.

Statistical analysis

We defined each trial as the third element of a high or low-probability triplet. Trills (e.g. 1-2-1) and repetitions (e.g. 1-1-1) were eliminated from the analysis because participants tend to show pre-existing response tendencies to these type of triplets (D. V. Howard et al., 2004; Janacsek et al., 2018; Takács et al., 2018; Unoka et al., 2017). The first seven button presses were also excluded from the analysis. Blocks were collapsed into four five-block-long segments (i.e., epochs) in the Different Instruction Phase (Epoch 1-4), and one epoch in the Similar Instruction Phase (Epoch 5) to facilitate data processing and to reduce intra-individual variability. We calculated the median reaction times (RTs) and the mean accuracy separately

for high- and low-probability triplets for each participant and for each epoch. Only correct responses were considered for the RT analysis.

To make sure that the observed effects were not due to pre-existing differences between the groups in terms of average speed or accuracy, we compared the median RTs (only for correct responses) and the accuracy of the two groups in the practice session with independent-samples t-tests. To investigate whether learning performance differed during the Different Instruction Phase, RTs and accuracy were analyzed with mixed-design ANOVAs with TRIPLET (high- vs. low-probability triplets) and EPOCH (1-4) as within-subject factors, and with GROUP (Accuracy Group and Speed Group) as between-subject factor. To look at whether there was a difference between groups in the Similar Instruction phase in terms of the ASRT performance, we analyzed RTs and accuracy of Epoch 5 with mixed-design ANOVAs with TRIPLET (high-frequency triplets and low-frequency triplets) as within-subject factor and with GROUP (Accuracy Group and Speed Group) as between-subject factor.

The instructions about the accuracy and speed during the experiment could cause major differences in the average RTs and accuracy between the two experimental groups. To make sure that our results on the learning measures are not due to the differences in the overall RTs and accuracy, we did an additional analysis with corrected scores. To correct for the average RT difference, we divided the learning scores (median RTs for low-probability triplets *minus* for high-probability triplets) by the average RTs of the given epoch for each participant and for each epoch. We corrected the accuracy scores similarly, except for that in this case, the learning scores were defined as median accuracy for high-probability triplets *minus* for the low-probability triplets. For the Different Instruction Phase, mixed-design ANOVAs were performed on the corrected RT and accuracy learning scores with EPOCH (1-4) as a within-subject factor and with Group (Accuracy Group and Speed Group) as between-subject factor. For the Similar Instruction Phase, independent samples t-tests were performed on the corrected RT and accuracy learning scores between the two experimental groups.

In all ANOVAs, the Greenhouse-Geisser epsilon (ε) correction was used if necessary. Corrected *df* values and corrected *p* values are reported (if applicable) along with partial eta-squared (η_p^2) as the measure of effect size. We used LSD (Least Significant Difference) tests for pair-wise comparisons. Moreover, we calculated Bayes-factors (BF) for the support of our non-significant, but relevant results. Bayesian independent samples t-tests were carried out by using JASP 0.8.03.0168 (JASP Team., 2017).

To check whether participants developed conscious knowledge about the learned statistical regularities, we compared the percentage of the generated high-probability triplets in the Inclusion-Exclusion Task to chance level (25%) separately for the two groups with one-sample t-tests. Additionally, we compared the performance in the inclusion and in the exclusion condition with paired samples t-tests, separately for both groups. To reveal if the level of explicitness differs between groups, we compared the percentage of high-probability triplets between groups both in the inclusion and in the exclusion condition with independent samples t-tests.

Additionally, to check whether the subjective preferences of the participant are related to the ability to follow the instructions, we correlated the average RTs and accuracy scores with the rates of the different items of the questionnaire.

Results

Did the two groups perform equally in average RTs and accuracy before learning?

First, we checked whether the groups differed in terms of their average RTs and accuracy during the practice session. No difference was found between groups neither in RTs ($t(59) = -0.477$, $p = 0.635$), nor in accuracies ($t(59) = -1.084$, $p = 0.283$). Therefore, we assumed that the differences observed following the instruction were not due to pre-existing differences between the groups regarding their speed or accuracy.

Did the learning performance measured by RTs differ between groups as a result of the different instructions?

First, we compared the median RT scores between the two groups in terms of epochs and triplet types (Figure 2). The EPOCH × TRIPLET × GROUP ANOVA revealed significant main effect of EPOCH ($F(1.972, 116.334) = 7.462$, $p < 0.001$, $\eta_p^2 = 0.112$), signaling a decrease of RTs during the course of the task (Figure 2A). A main effect of TRIPLET was also significant ($F(1,59) = 49.408$, $p < 0.001$, $\eta_p^2 = 0.456$): faster RTs were found to the high-probability triplets compared to the low-probability ones, revealing implicit statistical learning on RTs. The GROUP main effect was also significant ($F(1,59) = 51.859$, $p < 0.001$, $\eta_p^2 = 0.468$), signaling again the overall faster RTs of the Speed Group (Figure 2A). The EPOCH × GROUP interaction was approaching significance ($F(3,177) = 2.301$, $p = 0.079$, $\eta_p^2 = 0.038$), the rate of the RT decrease was higher in the Speed Group than in the Accuracy Group on

trend level. Importantly, the TRIPLET × GROUP interaction was proved to be non-significant ($F(1,59) = 0.480$, $p = 0.491$, $\eta_p^2 = 0.008$, $BF_{10} = 0.319$): the degree of RT learning did not differ between the two groups over the course of the learning, which was also supported by the Bayes factor (Figure 2C). The TRIPLET × EPOCH interaction proved to be significant ($F(3,177) = 5.662$, $p < 0.001$, $\eta_p^2 = 0.088$): In the first epoch, no difference was detected between high- and low-probability triplets, while learning (faster RTs for high- than for low-probability triplets) emerged starting from the second epoch. No difference was found in the time course of statistical learning across groups, signaled by a non-significant EPOCH × TRIPLET × GROUP interaction ($F(3,177) = 0.904$, $p = 0.441$, $\eta_p^2 = 0.015$).

We compared the corrected learning scores between the two groups in each epoch. The EPOCH × GROUP ANOVA on the corrected learning scores did reveal a main effect of EPOCH ($F(2.086,123.102) = 2.988$, $p = 0.048$, $\eta_p^2 = 0.048$), suggesting that, in accordance with the uncorrected data, learning scores did change over the course of the task, as the learning scores became larger. The main effect of GROUP proved to be non-significant ($F(1,59) < 0.001$, $p = 0.530$, $\eta_p^2 = 0.07$, $BF_{10} = 0.301$), which means – in accordance with the uncorrected data – that the two groups exhibited similar learning scores in the task. The EPOCH × GROUP interaction also did not reach significance ($F(3,177) = 1.390$, $p = 0.252$, $\eta_p^2 = 0.023$), indicating that, as in the uncorrected data, no group differences were found in the dynamics of learning over the epochs.

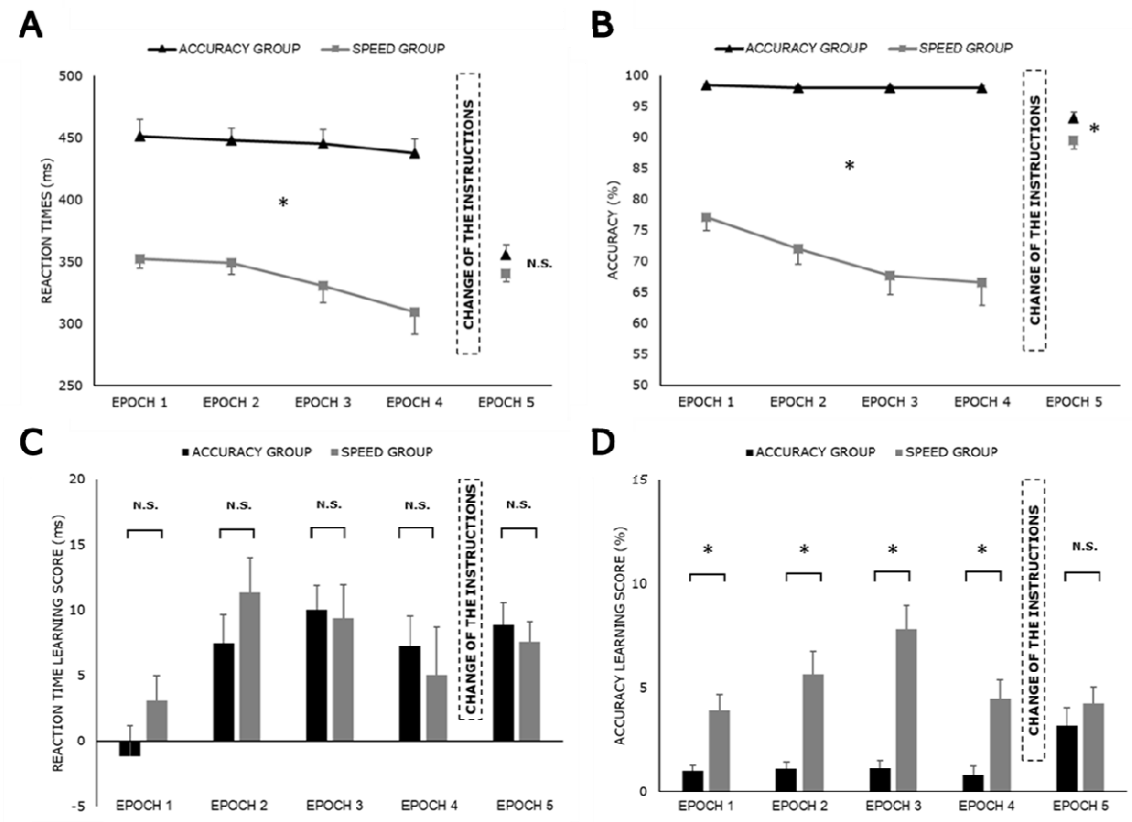

Figure 2. In the top row, the average RTs (A) and the average accuracies (B) are visualized for the two groups. The horizontal axis indicates the 5 epochs of the task, and the vertical axis the RTs in percentage (A) or the accuracies in milliseconds (B). Average RTs were significantly shorter and accuracies lower for the Speed Group from the first epoch, which means that the participants followed the instructions. After the change of the instructions (Epoch 5) - although the average scores of the two groups approached each other – the difference persisted for accuracies; however, the difference disappeared in case of the RTs. In the bottom row, the learning scores are visualized for the two groups in terms of RTs (C) and accuracies (D). Again, the horizontal axis indicated the 5 epochs of the task, but the vertical axis signals the learning scores. These scores were calculated by subtracting the RTs for the high-probability triplets from the low-probability ones (C) and by subtracting the accuracies for the low-probability triplets from the high-probability ones (D). Higher bars represent higher learning. In terms of RTs, a similar level of learning was measured in both groups in both phases. In terms of accuracy (C), learning was detected only in the Speed Group. However, after the change of the instructions, a similar level of learning was measured in both groups. The error bars represent the standard error in all figures.

Did the learning performance measured by accuracy differ between groups as a result of the different instructions?

We compared mean accuracy scores between the two groups in terms of epochs and triplet types (Figure 2B and 2D). The EPOCH × TRIPLET × GROUP ANOVA revealed significant main effect of EPOCH ($F(1.814, 107.001 = 8.411$, $p < 0.001$, $\eta_p^2 = 0.125$), revealing a decrease of accuracy as the task progressed. The main effect of TRIPLET was also significant ($F(1,59) = 93.883$, $p < 0.001$, $\eta_p^2 = 0.651$): participants were more accurate responding to

high-frequency triplets compared to the low-frequency probability ones, revealing implicit statistical learning. The main effect of GROUP was also significant ($F(1,59) = 117.397$, $p < 0.001$, $\eta_p^2 = 0.666$), signaling a general increased accuracy in the Accuracy Group. The EPOCH × GROUP interaction was significant ($F(3,177) = 7.083$, $p < 0.001$, $\eta_p^2 = 0.651$), indicating that accuracy decreased over the epochs in the Speed Group while it remained similarly high over all epochs in the Accuracy Group (Figure 2B). Contrary to the RT results, the TRIPLET × GROUP interaction was proved to be significant ($F(1,59) = 45.246$, $p < 0.001$, $\eta_p^2 = 0.434$): while the Speed Group showed more accurate responses to high-probability triplets compared to the low-probability ones, the Accuracy Group exhibited similarly accurate responses to high- and low-probability triplets (Figure 2D). The TRIPLET × EPOCH interaction proved to be significant ($F(3,177) = 3.690$, $p = 0.013$, $\eta_p^2 = 0.059$): participants' accuracy for low-probability triplets decreased over the course of training, while it remained relatively constant for high-probability triplets, which reflects increasing implicit statistical learning. The EPOCH × TRIPLET × GROUP interaction was also significant ($F(3,177) = 2.987$, $p = 0.033$, $\eta_p^2 = 0.048$), suggesting different dynamics of implicit statistical learning for the two groups, with increasingly greater learning in the Speed Group compared to the Accuracy Group.

We also compared the corrected accuracy learning scores between the two groups in each epoch. The EPOCH × GROUP ANOVA on the corrected learning scores revealed a significant main effect of EPOCH ($F(3,177) = 5.210$, $p = 0.002$, $\eta_p^2 = 0.081$), such that learning scores increased over the course of the task. Importantly, the main effect of GROUP proved to be significant again ($F(1,59) = 46.165$, $p < 0.001$, $\eta_p^2 < 0.439$): the Speed Group showed accuracy-related learning, while the Accuracy Group did not. The EPOCH × GROUP interaction was also significant ($F(3,177) = 4.822$, $p = 0.003$, $\eta_p^2 = 0.076$), indicating that increasingly greater learning scores only in the Speed Group.

Did the acquired competence on the ASRT task differ between groups when testing with the same instructions?

To answer this question, first, we calculated the median RTs separately for the high- and low-probability triplets at the Similar Instruction Phase and compared them between the two groups. The TRIPLET × GROUP ANOVA revealed a significant main effect of TRIPLET ($F(1,59) = 50.501$, $p < 0.001$, $\eta_p^2 = 0.461$), indicating the acquired knowledge on the task (as RTs on high-probability triplets were smaller than RTs on low-probability triplets). The main effect of GROUP did not reach significance ($F(1,59) = 2.207$, $p = 0.160$, $\eta_p^2 = 0.033$), which

means that after the instructions changed, the overall RT difference disappeared between groups (Figure 2A). However, the TRIPLET × GROUP interaction did not reach significance ($F(1,59) = 0.272$, $p = 0.604$, $\eta_p^2 = 0.005$, $BF_{10} = 0.292$) (Figure 2C). This indicates that irrespectively from the instruction during the learning, the two groups showed the same level of competence when no specific instructions were given regarding the importance of accuracy or speed. Although no difference was found in the average RTs in the Similar Instruction Phase between the groups, for the sake of completeness, we repeated the analysis with corrected learning scores. Again, no difference was found between groups regarding the learning score in the last epoch ($t(59) = 0.575$, $p = 0.568$, $BF_{10} = 0.300$).

Next, we compared the accuracies for the high- and low-probability triplets between the two groups. The TRIPLET × GROUP ANOVA revealed a significant main effect of TRIPLET ($F(1,59) = 39.955$, $p < 0.001$, $\eta_p^2 = 0.404$), indicating the acquired knowledge on the task in accuracy as well (more accurate responses for high-probability triplets compared to the low-probability ones). The main effect of GROUP was significant ($F(1,59) = 5.083$, $p = 0.028$, $\eta_p^2 = 0.079$), indicating that the overall difference in accuracy persisted after the change of the instructions (Figure 2B). The TRIPLET × GROUP interaction did not reach significance ($F(1,59) = 0.847$, $p = 0.361$, $\eta_p^2 = 0.005$, $BF_{10} = 0.373$), signaling a similar level of competence on the task after the change of the instruction (Figure 2D). We also compared the competence of the two groups with corrected learning scores. In this case, we also did not find difference in the competence between the two groups ($t(59) = -0.893$, $p = 0.376$, $BF_{10} = 0.365$).

Did the participants develop conscious knowledge about the statistical regularities and was it different between groups?

To reveal whether the acquired statistical knowledge remained implicit or became explicitly accessible for the participants, the Inclusion/Exclusion task was administered. Here, separately for the two groups, we compared the percentage of the generated high-probability triplets to chance level (25%) when participants were instructed to generate the learned sequence (Inclusion task) and when they were instructed to generate a sequence other than the learned one (Exclusion task; for further details see the Methods section). In the Accuracy Group, two participants were excluded from this analysis as they did not follow the instructions. Participants in the Accuracy Group generated 7.33% more high-probability triplets than chance level in the inclusion condition ($t(28) = 4.823$, $p < 0.001$). They generated high-probability triplets significantly above chance (29.81%) in the exclusion condition as

well ($t(28) = 4.039$, $p = 0.001$), indicating that they could not consciously control the emergence of this knowledge. We also compared the performance between the two tasks, and no difference was found ($t(28) = -1.571$, $p = 0.127$) in this group, thus participants' triplet knowledge can be regarded as implicit memory. In the Speed Group, two participants were excluded as they did not follow the instructions. Participants of the Speed Group generated 5.34% more high-probability triplets in the inclusion condition than it would have been expected by chance ($t(27) = 3.577$, $p = 0.001$). Similarly to the Accuracy Group, they also generated more high-probability triplets than expected by chance in the exclusion task (4.25%; $t(27) = 2.070$, $p = 0.048$). Comparing the inclusion and the exclusion conditions, the participants in the Speed Group generated a similar rate of high-probability triplets ($t(27) = -0.472$, $p = 0.641$), thus triplet knowledge remained implicit for participants in this group as well. The two groups showed similar performance both in the inclusion ($t(55) = 0.931$, $p = 0.356$) and in the exclusion conditions ($t(55) = 0.236$, $p = 0.815$).

Did the original preferences of the participants affect their performance on the task?

To check whether the subjective preferences on being fast or accurate in the real life were related to the ability to follow instructions, we used a questionnaire where the participants were asked about their preferences (see Methods for the questions). We correlated the questionnaire scores with the average RTs and accuracy of the participants separately for the two groups. We did not find any significant correlations between the average scores and the subjective rating about the preferences neither in the Accuracy Group nor in the Speed Group (all $p > 0.098$). It indicates that the preference of accuracy or speed, and whether the participants are rather fast or accurate in real life did not play a role in the ability to follow the instructions.

Discussion

In the present study, we aimed to test whether multiple behavioral sessions with different instructions can help disentangle competence from the performance. To this end, we instructed two groups of participants to be either fast or accurate while practicing an implicit probabilistic learning task; thereafter, in the testing phase, we assessed the accumulated knowledge of probabilistic regularities while both groups were instructed to be fast as well as accurate. This design enabled us to disentangle whether instructions during learning affect only the performance or they modify also the acquired knowledge, that is, the competence.

Participants who focused on their accuracy did not show measurable statistical learning when measured by accuracy, contrary to the participants who focused on their speed during learning; however, learning occurred to a similar extent in both groups when measured by RTs. Therefore, it appears that the speed instruction had an advantage when measured by accuracy, while instructions did not affect statistical learning performance when measured by RTs. Most importantly, no differences between the groups were found either in RTs or in accuracy in the testing phase. This suggests that despite the different instructions as well as the different performance during learning, a similar level of statistical knowledge (i.e., identical competence) was acquired with both instructions over the course of learning. Similar results were obtained when we controlled for the differences in average speed and accuracy between groups. Moreover, Bayesian statistical methods also supported the lack of difference between groups in terms of the acquired knowledge.

Our most important result is that we detected the same level of competence irrespective of the strategy during learning, both when measured by RTs and by accuracy. This finding has a number of implications. From a narrow, learning perspective, it suggests that statistical learning is so robust that instructions cannot influence the ability to extract the relevant pieces of information from the environment. It is in accordance with the findings that statistical knowledge persists and remains resistant to interference even after one-year (Kobor et al., 2017), or that it remains intact in certain disorders which are characterized by other types of cognitive dysfunctions (Csábi, Benedek, Janacsek, Katona, & Nemeth, 2013; Csábi et al., 2016; Csabi, Varszegi-Schulz, Janacsek, Malecek, & Nemeth, 2014; Nemeth, Csábi, Janacsek, Várszegi, & Mari, 2012; Nemeth, Janacsek, Balogh, et al., 2010; Unoka et al., 2017). In contrast to the deterministic learning tasks, which test patterns that occur with a 100% probability over time, the alteration of the random and pattern elements in the ASRT task produces a noisy, uncertain environment, which is similar to the natural environments of learning in everyday life (Fiser et al., 2010). However, our results showed that despite this uncertainty, a good level of statistical knowledge emerges over the course of learning, and it is proved equal even when learning occurs under different circumstances, with different strategies.

In accuracy learning measures, despite the lack of measurable statistical learning when focusing on being accurate, we did find evidence for statistical knowledge after the change of the instructions. In other words, despite the minimization of motor (response) errors during learning (performance), participants did acquire stable statistical knowledge (competence).

However, the same level of knowledge (i. e., the same level of competence) was obtained when focusing on speed, which resulted in a high amount of errors during learning. This result is especially interesting in the light of the theory that the brain is a Bayesian inference machine (Friston, 2010) because it contradicts the findings that committing errors facilitates learning (Bubic, Von Cramon, & Schubotz, 2010) as different amount of errors during learning resulted in the same level of statistical knowledge. Our brain learns associations between events through the continuous adjustments of the estimated probability distribution, i.e., the prior. After a prediction error, the prior should be updated in accordance with the new information about the probabilistic structure (Friston, 2010). Consequently, if motor errors during the learning were crucial for this process, then the large difference in the basic accuracy should lead to impaired statistical knowledge when learning occurs under the accuracy instruction compared to learning under the speed instruction. As it was not the case in our study, we might speculate that the motor aspect of prediction errors is not crucial for updating the priors during probabilistic statistical learning. This result also supports the fact that learning complex statistical regularities are more determined by perceptual than by motor factors, which is an ongoing debate in the field of skill learning (Hallgató, Gyori-Dani, Pekár, Janacsek, & Nemeth, 2013; Janacsek & Nemeth, 2012; Nemeth, Hallgató, Janacsek, Sándor, & Londe, 2009). However, it is also possible that a similar amount of errors might be detected with other methods, for example, by investigating eye-movements (Le Pelley, Beesley, & Griffiths, 2011; Wills, Lavric, Croft, & Hodgson, 2007). Nevertheless, based on our results, probabilistic statistical knowledge seems to emerge without the motor aspect of prediction errors during learning.

At the initial learning phase, similar levels of statistical learning were measured in RTs under both speed and accuracy instructions; however, only the speed instruction resulted in detectable statistical learning measured by accuracy. The fact that no group differences were found in RT learning scores is in contrast with the results of Hoyndorf et al (2009), as they found impaired implicit learning performance when accuracy instruction was given. In their study, participants performed a regular and a random task set during a number reduction task. They found that only the participants who performed under the speed instruction had increased speed for the regular task set. However, in their study, a preference for the regular task was found when compared to a non-learning group, which indicates that learning does occur to some extent under accuracy instructions. Yet it was not tested whether the accuracy and speed instructions result in the same level of acquired knowledge under similar

instructions, which proved to be equal in our study. Contrary to the results measured by RTs, we found a group difference in learning measured by accuracy: only the speed instruction resulted in measurable statistical learning during the initial learning phase. This can be explained by a ceiling effect caused by the instruction: as a result of the accuracy instruction, participants completed the task nearly without error, which made it impossible to measure statistical learning (as a difference scores between responses to high- vs. low-probability triplets) in that domain; however, statistical learning did occur, evidenced by the results of the testing phase. Taken together, these findings call for a more careful approach when we evaluate the learning phase in terms of *accuracy* measures, because focusing on being accurate can distort the learning scores of interest so much that, in certain cases, no learning can be detected at all, which otherwise could be shown by RTs.

From a broader, cognitive neuroscience perspective, it is essential to highlight the relationship between performance and competence. Most studies in the field of cognitive neuroscience measure learning at one time point, and draw conclusions about the brain-behavior relationships based on either the performance *or* the competence (Heideman et al., 2018; Rose et al., 2011; Thomas et al., 2004; N. B. Turk-Browne et al., 2010). Our study revealed that the competence on a certain skill can differ from the momentary performance, at least when the accuracy is used as an indicator. This result draws attention to the problem of using solely one session to evaluate learning. For example, if fatigue or boredom of the participants' changes when they concentrate on being fast or being accurate, without a testing phase, it can influence the conclusions we draw from our results. However, when measuring RTs, this contingency appears smaller, at least when investigating implicit probabilistic learning. Future studies should reveal to what extent it is generalizable to other types of learning, such as to more explicit or to non-statistical learning tasks. Moreover, non-learning tasks should also be tested, as general speed-up and changes in accuracy can be seen over the course of several cognitive tasks requiring fast decision-making, which can be modified by instructions. Nevertheless, based on our results, we recommend taking into consideration the possible differences between the measured competence and performance when designing learning studies.

By giving explicit instructions to focus either on accuracy or speed, we managed to manipulate the overall performance of the participants, as previous non-learning cognitive tasks also did (Aasen & Brunner, 2016; Christensen, Ivkovich, & Drake, 2001; Osman et al., 2000; Ullsperger, Bylsma, & Botvinick, 2004). However, one might question if our results

truly reflect the effect of instructions on learning. For example, one can argue that the instructions given in our study were not strong enough to manipulate the learning processes, and that is why we did not found differences in the acquired knowledge between the two groups. This, however, seems unlikely as the *average speed and accuracy* were effected by the instructions. Moreover, group differences also emerged in general skill learning as (1) participants who focused on their speed showed increasingly faster responses, and (2) participants who focused on their accuracy sustained a high level of accuracy during the learning phase compared to the other group. In contrast to these findings, the acquisition of statistical regularities was not affected by the instructions.

It can also be claimed that verbal instructions given at the beginning of the task might not be sufficient to regulate subjects' average speed and accuracy, as over time, participants tend to wane in favor of their own response tendencies (Heitz, 2014). In our case, this is also unlikely, because - at least for accuracy - the general difference between groups caused by the instructions (without the statistical learning component) persisted even when participants were no longer instructed to be fast or accurate. As there were no differences in the average RTs and accuracy scores in the practice sessions, before we gave distinct instructions to the two groups, the effects observed should be due to the instructions. Additionally, as no correlations were observed between the individual preferences and the average speed and accuracy during the task in neither group, it indicates that our results truly reflect the effect of instructions and that participants did not catch up their individually preferred response tendencies during the task.

To sum up, this is the first study that directly aims to disentangle competence from performance in a learning task. Our main results are the followings: first, from a narrower, learning perspective, our ability to pick-up statistical regularities in a noisy, uncertain environment seems to be so robust that explicit instructions do not influence it. This is of high importance because it means that statistical learning is at least partly independent from feedback or reward, and the lack of response (motor) errors do not disrupt the emergence of the knowledge about the environmental regularities. Future studies investigating whether this robustness is related to the implicit feature of the task or whether different types of learning are affected equally, seem warranted. Second, from a broader, methodological point of view, it appears that competence and performance can differ in certain cases. Accuracy instructions can mask the accumulating knowledge during learning when measured by accuracy, although statistical knowledge does emerge in these cases as well. Reaction time and accuracy data

often serve as a basis for correlations to establish brain-behavior relationships, while possibly, only the actual performance (but not the underlying competence) is measured. Based on our results, we suggest that the instructions given to participants should be carefully selected, and the possible differences between performance and competence should be taken into account when designing experiments, especially when accuracy is used as a main indicator of performance.

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References

Aasen, I. E., & Brunner, J. F. (2016). Modulation of ERP components by task instructions in a cued go/no-go task. *Psychophysiology*, *53*(2), 171–185. https://doi.org/10.1111/psyp.12563

Beilock, S. L., Bertenthal, B. I., Hoerger, M., & Carr, T. H. (2008). When Does Haste Make Waste? Speed-Accuracy Tradeoff, Skill Level, and the Tools of the Trade. *Journal of Experimental Psychology: Applied*, *14*(4), 340–352. https://doi.org/10.1037/a0012859

Beilock, S. L., Bertenthal, B. I., McCoy, A. M., & Carr, T. H. (2004). Haste does not always make waste: Expertise, direction of attention, and speed versus accuracy in performing sensorimotor skills. *Psychonomic Bulletin and Review*, *11*(2), 373–379. https://doi.org/10.3758/BF03196585

Bubic, A., Von Cramon, D. Y., & Schubotz, R. I. (2010). Prediction, cognition and the brain. *Frontiers in Human Neuroscience*, *4*(March), 1–15. https://doi.org/10.3389/fnhum.2010.00025

Christensen, C. A., Ivkovich, D., & Drake, K. J. (2001). Late positive ERP peaks observed in

stimulus-response compatibility tasks tested under speed-accuracy instructions. *Psychophysiology*, *38*(3), 404–416. https://doi.org/10.1017/S0048577201991176

Cleeremans, A., Destrebecqz, A., & Boyer, M. (1998). Implicit learning: News from the front. *Trends in Cognitive Sciences*, *2*(10), 406–416. https://doi.org/10.1016/S1364-6613(98)01232-7

Csábi, E., Benedek, P., Janacsek, K., Katona, G., & Nemeth, D. (2013). Sleep disorder in childhood impairs declarative but not nondeclarative forms of learning. *Journal of Clinical and Experimental Neuropsychology*, *35*(7), 677–685. https://doi.org/10.1080/13803395.2013.815693

Csábi, E., Benedek, P., Janacsek, K., Zavecz, Z., Katona, G., & Nemeth, D. (2016). Declarative and Non-declarative Memory Consolidation in Children with Sleep Disorder. *Frontiers in Human Neuroscience*, *9*(January). https://doi.org/10.3389/fnhum.2015.00709

Csabi, E., Varszegi-Schulz, M., Janacsek, K., Malecek, N., & Nemeth, D. (2014). The consolidation of implicit sequence memory in obstructive sleep apnea. *PLoS ONE*, *9*(10), 1–6. https://doi.org/10.1371/journal.pone.0109010

Destrebecqz, A, Peigneux, P., Laureys, S., Degueldre, C., Del Fiore, G., Aerts, J., … Maquet, P. (2005). neural correlates of implicit and explicit sequence learning: Interacting networks revealed. *Learning & Memory*, (Erderlyi 1986), 480–490. https://doi.org/10.1101/lm.95605.6

Destrebecqz, Arnaud, & Cleeremans, A. (2001). Can sequence learning be implicit? New evidence with the process dissociation procedure. *Psychonomic Bulletin and Review*, *8*(2), 343–350. https://doi.org/10.3758/BF03196171

Endrass, T., Schreiber, M., & Kathmann, N. (2012). Speeding up older adults: Age-effects on error processing in speed and accuracy conditions. *Biological Psychology*, *89*(2), 426–432. https://doi.org/10.1016/j.biopsycho.2011.12.005

Fiser, J., Berkes, P., Orbán, G., & Lengyel, M. (2010). Statistically optimal perception and learning: from behavior to neural representations. *Trends in Cognitive Sciences*, *14*(3), 119–130. https://doi.org/10.1016/j.tics.2010.01.003

Friston, K. (2010). The free-energy principle: A unified brain theory? *Nature Reviews*

Neuroscience, *11*(2), 127–138. https://doi.org/10.1038/nrn2787

Fu, Q., Dienes, Z., & Fu, X. (2010). Can unconscious knowledge allow control in sequence learning? *Consciousness and Cognition*, *19*(1), 462–474. https://doi.org/10.1016/j.concog.2009.10.001

Hallgató, E., Gyori-Dani, D., Pekár, J., Janacsek, K., & Nemeth, D. (2013). The differential consolidation of perceptual and motor learning in skill acquisition. *Cortex*, *49*(4), 1073–1081. https://doi.org/10.1016/j.cortex.2012.01.002

Healy, A. F., Kole, J. A., Buck-Gengler, C. J., & Bourne, L. E. (2004). Effects of prolonged work on data entry speed and accuracy. *Journal of Experimental Psychology: Applied*, *10*(3), 188–199. https://doi.org/10.1037/1076-898X.10.3.188

Heideman, S. G., van Ede, F., & Nobre, A. C. (2018). Temporal alignment of anticipatory motor cortical beta lateralisation in hidden visual-motor sequences. *European Journal of Neuroscience*, *48*(8), 2684–2695. https://doi.org/10.1111/ejn.13700

Heitz, R. P. (2014). The speed-accuracy tradeoff: History, physiology, methodology, and behavior. *Frontiers in Neuroscience*, *8*(8 JUN), 1–19. https://doi.org/10.3389/fnins.2014.00150

Horvath, K., Torok, C., Pesthy, O., Nemeth, D., & Janacsek, K. (2018). Explicit instruction differentially affects subcomponents of procedural learning and consolidation. *BioRxiv*, 433243. https://doi.org/10.1101/433243

Howard, J. H., & Howard, D. V. (1997). Age differences in implicit learning of higher order dependencies in serial patterns. *Psychology and Aging*, *12*(4), 634–656. https://doi.org/10.1037/0882-7974.12.4.634

Howard, D. V., Howard, J. H., Japikse, K., DiYanni, C., Thompson, A., & Somberg, R. (2004). Implicit Sequence Learning: Effects of Level of Structure, Adult Age, and Extended Practice. *Psychology and Aging*, *19*(1), 79–92. https://doi.org/10.1037/0882-7974.19.1.79

Hoyndorf, A., & Haider, H. (2009). The “Not Letting Go” phenomenon: Accuracy instructions can impair behavioral and metacognitive effects of implicit learning processes. *Psychological Research*, *73*(5), 695–706. https://doi.org/10.1007/s00426-008-0180-4

Jacoby, L. L. (1991). A process dissociation framework: Separating automatic from intentional uses of memory. *Journal of Memory and Language*, *30*(5), 513–541.

Janacsek, K., Borbély-Ipkovich, E., Nemeth, D., & Gonda, X. (2018). How can the depressed mind extract and remember predictive relationships of the environment? Evidence from implicit probabilistic sequence learning. *Progress in Neuro-Psychopharmacology and Biological Psychiatry*, *81*(September 2017), 17–24. https://doi.org/10.1016/j.pnpbp.2017.09.021

Janacsek, K., & Nemeth, D. (2012). Predicting the future: From implicit learning to consolidation. *International Journal of Psychophysiology*, *83*(2), 213–221. https://doi.org/10.1016/j.ijpsycho.2011.11.012

JASP Team. (2017). *JASP (Version 0.8.3.1) [Computer software]*.

Jiménez, L., Vaquero, J. M. M., & Lupiáñez, J. (2006). Qualitative differences between implicit and explicit sequence learning. *Journal of Experimental Psychology: Learning Memory and Cognition*, *32*(3), 475–490. https://doi.org/10.1037/0278-7393.32.3.475

Juhasz, D., Nemeth, D., & Janacsek, K. (2019). Is there more room to improve? The lifespan trajectory of procedural learning and its relationship to the between- and within-group differences in average response times. *PLOS ONE*, *14*(7), e0215116. https://doi.org/10.1101/593582

Kiss, M., Nemeth, D., & Janacsek, K. (2019). Stimulus presentation rates affect performance but not the acquired knowledge – Evidence from procedural learning. *BioRxiv*, *650598*.

Kobor, A., Janacsek, K., Takacs, A., & Nemeth, D. (2017). Statistical learning leads to persistent memory: Evidence for one-year consolidation. *Scientific Reports*, *7*(1), 1–10. https://doi.org/10.1038/s41598-017-00807-3

Kóbor, A., Takács, Á., Kardos, Z., Janacsek, K., Horváth, K., Csépe, V., & Nemeth, D. (2018). ERPs differentiate the sensitivity to statistical probabilities and the learning of sequential structures during procedural learning. *Biological Psychology*, *135*(April), 180–193. https://doi.org/10.1016/j.biopsycho.2018.04.001

Kole, J. A., Healy, A. F., & Bourne Jr., L. E. (2008). Using Route and Survey Information to Generate Cognitive Maps. *Applied Cognitive Psychology*, *23*(2), 223–235. https://doi.org/10.1002/acp

Le Pelley, M. E., Beesley, T., & Griffiths, O. (2011). Overt Attention and Predictiveness in Human Contingency Learning. *Journal of Experimental Psychology: Animal Behavior Processes*, *37*(2), 220–229. https://doi.org/10.1037/a0021384

Nemeth, D., Csábi, E., Janacsek, K., Várszegi, M., & Mari, Z. (2012). Intact implicit probabilistic sequence learning in obstructive sleep apnea. *Journal of Sleep Research*, *21*(4), 396–401. https://doi.org/10.1111/j.1365-2869.2011.00983.x

Nemeth, D., Hallgató, E., Janacsek, K., Sándor, T., & Londe, Z. (2009). Perceptual and motor factors of implicit skill learning. *NeuroReport*, *20*(18), 1654–1658. https://doi.org/10.1097/WNR.0b013e328333ba08

Nemeth, D., Janacsek, K., Balogh, V., Londe, Z., Mingesz, R., Fazekas, M., … Vetro, A. (2010). Learning in autism: Implicitly superb. *PLoS ONE*, *5*(7). https://doi.org/10.1371/journal.pone.0011731

Nemeth, D., Janacsek, K., Londe, Z., Ullman, M. T., Howard, D. V., & Howard, J. H. (2010). Sleep has no critical role in implicit motor sequence learning in young and old adults. *Experimental Brain Research*, *201*(2), 351–358. https://doi.org/10.1007/s00221-009-2024-x

Oldfield R.C. (1971). The assessment and analysis of handedness: The Edinburgh inventory. *Neuropsychologia*, 97–113.

Osman, A., Lou, L., Muller-Gethmann, H., Rinkenauer, G., Mattes, S., & Ulrich, R. (2000). Mechanisms of speed-accuracy tradeoff: Evidence from covert motor processes. *Biological Psychology*, *51*(2–3), 173–199. https://doi.org/10.1016/S0301-0511(99)00045-9

Perruchet, P., & Pacton, S. (2006). Implicit learning and statistical learning: one phenomenon, two approaches. *Trends in Cognitive Sciences*, *10*(5), 233–238. https://doi.org/10.1016/j.tics.2006.03.006

Reber, A. (1993). *Implicit learning: An essay on the cognitive unconscious*.

Rose, M., Haider, H., Salari, N., & Buchel, C. (2011). Functional Dissociation of Hippocampal Mechanism during Implicit Learning Based on the Domain of Associations. *Journal of Neuroscience*, *31*(39), 13739–13745. https://doi.org/10.1523/jneurosci.3020-11.2011

Song, S., Howard, J. H., & Howard, D. V. (2007). Sleep Does Not Benefit Probabilistic Motor Sequence Learning. *Journal of Neuroscience*, *27*(46), 12475–12483. https://doi.org/10.1523/jneurosci.2062-07.2007

Takács, Á., Kóbor, A., Chezan, J., Éltető, N., Tárnok, Z., Nemeth, D., … Janacsek, K. (2018). Is procedural memory enhanced in Tourette syndrome? Evidence from a sequence learning task. *Cortex*, *100*(February), 84–94. https://doi.org/10.1016/j.cortex.2017.08.037

Thomas, K. M., Hunt, R. H., Vizueta, N., Sommer, T., Durston, S., Yang, Y., & Worden, M. S. (2004). Evidence of developmental differences in implicit sequence learning: An fMRI study of children and adults. *Journal of Cognitive Neuroscience*, *16*(8), 1339–1351. https://doi.org/10.1162/0898929042304688

Tóth, B., Janacsek, K., Takács, Á., Kóbor, A., Zavecz, Z., & Nemeth, D. (2017). Dynamics of EEG functional connectivity during statistical learning. *Neurobiology of Learning and Memory*, *144*, 216–229. https://doi.org/10.1016/j.nlm.2017.07.015

Turk-Browne, N. B., Scholl, B. J., Johnson, M. K., & Chun, M. M. (2010). Implicit Perceptual Anticipation Triggered by Statistical Learning. *Journal of Neuroscience*, *30*(33), 11177–11187. https://doi.org/10.1523/jneurosci.0858-10.2010

Turk-Browne, Nicholas B, Scholl, B. J., Chun, M. M., & Johnson, M. K. (2009). Neural evidence of statistical learning: efficient detection of visual regularities without awareness. *Journal of Cognitive Neuroscience*, *21*(10), 1934–1945. https://doi.org/10.1162/jocn.2009.21131

Ullsperger, M., Bylsma, L. M., & Botvinick, M. M. (2004). The conflict-adaptation effect□: it ’ s not just priming. *Cognitive, Affective, & Behavioral Neuroscience*, *5*(4), 467–472.

Unoka, Z., Vizin, G., Bjelik, A., Radics, D., Nemeth, D., & Janacsek, K. (2017). Intact implicit statistical learning in borderline personality disorder. *Psychiatry Research*, *255*(May), 373–381. https://doi.org/10.1016/j.psychres.2017.06.072

Wills, A. J., Lavric, A., Croft, G. S., & Hodgson, T. L. (2007). Predictive learning, prediction errors, and attention: Evidence from event-related potentials and eye tracking. *Journal of Cognitive Neuroscience*, *19*(5), 843–854. https://doi.org/10.1162/jocn.2007.19.5.843

Zhang, J., & Rowe, J. B. (2014). Dissociable mechanisms of speed-accuracy tradeoff during

visual perceptual learning are revealed by a hierarchical drift-diffusion model. *Frontiers in Neuroscience*, *8*(8 APR), 1–13. https://doi.org/10.3389/fnins.2014.00069