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ORIGINAL ARTICLE

The impact of implicit and explicit suggestions that 'there is nothing to learn' on implicit sequence learning

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Abstract
We can sometimes efficiently pick up statistical regularities in our environment in the absence of clear intentions or awareness, a process typically referred to as implicit sequence learning. In the current study, we tried to address the question whether suggesting participants that there is nothing to learn can impact this form of learning. If a priori predictions or intentions to learn are important in guiding implicit learning, we reasoned that suggesting participants that there is nothing to learn in a given context should hamper implicit learning. We introduced participants to random contexts that indicated that there was nothing to learn, either implicitly (i.e., by presenting blocks of random trials in "Experiment 1"), or explicitly (i.e., by explicitly instructing them in "Experiment 2"). Next, in a subsequent learning phase, participants performed an implicit sequence learning task. We found that these implicit or explicit suggestions that 'there was nothing to learn' did not influence the emergence of implicit knowledge in the subsequent learning phase. Although these findings seem consistent with simple associative or Hebbian learning accounts of implicit sequence learning (i.e., not steered by predictions), we discuss potential limitations that should inform future studies on the role of a priori predictions in implicit learning.

Introduction

Implicit learning has been defined as learning without awareness of what is being learned—or even of the fact that something was learned to begin with (e.g., Reber, 1989). Such implicit learning reveals itself in indirect performance measures such as speed and accuracy of responding. Many of our cognitive abilities such as language, perception, motor and social skills are thought to be, at least partially, a result of implicit learning. These skills reflect our ability to adapt to the regularities of the world without our conscious intention to do so, without a clear awareness of the learned knowledge and without external supervision (Perruchet & Pacton, 2006). Furthermore, these regularities are often sequential. For example, when a child is learning to ride a bike it has to coordinate multiple steps of action in a specific sequence. Nevertheless, it is very hard to explain to someone else how we keep our balance (although implicit learning can also lead to explicit knowledge, e.g., Rebuschat & Williams, 2012). It is something you can only learn by acquiring the implicit knowledge yourself. Another example of implicit sequence learning is our intuitive understanding of grammar. Even children that have not studied the underlying grammar rules of their native language can differentiate grammatical from ungrammatical sentences.

While such implicit sequence learning abilities have been validated across various experimental paradigms (e.g., Nissen & Bullemer, 1987; Reber, 1967; but see Vadillo, Konstantinidis & Shanks, 2016) and its features have been well studied (e.g., the role of awareness, the type of representations, for a review see Abrahamse et al., 2010), it is still unclear what drives this form of learning. Recent frameworks on the "predictive brain" (see the review article of Bubic, von Cramon & Schubotz, 2010 and Clark, 2013) suggest an important role for predictions and expectations in (implicit) learning. Here, it is thought that the brain learns

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by a pervasive tendency to predict the environment based on prior knowledge, thereby emphasizing the importance of context and expectations in guiding and constructing our knowledge. In novel contexts, no prior knowledge is available, and predictions could be formed by analogy (Bar, 2007) or by randomly chunking together stimuli (Thiessen, 2017). These rudimentary predictions would then be adjusted by prediction errors until the chunks reflect the statistical structure of the environment. In line with a predictive account of learning, multiple studies have shown that people (and monkeys) develop expectations towards sequential stimuli (as evidenced by anticipatory eye movements or predictive mouse trajectories, e.g., Dale et al., 2012; de Kleijn et al., 2018; Jiang et al., 2014; Marcus et al., 2006; Miyashita et al., 1996). These studies primarily show that predictions or expectations result from implicit learning, and therefore, support predictive accounts of implicit learning. However, another interesting question relates to the importance of predictions or expectations on shaping learning a priori.

Some studies have found that the content and amount of implicit sequence learning are sensitive to how participants a priori conceptualize the task set (the stimuli, responses, instructions and goals that make up the task). For example, Gaschler, Frensch, Cohen and Wenke (2012) have shown that the instructed stimulus–response mappings determine the content of implicit sequence learning. They manipulated the instructions of an implicit sequence learning paradigm by referring to the response keys in terms of their spatial position or in terms of their color. Participants only acquired color-coded sequence knowledge when they received the color-coded instructions (and spatial-coded sequence knowledge arose independent of the instructional manipulation). Halvorson, Wagschal and Hazeltine (2013) manipulated their instructions for two tasks. One task contained regularities that could be learned, while the other task was random. One group of participants was told that there were two separate tasks, while the other group was told they had to conceptualize the tasks as one. Sequence learning was impaired when participants conceptualized the tasks as one, suggesting that the random task interfered with learning but only when this task was conceptualized as part of the task set. These studies suggest that while participants are (in general) not aware that they are learning or what they are learning, the content of learning can be influenced by a priori conceptualizations and expectations about the task set (see also Freedberg, Wagschal & Hazeltine, 2014; Gamble, Lee, Howard & Howard, 2014).

However, while these studies do show that a priori expectations are important in shaping implicit learning—which can be considered consistent with a predictive account of implicit learning (e.g., Bubic et al., 2010)—they only do so by raising attention to stimulus features or task structures in which the implicit sequences are embedded. Here, we take another approach and investigate whether implicit learning can be influenced by changing expectations about the actual regularities that are present in the current context. More specifically, we established contexts which indicated that there was nothing to be learned prior to a learning phase. The rationale is that if a priori predictions are important in shaping and guiding implicit learning, learning that there is nothing to learn in a given context should hamper implicit sequence learning in that context. To this end, we designed two experiments in which we introduced participants to random contexts. In the first experiment, the cue for randomness consisted of blocks of trials that were randomly organized (i.e., no inter-trial sequential regularities) which were presented to an experimental but not a control group. In the second experiment, the cue for randomness consisted of the explicit instruction that sequential regularity was present in some but not all parts of the experiment (while in fact such regularity was always there). In both experiments, we expected less implicit learning immediately after ("Experiment 1") or during ("Experiment 2") a task containing a cue for randomness.

Experiment 1

Method

Experimental design and hypotheses Participants were divided into two groups that both performed a two-phase experiment. We used the Alternating Serial Reaction Time task (ASRT; Howard & Howard, 1997) to assess implicit sequence learning, in which a repeating four-item sequence is interspersed with random trials (i.e., S1–R–S2–R–S3–R–S4–R–S1–R–S2 …). This task has been argued to provide a cleaner assessment of implicit learning (Howard et al., 2004; for details see below) compared to the standard Serial Reaction Time task (SRT, Nissen & Bullemer, 1987) as it significantly hinders the development of awareness. The goal of this first experiment was to investigate whether a first phase without any regularities, suggesting a random context, would impair subsequent implicit sequence learning in a second, regular phase. Hence, in a first phase, the experimental group performed the ASRT without inter-trial sequential regularities, while the control group performed a Go/noGo task. In the subsequent second phase, both groups performed the ASRT with its typical inter-trial sequential regularity. We hypothesized that performing the 'ASRT' but without a sequence (random context) would hamper subsequent sequence learning in the regular version of the ASRT task (i.e., with a sequence). This would result in the experimental group learning less (slower) as compared to the control group in the second phase. The paradigms, data and analyses scripts are available on the Open Science Framework (https://osf.io/qbvka/).

Participants The hour-long experiment was performed by 69 participants who all signed an informed consent form. These participants were all psychology students of Ghent University and were compensated with course credits. Three participants could not finish their experiment due to computer crashes and these participants were excluded from the analysis ($n = 66$). The participants were randomly assigned to the experimental group ($n = 33$, $M_{age} = 19.42$, $SD_{age} = 1.83$, 18 male) or the control group ($n = 33$, $M_{age} = 20.36$, $SD_{age} = 4.81$, 15 male). Our sample size was determined by the conclusiveness of our initial findings. Given that the first sample ($n = 66$) resulted in a Bayes factor > 6 (or < 1/6), we stopped data collection (Schonbrodt, Wagenmakers, Zehetleitner & Perugini, 2017).

Materials Our main paradigm was the ASRT (Howard & Howard, 1997). The original task of Howard and Howard (1997) was used and adapted to fit the current experiment with the E-Prime 2.0 software (Psychology Software Tools, Pittsburgh, PA). In this task, four white circles with a black border are presented in the center of the screen from left to right on a white background. When one of the circles turns black (the target), participants are instructed to respond as soon and as accurate as possible. Participants have to press one of the four keys which are spatially aligned with these four circles (i.e., participants have to respond to the left-most circle on screen by pressing the left-most response button etc.; "z", "x", "." and "/" on a QWERTY keyboard). Participants use their left hand for the two left-most keys and use their right hand for two right-most keys. Only when a correct response is made, the circle instantly turns white again and after a Response-to-Stimulus Interval (RSI) of 120 ms, another circle will turn black (the target). There is no response deadline or stimulus time out.

The order of the targets follows a probabilistic sequence. Each participant is given a permutation of the simple pattern 1234 (e.g., 1423, with 1 indicating the left-most circle and 4 to right-most circle). This pattern is not merely repeated (e.g., 14231423) but interweaved with random stimuli (i.e., 'r', random with replacement; a random selection of one of the four possible circle positions). This leads to a probabilistic structure (1r4r2r3r1r4r2r3r) in terms of high- and low-frequency triplets (structure in three subsequent stimuli, in which the first stimulus is predictive of the outcome two stimuli further). For example, the sequences 1r4, 4r2, 2r3 and 3r1 are presented more frequently and thus 1 is predictive of 4 etc. There are 64 possible triplets, of which the 16 possible high-frequency triplets occur 62.5% of the time while the other 48 low-frequency triplets occur only 37.5% of the time. Participants typically respond faster to the high-frequency triplets compared to the low-frequency triplets, presumably indicating that they picked up the regularity of these structures (i.e., they implicitly learned).

Each block starts with eight stimuli that are completely random. Next, the actual sequence starts for 50 trials (58 trials in total per block). After each block, participants are shown their accuracy and reaction time. The goal was to steer participants toward 92% accuracy. Participants were told to "focus more on accuracy" if accuracy was below 91% and to "focus more on speed" if accuracy was above 93%. They would receive the message "Please continue" if accuracy was between 91 and 93% (cf. Song, Howard & Howard, 2008). Hereafter, participants took a short self-paced break (minimum 5 s). Participants performed 28 blocks of the ASRT with a sequence (divided into seven bins or 'epochs' of four blocks for analysis convenience).

Before this task, participants in the experimental group performed exactly the same task, but with no predetermined stimuli, leading to no structure in the stimuli (e.g., rrrrrrrr, i.e., on each trial the stimulus was randomly chosen) for 14 blocks. These 14 blocks were divided into four epochs for the analyses (3–4–4–3 blocks, respectively). The control group performed a Go/noGo task (also programmed in E-prime 2.0). The amount of trials and duration of events within this task were chosen to match the duration of the experiment in the experimental group (the ASRT without a sequence). In this task, participants were presented with a colored rectangle on each trial, and the goal was to respond to all the colored rectangles (with the "p" key) and withhold responding on the blue rectangle. On each trial, a fixation cross was presented for 150 ms, after which a rectangle was presented for 750 ms or until a response was made. Participants received feedback if they responded when there was a blue rectangle, or did not respond within the stimulus time out when the rectangle was not blue ("wrong!" for 200 ms). One block contained 48 trials of which 4 trials were blue rectangles (noGo trials) and 44 trials were differently colored rectangles (11 possible colors, excluding blue; Go trials) presented in a random order. After each block, participants could take a self-paced break (minimum 5 s). Participants performed this task for 14 blocks (divided into 4 epochs; 3–4–4–3 blocks, respectively). Although the analysis of this training phase was not central to our hypothesis, we also analyzed the data from phase 1 using other groupings of epochs (2–4–4–4, 4–4–4–2 and 3.5–3.5–3.5–3.5) which reached the same results as reported below.

Procedure Participants were seated in front of a computer cubicle in a dimly lit room (up to six participants in one session). They were asked to sign an informed consent after which they could read the instructions. Participants in the experimental group started with the ASRT that did not contain a sequence while participants in the control group started with the Go/noGo task. Next, both groups performed the ASRT task with a sequence. After the experiment, participants were asked to complete the Free Will Inventory (FWI; Nadelhoffer, Shepard, Nahmias, Sripada & Ross, 2014). This questionnaire was used to address a secondary research question that was not related to the current working hypothesis and will not be further discussed. Finally, participants were debriefed and course credit was given. The experiment lasted one hour.

Data reduction The first eight practice trials and first two experimental trials of each block were deleted. The 28 blocks were then divided into seven epochs of four blocks each to facilitate data processing. The frequency of each possible triplet combination was calculated to categorize them into low- or high-frequency triplets. Any triplet where one of the three trials contained an error was excluded from the RT analysis. Two specific kinds of low-frequency triplets were also deleted: repetitions (e.g., 111, 333) and trills (e.g., 232, 434). This is done because people often show pre-existing response tendencies to these and by eliminating them we ensured that the difference between low- and high-frequency triplets are due to learning and not pre-existing tendencies (Nemeth et al., 2010). Next, the hit rate and median RT were calculated for each triplet type (low and high frequencies), epoch (1–7) and subject separately. The median is the typical measure that is used in the literature on the ASRT (e.g., Howard et al., 2004; Nemeth et al., 2010). The ASRT without a sequence was analyzed in the same way, although without the triplet factor. It was verified during the data reduction procedure that this version did not harbor any regularities (i.e., in the ASRT without a sequence the occurrence percentage of all triplets was closely centered around its mean ($M = 7\%$, SD = 1%), which is typically not the case in the ASRT with a sequence ($M = 7\%$, SD = 5%). Also for this phase, trills (e.g., 232) and repeats (e.g., 222) were not included in the analysis. The Go/noGo task was analyzed by calculating the median RT per epoch (only Go trials) and calculating the hit rate as a function of epoch and action (Go, noGo).

Results

Phase 1 The control group ($n = 33$) started the experiment with the Go/noGo task (14 blocks divided into four epochs). A one-way repeated measures (RM) ANOVA was conducted with epoch (1–4) as within-subject (WS) factor for the reaction time (RT) measure (Go trials only). The degrees of freedom of factors that violate the assumption of sphericity will be corrected using Greenhouse–Geisser estimates of epsilon from here on. The results can be found in Table 1. The main effect of epoch was not significant, $F(2.115, 67.688) = 0.677$, $p = 0.519$, $\eta p^2 = 0.021$, $\varepsilon = 0.705$. Participants in the control group did not get significantly faster or slower over the epochs. A RM ANOVA with epoch and action type (Go, noGo) on the hit rate revealed only an effect of action type, $F(1, 32) = 115.759$, $p < 0.001$, $\eta p^2 = 0.783$, as participants were less accurate during Go trials relative to noGo trials. The experimental group ($n = 33$) started the experiment with a version of the ASRT that did not contain a sequence (14 blocks, divided into 4 epochs for the analysis). A one-way repeated measures ANOVA was conducted with RT as the dependent measure and epoch (1–4) as a WS factor. The main effect of epoch was significant, $F(1.891, 60.509) = 15.925$, $p < 0.001$, $\eta p^2 = 0.332$, $\varepsilon = 0.630$. Participants became faster over the four epochs. The same RM ANOVA with hit rate as the dependent measure also revealed an effect of epoch, $F(3, 96) = 5.217$, $p = 0.002$, $\eta p^2 = 0.140$, indicating that participants got less accurate throughout the epochs.

Phase 2 The performance of the two groups was compared on the ASRT containing a sequence (28 blocks divided into 7 epochs). A RM ANOVA was conducted with triplet (low frequency, high frequency) and epoch (1–7) as WS factors and group (experimental, control) as between-subject (BS) factor on the median RT measure (see Fig. 1a for the results).

All main effects were significant, $F(1, 64)\text{s} > 17.411$, $p\text{s} < 0.001$, indicating faster RTs for high frequency triplets ($M = 346.469$ ms, SE = 4.071; low-frequency triplets, $M = 355.133$, SE = 3.874), the experimental group

Table 1 Performance for the two groups in the first phase of the experiment

	Control group (Go/noGo task)			Experimental group (ASRT without sequence)	
	RT	Hit rate		RT	Hit rate
		noGo (blue)	Go		
Epoch 1	316 (10.5)	0.997 (0.001)	0.732 (0.031)	386 (6.7)	0.930 (0.005)
Epoch 2	315 (9.7)	0.998 (0.001)	0.746 (0.028)	371 (5.7)	0.913 (0.006)
Epoch 3	323 (8.5)	0.999 (0.001)	0.722 (0.028)	368 (4.8)	0.908 (0.004)
Epoch 4	313 (7.5)	0.996 (0.001)	0.692 (0.033)	362 (3.9)	0.907 (0.006)

Median reaction times in milliseconds. Standard error of the mean between parentheses

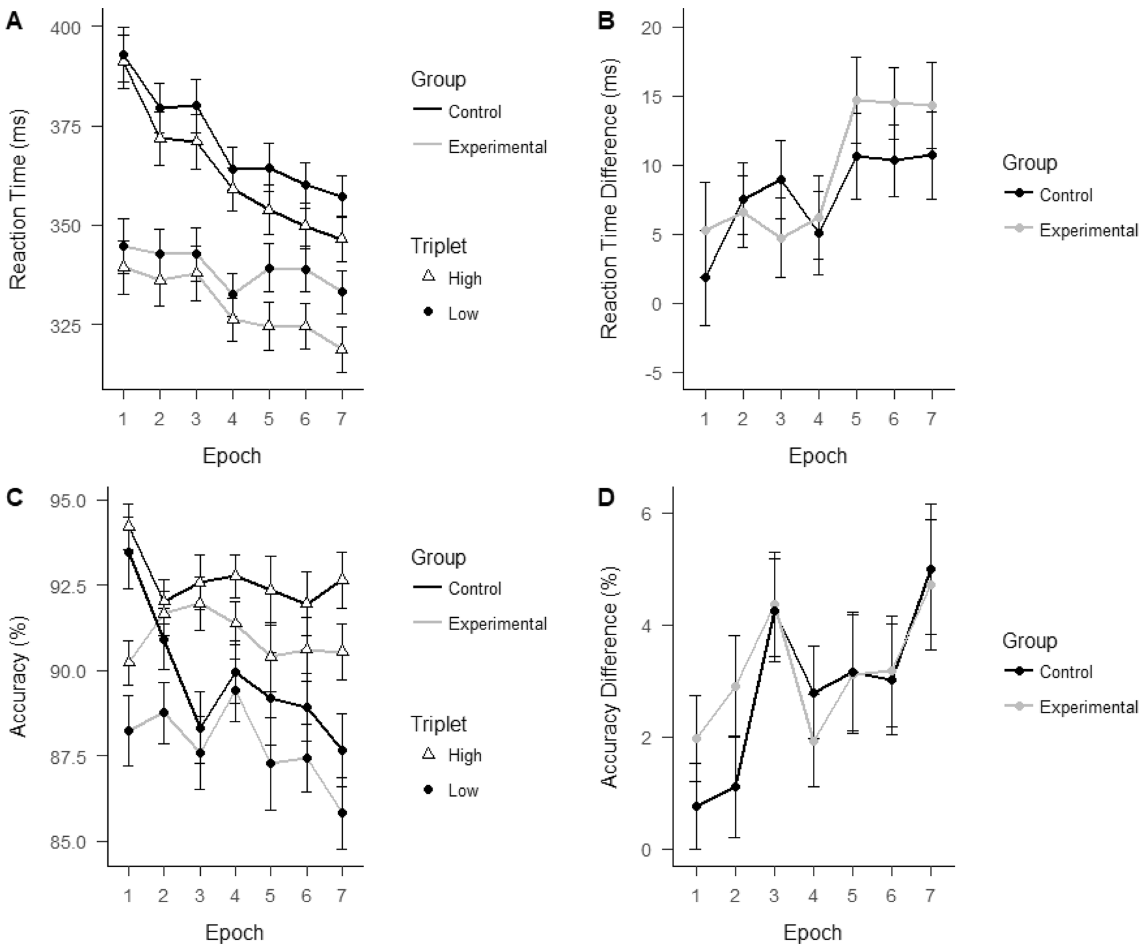

Fig. 1 Interaction plots. **a** The reaction times for both groups and triplet types across epochs. **b** The difference score between high- and low-frequency triplets. **c** The accuracy (hit rate) for both groups and triplet types across epochs. **d** The accuracy difference between high- and low-frequency triplets. **b**, **d** The magnitude of learning directly. We expected that the experimental group would learn less, but this was not observed. Error bars denote standard error of the mean

($M=334.361$, SE$=5.572$; the control group, $M=367.240$, SE$=5.572$), and throughout the epochs. Moreover, a significant interaction between epoch and group was observed, $F(6, 384)=7.315$, $p<0.001$, $\eta p^2=0.103$. The experimental group was faster than the control group, but this difference became smaller throughout the epochs. The initial difference is most probably due to the fact that the experimental group already performed the ASRT (without a sequence) during the first phase of the experiment. There was also an interaction effect of epoch by triplet, $F(6, 384)=3.590$, $p=0.002$, $\eta p^2=0.053$, indicating that the main effect of triplet (i.e., the learning score, see Fig. 1b) became larger over epochs. The crucial interaction between triplet and group, which would indicate differences in sequence-specific learning between groups as expected, was not significant, $F(1, 64)=0.609$, $p=0.438$, $\eta p^2=0.009$. Similarly, the three-way interaction between triplet, epoch, and group did not reach significance, $F(6, 384)=0.634$, $p=0.703$, $\eta p^2=0.010$. A Bayesian independent-samples *t* test (one sided: the experimental group has a lower learning score relative to the control group) comparing the average learning score between groups revealed evidence in favor of the null hypothesis, $BF_{01}=6.448$. This Bayes Factor (BF_{01}) means that the data were 6.448 times more likely to have occurred under the null hypothesis than under the alternative hypothesis (experimental < control).

The same RM ANOVA was conducted with accuracy as the dependent measure (the results can be found in Fig. 1c) and revealed the same main effects, $F(1, 64)\text{s}>4.482$, $p\text{s}<0.038$, as accuracy was higher for high frequency triplets ($M=0.918$, SE$=0.004$; low-frequency triplets, $M=0.888$, SE$=0.005$), the control group ($M=0.912$, SE$=0.006$; the experimental group, $M=0.894$, SE$=0.006$) and earlier epochs. Again, we observed an interaction between epoch and group, $F(6, 384)=2.692$, $p=0.014$, $\eta p^2=0.040$, as the group difference decreased throughout the epochs. The initial large difference might have been due to the fact that the control group was not yet adapted to the task resulting in a speed-accuracy tradeoff (these participants are learning the task more slowly but also more accurately). The same interaction between epoch and triplet was observed in the accuracy measure, $F(6,384)=3.388$, $p=0.003$, $\eta p^2=0.050$, indicating that there sequence-specific learning became greater throughout the epochs. Yet, the crucial triplet by group interaction (see Fig. 1d) and three-way interaction were not significant, $F(6,384)\text{s}<0.452$, $p\text{s}>0.562$. A Bayesian independent-samples t test (one sided: the experimental group has a lower accuracy difference relative to the control group) comparing the average accuracy difference (high–low-frequency triplets) between groups revealed evidence in favor of the null hypothesis, $BF_{01}=5.786$. In sum, these results suggest that both groups learned but that the amount of learning did not differ between groups.

Discussion

We expected that performing the ASRT without a sequence would impair implicit learning compared to a group that first performed another unrelated task (Go/noGo task). Our rationale was that experience on the ASRT without regularities would demotivate predictive processing, and assuming that a priori prediction is important in shaping implicit learning, the experimental group would, therefore, learn less relative to the group that performed the unrelated task. Our results did not support our hypothesis. It was found that participants in both groups learned sequence-specific knowledge in the ASRT in phase 2 (lower RT and higher accuracy towards high-frequency triplets relative to low-frequency triplets). Furthermore, the difference between high- and low-frequency triplets in RT and accuracy increased throughout the task suggesting that participants learned more as the task progressed. However, we did not observe a difference between the groups in learning on both the RT and accuracy measurements. Bayesian analyses further supported the null hypothesis that there is no difference in learning between the groups.

In sum, the results of "Experiment 1" did not support our hypothesis. To further investigate whether implicit learning could be impaired after learning that there is nothing to learn, we devised another experiment in which we manipulated the instructions between two groups who performed exactly the same ASRT task. Specifically, the instructions either explicitly stated that the order of the targets in the ASRT would be random, or that the order would follow a complex sequence. In reality, the order of the stimuli in the ASRT always followed a sequence.

Experiment 2

Method

Experimental design and hypotheses The goal of the second experiment was to investigate whether random instructions (i.e., instructions stating that there is no sequence in the ASRT) would diminish learning relative to sequence instructions (i.e., instructions stating that there is a complex sequence in the ASRT). Typically, no statements about sequences are made in the instructions. We assumed that the instructions indicating that there is nothing to learn would hamper implicit learning, assuming that prior expectations are important in guiding implicit learning. The instructions were manipulated within subjects across two phases. The random first group started with the random instructions in the first phase, while the sequence first group started with the sequence instructions. In the second phase, the instructions were reversed and participants again performed the task. This allowed for both within- and between-subject comparisons. Specifically, similar to "Experiment 1", we also compared the effects across subjects by looking at the first phase only. Both analyses have their limitations and advantages. The between-subject comparison is not confounded with order/learning effects but runs on decreased statistical power, while the latter is not the case for the within-subject comparison.

Participants The experiment lasted 50 min and was performed by 58 participants who all signed an informed consent form. These participants were all psychology students from Ghent University and were compensated with course credits. The participants were randomly assigned to the sequence ($n=28$, $M_{age}=18.893$, $SD_{age}=1.343$, 7 male) or the random group ($n=30$, $M_{age}=19$, $SD_{age}=0.743$, 9 male). Our sample size was determined by the conclusiveness of our initial findings. Given that the first sample ($n=58$) resulted in a Bayes factor > 6 (or < 1/6), we stopped data collection (Schönbrodt et al., 2017).

Materials Both groups performed the ASRT (Howard & Howard, 1997), as described in the method section of "Experiment 1". Each group performed this task in two phases. For each phase and each group, there was always a fixed sequence in the task, which did not change between phases. The only difference between groups and phases were the instructions. The exact instructional manipulation can be found in the "Appendix".

In each phase of the experiment, participants were explicitly encouraged to answer as fast and accurate as possible. This was done to avoid active searching for sequences after the sequence instructions, and thus to keep the two groups as comparable as possible in terms of general RT. It was in our interest to manipulate how participants conceptualize the task a priori (i.e., as a random environment or a predictive environment) according to the received instructions (random vs. sequence instructions) and investigate the effect of this manipulation on sequence-specific learning, without activating explicit searching strategies.

Procedure The procedure was similar to "Experiment 1". Different from "Experiment 1", each phase consisted of 20 blocks instead of 28 blocks, and the task always contained a sequence (which was identical between phases). Between phases, the instructions were adapted verbally. After the experiment, participants were asked to fill in the Free Will Inventory (FWI; Nadelhoffer et al., 2014) and the Need for Cognition scale (NFC; Cacioppo & Petty, 1982). These questionnaires were used to address secondary research questions that were not related to the current working hypothesis and will not be further discussed. Finally, participants were debriefed and course credit was given. The experiment lasted fifty minutes.

Results

Within-Subject comparison First, we investigated the effects of instruction type (random vs. sequence instructions) within subjects. We conducted a RM ANOVA on median RTs with instruction type (random, sequence), epoch (1–5) and triplet type (low frequency, high frequency) as WS factors, and group as a BS factor to control for order effects. The main effects of epoch and triplet type were significant, $F(1,56)\text{s} > 85.681$, $p\text{s} < 0.001$, as RTs were lower for high-frequency triplets ($M = 348.247$, SE = 3.656; low-frequency triplets, $M = 358.422$, SE = 3.594) and decreased through the epochs. On the other hand, the main effects of instruction type and group were not significant, $F(1,56)\text{s} < 2.221$, $p > 0.142$. Crucially, there was no two-way interaction showing a modulation of the main effect of triplet by instruction type, $F(1, 56) < 0.001$, $p = 0.992$, $\eta p^2 < 0.001$. Instead, there was a three-way interaction between instruction type, triplet type, and group, $F(1, 56) = 32.553$, $p < 0.001$, $\eta p^2 = 0.368$, suggesting that learning (i.e., the difference between low- and high-frequency triplets) was highest in the sequence first group after the random instructions but also in the random first group after the sequence instructions. In other words, learning was more sensitive to the actual phase of the experiment (phase 2 > phase 1) than to the instructional manipulation, which can be explained by the fact that the same sequence was used across phases. A similar interpretation fits the interaction effect between instruction type, epoch and group, $F(4, 224) = 45.448$, $p < 0.001$, $\eta p^2 = 0.448$, which seems to show that the decrease in RT across epochs was most sensitive to the actual phase of the experiment (phase 1 > phase 2). The remaining interaction effects were not significant, $F(4,224)\text{s} < 2.276$, $p\text{s} > 0.062$. The same RM ANOVA with accuracy as the dependent measure revealed identical effects. The main effects of epoch and triplet type were significant, $F(4,224)\text{s} > 11.461$, $p\text{s} < 0.001$, as accuracy was higher for high-frequency triplets ($M = 0.916$, SE = 0.005; low-frequency triplets, $M = 0.880$, SE = 0.006) and decreased throughout the epochs. The main effects of instruction type and group were not significant, $F(1,56)\text{s} < 0.604$, $p > 0.440$ and neither did we find the crucial two-way interaction of triplet and instruction type, $F(1, 56) = 1.291$, $p = 0.261$, $\eta p^2 = 0.023$. Instead, there was a three-way interaction between instruction type, triplet type and group, $F(1, 56) = 15.822$, $p < 0.001$, $\eta p^2 = 0.220$, and between instruction type, epoch and group, $F(2.728,152.779) = 3.480$, $p = 0.021$, $\eta p^2 = 0.059$, again showing that learning was more sensitive to the phase of the experiment rather than to the instructional manipulation.

Bayesian paired *t* tests comparing the average learning score (one sided: random instructions lead to less learning relative to sequence instructions) revealed evidence in favor of the null hypothesis for both the RT and accuracy analyses, $BF_{01} = 6.117$ and $BF_{01} = 2.963$, respectively (Fig. 2).

Between-subject comparisons The within-subject comparison clearly indicated that there were very strong order effects, likely driven by the fact that the sequence was identical across phases. Therefore, we also compared the groups on their performance in the first phase only. The random first group received the random instructions in this phase, while the sequence first group received the sequence instructions. A RM ANOVA was conducted with triplet type (low frequency, high frequency) and epoch (1–5; 4 blocks averaged per epoch) as WS factors and group (sequence, random) as BS factor on the median RTs (see Fig. 3a for the results). The main effects of epoch and triplet type were highly significant, $F(1,56)\text{s} > 27.833$, $p\text{s} < 0.001$, indicating faster RTs for high-frequency triplets ($M = 366.304$, SE = 4.136; low-frequency triplets, $M = 372.497$, SE = 4.052) and a decrease throughout the epochs (epoch 1, $M = 387.084$, SE = 4.656; epoch 5, $M = 353.067$, SE = 4.177). We tried to motivate participants to respond as fast as possible regardless of the actual instructions (to not contaminate the design with explicit hypothesis testing strategies/processes after the sequence instructions), and while the random group ($M = 363.842$, SE = 5.631) was numerically faster than the sequence group ($M = 374.959$, SE = 5.829), this difference was not significant, $F(1, 56) = 1.882$, $p = 0.176$, $\eta p^2 = 0.033$.

Crucially, we hypothesized that the difference between high- and low-frequency triplets would be greater in the sequence group than the random group. However, there was no interaction between triplet and group, $F(1, 56) = 2.630$, $p = 0.110$, $\eta p^2 = 0.045$. There was a trend for an increasing learning effect over time (interaction between triplet and epoch), $F(4, 224) = 2.354$, $p = 0.055$, $\eta p^2 = 0.040$ (see Fig. 3b). The other interaction effects were not significant, $p > 0.100$. Interestingly, if anything, close inspection of Fig. 3b reveals that in contrast to our expectations, the random first group seemed to show a larger effect of triplet ($M = 8.350$, SE = 2.674) than the sequence group ($M = -3.982$, SE = 3.120) in the first epoch. A post hoc independent-samples t test showed that this difference between groups was indeed significant, $t(56) = 3.013$, $p = 0.004$.

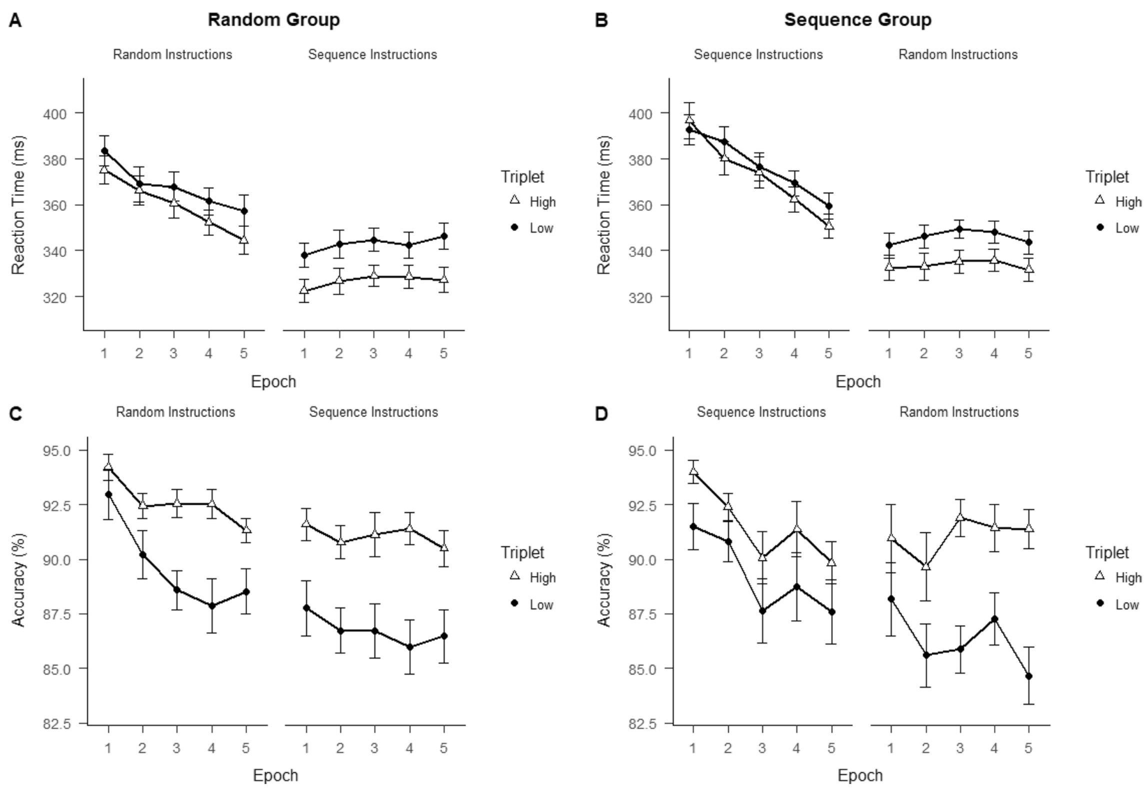

Fig. 2 Within-subject comparisons. Columns (A/C vs B/D) show results from the same group (random vs sequence), while rows (A/B vs C/D) show results for the same measure (RT vs accuracy). The random group started with the random instructions while the sequence group started with the sequence instructions. Learning (i.e., the difference in RT or accuracy between low- and high-frequency triplets) seemed to emerge as a function of time spent on the task rather than our instruction manipulation (random < sequence instructions). Error bars denote standard error of the mean

However, this effect should be interpreted with caution given that the interaction between group, triplet type and epoch did not reach significance, $F(4, 224) = 1.871$, $p = 0.117$, $\eta p^2 = 0.032$.

The RM ANOVA on accuracy showed the same effects as the ANOVA on RTs. Again, the interaction between triplet and condition was not significant, $F(1, 56) = 0.788$, $p = 0.379$, $\eta p^2 = 0.014$; see Fig. 3c, d).

Further supporting these conclusions, Bayesian independent-samples t tests (one sided: random instructions lead to less learning relative to sequence instructions) comparing the average learning score revealed evidence in favor of the null hypothesis for both the RT and accuracy analyses, $BF_{01} = 8.837$ and $BF_{01} = 6.424$, respectively.

Discussion

In this second experiment, we expected that random instructions would result in less implicit learning than sequence instructions, assuming that a priori expectations are important in guiding implicit learning. The results did not confirm our hypothesis. Instead, they showed evidence in favor of the null hypothesis (i.e., no difference between both groups in terms of learning). Both groups showed learning effects (faster RTs and higher accuracy for high-frequency triplets than low-frequency triplets), but learning was mostly affected by time spent on the task, irrespective of the instructions. We did not find a significant difference in terms of mean RT between the groups suggesting that participants with sequence instructions were not actively searching for sequences.

General discussion and conclusion

The goal of the current study was to find evidence for the hypothesis that a priori expectations are important in guiding and shaping implicit sequence learning. To this end, we established random contexts by exposing participants to a random environment prior to learning ("Experiment 1") and by explicitly instructing participants that the order of the stimuli was random ("Experiment 2"). The rationale behind the experiments was that if a priori predictions and expectations are crucial to form implicit learning, an idea that follows from predictive accounts of learning (e.g., Bubic,

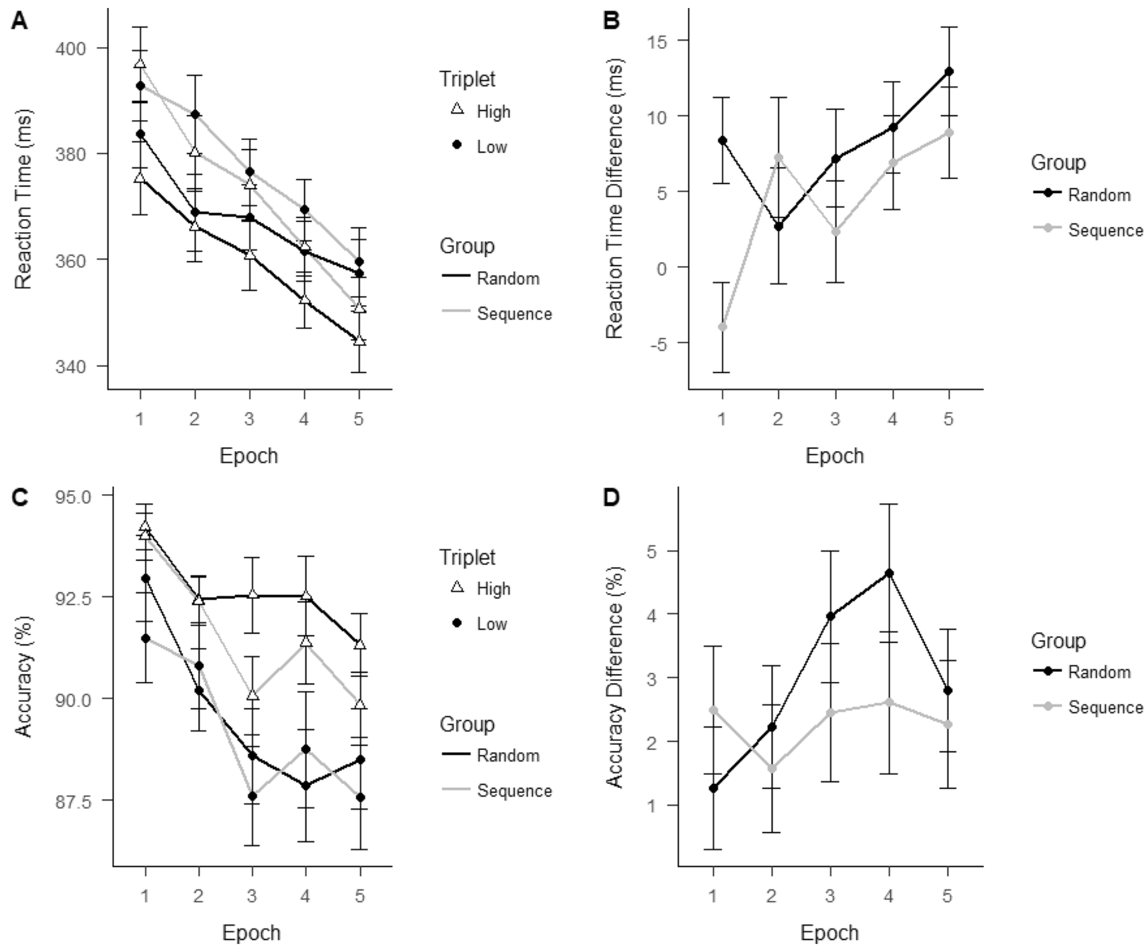

Fig. 3 Between-subject comparison. **a** The reaction time for both groups and triplet types across the epochs. **b** The learning score which is the difference between high- and low-frequency triplets across groups. **c** The accuracy (hit rate) for both groups and triplet types across epochs. **d** The accuracy difference between high- and low-frequency triplets. **b**, **d** Magnitude of learning directly. Learning does not seem to differ according to the group. If anything, it does in in the first epoch, but this difference is in the opposite direction of what we expected. Error bars denote standard error of the mean

von Cramon & Schubotz, 2010; Clark, 2013), then learning should be impeded by expecting that there is nothing to learn. The current results do not support this hypothesis. In both experiments, we found no differences in implicit sequence learning between the groups that were exposed to a random context compared to the groups that were not exposed to a random context. Importantly, however, the current study also has certain limitations that warrant caution before making more general conclusions regarding the importance of expectations in guiding implicit learning, which we will discuss below.

Nevertheless, if we assume the manipulation was successful, these findings can be seen as generally consistent with simple co-activation accounts (Hebbian learning; Hebb, 1949) of implicit sequence learning rather than learning accounts where predictions drive learning (Rescorla and Wagner, 1972) or phenomena such as latent inhibition (Lubow, 1973), in which pre-exposure to a context harms future learning with stimuli in this context. They are also consistent with the seminal findings of Perruchet (1985), often referred to as the Perruchet effect. In the original experiment, participants were presented a tone on each trial (conditioned stimulus, CS) that was followed by an air puff to the cornea (unconditioned stimulus, US) on half of the trials resulting in eye blinks (conditioned response, CR). The number of reinforced (CS–US pairing) and non-reinforced trials (CS alone) that repeated one another was varied. Expectancy ratings were given before each trial and followed the gamblers fallacy: an increasing number of reinforced trials decreased the expectancy of the air puff, while an increased number of non-reinforced trials increased the expectancy of the air puff. Curiously, however, the CR (eye blinks) showed the opposite pattern: an increasing number of reinforced trials increased the probability of a CR and an increasing number of non-reinforced trials decreased the probability of a CR. This finding demonstrates a dissociation between (implicit) learning and conscious expectations. Later this was also replicated in RT experiments where the US was replaced with a visual cue to which participants had to respond as quickly as possible (Perruchet, Cleeremans & Destrebecqz, 2006). Consistent with this, a very recent study by Tran, Harris, Harris & Livesey (2020) has shown a similar dissociation between corticospinal motor excitability, RT and expectancy (also see Verbruggen et al., 2016, who used a predictable rather than random sequence).

In "Experiment 2", our goal was to manipulate how participants conceptualize the task set through instructions. This instructional manipulation is similar, yet distinct from previous studies aiming to investigate the effect of explicit rule-searching strategies on implicit learning through instructional manipulation (Reber, 1976; Howard & Howard, 2001; Song et al., 2007). Here, participants are encouraged (Reber, 1976) or even aided (Howard & Howard, 2001; Song et al., 2007) in finding the complex patterns. In contrast, we aimed to manipulate participants' expectations about the task set (can I expect random or structured material?) without having participants engage in actually finding regularities. We aimed to discourage explicit rule-searching strategies by demanding fast and accurate responses, and did not mention anything other than that "a complex sequence was present". Yet, our results are similar to the studies that did encourage explicit rule-searching strategies: explicit instructions did not hinder learning from occurring, at least in young participants (Howard & Howard, 2001; Song et al., 2007, but note that learning was hindered in artificial grammar learning by explicit instructions, Reber, 1976).

Notably, other studies did find that the content of learning can be determined by expectations or a priori conceptualizations of the task set (e.g., Freedberg, Wagschal & Hazeltine, 2014; Gamble, Lee, Howard and Howard, 2014; Gaschler et al., 2012). Perhaps, convincing participants that their current environment is indeed random requires more rigorous manipulations than the ones that were used in our experiments. In our first experiment, participants in the experimental group first performed the ASRT without a sequence for 14 blocks (the random context). It is possible that this phase was simply not long enough (± 15 min) to demotivate learning from occurring. Perhaps a more prolonged experience in a random environment is necessary to impair predictive processes. Alternatively, other control tasks should be explored as well. While we tried to match our control task in "Experiment 1" for both complexity, length and difficulty (while still being sufficiently different than the ASRT task), the Go/noGo task is a cognitive control task, and it has been argued that high levels of cognitive control and executive function can impede sequence learning (Bocanegra & Hommel, 2014; Virag et al., 2015). The Go/noGo task was also not bimanual in nature, unlike the ASRT. In addition, the Go/noGo task could have discouraged learning as it is not predictable when participants have to respond (i.e., it is also a random context). Therefore, future studies should contrast the random context with a context in which predictions are useful.

In "Experiment 1", the random and sequence context were separated by a small break. This break might also have signaled a change in context, even without participants necessarily knowing what this change constitutes. Nevertheless, such a 'reset' of context might then re-activate predictive processing or other sequence learning mechanisms that were potentially demotivated by the random context. Future replications might choose to manipulate the transition from a random to a sequence context in a subtler manner, avoiding the use of any explicit cues in the environment that might signal a change in context. In "Experiment 2", receiving one form of instruction (e.g., sequence instructions) might affect the believability of the instruction in the subsequent phase (e.g., random instructions). Therefore, when making the within-subject comparison (comparing learning in phase 1 versus phase 2), one should take into account the order effects related to the instructional manipulation, and learning of the sequence. The between-subject comparison (comparing learning from phase 1 in the sequence-instruction first versus the random-instruction first group) does not require these additional considerations. However, the interpretation of the between-subject comparison is limited by the fact that our sample size is not tailored for between-subject comparison. Another limitation of our study is that we did not include a manipulation check to verify that our manipulation actually affected the expectations of our participants. Future studies should include manipulation checks that make it possible to verify whether participants' expectations about the presence of sequence patterns are successfully discouraged.

To conclude, the current investigations found no evidence to support the hypothesis that a priori expectations of randomness demotivate implicit sequence learning. While these findings are generally consistent with a Hebbian (non-prediction-error driven) account of implicit sequence learning and with other findings similarly showing no effect of explicit predictions on more implicit influences on behavior (Perruchet, 1985; Perruchet et al., 2006; Tran et al., 2020; Verbruggen et al., 2016), future studies are necessary to further confirm and study the generalizability of these observations. A deeper understanding of the mechanisms that drive implicit sequence learning would impact our understanding of many cognitive abilities from pure motor skills to language and complex social functioning.

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Author contributions All authors developed the study concept and contributed to the study design. Data collection and analysis was performed by LV under the supervision of the other authors. The manuscript was drafted by LV in cooperation with all other authors. All authors approved the final version of the manuscript for submission.

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Data availability The materials and data are available on the Open Science Framework (https://osf.io/qbvka/).

Compliance with ethical standards

Conflict of interest The authors have no competing interests to declare.

Ethics approval All procedures applied in the present experiment were carried out with adequate understanding and written consent of the subjects and are in accordance with the Declaration of Helsinki.

Consent to participate All procedures applied in the present experiment were carried out with adequate understanding and written consent of the subjects.

Consent for publication All subjects provided consent to publish and report on their anonymized data.

Code availability The code for the analyses is available on the Open Science Framework (https://osf.io/qbvka/).

Appendix: Instructional manipulation from "Experiment 2"

Participants received the following instructions in Dutch (after the general task instructions):

> "In some parts of the experiment, the order of the targets will follow a complex order, and in other parts of the experiment the order will be completely random."
> ("De opeenvolging van de targets zal in sommige delen van het experiment onderhevig zijn aan een complexe volgorde, en is in andere delen van het experiment volledig willekeurig.").
>
> Then, for the random group the instructions stated:
>
> "In this first part of the experiment, the order of the targets will be completely random."
> ("In dit eerste deel van het experiment is de opeenvolging van de targets compleet willekeurig.")
>
> While for the sequence group the instructions stated:
>
> "In this first part of the experiment, the order of the targets will follow a complex order."
> ("In dit eerste deel van het experiment is de opeenvolging van de targets onderhevig aan een complexe volgorde.")
>
> For the second phase, the random group was told verbally:
>
> "In this second part of the experiment, the order of the targets will follow a complex order. However, keep responding as fast and as accurate as possible."
> ("In dit tweede deel van het experiment is de opeenvolging van de targets onderhevig aan een complexe volgorde. Blijf echter zo snel en accuraat mogelijk antwoorden.").
>
> While the sequence group was told:
>
> "In this second part of the experiment, the order of the targets will be completely random. However, keep responding as fast and as accurate as possible."
> ("In dit tweede deel van het experiment is de opeenvolging van de targets compleet willekeurig. Blijf echter zo snel en accuraat mogelijk antwoorden.")

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