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Detection of Regularities in a Random Environment

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Abstract

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Regularity detection, or statistical learning, is regarded as a fundamental component of our cognitive system. To test the ability of human participants to detect regularity in a more ecological situation (i.e., mixed with random information), we used a simple letter-naming paradigm in which participants were instructed to name single letters presented one at a time on a computer screen. The regularity consisted of a triplet of letters that were systematically presented in that order. Participants were not told about the presence of this regularity. A variable number of random letters were presented between two repetitions of the regular triplet making this paradigm similar to a Hebb repetition task. Hence, in this Hebb-naming task, we predicted that if any learning of the triplet occurred, naming times for the predictable letters in the triplet would decrease as the number of triplet repetitions increased. Surprisingly, across four experiments, detection of the regularity only occurred under very specific experimental conditions and was far from a trivial task. Our study provides new evidence regarding the limits of statistical learning and the critical role of contextual information in the detection (or not) of repeated patterns.

*Keywords:* regularity detection, statistical learning, implicit learning

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## Detection of Regularities in a Random Environment

49           We often encounter the same objects, symbols, sounds and sensations time and time  
50 again, and they tend to show up in a variety of contexts. One of the basic functions  
51 underlying human cognitive processes is our ability to detect such invariant or regular  
52 information within environmental variations. *Regularity detection*, also often labelled  
53 *statistical learning* (SL), *implicit learning*, or *implicit statistical learning* (Christiansen, 2019;  
54 Monaghan & Rebuschat, 2019; Perruchet & Pacton, 2006; Thiessen, Kronstein, & Hufnagle,  
55 2013; Rey, Minier, Malassis, Bogaerts, & Fagot, 2018) is commonly assumed to be a gradual  
56 process by which individuals experience a patterned sensory input and, by mere repeated  
57 exposure to this regularity, implicitly derive knowledge of its underlying structure, using it to  
58 update their predictions of future events (e.g., Fine & Jaeger, 2013; Misyak, Christiansen, &  
59 Tomblin, 2010).

60           Standard SL tasks involve a visual or auditory familiarization stream, comprising a set  
61 of regularities, that is usually followed by an offline test phase (e.g., Aslin, Saffran, &  
62 Newport, 1998; Fiser & Aslin, 2001; Reber, 1967; Saffran, Aslin & Newport, 1996). In the  
63 test phase, participants are asked to judge the familiarity of sequences that are either  
64 consistent or inconsistent with the familiarization stream. The test score captures the total  
65 amount of learning that occurred by the end of the familiarization phase (see Siegelman,  
66 Bogaerts, Christiansen, & Frost, 2016). The seminal findings of Saffran and colleagues  
67 inspired a large research community to focus on the ability to extract adjacent patterns of  
68 visual or auditory input, with little variation in the information contained in the stream. In  
69 most experiments, therefore, the familiarization phase featured a set of regular patterns of  
70 different kinds that were combined in a semirandom manner to form a continuous  
71 familiarization stream (e.g., 11 syllables arranged in six triplets; Batterink, Reber, Neville, &

72 Paller, 2015; 24 abstract shapes arranged in eight triplets; Bogaerts, Siegelman, & Frost,  
73 2016; 12 aliens arranged in four triplets; Arciuli & Simpson, 2012).

74 The present study featured a slightly different situation - possibly slightly more  
75 ecological - in which a single regular pattern was inserted into random information.  
76 Participants were shown a series of single letters displayed one at a time in the centre of a  
77 computer screen, and were simply instructed to name each letter. A single triplet of letters  
78 repeatedly appeared, in between random sequences of other letters. Participants were not,  
79 however, informed about the presence of a repeated pattern. If participants started to  
80 anticipate the predictable letters in the triplet (i.e., the second and third letters for which the  
81 transitional probability was equal to 1), then naming onsets for these letters would gradually  
82 decrease over time.

83 The presentation of a single regularity interspersed by noise sequences is very similar  
84 to the Hebb repetition task (Hebb, 1961). Hebb asked his participants to perform an  
85 immediate serial recall task in which one specific supraspan sequence was repeated every  
86 third trial. He found that the recall performances improved with the repetition of the regular  
87 pattern (for more recent studies using the Hebb task, see Bogaerts, Siegelman, Ben-Porat, &  
88 Frost, 2017; Ordonez Magro, Attout, Majerus, & Szmalec, 2018; Page & Norris, 2009;  
89 Szmalec, Duyck, Vandierendonck, Mata, & Page, 2009). Our experimental paradigm differed  
90 from the Hebb task on the nature of the regularity (letter triplet vs. supraspan sequence of  
91 items), the process elicited by the task (serial recall vs. naming), and the dependent variable  
92 (recall performance vs. response times). However, due to its similarities with the Hebb  
93 repetition task, it could be identified as a “Hebb-naming task”.

94 Studying regularity extraction under these specific conditions as opposed to standard  
95 offline tasks has two main advantages. First, if learning is observed with standard SL tasks, it  
96 is usually difficult to determine what has been learned exactly (e.g., did participants learn a

97 little about each of the patterns, or did they pick up on just a few? see Siegelman, Bogaerts,  
98 Armstrong, & Frost, 2019), whereas the answer to that question should be more  
99 straightforward in the present situation. Second, the naming task could serve as an online  
100 learning measure, allowing us to trace the trajectory of learning. The reasoning here was that  
101 if participants managed to extract the regularity, the predictability of its constituent elements  
102 would increase over time (i.e., with repeated presentations of the regularity), leading to a  
103 decrease in naming latencies for predictable letters. By looking at the change in naming  
104 latencies across repeated presentations of the regularity, we would be able to study the  
105 temporal dynamics of regularity detection under different learning conditions.

106         Although the idea of using naming as an online measure of regularity detection is  
107 relatively novel, the idea of measuring regularity extraction *online* is not. Several recent  
108 studies have used other novel behavioural experimental strategies to track learning as it  
109 unfolds, in both SL and artificial grammar learning (AGL) paradigms. These strategies  
110 typically involve asking participants to detect a target (e.g., Batterink, 2017; Gómez, Bion, &  
111 Mehler, 2011; Turk-Browne, Jungé, & Scholl, 2005) or presenting an auditory sequence  
112 where the participants' task is to select the written equivalent of the auditory stimuli from a  
113 grid of options on the monitor (e.g., Dale, Duran, & Morehead, 2012; Misyak et al., 2010).  
114 Additional examples are self-paced SL and AGL tasks (Karuza, Farmer, Fine, Smith, &  
115 Jaeger, 2014; Siegelman, Bogaerts, Kronefeld, & Frost, 2016), in which participants follow  
116 the familiarization sequence at their own speed. In all these paradigms, faster button press or  
117 mouse click responses for predictable stimuli than for unpredictable stimuli are assumed to be  
118 an indication of (implicit) regularity learning<sup>1</sup>.

119         We know from the extensive SL, AGL and implicit learning literature that individuals  
120 are able to extract structure, and two main theoretical approaches to regularity learning have

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<sup>1</sup> Several studies also used EEG recordings to track online changes in event-related potentials when participants are exposed to an artificial language (e.g., Abla, Katahira, & Okanoya, 2008; François et al., 2017; Rodríguez-Fornells, Cunillera, Mestres-Missé, & de Diego-Balaguer, 2009).

121 been applied to date: the bracketing approach and the clustering approach (Swingley, 2005;  
122 see also Frank, Goldwater, Griffiths, & Tenenbaum, 2010). The *bracketing approach*, with  
123 the simple recurrent network (SRN, Elman, 1990) as its most famous computational instance,  
124 assumes that we learn to predict the next stimulus in a given context, based on the transitional  
125 probabilities between sequence elements. The *clustering approach*, by contrast, assumes that  
126 sensitivity to co-occurrences arises from the chunking that results from the repetition of  
127 groups of elements. PARSER (Perruchet & Vinter, 1998) and TRACX (French, Addyman, &  
128 Mareschal, 2011) are probably the best known models instantiating this approach (see also  
129 McCauley & Christiansen, 2019).

130         Although they assume different learning mechanisms, these approaches are actually  
131 quite hard to tell apart, as they make similar predictions regarding most experimental SL  
132 settings. Interestingly, they do make different predictions regarding the temporal dynamics of  
133 learning small regular sequences embedded within larger ones (e.g., a sequence of three  
134 items, ABC, where A was consistently followed by B, and B by C). Based on the assumption  
135 that prior contextual information can influence pattern extraction, the *SRN model* predicts an  
136 advantage for the final part of an embedded sequence (e.g., slower learning of the first two  
137 items than of the final one). By contrast, *PARSER* assumes that the input material is subjected  
138 to random attentional exploration, and predicts that there will be no difference between the  
139 beginning and end of the sequence. *TRACX* assumes that chunks are constructed on a left-to-  
140 right basis, leading to the prediction that AB will be learned before BC.

141         Evidence accumulated over the past decade supports the chunking approach (e.g.,  
142 Giroux & Rey, 2009; Orbán, Fiser, Aslin, & Lengyel, 2008; but see also Franco &  
143 Destrebecqz, 2012), and TRACX has been proved to outperform the other models in  
144 simulating several benchmark effects of regularity extraction (French et al., 2011). However,  
145 the results of some recent studies have highlighted new constraints for chunking-based

146 models (Kim, Seitz, Feenstra, & Shams, 2009; Turk-Browne et al., 2005; see also Minier,  
147 Fagot, & Rey, 2016, for similar results in baboons). These studies of learning 3-item patterns  
148 found that C is learned faster than B, which can be interpreted as an effect of the strong  
149 contextual information AB preceding C, compared with the weaker contextual information A  
150 preceding B. This can be accounted for by an associative learning mechanism, but runs  
151 counter to the predictions by the aforementioned chunking models. However, to date, it is not  
152 clear whether the learning advantage for the final stimulus in a repeated pattern is observed in  
153 other learning situations, such as the extraction of a single regular pattern hidden in noise.  
154 The first goal of the present set of experiments was therefore to study the detection dynamics  
155 of a regular letter triplet and to test the replicability of previous findings showing faster  
156 learning for the letter in the last position of the triplet (i.e., C) compared with the one in the  
157 second position (i.e., B).

158         The second goal was to ask how regularity extraction is influenced by different  
159 learning conditions, that is, how do the characteristics of the pattern and its environment  
160 affect learning? Interestingly, SL models (e.g., SRN, PARSER or TRACX) state that if the  
161 contextual information is made up of different elements of the regular pattern, then the  
162 critical factors for detecting this regularity will be the number of repetitions and the amount  
163 of interfering information inserted between two repetitions of the regular pattern. With a  
164 sufficient number of repetitions and a limited amount of interfering information, these models  
165 therefore predict that participants will have no difficulty detecting the regular pattern. We  
166 examined whether the evidence yielded by the present set of experiments supported this  
167 claim.

### 168 Overview of the Experiments

169         Our study comprised four experiments. Experiment 1 tested the extraction of a  
170 repeated triplet made up of consonants that alternated with random noise (sequences of two to

171 five letters, randomly selected from a set of five different consonants). Experiment 2 tested  
172 the extraction of a similar statistical regularity, but in contrast to the first experiment, the  
173 repeated triplet was made up of vowels. In Experiment 3, we changed the nature of the  
174 random (i.e., unstructured) noise separating the triplet repetitions, such that although the  
175 noise sequences were still two to five letters long, these were drawn from a set of 14  
176 consonants. Finally, Experiment 4 was identical to Experiment 3, except that the random  
177 sequences between repetitions of the triplet were shorter (no more than three letters). The  
178 data yielded by these four experiments are available on Open Science Framework at  
179 [https://osf.io/dyb4u/?view\\_only=d35620f91740450b9a915643f6c49308](https://osf.io/dyb4u/?view_only=d35620f91740450b9a915643f6c49308).

## 180 Experiment 1

### 181 Method

#### 182 Participants

183 A total of 21 adults (7 men, 14 women;  $M_{age} = 20.15$  years), all native French speakers  
184 and students at Aix-Marseille University, took part in the study in exchange for a course  
185 credit. All reported normal or corrected-to-normal vision, and none reported a history of  
186 attention problems or reading disabilities.

#### 187 Procedure and materials

188 The experiment was run on a portable computer equipped with a serial response box  
189 and an Audio-Technica microphone. The microphone was fixed to an adjustable stand and  
190 positioned approximately 3 cm from the participant's mouth.

191 The naming task, administered via E-Prime 2.0 (Schneider, Eschman, & Zuccolotto,  
192 2002), involved the sequential presentation of individual letters in 70-point Arial white font  
193 in the centre of a black background. Participants were instructed to read aloud each letter as  
194 fast as possible. Speech onset and accuracy were recorded for each letter. Accuracy was  
195 scored by an experimenter present in the testing room, who scored errors but also (rare)

196 microphone failures as incorrect responses. Each letter stayed on the screen until the  
197 microphone was triggered at speech onset. The next letter then appeared after a fixed  
198 interstimulus interval (ISI) of 800 ms.

199         Participants first performed a microphone test, which also allowed them to familiarize  
200 themselves with the task. The microphone test consisted of 12 randomly selected naming  
201 trials. The actual rapid naming experiment consisted of 3 blocks of 100 trials (i.e., individual  
202 letter presentations) each. The letter stream that participants were exposed to was constructed  
203 from a set of printed consonants (F, H, L, M, N, P, R, S, T). Eight letters were randomly  
204 drawn from this set for each participant: three letters were used for the repeated triplet, and  
205 triplet repetitions (15 per block, 45 in total) were always separated by two to five random  
206 consonants, chosen from the five remaining letters. Frequency was balanced across the noise  
207 letters for each block of 100 trials. The repeated triplet was never a three-letter alphabetic run  
208 (e.g., LMN) or a well-known (French) abbreviation. The letters making up the triplet and  
209 their serial order were counterbalanced across participants.

210         Participants could take a break after every block. After Blocks 1 and 2, participants  
211 received oral feedback telling them that they were performing well, but had to try to speed up  
212 (this feedback was given independently of their actual performance or speed). In total, the  
213 naming task lasted approximately 10-15 minutes.

214         All participants responded to a short questionnaire after completing the naming task.  
215 In standard SL experiments participants are typically tested after the exposure phase with a 2-  
216 alternative forced choice task, testing the recognition of regular patterns against different  
217 foils. Given that our focus is on a learning situation with only one regular triplet, building a  
218 2-AFC task was problematic because it would be impossible to control for the frequency of  
219 the regular triplet and the foils. We therefore opted for a questionnaire to get information  
220 about the participants' explicit knowledge of the regularity (acknowledging that this might be



245 dependent variable. The fixed effect variables included in the model were position (1-3) and  
 246 repetition number (1–45), as well as their two-way interaction. Position was sum-coded  
 247 (Position 1: -1 1; Position 2: 1 0; Position 3: 0 1), and repetition was mean-centred here and  
 248 in all subsequent models. The model included the maximum random effect structure that  
 249 allowed convergence (Barr, 2013; Barr et al., 2013):  $SOL \sim Position + Repetition +$   
 250  $Position:Repetition (1 + Position + Repetition + Position:Repetition | Participant)^3$ . In other  
 251 words, we had a random intercept for participant and a random by-participant slope for  
 252 position, repetition and the Position x Repetition interaction. It should be noted that triplet  
 253 learning was predicted to result in a main effect of position (with faster SOLs for predictable  
 254 2<sup>nd</sup> and 3<sup>rd</sup> positions) and a Position x Repetition interaction.

255 The results of the model are summarized in Table 2. We only found a significant effect  
 256 of repetition, with the negative coefficient for this effect reflecting an acceleration (faster  
 257 SOLs) over the course of the experiment. Model comparison with a likelihood-ratio test  
 258 (following the guidelines established by Barr et al., 2013) revealed that neither the main  
 259 effect of position,  $\chi^2(2) = 0.58, p = 0.75$ , nor the Position x Repetition interaction effect,  $\chi^2(2)$   
 260  $= 3.25, p = 0.20$ , significantly improved the model fit.

261 -- Table 2 about here --

262 In a second analysis, we tested whether there was evidence for significant learning at  
 263 the group level for each of the blocks. Learning was quantified as the difference score  
 264 between mean log-transformed naming SOLs for unpredictable letters (Position 1) versus  
 265 predictable letters (Positions 2 and 3). As such, a positive score could be interpreted as  
 266 evidence for learning. We opted for the use of log-transformed SOLs (rather than the raw

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<sup>3</sup> It should be noted that we did not include letter identity as a random effect in the model, as this would have led to many instances of nonconvergence (across the four experiments). Although this could potentially have left us with more unexplained variance, it was not a concern, as in each experiment, the triplets were either randomly selected for each participant and/or letter position was counterbalanced, ensuring that any biases for individual letters were averaged out.

267 values) to control for the baseline differences in the speed of participants' naming responses  
 268 (see Siegelman et al., 2019).<sup>4</sup> When we compared the mean learning difference score for each  
 269 of the three blocks (see Table 1) with the hypothetical mean 0 using a one-sample *t* test, and  
 270 found no evidence of significant learning (i.e., mean SOL difference score significantly  
 271 greater than zero) in any of the blocks (all *ts* > 1 and *p*<sub>one-tailed</sub> > .10).

## 272 Questionnaire

273 Eight of the 21 participants reported noticing a repeated pattern. Only one of them  
 274 correctly recalled the triplet (i.e., all three letters in the right order), but five other participants  
 275 correctly reported one subsequence (either Letters 1&2 or Letters 2&3).

## 276 Discussion

277 Surprisingly, the results of this first experiment showed that there was no significant  
 278 acceleration for predictable letters. Furthermore, SOLs were not influenced by the serial  
 279 position of the letter within the triplet. A number of participants noticed the presence of a  
 280 repeated sequence, but most were unable to accurately recall the triplet. Although the  
 281 presence of the repeated triplet looked obvious from the point of view of the experimenters,  
 282 the majority of participants did not even notice it. Regularity detection in this specific  
 283 experimental situation, in which attentional processing was oriented toward the naming of  
 284 each letter, was apparently very limited for most participants.

285 This surprising result is at odds with the predictions of current SL models. Assuming  
 286 that participants have to pay attention and process each letter in order to retrieve and produce

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<sup>4</sup>To exemplify the influence of the log transformation, let us consider two participants with a mean difference of 100 ms between unpredictable and predictable letters, but a different baseline SOL: P1 unpredictable = 500 ms, predictable = 400 ms; P2 unpredictable = 300 ms, predictable = 200 ms. Because of the baseline difference, P2's relative acceleration for predictable stimuli was far greater. The difference between predictable and unpredictable stimuli after log-transforming the SOLs reflects this, with 0.22 for P1 and 0.41 for P2.

287 its name, these models predict that the residual activation for Letter 1 generated at trial  $t-1$   
288 should enhance the activation of Letter 2 at trial  $t$ , merely through associative learning  
289 mechanisms. With sufficient repetitions, these transient memory traces should be reinforced,  
290 and the activation of Letter 1 should gradually come to predict and pre-activate the neural  
291 population coding for Letter 2. Apparently, for the majority of participants, the present  
292 experimental conditions were ineffective in producing this mandatory associative learning of  
293 adjacent patterns, indicating that we reached the limit of these mechanisms here.

294 The three following experiments were conducted to clarify this surprising result. In  
295 Experiment 2, we tested the extraction of a repeated triplet of vowels (e.g., A, O, U). Given  
296 that the letters for the triplet were drawn from a different category than the set of random  
297 letters, which were all consonants, we expected the repeated triplet to be more salient, and the  
298 detection of the regularity more efficient.

## 299 Experiment 2

### 300 Method

#### 301 Participants

302 A different sample of 21 native French adults (2 men, 19 women;  $M_{\text{age}} = 19.81$  years)  
303 took part in the experiment in exchange for a course credit or payment. As in the previous  
304 experiment, all the participants had normal or corrected-to-normal vision, and none of them  
305 reported a history of attention problems or reading disabilities.

#### 306 Procedure and materials

307 The naming task procedure was identical to the one used in Experiment 1. The  
308 material, however, was different, in that the regular triplet was made up of three vowels. We  
309 always used the same three vowels (A, O, U), but their order was counterbalanced across  
310 participants. The regular triplet was inserted into a random sequence of consonants drawn  
311 from a set of five consonants (F, L, N, R, S), and the triplet repetitions (15 per block) were

312 always separated by two to five random consonants.

313

### 314 Results

315 Only correct responses (97.22% of the data) were analysed. Trials where the stimulus  
316 presentation onset was delayed by more than 10 ms were excluded (0.98% of the data), as  
317 were four data points with SOLs exceeding 800 ms.

318 Table 3 summarizes the results of Experiment 2. The plot in Figure 3 suggests that  
319 letter predictability had a strong effect on SOLs, and this was confirmed by the results of our  
320 statistical analysis.

321 -- Table 3 about here –

322 -- Figure 3 about here –

323 The mixed model used to analyse the data of Experiment 2 was identical to the model  
324 we used in Experiment 1. Its results are summarized in Table 4.

325 -- Table 4 about here –

326 We found a significant effect of repetition, with the negative coefficient for this effect  
327 reflecting a decrease in SOLs. The coefficients for the effect of Position 3 reflect the fact that  
328 SOLs were significantly faster for predictable Position 3 letters relative to the mean SOL  
329 across all positions. Finally, a significant negative interaction coefficient indicated a  
330 significantly greater acceleration for Position 3 letters relative to the mean acceleration across  
331 all positions. Model comparison revealed that both the main effect of position,  $\chi^2(2) = 21.80$ ,  
332  $p < 0.001$ , and the Position x Repetition interaction effect,  $\chi^2(2) = 70.43$ ,  $p < 0.001$ , were  
333 significant. A follow-up analysis revealed that pairwise position contrasts were significant for  
334 Position 1 - Position 2,  $t(21.01) = 4.58$ , Tukey-adjusted  $p < 0.001$ , and Position 1 - Position 3,  
335  $t(20.13) = 5.99$ , Tukey-adjusted  $p < 0.001$ , but not for Position 2 - Position 3,  $t(19.97) = 2.38$ ,  
336 Tukey-adjusted  $p = 0.07$ ).

337           When we looked at learning as the difference score between log-transformed SOLs  
338 for unpredictable and predictable letters, we found strong evidence for learning even in the  
339 first block,  $t(20) = 5.09$ ,  $p_{\text{one-tailed}} < .001$ , and learning increased further with exposure,  $t(20) =$   
340  $3.21$ ,  $p_{\text{one-tailed}} < .001$  for Block 2;  $t(20) = 4.03$ ,  $p_{\text{one-tailed}} < .001$  for Block 3 (see Table 3)<sup>5</sup>.

#### 341       Questionnaire

342           Nineteen of the 21 participants reported noticing a repeated pattern, and 14 of them  
343 correctly recalled the triplet. Two other participants correctly reported one subsequence  
344 (Letters 1&2 or Letters 2&3).

#### 345       Discussion

346           The results of Experiment 2, in contrast to those of our first experiment, revealed clear  
347 effects of predictability on SOLs. Shorter SOLs were observed for the second and third letters  
348 in the repeated triplet, and this difference increased across repetitions. Results further showed  
349 an increased naming advantage for Position 3 over Position 2—a pattern consistent with  
350 previous findings (e.g., Minier et al., 2016).

351           The use of different letter categories for the structured and unstructured material  
352 (vowels in the triplet and consonants in the noise) may, of course, have served as a cue that  
353 facilitated the parsing of the continuous sequence and the extraction of the regular triplet  
354 pattern. Participants' responses to the awareness questionnaire suggest that, for at least 90%  
355 of them, the resulting knowledge about the structure was conscious. This result therefore  
356 indicates that regularity detection is possible within this experimental paradigm, though only  
357 if the regular triplet is made more salient than the random information.

358           Returning to the question of why no learning was observed in Experiment 1, one  
359 possible explanation is that the regularity was presented within noise that was still relatively

---

<sup>5</sup> It should be noted that we only compared predictable versus unpredictable vowels here, so even though vowels and consonants may not trigger the voice key in the same way (thus affecting SOLs), this could not bias our analyses.

360 structured. That is, given that the noise letters were drawn from a set of just five consonants,  
361 the theoretical mean transitional probability between the different noise letters was .25.  
362 Participants' responses on the post-task questionnaire indicated that regularities were also  
363 detected in the unstructured noise material. We tentatively suggest that the structure  
364 perceived in the noise may have interfered with the extraction of the actual triplet. In  
365 Experiment 3, we sought to increase the signal-to-noise ratio, without giving any cues for the  
366 regular triplet. We tested whether we could find evidence for regularity detection in a  
367 consonant-only version of the task using *noisier* noise. Therefore, instead of selecting them  
368 from a set of five consonants, we drew the noise letters from a set of 14 consonants, making  
369 the transitional probabilities between noise letters much smaller than they were in Experiment  
370 2.

### 371 Experiment 3

#### 372 Method

##### 373 Participants

374 A sample of 22 native French speakers (7 men, 15 women;  $M_{age} = 21.73$  years) took  
375 part in the study in exchange for either a course credit or a payment.

##### 376 Procedure and materials

377 The procedure was identical to the one used in Experiments 1 and 2. The letter stream  
378 was constructed with the full set of 20 French consonant letters minus W (referred to in  
379 French as *double V* [double U], and the low-frequency letters Q and X (hence, a set of 17).  
380 Three letters were used to construct the triplet (as before, the letter organization of the triplet  
381 was counterbalanced across participants), while the 14 remaining letters were used for the  
382 unstructured noise. Triplet repetitions (15 per block) were always separated by two to five  
383 randomly structured consonants, as in the previous experiments.



407 underlying statistical structure of the letter stream – as reflected by a difference score  
408 between SOLs for unpredictable and predictable letters that was significantly greater than  
409 zero,  $t(20) = .99$ ,  $p_{\text{one-tailed}} = .17$ . Significant learning was apparent in the subsequent learning  
410 blocks:  $t(20) = 2.64$ ,  $p_{\text{one-tailed}} < .01$  for Block 2, and  $t(20) = 1.69$ ,  $p_{\text{one-tailed}} = .05$  for Block 3  
411 (see Table 5).

#### 412 Questionnaire

413 Thirteen of the 21 participants reported noticing a recurrent letter sequence. Three of  
414 them could recall the whole triplet, and two others correctly recalled one subsequence  
415 (Letters 1&2 or Letters 2&3).

#### 416 Discussion

417 In line with the results of Experiment 2, the difference in SOLs between unpredictable  
418 and predictable letters increased across blocks. It should be noted that the online learning  
419 effect was substantially smaller than the one observed for the vowel triplet. Significant  
420 learning also emerged later (in the second block rather than in the very first). Unsurprisingly,  
421 in the absence of any cue other than the statistical properties of the stream, far fewer  
422 participants were able to explicitly recall the repeated triplet (3/21 vs. 14/21 for Experiment  
423 2).

424 A key result of these first three experiments was that the context in which the regular  
425 patterns were presented influenced online learning performances. To account for the lack of  
426 online learning in our first experiment, we tentatively hypothesized that the statistical  
427 structure in the noise interfered with the extraction of the actual triplet. The fact that we  
428 found learning under nearly identical learning conditions, the only difference being the set of  
429 letters used to construct the noise sequences, suggests that the degree of latent structure in the

430 noise sequences affected the detection of the regularity<sup>6</sup>. This result is problematic for most  
431 SL models. Recall of the letters making up the regular triplet should not have been affected  
432 by the manipulation of the noise information in Experiment 3, and results should have been  
433 the same as those in Experiment 1.

434 Previous research has demonstrated that learners form expectations about the kind of  
435 structure present in an information stream, based on previous exposure to other streams  
436 (Lew-Williams & Saffran, 2012), and may therefore fail to learn structures that conflict with  
437 their expectations (Gebhart, Aslin, & Newport, 2009). A similar conflict may occur within a  
438 single stream when wrong expectations are formed on the basis of the noise information  
439 (which was not sufficiently noisy in Experiment 1). In that case, participants may keep in  
440 mind a random repetition (which is more likely to occur in Experiment 1 due to the small  
441 number of filler letters) and this expectation may interfere with the discovery of the genuine  
442 regularity. An alternative (though not necessarily mutually exclusive) interpretation relates to  
443 memory constraints (Frank & Gibson, 2011; Frank, Goldwater, Griffiths, & Tenenbaum,  
444 2010). The presence of quasi-regularities in the noise sequences may be disadvantageous if  
445 they are being kept active in working memory. This could be especially true in the context of  
446 a demanding task such as rapid naming that presumably takes up capacity itself.

447 In the fourth and final experiment, we aimed to determine the effect of reducing the  
448 distance between occurrences of the regular pattern. All SL models predict that shorter noise  
449 sequences between triplet repetitions should lead to improved learning.

450

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<sup>6</sup> It should be noted that although the triplet was repeated the same number of times (45) in each of the experiments, the relative frequency of triplet letters versus noise letters was higher in Experiment 3 than in Experiment 1. This factor may have contributed to participants' better learning performances. Faster SOLs for Position 1 than for noise letters (see Fig. 5) suggest that participants also picked up on the greater frequency of the first letter in the triplet. However, given that the difference between unpredictable Position 1 and predictable Positions 2 and 3 increased, this frequency effect cannot fully account for the data.

451 Experiment 4452 Method453 Participants

454 A sample of 24 native French speakers (4 men, 20 women;  $M_{\text{age}} = 20.1$  years) took part  
455 in the study in exchange for a course credit.

456 Procedure and materials

457 The procedure used in Experiment 4 was identical to the one used in Experiment 3,  
458 except that triplet repetitions were always separated by no more than three randomly arranged  
459 consonants (rather than the two to five randomly arranged consonants in Experiments 1-3).  
460 As the total number of trials was identical to the number in the three previous experiments  
461 (300 trials in three blocks of 100 trials), there were 62 rather than 45 triplet repetitions.

462 Results

463 Only correct responses (97.17% of the data) were analysed. Trials where the stimulus  
464 presentation onset was delayed by more than 10 ms were excluded (0.97% of the data), as  
465 were 11 data points with SOLs exceeding 800 ms.

466 The results of Experiment 4 are summarized in Table 7 and Figure 5.

467 -- Table 7 about here --

468 -- Figure 5 about here --

469 The model included the maximum random effect structure that allowed convergence  
470 (Barr, 2013; Barr et al., 2013):  $\text{SOL} \sim \text{Position} + \text{Repetition} + \text{Position} \times \text{Repetition} (1 +$   
471  $\text{Position} + \text{Position} \times \text{Repetition} | \text{Participant})$ . The results of the model are summarized in  
472 Table 8.

473 -- Table 8 about here --

474 There was a significant effect of repetition and the predicted effect of position: overall

475 SOLs were significantly faster for the predictable Position 3 compared with the mean across  
 476 all positions. Finally, the significant negative interaction coefficient indicated greater  
 477 acceleration for Position 3 across repetitions, relative to the mean acceleration for all  
 478 positions. Model comparisons revealed a significant main effect of position,  $\chi^2(2) = 12.82$ ,  $p$   
 479  $< .01$ , and a significant Position x Repetition interaction,  $\chi^2(2) = 8.05$ ,  $p = .018$ . Pairwise  
 480 position contrasts were significant for Position 1 - Position 2,  $t(23.02) = 3.85$ , Tukey-adjusted  
 481  $p < 0.01$ , and Position 1 - Position 3,  $t(22.98) = 3.647$ , Tukey-adjusted  $p < 0.01$ , but not for  
 482 Position 2 - Position 3,  $t(22.94) = 1.32$ , Tukey-adjusted  $p = 0.40$ .

483 One-sample  $t$  tests revealed that participants already exhibited significant learning of  
 484 the underlying statistical structure of the letter stream in the first block,  $t(23) = 2.94$ ,  $p_{\text{one-tailed}}$   
 485  $< .01$ , which remained significant in subsequent learning blocks, with  $t(23) = 2.89$ ,  $p_{\text{one-tailed}} <$   
 486  $.001$  for Block 2, and  $t(23) = 3.84$ ,  $p_{\text{one-tailed}} < .001$  for Block 3 (see Table 7).

487 To directly compare learning in the current experiment with learning in Experiment 3,  
 488 we ran another linear mixed model on the data for the two experiments, subsetting the data of  
 489 Experiment 4 to include only the first 45 repetitions. In this model, learning score was the  
 490 dependent variable, and experiment, repetition and the Experiment x Repetition interaction  
 491 were fixed effects with a random by-participant intercept. Experiment was sum-coded  
 492 (Experiment 3: -1; Experiment 4: 1). We found significant main effects of Experiment ( $\beta =$   
 493  $0.04$ ,  $SE = 0.01$ ,  $p < .001$ ) and Repetition ( $\beta = 0.005$ ,  $SE = 0.001$ ,  $p < .001$ ), and a significant  
 494 interaction effect ( $\beta = 0.002$ ,  $SE = 0.001$ ,  $p < .001$ ), confirming stronger learning in  
 495 Experiment 4 than in Experiment 3 (see also Fig. 6).

496 -- Figure 6 about here --

#### 497 Questionnaire

498 Nineteen of the 24 participants reported noticing a recurrent letter sequence. Thirteen

499 could recall the whole triplet, while four others correctly recalled one subsequence (Letters  
500 1&2 or Letters 2&3).

### 501 Discussion

502 In Experiment 4, we tested the prediction that shorter noise sequences between triplet  
503 repetitions would further improve learning in the naming task. Results showed that overall  
504 learning scores were indeed higher than in Experiment 3. With its 17 additional repetitions,  
505 the present experiment also provided information regarding the trajectory of SOLs in the later  
506 stages of pattern learning. Interestingly, the decrease in SOLs for predictable letters continued  
507 unabated across the 62 repetitions (no sign of reaching asymptote).

### 508 General Discussion

509 In the present study, participants had to name out loud single letters that were  
510 displayed one at a time on a computer screen. Unbeknownst to them, the stream contained a  
511 repeated letter triplet. Our data suggest that SOLs were sensitive to online statistical  
512 computations: with exposure, SOLs for the predictable second and third letters in the repeated  
513 triplet decreased. However, this effect was only present when the information stream had  
514 what could be described as a high signal-to-noise ratio. To be detected, the triplet either had  
515 to have a salient feature compared with the noise information (Exp. 2), or the noise sequences  
516 between successive presentations of the regular pattern had to be sufficiently noisy (Exp. 3)  
517 or short (Exp. 4). Otherwise, the regular pattern remained undetectable for most participants  
518 (Exp. 1).

519 Taken together, the results of our four experiments have two main implications for  
520 models of implicit SL. First, they show that although SL mechanisms are powerful, they also  
521 have limitations. The detection of co-occurrences and regularities does not systematically  
522 take place when participants are exposed to a repeated regular pattern of adjacent items, even  
523 if this pattern is relatively simple. Mere repetition is not a sufficient condition for a regularity

524 to stand out from a stream of variable information, and for participants to detect it. The  
525 regular pattern will be detected either because of a feature that makes it salient with respect to  
526 the surrounding variable information (i.e., vowels vs. consonants; Exp. 2) or because the  
527 mean interval between two repetitions is small enough for the memory trace of the co-  
528 occurrences to be sufficiently reinforced (Exp. 4). This raises important issues, such as the  
529 role of regularity learning in more natural contexts, as well as educational ones. In language  
530 learning in particular, a field in which SL has become a dominant theoretical construct in  
531 recent years, the current findings point to the limitations of our implicit co-occurrence  
532 learning abilities.

533         Second, the present results indicate that the context or surrounding information in  
534 which the regularities are presented may matter for SL (Exp. 1 & 3). If the variable context is  
535 not variable enough, associative learning mechanisms may extract co-occurrences that have  
536 sufficiently strong transitional probabilities, but which are irrelevant. This is an issue that has  
537 so far received too little attention, as almost all previous research has used input streams with  
538 a similar latent structure, repeating  $n$  (usually between four and eight) triplets or pairs with a  
539 transitional probability of 1 between the items within each one (Siegelman et al., 2016).

540         The present data also replicate previous findings on the dynamics of regularity  
541 extraction. The results of Experiment 2, where we tested a vowel triplet in consonant noise,  
542 revealed greater acceleration for Position 3 versus Position 2 letters, and we saw a similar  
543 trend in Experiments 3 and 4. This could be interpreted as an effect of context on the learning  
544 of the final stimulus in a repeated triplet (i.e., the final stimulus benefits from the contextual  
545 information provided by the stimuli that consistently precede it), in line with the effect  
546 described by Minier et al. (2016) in the motor sequence learning trajectory of baboons. It  
547 therefore suggests that in a verbal SL task, greater contextual information facilitates  
548 prediction (see also Rey, Minier, Malassis, Bogaerts, & Fagot, 2018). As argued by Minier et

549 al. (2016), this learning advantage for the final item or embedded pattern is predicted by the  
550 SRN model, but poses challenges for chunking models such as PARSER, which predicts no  
551 difference between learning for the initial (Letters 1&2 in a triplet) and final (Letters 2&3)  
552 embedded patterns, or TRACX, which predicts faster learning for the initial one (Letters  
553 1&2) - the opposite of what we found.

#### 554 Prospects and limitations

555         We believe that the Hebb-naming paradigm described here offers a simple  
556 behavioural approach to studying learning dynamics online, suitable for studying how fast  
557 and with which trajectory learners capture the statistical properties of incoming sensory  
558 information. It could be used to complement existing offline measures and might help to  
559 overcome some of the psychometric shortcomings of offline measures, such as test  
560 interference. As a more implicit and direct measure (see also Isbilen, Frost, Monaghan, &  
561 Christiansen, 2018), SOL might prove particularly useful for studying SL in young children  
562 (e.g., Arnon, 2019; Lammertink, van Witteloostuijn, Boersma, Wijnen, & Rispens, 2018) or  
563 certain patient groups (e.g., amnesic patients; Schapiro, Gregory, Landau, McCloskey, &  
564 Turk-Browne, 2014) who have difficulty with the 2-AFC testing format. It also has a  
565 considerable advantage (over for example the RT-based measure in an SRT task) due to the  
566 many degrees of freedom in constructing the regular sequence (e.g., contrary to the SRT task,  
567 it is possible to have several sequences with transitional probabilities of 1). It could be  
568 employed with all sorts of nameable stimuli with large set sizes (e.g., pictures, words) and  
569 with different types of regularities. By extension, this measure could also be included in  
570 verbal AGL and Hebb repetition paradigms.

571         The above formulation “as a more implicit and direct measure” requires some further  
572 clarification. We worked on the premise that faster SOLs for predictable letter stimuli can  
573 occur when learning is implicit, that is, when the stream of letters is processed without “the

574 conscious intention to find out whether the input information contains regularities” (Hulstijn,  
575 2005, p. 131). However, this does not mean that the learning trajectories we observed were  
576 uniquely shaped by implicit learning processes (Andringa & Rebushat, 2015). In each of the  
577 experiments, by the end of the task (i.e., after several dozen repetitions) several participants  
578 displayed conscious knowledge of the regularity that had been learned, and the pattern of  
579 questionnaire results across our four experiments suggests that either awareness emerged  
580 with increased implicit learning, or some emerging awareness of the regularity (while  
581 participants were engaged in the naming task) amplified the online learning effect as we  
582 measured it. Splitting participants from Experiment 4 in two groups of similar sizes (i.e.,  
583 participants who could recall vs. who could not recall the repeated sequence of letters (with  $N$   
584 = 13 and  $N = 11$ , respectively), we indeed found that the interaction between Position 3 and  
585 Repetition was significant for those who could recall the sequence ( $\beta = -1.22$ , CI [-2.06, -  
586 0.37],  $p < .02$ ) but not for the other group ( $\beta = -0.51$ , CI [-1.23, 0.21],  $p = 0.191$ ).

587         Although the present investigation goes some way toward the development of a Hebb  
588 naming SL task, future research will have to examine whether the task can be adapted to  
589 other types of verbal stimuli and to the auditory modality (where the participants are asked to  
590 shadow rather than to name), and whether it can also be employed to study different types of  
591 regularities (e.g., nonadjacent co-occurrences). Furthermore, from a psychometric  
592 perspective, it is important to examine whether the online naming measure can reliably tap  
593 into individual performances on the task and predict offline performance.

#### 594 Conclusion

595         We asked participants to name letters presented in continuous letter sequences and  
596 measured their SOLs in four experiments. Overall, our data suggest that SOLs are sensitive to  
597 stimulus predictability and to online statistical computations. Our results also highlight the  
598 influence of the context in which a regular pattern is presented, and a major limitation of

599 implicit co-occurrence learning abilities in the context of an active naming task.

600

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610 Open Practices Statements

611 Data and materials for all the experiments are available on Open Science Framework.  
612 None of the experiments were preregistered.

613 Conflict of Interest

614 AR, LB, LT, GB, AF, and BF declare that they have no conflict of interest.

615 Ethical Approval

616 All procedures in the present experiments involving human participants were  
617 performed in accordance with the ethical standards of the institutional and/or national  
618 research committee and with the 1964 Declaration of Helsinki and its later amendments or  
619 comparable ethical standards.

620 Informed Consent

621 Informed consent was obtained from each of the participants included in the study.

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757 Table 1758 *Means and Standard Deviations for Raw Speech Onset Latencies (SOLs) and Learning*759 *Scores in Experiment 1*

	Block 1	Block 2	Block 3	Total
Raw SOL				
Position 1	411 (68)	382 (67)	376 (71)	389 (70)
Position 2	413 (73)	388 (67)	364 (84)	388 (77)
Position 3	415 (67)	389 (73)	376 (72)	393 (72)
Learning score	0	-.02	.02	

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761

762 Table 2763 *Results of the Mixed Model for Experiment 1*

Predictor	$\beta$	CI	SE	<i>p</i>	
(Intercept)	390.3	[376.3 , 404.3]	7.1	< .001	***
Position 2	-1.9	[-8.7 , 4.8]	3.4	.58	
Position 3	2.9	[-4.8 , 10.6]	3.9	.47	
Repetition	-1.2	[-1.7 , -0.8]	0.2	< .001	***
Position 2: Repetition	-0.2	[-0.5 , 0.1]	0.2	.14	
Position 3: Repetition	0	[-0.3 , 0.3]	0.2	.99	

764 *Note.* Position was sum-coded.

765

766 Table 3767 *Means and Standard Deviations for Raw Speech Onset Latencies (SOLs) and Learning*768 *Scores in Experiment 2*

	Block 1	Block 2	Block 3	Total
Raw SOL				
Position 1	382 (66)	343 (64)	334 (73)	352 (71)
Position 2	364 (76)	299 (84)	270 (93)	311 (93)
Position 3	352 (75)	284 (106)	248 (107)	295 (106)
Learning score	.07	.16	.25	

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771 Table 4772 *Results of the Mixed Model for Experiment 2*

Predictor	$\beta$	CI	SE	<i>p</i>	
(Intercept)	320.2	[299.9 , 340.5]	10.3	< .001	***
Position 2	-8.9	[-17.2 , -0.7]	4.2	.04	*
Position 3	-24.3	[-33.1 , -15.4]	4.5	< .001	***
Repetition	-2.5	[-3.3 , -1.8]	0.4	< .001	***
Position 2: Repetition	-0.4	[-0.8 , -0.02]	0.2	.05	*
Position 3: Repetition	-0.8	[-1.2 , -0.3]	0.2	0.004	***

773 *Note.* Position was sum-coded.

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775

776 Table 5777 *Means and Standard Deviations for Raw Speech Onset Latencies (SOLs) and Learning*778 *Scores in Experiment 3*

	Block 1	Block 2	Block 3	Total
Raw SOL				
Position 1	404 (57)	397 (66)	396 (66)	399 (63)
Position 2	404 (59)	377 (72)	376 (80)	386 (72)
Position 3	390 (58)	363 (92)	370 (89)	375 (82)
Learning score	.01	.07	.09	

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780

781 Table 6782 *Results of the Mixed Model for Experiment 3*

Predictor	$\beta$	CI	SE	$p$	
(Intercept)	386	[351, 421]	17.91	< .001	***
Position 2	-0.9	[-5.6, 3.7]	2.37	.71	
Position 3	-12.3	[-23.7, -0.9]	5.81	.06	
Repetition	-0.5	[-1.4, 0.35]	0.45	.26	
Position 2: Repetition	-0.3	[-0.68, 0.09]	0.19	.16	
Position 3: Repetition	-0.1	[-0.64, 0.44]	0.28	.72	

783 *Note.* Position was sum-coded.

784 Table 7785 *Means and Standard Deviations for Raw Speech Onset Latencies (SOLs) and Learning*786 *Scores in Experiment 4*

	Block 1	Block 2	Block 3	Total
Raw SOL				
Position 1	429 (64)	414 (69)	418 (75)	420 (70)
Position 2	405 (78)	377 (95)	344 (120)	375 (102)
Position 3	404 (82)	357 (122)	328 (127)	363 (116)
Learning score	.08	.21	.34	

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790 Table 8791 *Summary of the Fixed Effects in the Mixed Model for Experiment 4*

Predictor	$\beta$	CI	SE	$p$	
(Intercept)	395.3	[374.3 , 416.4]	10.2	< .001	***
Position 2	-7.3	[-14.9 , 0.4]	3.8	.07	
Position 3	-17.8	[-30.6 , -5]	6.1	< .01	**
Repetition	-1.4	[-2.2 , -0.6]	0.4	< .001	***
Position 2: Repetition	-0.05	[-0.3 , 0.2]	0.14	.74	
Position 3: Repetition	-0.8	[-1.4 , -0.3]	0.2	< .01	**

792 *Note.* Position was sum-coded.

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794

795 Figure Captions

796

797 Figure 1. Density plot of speech onset latencies showing the fitted normal distribution in blue,  
798 with a red line indicating our cut-off score.

799 Figure 2. Plot with smoothed estimate of mean speech onset times in Experiment 1 as a  
800 function of letter position and number of repetitions. Grey-shaded areas indicate 95%  
801 confidence intervals around linear regression lines. Dashed lines represent the best linear fit.

802 Figure 3. Plot with smoothed estimate of mean speech onset times in Experiment 2 as a  
803 function of letter position and number of repetitions. Grey-shaded areas indicate 95%  
804 confidence intervals around linear regression lines. Dashed lines represent the best linear fit.

805 Figure 4. Plot with smoothed estimate of mean speech onset times in Experiment 3 as a  
806 function of letter position and number of repetitions. Grey-shaded areas indicate 95%  
807 confidence intervals around linear regression lines. Dashed lines represent the best linear fit.

808 Figure 5. Plot with smoothed estimate of mean speech onset times in Experiment 4 as a  
809 function of letter position and number of repetitions. Grey-shaded areas indicate 95%  
810 confidence intervals around linear regression lines. Dashed lines represent the best linear fit.

811 Figure 6. Comparison of learning scores and their changes across repetitions for all-  
812 consonant triplet in consonant-noise experiments. Grey-shaded areas indicate 95%  
813 confidence intervals around linear regression lines. Dashed lines represent the best linear fit.

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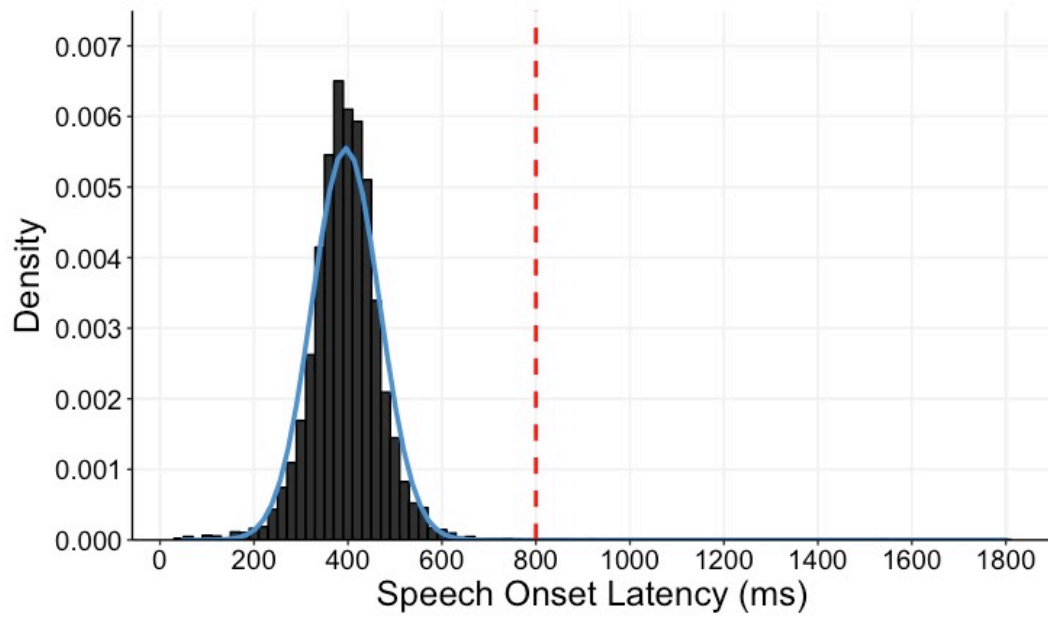
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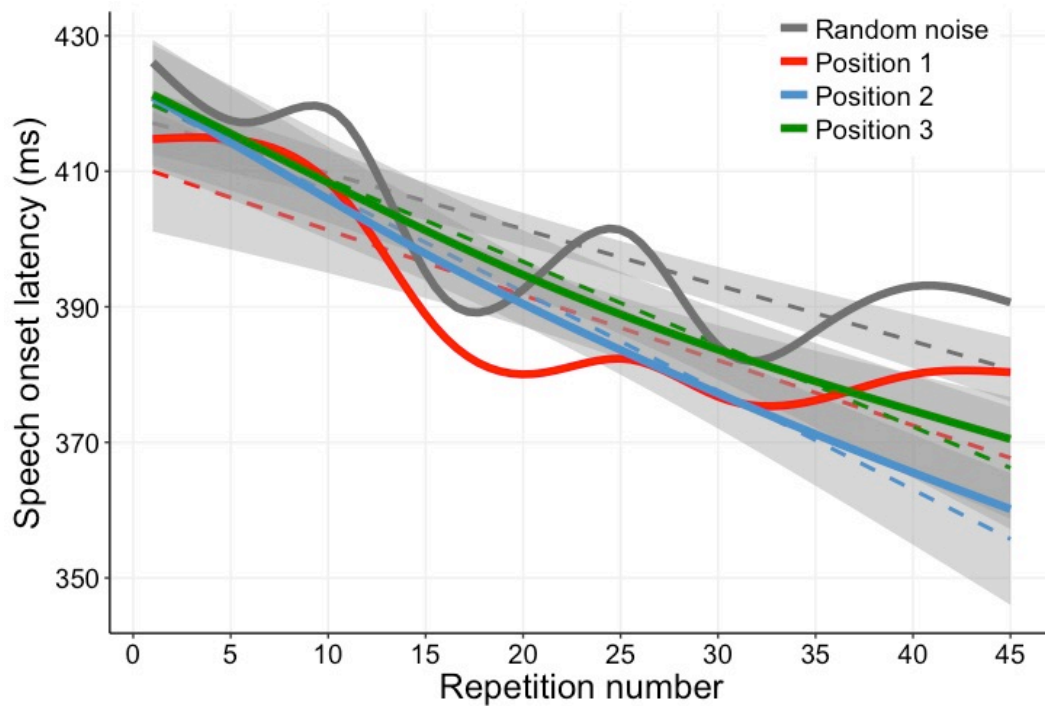
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Figure 1

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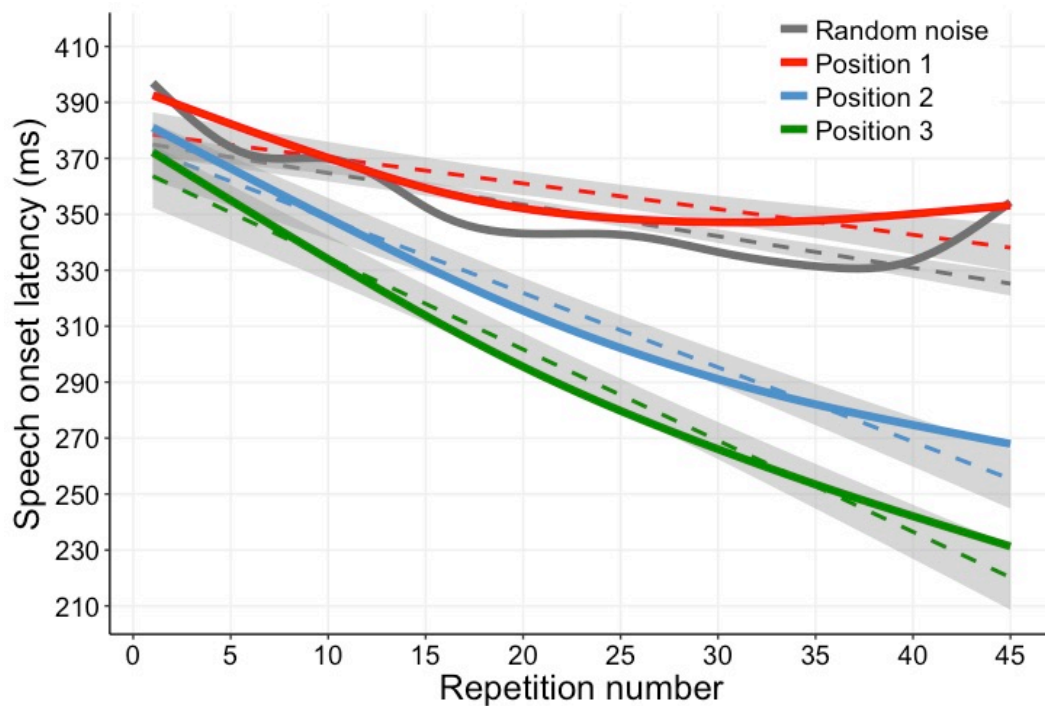
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Figure 2

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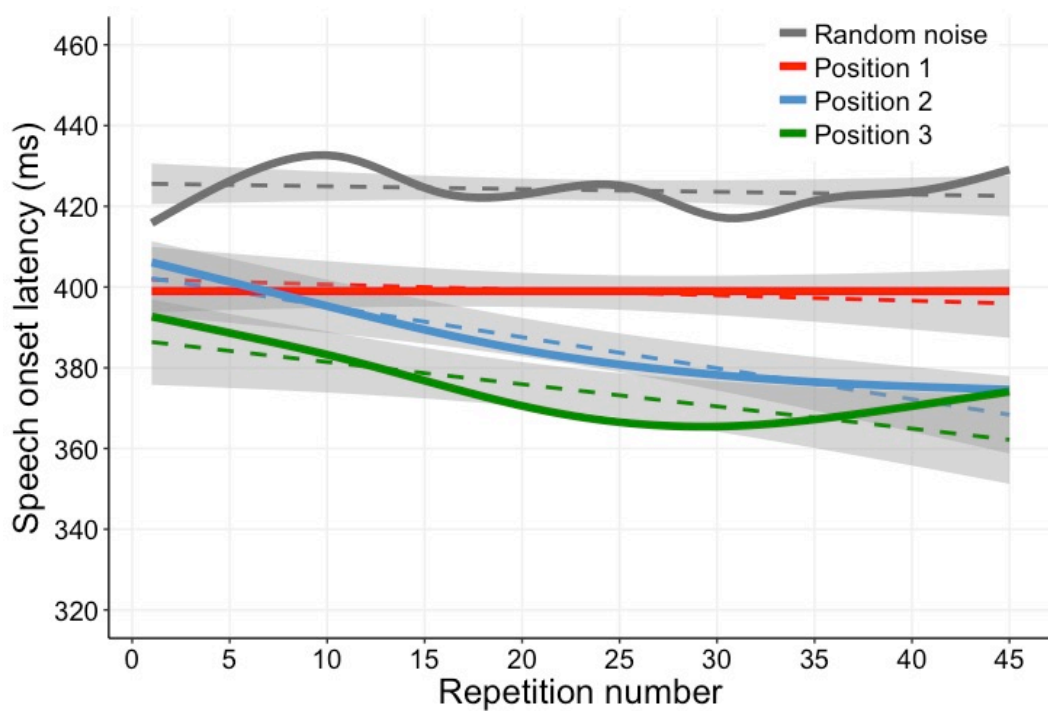
Figure 3

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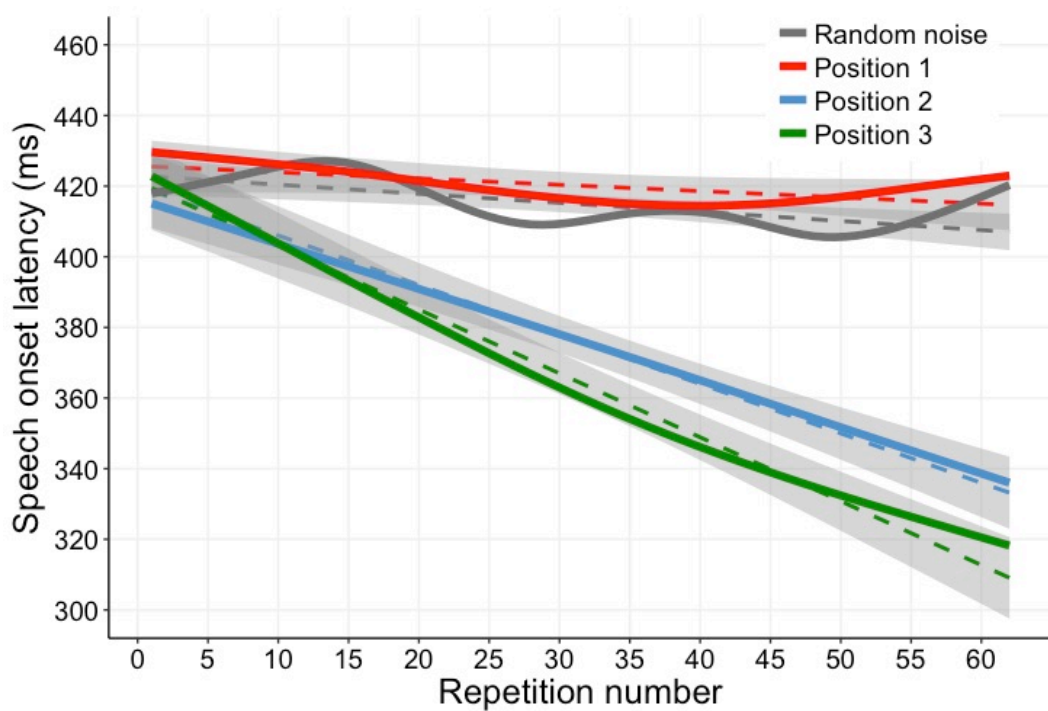
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Figure 4

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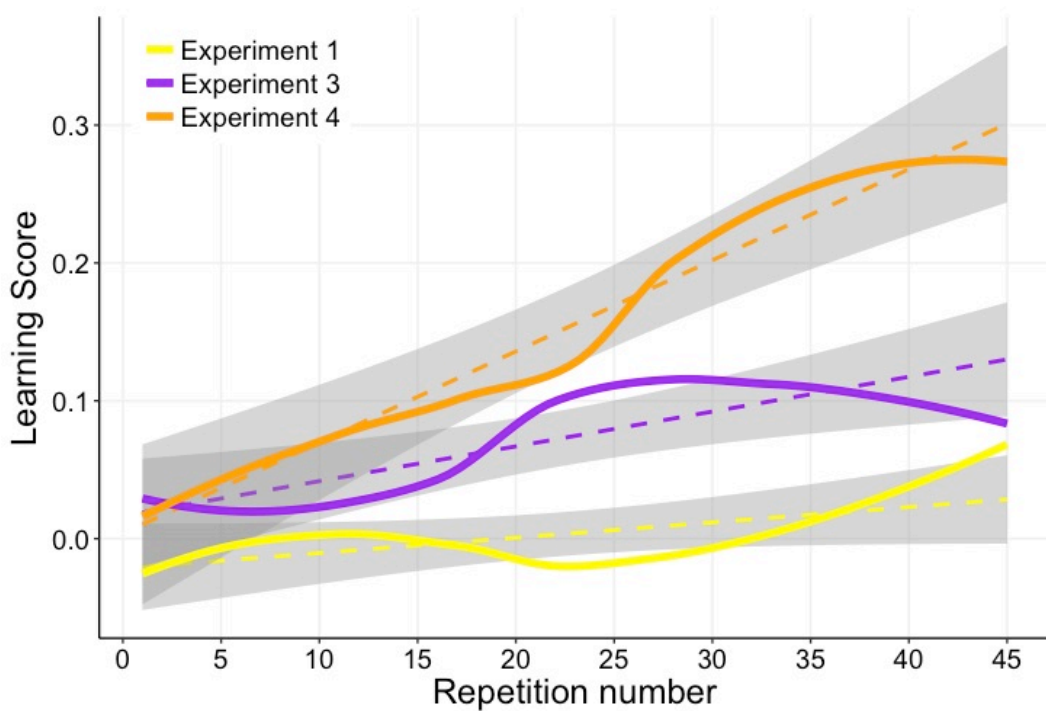
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Figure 5

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Figure 6

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