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The Dynamics of Chunking
in Humans (*Homo sapiens*) and Guinea baboons (*Papio papio*)

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Running head: THE DYNAMICS OF CHUNKING

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Abstract

Chunking is an important cognitive process allowing the compression of information in short-term memory. The aim of this study is to compare the dynamics of chunking during the learning of a visuo-motor sequence in humans (*Homo sapiens*) and Guinea baboons (*Papio papio*). We duplicated in humans an experimental paradigm that has been used previously in baboons. On each trial, human participants had to point to a moving target on a touch screen. The experiment involved the repetition of the same sequence of 9-items over a thousand trials. To reproduce as much as possible the conditions under which baboons performed the task, human participants were tested at their own pace. Results revealed that baboons and humans shared similar chunking dynamics: in both species, the sequence was initially parsed into small chunks that became longer and fewer with practice through two reorganization mechanisms (recombinations and concatenations). Differences were also observed regarding the global decrease in response times that was faster and more pronounced in humans compared to baboons. Analyses of these similarities and differences provide new empirical evidence for understanding the general properties of chunking mechanisms in sequence learning and its evolution across species.

Keywords: chunking, sequence learning, comparative cognition

43 Chunking is a core cognitive ability that allows the cognitive system to compress
44 information in short term memory, as its capacity is limited (Mathy & Feldman, 2012; Miller,
45 1956). Chunking is defined as the process of associating and grouping several items together
46 into a single processing unit, i.e., a chunk (Gobet et al, 2001; Gobet, Lloyd-Kelly, & Lane, 2016)
47 and the emergence of chunks is commonly believed to be rooted in elementary associative
48 processes (i.e., Hebbian learning, Perruchet & Vinter, 2002; Rey et al., 2019). Contrary to what
49 Miller (1956) initially suggested, chunks are limited in storage, and several studies report a
50 typical chunk size of 3 or 4 items (Allen & Coyne, 1988; Chase & Simon, 1973; Johnson, 1970).
51 This limitation has implications when one has to process a long sequence of items that appears
52 repeatedly in the same order. In that specific case, processing of the long sequence usually
53 requires to split it into smaller processing chunks, a result that has been reported notably in
54 the field of perceptual-motor sequence learning.

55 Motor sequence learning is the process by which a specific sequence of movements is
56 executed with increased speed and accuracy (Willingham, 1998), and chunking has been
57 considered as the main motor sequence integration mechanism (Diedrichsen & Kornysheva,
58 2015; Wymbs et al., 2012). Indeed, both human and non-human animals have been shown to
59 spontaneously segment sequences in chunks of 3 or 4 items as indicated by long temporal
60 gaps emerging between successive responses and marking chunk boundaries (e.g., in humans,
61 Abrahamse et al., 2013; Bottary et al., 2016; in rhesus monkeys, Scarf et al., 2018; in pigeons,
62 Terrace, 1991).

63 Some studies were also interested in the temporal aspect of chunking and how
64 chunking patterns evolve with practice. Throughout extended practice, chunks were found, in
65 human and non-human primates, to evolve and grow larger as if more compression of
66 information was possible with increasing familiarity with the sequence (e.g., Acuna et al.,

67 2014; Bera et al., 2021; Ramkumar et al., 2016, Wright et al., 2010). One mechanism proposed
68 to account for this growth of chunks is the *concatenation* of chunks (Verwey, 2001; Wright et
69 al., 2010). Concatenation is described as independent chunks being executed more fluidly with
70 practice and with a decrease of the temporal gap between them leading to a single and longer
71 chunk (Abrahamse et al., 2013). However, the detailed dynamics by which this evolution is
72 possible remain unclear and no research has been done in humans to precisely study the
73 evolution of chunks boundaries, trial-by-trial or by grouping trials together at different steps
74 of practice.

75 In non-human primates (*Macaca mulatta*), Ramkumar et al. (2016) proposed a model
76 of efficiency computation trade-off based on their observations suggesting that to limit the
77 cost of computation, learning new sequences of movements starts with many short chunks.
78 With practice, the execution of short chunks becomes more efficient, which reduces the
79 computation's complexity. This increase in efficiency for short chunks would promote more
80 complex computations leading to the development of longer chunks.

81 We have recently conducted a similar study on Guinea baboons (*Papio papio*) on the
82 role of extended practice in the formation and the evolution of chunks (Tosatto, Fagot,
83 Nemeth, & Rey, 2022). Our experiment was presented in freely accessible operant
84 conditioning test systems referred to as Automated Learning Devices for Monkeys (ALDM,
85 Fagot & Bonté, 2010). The task was a serial response time (SRT) task where baboons had to
86 point to a moving target on a touchscreen and were repeatedly exposed to the same sequence
87 composed of 9 different locations during 1,000 trials. This study replicated the increase in
88 chunks size throughout the repeated production of the sequence. However, we also observed
89 that the dynamics of chunking was governed by two (instead of one) reorganization
90 mechanisms. Indeed, as in previous studies, we observed *concatenations*, i.e., the process by

91 which the temporal gap between two successive chunks decreases leading to a single and
92 longer chunk. But we also observed a new mechanism, *recombinations*, i.e., the emergence
93 of a new segmentation pattern, such as two chunks of 3 items become a chunk of 4 items
94 followed by a chunk of 2 items.

95 In the present study, we aimed at replicating this study with human participants to
96 compare the dynamics of chunking in both species. We tried to test humans in similar
97 conditions to the ones baboons experienced, using a self-paced task similar to the self-paced
98 access by baboons to the ALDM test systems, and an apparatus as close as possible to the one
99 used in baboons. Indeed, many studies have to adapt typical sequence learning experimental
100 paradigms used in humans (i.e., key-pressing tasks) when testing non-human primates, due
101 to differences in fine motor skills. In the present case, the pointing task used by Tosatto et al.,
102 (2022; see also Malassis, Rey & Fagot, 2018; Minier, Fagot & Rey, 2016; Rey et al., 2019) is
103 suitable for both species and has been adapted here from non-human primates to humans.
104 For that purpose, we did not provide explicit instructions to human participants as studies
105 with non-human animals cannot include explicit verbal instructions. With such similar
106 conditions, we expected similar dynamics in the evolution of chunks in human and non-human
107 primates: an initial segmentation into small chunks that should increase in size with practice
108 through concatenation and recombination mechanisms. However, because humans benefit
109 from their language recoding skills, we were also expecting differences in the dynamics of
110 these learning and chunking processes.

111 **Method**

112 **Participants**

113 In Tosatto et al. (2022), there were thirteen female and five male Guinea baboons
114 (*Papio papio*, age range 2.8—23.7 years). In the present study, 11 human participants

115 between 18 and 35 years old (*Mean*= 26.5) took part in this experiment (6 women and 5 men)
116 in exchange of a 20€ reward. For practical reasons, they were recruited among PhD
117 candidates, engineers and post-doctorates from our lab so that they could participate to the
118 experiment every day, at will. All participants were right-handed, had no learning disability
119 and normal or corrected-to-normal vision.

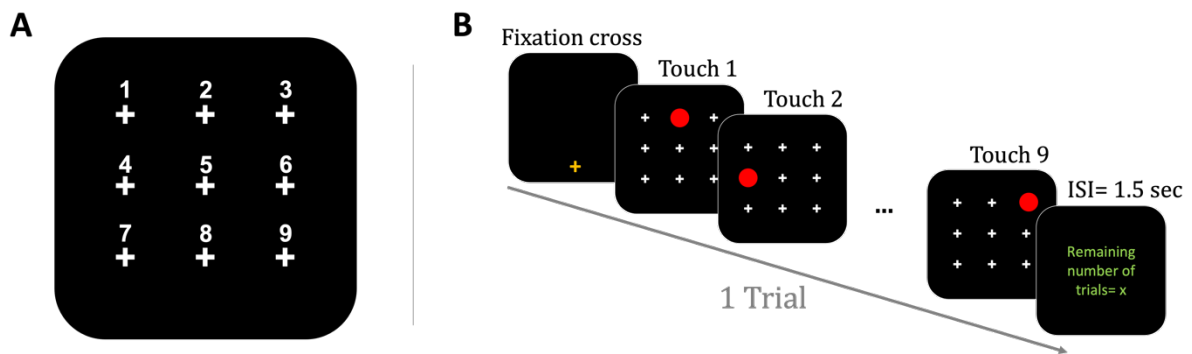
120 Out of these 11 participants, 4 of them were not completely naïve as they had already
121 heard about the content of first author's thesis and the task used with the baboons. However,
122 none of these 4 participants participated in a previous similar study. Moreover, even though
123 they knew about the experimental paradigm, they were not informed of the specific
124 manipulation done in this experiment and especially, about the main feature of this
125 experiment, namely that the same sequence would be repeated 1,000 times. Therefore, they
126 had no reason to pick up this regularity faster than the more naïve participants. The remaining
127 7 participants were either new to the lab or never heard of the studies led in our team. To test
128 if there was a difference between these two groups while performing the experiment, we
129 report in the result section an analysis suggesting that there was no quantitative difference
130 between these two groups.

131 **Materials**

132 ***Apparatus and stimuli***

133 The apparatus, task and stimuli were identical to the one used in Tosatto et al. (2022)
134 in baboons. The experiment was controlled by E-prime (Version 2.0, Psychology Software
135 Tools, Pittsburgh, PA, USA) and ran on a HP ProBook 650 G1 computer connected to a 32''
136 liyama touch screen. Figure 1 illustrates the timeline of the experimental trials. The touch
137 screen was divided into nine equidistant predetermined locations represented by white
138 crosses on a black background, virtually labeled as position 1 to 9. A trial began with the

139 presentation of a yellow fixation cross at the bottom center of the screen. Once pressed, the
 140 fixation cross disappeared and the nine white crosses were displayed, one of them being
 141 replaced by the target, a red circle. When the target was touched, it was immediately replaced
 142 by the cross. The next position in the sequence was then replaced by the red circle until it was
 143 touched, and a new position was displayed. At the end of the sequence, the computer
 144 displayed the remaining number of trials to complete the experiment. The time elapsed
 145 between the appearance of the red circle and the baboon's (or human's) touch on this circle
 146 was recorded as the response time (RT).



147
 148 **Figure 1:** Experimental display and stimulus presentation. A. Display of the 9 equidistant
 149 predetermined locations (white crosses) virtually labeled as position 1 to 9 (i.e., only the white
 150 crosses were displayed, not the numbers). B. Example of a single trial. After a first touch on
 151 the fixation cross, the subject had to touch the red dot when it appeared in each location.
 152

153 ***Design of the sequences***

154 To control for the motor difficulty of the transitions to be produced in the sequence, a
 155 random phase of sequence production was first conducted, where 10 human participants
 156 performed random sequences of nine positions for 180 trials. Based on these random trials, a
 157 baseline measure for all possible transitions from one location to another was computed by
 158 calculating mean RTs for each transition (e.g., from position 1 to 9), leading to a 9x9 matrix of
 159 mean RTs calculated over the entire group (see Appendix A).

160 Based on these baseline measures, we designed two sequences of nine serial positions
161 for which each transition T was faster (or equally fast) to produce than the next one (i.e.,
162 $T_1 \leq T_2 \leq \dots \leq T_8$, with T_1 being the transition from Position 1 to Position 2 of the sequence). This
163 way, a decrease in RT for a given transition can be interpreted as the anticipation (or learning)
164 that Position n is following Position $n-1$. To control for a specific sequence bias, we designed
165 two sequences, each participant being assigned randomly either with Sequence 1 or 2.

166 **Procedure**

167 Participants were informed they were recruited for a self-paced cognitive task and that
168 they would not get any oral or written instructions regarding how to perform the task. The
169 only instructions provided on the touch screen when beginning the experiment were "*Touch*
170 *to start the task*". They were informed that they had to produce 1,100 trials to complete the
171 task, and that they had to complete it within three weeks in order to get the financial reward.
172 The task started with a training block of 100 random sequences to help participants familiarize
173 with the device. Unbeknownst to them, they were then assigned with either Sequence 1 (N=5)
174 or Sequence 2 (N=6) and they had to produce it repeatedly for the next 1,000 trials. RTs for
175 each position of the sequence were recorded for all the trials.

176 The computer and touch screen were placed in a corner of the lunchroom of the lab,
177 on a high table, so that they could come and perform some trials standing at any time during
178 office hours. They accessed their own task by touching an icon to their name, and each time
179 they would touch their icon, the system resumed the trial list where the participant left it at
180 its previous visit. The system would resume to the home page after 10 seconds of inactivity.
181 As for baboons, if participants touched an inappropriate location (incorrect trial) or failed to
182 touch the screen within 5,000ms after the red circle's appearance (aborted trial), a green
183 screen was displayed for 1,500ms as a marker of failure. Aborted trials were not retained and

184 therefore presented again, while incorrect trials were discarded. After each trial, a screen
185 indicating the number of trials remaining was displayed for 1.5 second, informing the
186 participants on their progression. That procedure was introduced to implement a reward on
187 every trial that would mimic the food reward received by baboons on every correct trial in
188 Tosatto et al. (2022).

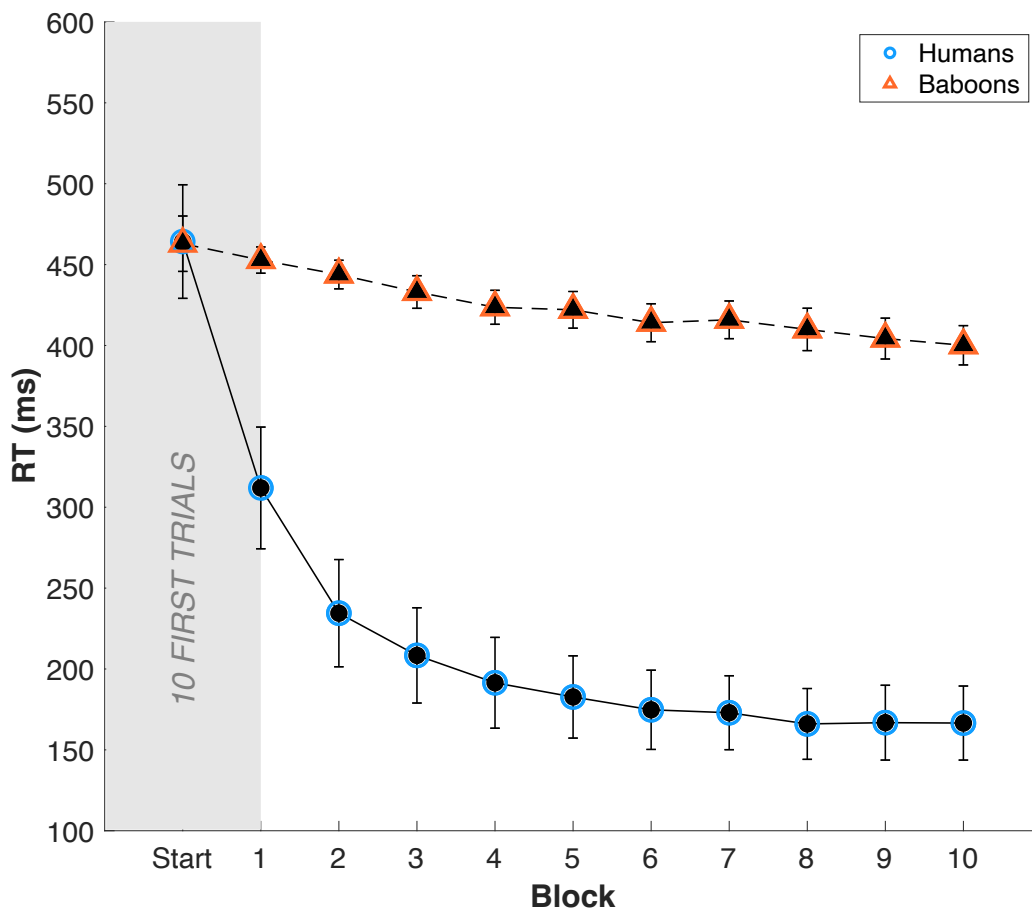
189 **Results**

190 On average, humans required 4.27 days ($SD=1.49$) to complete the 1,000 trials, with a
191 mean of 234.04 trials per day. Incorrect trials were removed from the dataset (11.11% vs.
192 7.8% for baboons). RTs for each of the nine positions and for the 1,000 trials were divided into
193 10 Blocks of 100 trials. This segmentation was like the one used previously in baboons (Tosatto
194 et al., 2022) in order to directly compare the evolution of sequence learning and the formation
195 of chunks in humans and baboons. RTs greater than 1,000ms were excluded as well as RTs
196 greater than 2.5 standard deviations from the subject's mean per block for each of the nine
197 possible positions (1.82% vs. 24,4% for baboons). This difference in the exclusion of outlier
198 values was due to situations in which baboon's first response was not recorded by the
199 computer, because their hands were dirty. In this situation, they had to touch the screen
200 again, and longer RTs were recorded (that were on average twice longer compared to the first
201 responses).

202 **Sequence learning**

203 To get a general index of sequence learning in both species throughout the repeated
204 1,000 trials, we computed on each trial the average of the 9 RTs collected on each of the 9
205 positions of the sequence. This evolution of mean RTs for all participants and for each species
206 is presented in Figure 2 (the baboon data are from Tosatto et al., 2022). A repeated measures
207 ANOVA with Block (1-10) as a within factor and Species (Human v. Baboon) as a between

208 factor was computed on these mean RTs for baboons and humans. In both species, the effect
 209 of Block was highly significant (Block 1, $M_{baboon}=452.8$, $SD=45.3$; Block 10, $M_{baboon}=400.1$,
 210 $SD=56.3$; Block 1, $M_{humans}=311.93$, $SD=63.66$; Block 10, $M_{humans}=166.58$, $SD=44.36$),
 211 $F(1,1)=170.61$, $p<.001$, $\eta^2=0.791$., indicating that mean RTs decreased throughout the blocks
 212 of trials and that monkeys and humans learned the sequence. The effect of Species was also
 213 highly significant, indicating that humans were faster on average than baboons, $F(1,9)=86.88$,
 214 $p<.001$, $\eta^2=0.054$. Finally, the interaction between Block and Species was also highly
 215 significant, showing that RTs decreased faster for humans than baboons, $F(1,1)=22.1$, $p<.001$,
 216 $\eta^2=0.014$.



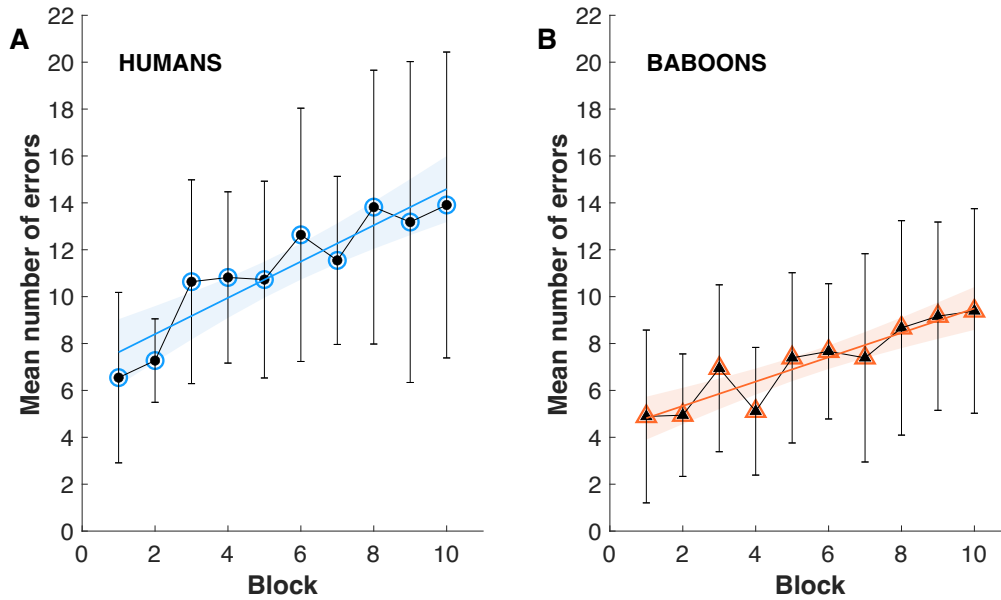
217 **Figure 2:** Evolution of the mean RT per Block for humans and baboons. Mean RTs per block
 218 for humans (blue circles) and baboons (orange triangles), each block contains 100 trials. The
 219 first dot in both curves represents the mean RT for the 10 first trials of the task. The overlap
 220 of RTs in the beginning of the task illustrates how potential motor constraints in the two
 221 species did not influence the initial RTs, but humans show a stronger increase in speed in the
 222 first block of 100 trials.

224 As mentioned in the Participant section, we conducted an ANOVA on the mean
225 response times computed for each participant, each block and over all positions in order to
226 check if there was a difference between the 7 naïve participants and the 4 less naïve
227 participants in the way they learned the sequence. Block was used as a repeated within-
228 participants factor and Group as a between-participants factor. We found no significant effect
229 of Group ($F(1,9)=2.46$, $p=.15$), a significant effect of Block ($F(1,9)=43.23$, $p<.001$), and more
230 importantly, a non-significant interaction effect of Group x Block ($F(1,9)=.83$, $p=.46$). These
231 results suggest that there was no noticeable difference between the naïve and less naïve
232 human participants.

233 For humans and baboons, we also computed the mean number of errors that were
234 produced for each participant and each block of 100 trials (irrespective of error position).
235 Figure 3 shows that the mean number of errors significantly increased in both species along
236 the experiment (for humans: $F(1,8)=45.8$, $p<.001$, Adjusted $R^2= .83$; for baboons:
237 $F(1,8)=49$, $p<.001$, Adjusted $R^2= .84$) indicating that they both produced a speed-accuracy
238 trade-off (i.e., the decrease in RTs was accompanied by an increase in the number of errors).

239

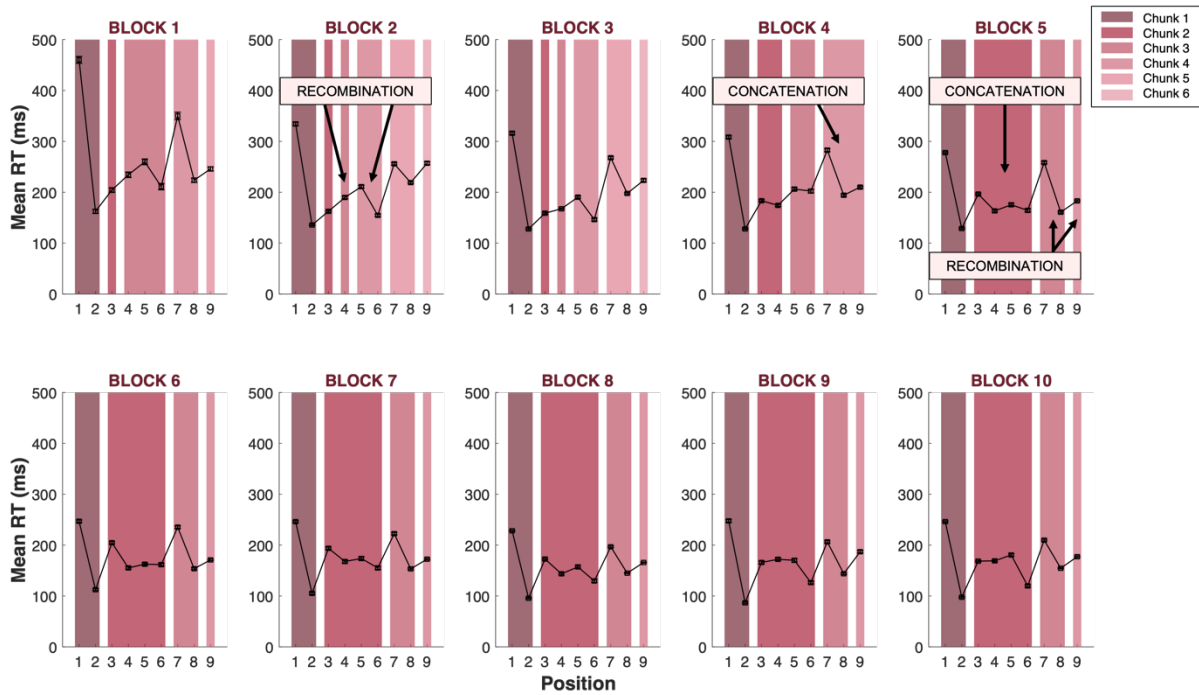
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241
 242 **Figure 3:** Evolution of the mean number of errors per Block for humans and baboons. Mean
 243 number of errors per block for humans (A) and baboons (B). Solid lines represent linear
 244 regressions fitted to each dataset and shaded areas represent predicted 95% confidence
 245 intervals.

246
 247 **Evolution of chunks**

248 To study the evolution of the chunking pattern of the sequence, we adopted the same
 249 method as the one previously used for baboons (i.e., Tosatto et al., 2022). For each
 250 participant, the 1,000 trials were divided into 10 blocks of 100 trials. For each participant and
 251 each block, mean RTs were computed for each of the 9 positions composing the repeated
 252 sequence (see Figure 4 for an illustration this procedure for one participant). For each
 253 participant and each block, the following rule was applied systematically to determine the
 254 chunking pattern on each block. For each successive positions n and $n+1$ of the sequence, if
 255 the mean RT on position $n+1$ was significantly higher than the mean RT on position n , then
 256 this difference was supposed to mark a chunk boundary (Kennerly et al., 2004). Statistical
 257 significance was assessed through paired-sample t-tests for each pair of successive positions
 258 (with a p -value of .01). With this procedure, we obtained a chunking pattern for each
 259 participant and each block, which allowed us to compute the mean number of chunks and the
 260 mean chunk size for each block, and for the entire group of participants (baboons or humans).



261

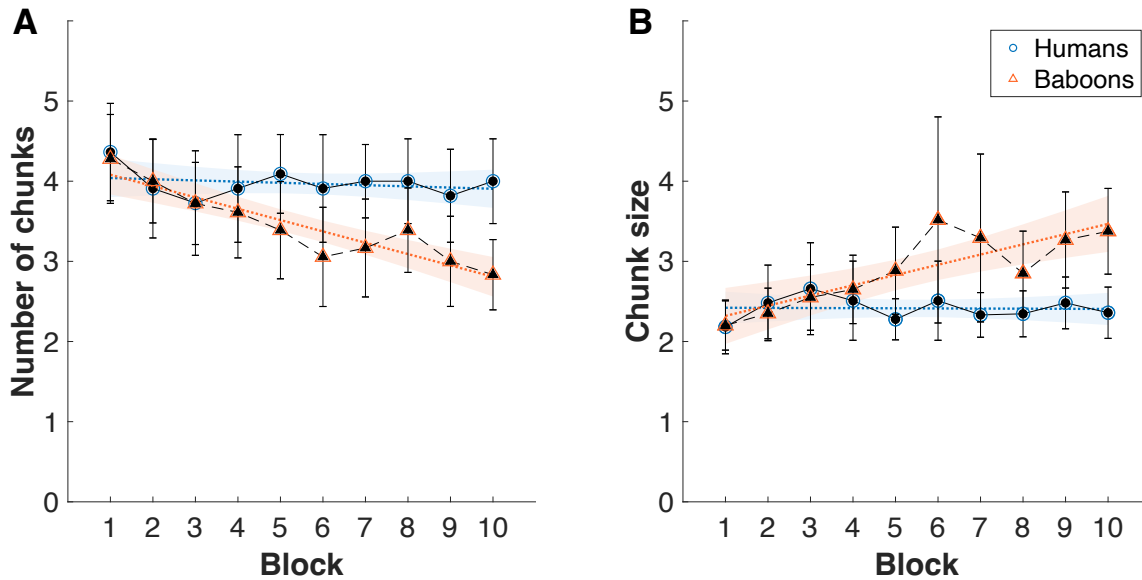
262 Figure 4: Evolution of the chunking pattern for one participant throughout the task. Mean
 263 response times and 95% confidence intervals per block and position for one participant
 264 throughout the experiment. The segmentation of blocks used in this figure is 10 Blocks of 100
 265 trials. The rule we used to identify chunks (i.e., a significant increase between two successive
 266 positions marks a chunk boundary) produced a specific chunking pattern on each block that is
 267 represented by segments of graded colors (one for each chunk). For example, in Block 5, the
 268 sequence was segmented into 4 chunks, the size of each chunk being in that case: 2-4-2-1. An
 269 example of a concatenation is observable between Block 4 and Block 5, where the second
 270 chunk (items 3 and 4) and the third chunk (items 5 and 6) from Block 4 are grouped into a
 271 single chunk in Block 5 (comprising items 3, 4, 5 and 6). An example of a recombination is
 272 observable between Block 1 and Block 2, where the items 4 to 6 are grouped in a single chunk
 273 in Block 1 but are later recombined in Block 2 in two chunks (a chunk comprising item 4 and a
 274 chunk comprising items 5 and 6).

275

276

In both baboons and humans, we conducted two linear regressions on the mean
 277 number of chunks and on the mean chunk size, respectively, using the number of blocks as a
 278 predictor (see Figure 5). In baboons, we observed that the number of chunks significantly
 279 decreased across blocks, $F(1,8)=50, p<.001, \text{Adjusted } R^2=.85$, and that the average chunk size
 280 significantly increased across blocks, $F(1,8)=20.2, p<.01, \text{Adjusted } R^2=.68$. In humans however,
 281 the same analyses showed no significant decrease on the mean number of chunks, $F(1,8)=.59,$
 282 $p=.46, \text{Adjusted } R^2= -.05$, and no significant increase on mean chunk size, $F(1,8)=.01, p=.92,$

283 Adjusted $R^2 = -.12$. A one way ANOVA lead on chunk sizes indicated a significant effect of
 284 Species, $F(1,27)=4.27$, $p=.049$, $\eta^2=.054$, showing a smaller chunk size in humans compared to
 285 baboons ($M_{humans}=2.4$; $SD=0.44$; $M_{baboons}= 2.9$; $SD= .69$).



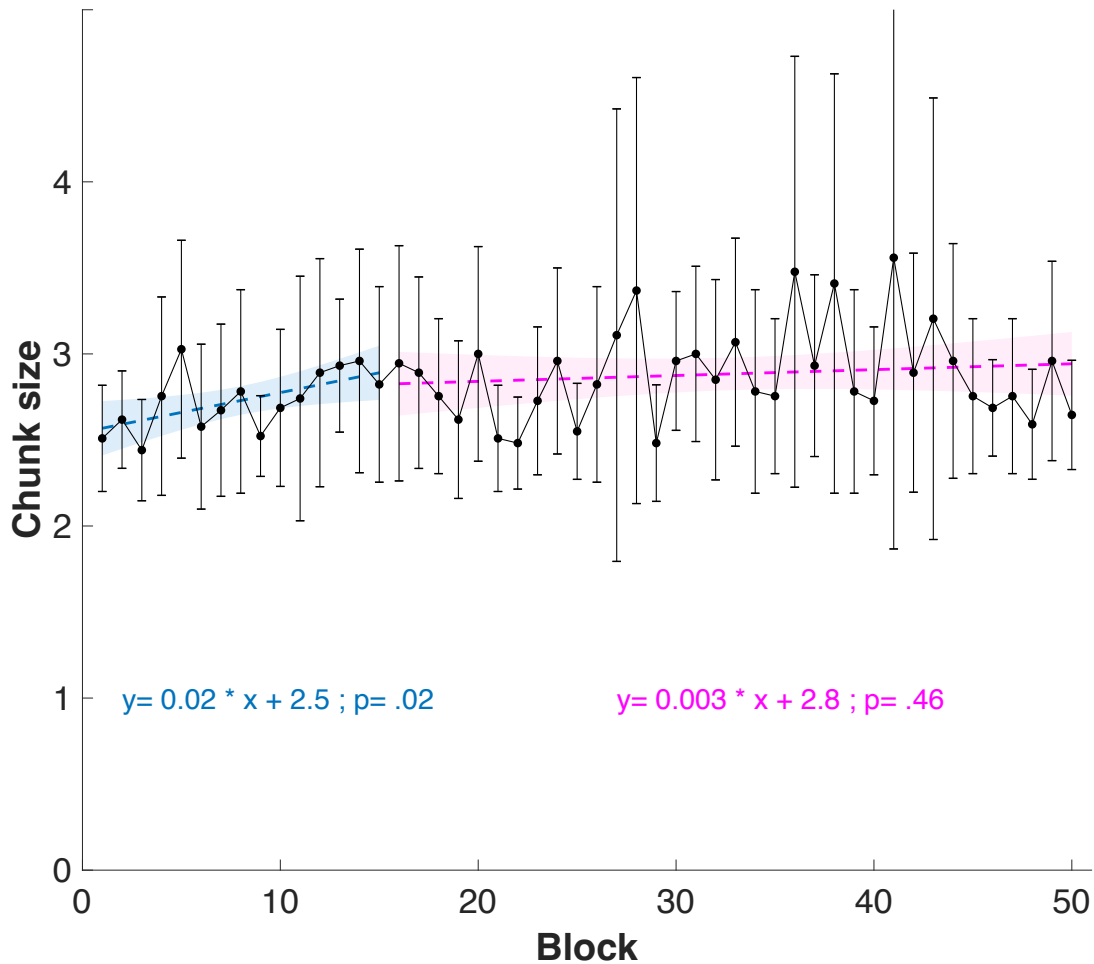
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287 Figure 5: Evolution of chunks in humans and baboons over the whole task. A. Mean number of
 288 chunks per block in humans (blue circles) and baboons (orange triangles). B. Mean chunk
 289 size per block of 100 trials in humans (blue circles) and baboons orange triangles). Dotted lines
 290 represent fitted linear regressions and shaded areas represent predicted confidence intervals.

291

292 However, as indicated by the evolution of the mean RT per Block (i.e., Figure 2), the
 293 dynamics of sequence learning is very different between humans and baboons. Indeed,
 294 baboons appear to have a linear decrease in mean RTs per trial across blocks, whereas mean
 295 RTs in humans decrease rapidly during the first blocks and then, reach a plateau with mean
 296 RTs being smaller on average than 200 ms. To take this evolution into account, we used a
 297 broken stick linear regression (Quandt, 1960) fitted to the mean RT per trial to determine the
 298 slope of the evolution of RTs before and after the plateau (see Supplementary Figure 1). This
 299 analysis confirmed a decrease in RTs for humans during the first 300 trials, with a slope
 300 coefficient of $-.47$ and a flatter slope of $-.04$ later in the task, with a breakpoint after the 299th
 301 trial.

302 Based on this analysis, we looked more closely at the evolution of chunk size during
303 the first 300 trials by dividing the human data in blocks of 20 trials, as well as during the 700
304 last trials. We conducted two linear regressions on these two subsets (i.e., from Trial 1 to 300
305 and from Trial 301 to 1000) on the mean chunk size per Block. Consistent with the results
306 obtained with baboons, we observed a significant increase on mean chunk size, $F(1,13)=6.72$,
307 $p=.02$, Adjusted $R^2=.29$, in the first subset (i.e., from Trial 1 to 300), followed by a stabilization
308 on mean chunk size in the second subset (i.e., from Trial 301 to 1000), $F(1,33)=0.55$, $p=.46$,
309 Adjusted $R^2= -.01$ (see Figure 6). To sum up, these results indicate that mean chunk size per
310 block of 20 trials in humans increases in the first 300 trials and stabilizes in the remainder of
311 the task. When interpreted in light of baboon's data, this analysis suggests that learning
312 followed the same path in the two species, corresponding to an increase in mean chunk size
313 and a decrease in the mean number of chunks. However, the learning process was overall
314 much faster in humans (i.e., within the first 300 trials) than in baboons.



315

316 **Figure 6:** Evolution of mean chunk size in humans over 50 Blocks of 20 trials. Mean chunk size
 317 per block of 20 trials in humans increases in the first 300 trials (in blue) and stabilizes in the
 318 remainder of the task (in pink). Dotted lines represent fitted linear regressions and shaded
 319 areas represent predicted 95% confidence intervals.

320

321 **Chunks reorganizations**

322 Tosatto et al. (2022) showed that chunking patterns in baboons are continuously
 323 reorganized throughout the experiment following two reorganization mechanisms:
 324 concatenations and recombinations. In baboons, these two mechanisms were observed
 325 equally often, and this did not change across the experiment. In humans, the same two
 326 mechanisms were also observed throughout the task and in all subjects (see Figure 3 for an
 327 illustration of each mechanism). To study the distribution of reorganizations, we counted the
 328 number of each type of reorganization for each Block of 20 trials and for each subject (see

329 Table 1). A Block by Mechanism ANOVA analysis revealed an effect of Mechanism, the number
 330 of concatenations ($\Sigma_{concatenations}= 172$) being smaller than the number of recombinations
 331 ($\Sigma_{recombinations}= 205$), $F(1,1)= 6.69$; $p= .03$, $\eta^2= .003$) but no effect of Block ($F(1,48)= .74$; $p= .91$,
 332 $\eta^2= .02$) and no interaction ($F(1,48)= 1.02$; $p= .44$, $\eta^2= .06$).

333 Table 1: Sum of concatenations and recombinations per block.

Block	Concatenation	Recombination	Block	Concatenation	Recombination
2	5	7	27	4	6
3	2	7	28	7	3
4	6	4	29	0	7
5	3	1	30	8	2
6	2	5	31	3	4
7	2	4	32	0	4
8	3	3	33	4	1
9	4	5	34	2	6
10	3	3	35	4	4
11	4	6	36	7	3
12	4	2	37	3	6
13	6	2	38	5	3
14	2	6	39	0	7
15	4	5	40	4	3
16	3	6	41	4	4
17	5	4	42	3	6
18	2	3	43	5	4
19	2	4	44	3	3
20	4	0	45	3	4
21	2	7	46	3	3
22	5	4	47	2	4
23	5	2	48	2	4
24	4	5	49	6	3
25	0	5	50	3	7
26	5	4	-	-	-
Total				172	205

334

335 **Discussion**

336 This study’s primary goal was to compare humans and baboons in a similar sequence
 337 learning task to analyze the dynamics of the evolution of chunks and the underlying

338 mechanisms shared between species. Tosatto et al. (2022) showed that baboons learn the
339 overall sequence of 9 items as their mean RT decreases throughout blocks of trials, with a
340 mean 53 ms decrease between Block 1 and 10 for all baboons. Additionally, baboons initially
341 segment the sequence into small chunks of items that are reorganized throughout learning
342 via two mechanisms: concatenations and recombinations. Thanks to these reorganizations,
343 chunks become progressively larger and fewer while the sequence is learned.

344 In the present study, we asked human participants to perform the self-paced sequence
345 learning task administered to baboons by implementing very similar experimental conditions.
346 We first found that mean RTs per block decreased significantly faster for humans than for
347 baboons. Humans learnt the sequence more rapidly and reached a plateau performance after
348 the third block (i.e., 300 trials), with a mean 166 ms decrease between Block 1 and 10. This
349 larger difference could be explained by a difference in general learning skills between human
350 and baboons. Indeed, it has been suggested that there are both quantitative and qualitative
351 differences in learning among animals, with different species learning at different rates
352 (Bitterman, 1965; 1975). It has also been shown that more trials are required to master the
353 same sequential memory task in other species compared to humans (e.g., Ghirlanda et al.,
354 2017). Moreover, a fundamental difference between humans and baboons is the use of
355 language and verbal recoding (also called explicit-declarative cognition, Smith and Church,
356 2018), which could mediate the difference in learning rates. Humans can indeed recode the
357 task verbally and explicitly notice that the same sequence is repeatedly presented. A verbal
358 encoding of the sequences might affect their processing, as suggested by Rey et al. (2019) who
359 also found processing differences between humans and baboons in a pointing task of 9-items,
360 but with a much more complex sequence structure (3 subsequences of 3 items were here
361 randomized to form on each trial a different sequence of 9 items). In this study, both baboons

362 and humans were able to extract local regularities but only humans managed to learn the
363 underlying complete global structure of the 9-item sequences, an ability hypothesized to be a
364 by-product of human explicit-declarative skills.

365 Analogously, in our study, humans may perform the task more explicitly than baboons:
366 the small but significant decrease in RT in baboons indicate that they are still tracking the
367 target after 1,000 trials. They are able to predict the next target or the few next targets that
368 are part of the same chunk, but may be unable to completely extract the structure of the 9-
369 items sequence or may need more trials to do so. Humans, however, show a fast and strong
370 decrease in RTs, and appear to switch from a purely pointing task, in which they track a target,
371 to a task where they perform a motor sequence from memory. This evolution is consistent
372 with the predictions of the Dual Processor Model (Verwey, 2001), in which a cognitive
373 processor plans the structure of actions towards a goal and a motor processor executes the
374 movements appropriate to the goal. In this view, while performing a familiar sequence, the
375 processing load weighting on the cognitive processor is reduced and there is a greater
376 involvement of the motor processor. Verbal reports from our human participants also indicate
377 that they were all conscious that the stimuli formed a repeated sequence. However, most
378 participants were unable to verbalize specific strategies used to perform the task. One
379 participant mentioned that she spontaneously had a rhythm associated with a melody in mind
380 while performing the sequence but could not remember if she had used the melody to
381 segment the sequence while learning, or if this melody strategy appeared after the sequence
382 was learned.

383 Another factor influencing the evolution of mean RTs is related to the evolution of
384 accuracy in participants, i.e., the presence of a speed-accuracy trade-off. Indeed, it is well-
385 known that, during the automatization of a task, the speed gain results in a decrease in

386 accuracy, which is observed in many cognitive tasks (e.g., sequence learning, Vekony et al.,
387 2020; decision making, Standage et al., 2015; see Heitz, 2014 for a review). Here, we observe
388 that the mean RTs decrease throughout the task but this is at the cost of an increase of errors.
389 One might think it is an odd outcome that practice leads to more errors, but it certainly results
390 from a shallower processing of the overall sequence and an increased speed in performance.
391 This trade-off is present in both species, but the decrease in RTs and increase in errors are
392 more pronounced in humans indicating that, while baboons increase in speed throughout the
393 task, they are also maintaining a more accurate performance. The different pattern of speed
394 accuracy trade-off in the two species could be explained by the different goals towards which
395 each species is performing the task. Indeed, reward is given after each trial for both species
396 but the outcome after an error is slightly different for baboons and humans. Baboons get a
397 food reward if the trial is correctly executed but no reward and a green screen after an error.
398 Baboons are therefore more motivated to execute the sequence correctly and this accuracy
399 goal comes at the cost of speed. On the other hand, humans get an indication of their
400 progression after each trial as a reward, which could orient their goal towards the end of the
401 task and motivate them to prioritize speed over accuracy. Even in the case of an error, humans
402 seemingly get the same aversive stimulus as baboons, a green screen that increases the time
403 until the next trial. But they can quickly understand that failed trials are not presented again
404 as they are aware of their progression in the task. Therefore, an error in the human
405 experiment does not cost the human their reward, whereas in the baboon experiment, it does,
406 as the reward, i.e., food, is lost.

407 These differences in the evolution of mean RT also seem to impact the evolution of
408 chunks, which is our second main result. We initially used the same segmentation of blocks
409 (i.e., 100 trials per block) to compare the evolution of chunks in the two species. While the

410 literature has reported an increase in chunks size in some cases in humans, we could not find
411 it here and it was also very different from the dynamics observed in baboons. However, this
412 was done before considering the difference in learning rates between these species, and
413 closely looking at the mean RT in humans informed us on their general learning of the
414 sequence, which was strongly related to the dynamics of chunking (Sakai et al., 2003). We
415 found that the main sequence learning processes occurred during the first 300 trials as
416 performance then reached a plateau in speed, and by segmenting these trials in finer blocks,
417 we observed the same dynamic of increase in chunk size as in baboons. This suggests that
418 sequence learning processes rely on the same general associative learning mechanisms in
419 both humans and baboons, but differ in their temporal course due to the way humans and
420 baboons performed the task. It is also worth noting that the mean chunk size is becoming
421 larger in baboons compared to humans throughout the task. While we were unable to
422 determine the reason for this difference, we can hypothesize that humans may not need to
423 compress the information as much as baboons to memorize this sequence, allowing them to
424 hold more small chunks in working memory, rather than producing larger chunks. In this view,
425 it would be interesting to confront humans to longer sequences in future experiments, as a
426 sequence more challenging for their working memory may lead them to form larger chunks.

427 Finally, our third main result deals with the mechanisms underlying the evolution of
428 chunks, namely concatenations and recombinations. In this study, we found that the same
429 mechanisms found in baboons were present in humans, with a significant predominance of
430 recombinations over concatenations. As it was suggested for baboons (Tosatto et al., 2022),
431 the presence of concatenations suggest that when two chunks are stable, they could be
432 concatenated more easily into one. On the other hand, recombinations would be a way to
433 make the chunking pattern evolve by testing a better combination of chunks, both easier to

434 perform from a motor point of view and easier to integrate in memory. In this view, it is
435 possible that motor chunks could be more flexible in humans, hence leading to a greater
436 number of recombinations. More specifically, it appears that reorganizations do not
437 completely stop after the chunk size has stopped evolving (we found no significant effect of
438 Block on reorganizations). This could indicate that humans are still trying to optimize their
439 motor performance after chunks have reached an optimal size, which again corroborates the
440 idea that motor processes are dominant in the last part of the task when the sequence is very
441 familiar, and the only stake is a fast performance.

442 Overall, these data provide new evidence on the dynamics of chunking in human and
443 non-human primates during sequence learning, the features of these dynamics that are
444 shared by these species, and the specificity of human performances. This is, to our knowledge,
445 the first attempt at comparing humans and non-human primates in the closest conditions
446 possible in a sequence learning task and at implementing a completely self-paced task in
447 humans. The fact that both species share the same chunking dynamics during the initial phase
448 of learning suggest that these associative learning mechanisms have a long evolutionary
449 history that certainly precedes the emergence of both species.

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459

Open Practices Statements

460 Data from the experiment in humans are available on Open Science Framework at
461 https://osf.io/pnv43/?view_only=e9774b7201944064ba4623dd0ba22721 and data from the
462 experiment in baboons are available on the same platform at <https://osf.io/xcw95/>.

463

Conflict of Interest

464 LT, JF, and AR declare that they have no conflict of interest.

465

Ethics Statement

466 All procedures in the present experiments involving human participants were
467 performed in accordance with the ethical standards of the institutional and/or national
468 research committee and with the 1964 Declaration of Helsinki and its later amendments or
469 comparable ethical standards. Written consent was obtained from all participants in this
470 study.

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554 **Appendix A**

555 *Mean response times over 10 participants for each of the 72 possible transitions calculated*
 556 *from 180 random trials.*

1 st position in Transition	2 nd position in Transition								
	1	2	3	4	5	6	7	8	9
1	-	524	527	574	457	499	549	559	566
2	567	-	535	534	465	491	531	517	591
3	564	507	-	537	439	514	525	513	615
4	573	499	516	-	440	482	578	519	551
5	571	511	514	535	-	486	534	508	561
6	577	500	516	525	456	-	533	498	585
7	589	506	542	530	431	491	-	505	568
8	576	535	534	522	438	473	532	-	557
9	575	523	522	543	431	483	534	513	-

557 *Note.* All transitions are in milliseconds (ms) and correspond to the time elapsed between the
 558 disappearance of the red circle from the 1st position of the Transition and the participant's touch on the 2nd
 559 position of the Transition.