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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

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

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

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

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

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

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

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

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

Method

Participants

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

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

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

Materials

Apparatus and stimuli

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

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

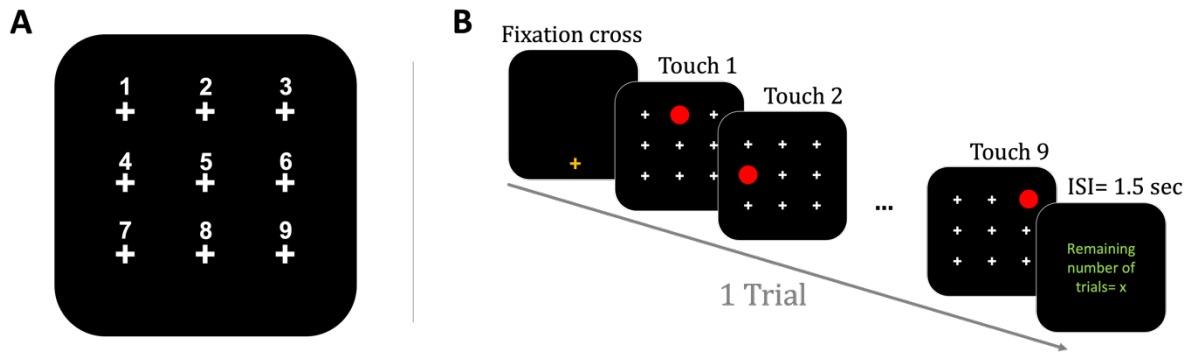

Figure 1: Experimental display and stimulus presentation. A. Display of the 9 equidistant predetermined locations (white crosses) virtually labeled as position 1 to 9 (i.e., only the white crosses were displayed, not the numbers). B. Example of a single trial. After a first touch on the fixation cross,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

Design of the sequences

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

Based on these baseline measures, we designed two sequences of nine serial positions for which each transition T was faster (or equally fast) to produce than the next one (i.e., T1≤T2≤…≤T8, with T1 being the transition from Position 1 to Position 2 of the sequence). This way, a decrease in RT for a given transition can be interpreted as the anticipation (or learning) that Position *n* is following Position *n-1*. To control for a specific sequence bias, we designed two sequences, each participant being assigned randomly either with Sequence 1 or 2.

Procedure

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

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

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

Results

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

Sequence learning

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

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

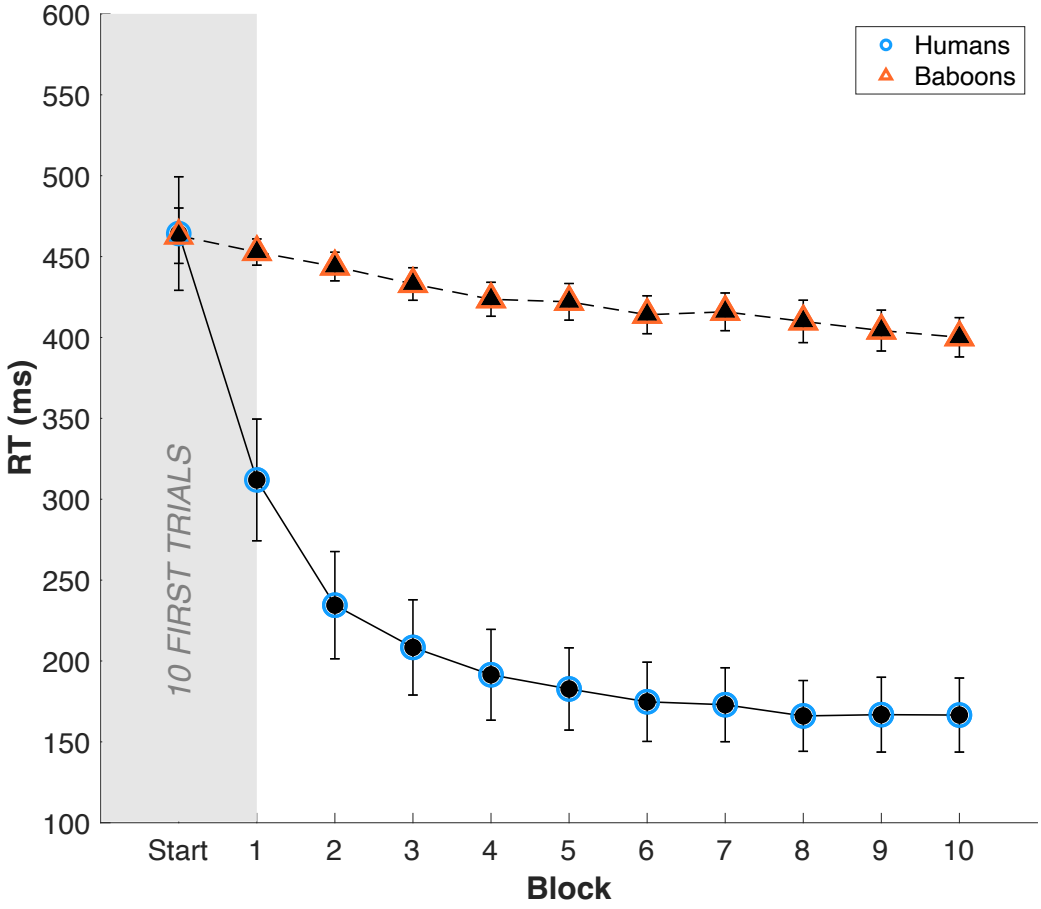

Figure 2: Evolution of the mean RT per Block for humans and baboons. Mean RTs per block for humans (blue circles) and baboons (orange triangles), each block contains 100 trials. The first dot in both curves represents the mean RT for the 10 first trials of the task. The overlap of RTs in the beginning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

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

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

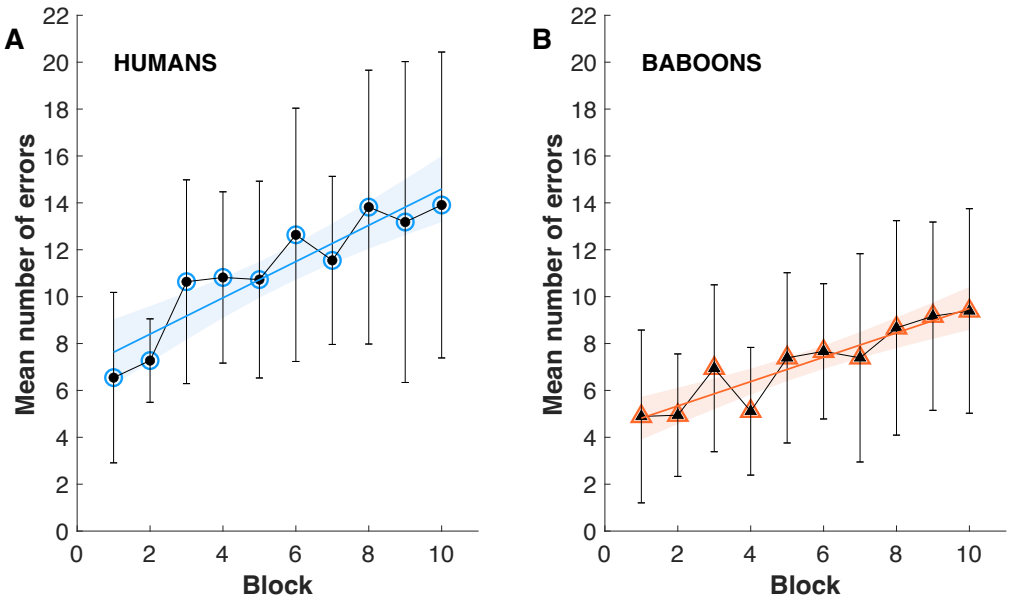

Figure 3: Evolution of the mean number of errors per Block for humans and baboons. Mean number of errors per block for humans (A) and baboons (B). Solid lines represent linear regressions fitted to each dataset and shaded areas represent predicted 95% confidence intervals.

Evolution of chunks

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

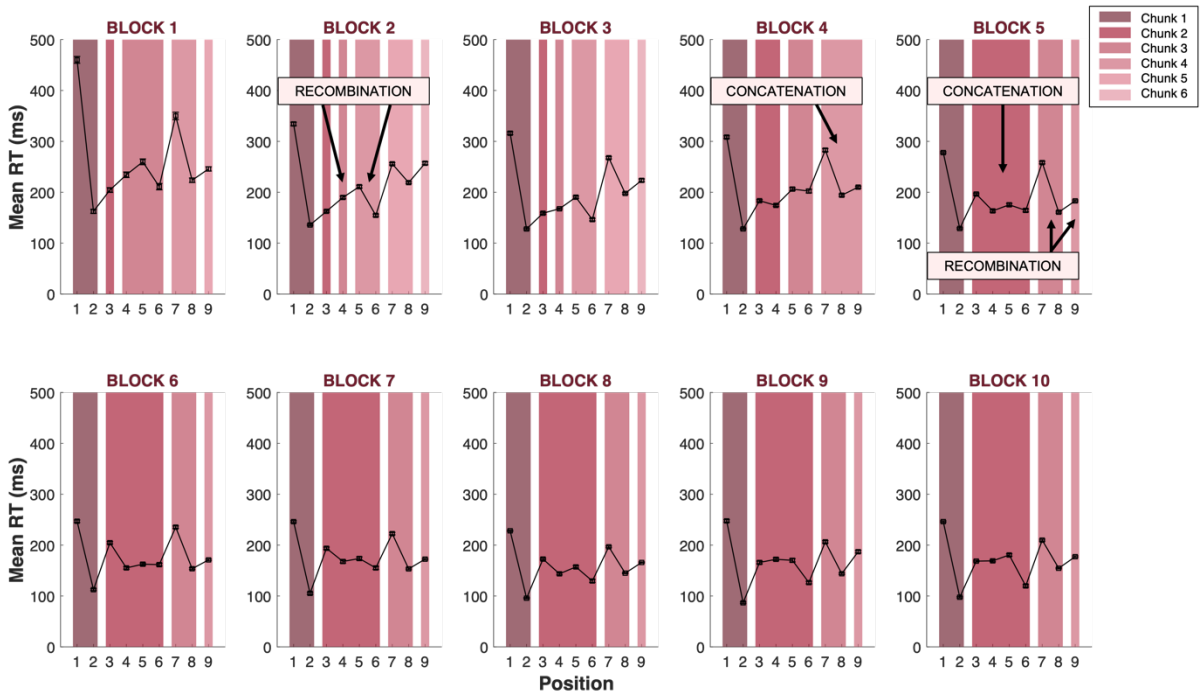

Figure 4: Evolution of the chunking pattern for one participant throughout the task. Mean response times and 95% confidence intervals per block and position for one participant throughout the experiment. The segmentation of blocks used in this figure is 10 Blocks of 100 trials. The rule we used to identify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

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

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

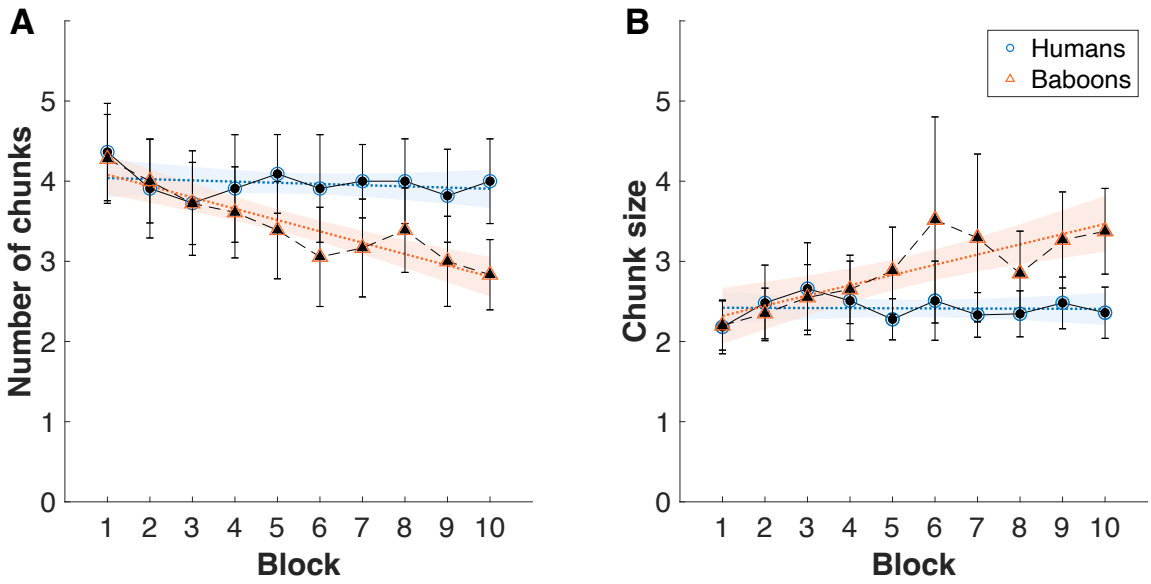

Figure 5: Evolution of chunks in humans and baboons over the whole task. A. Mean number of chunks per block in humans (blue circles) and baboons (orange triangles). B. Mean chunk size per block of 100 trials in humans (blue circles) and baboons orange triangles). Dotted lines represent fitted linear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

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

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

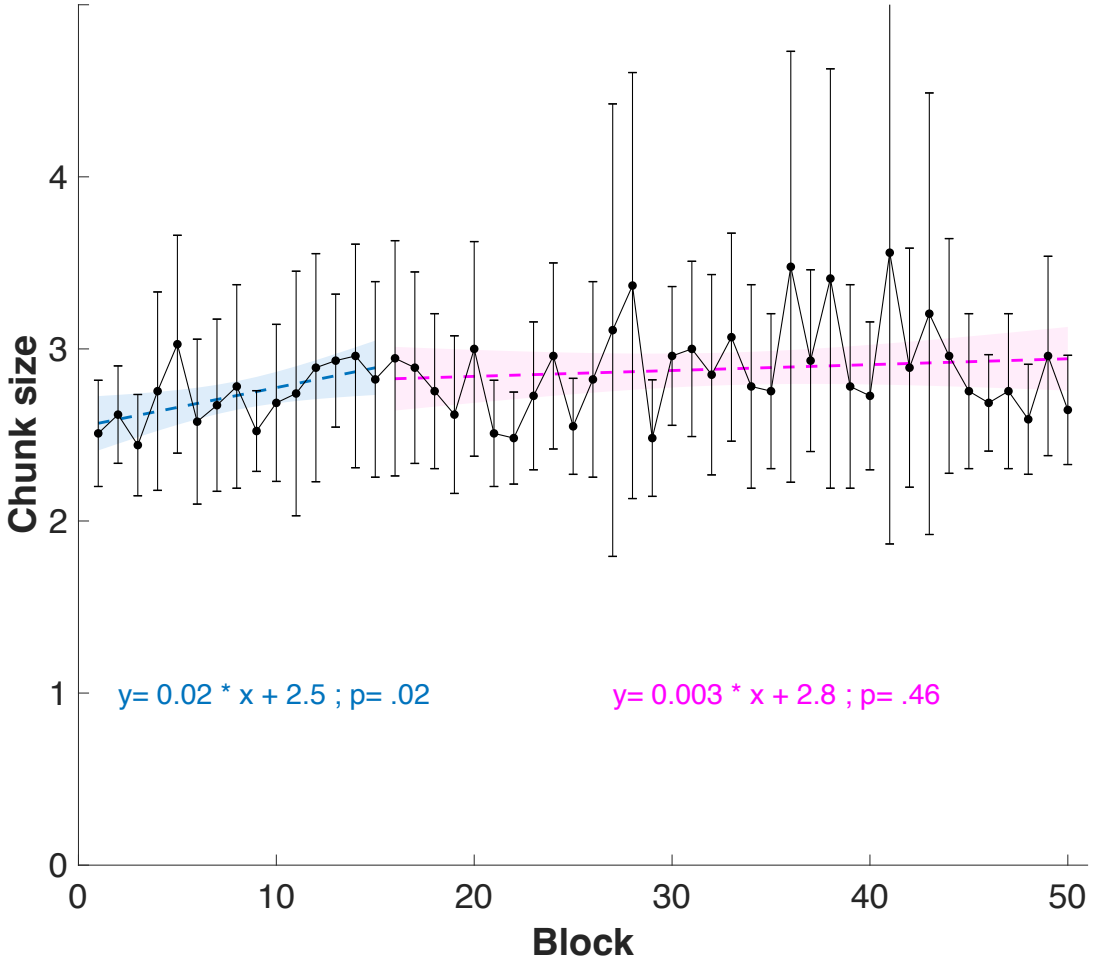

Figure 6: Evolution of mean chunk size in humans over 50 Blocks of 20 trials. Mean chunk size per block of 20 trials in humans increases in the first 300 trials (in blue) and stabilizes in the remainder of the task (in pink). Dotted lines represent fitted linear regressions and shaded areas represent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

Chunks reorganizations

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

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

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

Discussion

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

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

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

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

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

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

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

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

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

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

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

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

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Open Practices Statements

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

Conflict of Interest

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

Ethics Statement

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

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Appendix A

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

1st position in Transition	2nd 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	-

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