

Sequence Learning and Chunk Stability in Guinea Baboons (Papio papio)

Laure Tosatto, Joël Fagot, Arnaud Rey

▶ To cite this version:

Laure Tosatto, Joël Fagot, Arnaud Rey. Sequence Learning and Chunk Stability in Guinea Baboons (Papio papio). Revue de Primatologie, 2023, 14 (14), pp.69-81. 10.4000/primatologie.16706 . hal-04370157

HAL Id: hal-04370157 https://hal.science/hal-04370157

Submitted on 2 Jan 2024

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers. L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

Sequence Learning and Chunk Stability in Guinea Baboons (Papio papio)

Apprentissage de séquence et stabilité des chunks chez les babouins de Guinée (*Papio papio*)

Laure Tosatto, Aix Marseille Univ, CNRS, LPC, Marseille, France & Aix Marseille Univ, ILCB, Aix-en-Provence, France, auteur pour la correspondance : <u>laure.tosatto@univ-amu.fr</u>

Joël Fagot[,] Aix Marseille Univ, CNRS, LPC, Marseille, France & Aix Marseille Univ, ILCB, Aixen-Provence, France & Station de Primatologie Celphedia, CNRS, Rousset, France joel.fagot@univ-amu.fr

Arnaud Rey, Aix Marseille Univ, CNRS, LPC, Marseille, France & Aix Marseille Univ, ILCB, Aixen-Provence, France

arnaud.rey@cnrs.fr

Abstract

Chunking mechanisms, the processes of grouping several items together into a single processing unit, are central to several cognitive processes in human and non-human primates and notably to the acquisition of visuomotor sequences. Individuals segment sequences into chunks to perform visuomotor tasks more fluidly, rapidly, and accurately. Using an operant conditioning device, we previously studied the precise mechanisms by which chunks are formed and reorganized during sequence learning. Eighteen Guinea baboons (Papio papio) repeatedly produced the same fixed sequence of nine movements during 1,000 trials by pointing to a moving target on a touch screen. We found that chunking patterns are reorganized during the course of learning, with chunks becoming progressively fewer and longer. We also identified two forms of reorganization of the chunking pattern: the recombination of preexisting chunks and the concatenation of two distinct chunks into a single one. To understand the conditions under which these reorganizations occur, we study here how the stability of a chunk and the stability of chunk boundaries are related to these reorganizations. Our analyses showed that less stable chunks and less stable boundaries are more likely to produce reorganizations. These results provide new evidence about the finegrained dynamics of chunking mechanisms during sequence learning.

Keywords: sequence learning; associative learning; chunking

Résumé

Les mécanismes de chunking, processus par lesquels plusieurs items sont regroupés pour former une unité fonctionnelle, sont centraux dans de nombreux processus cognitifs chez les primates humains et non-humains, et particulièrement lors de l'acquisition de séquences visuomotrices. Les individus segmentent les séquences en *chunks* pour réaliser les tâches visuomotrices plus fluidement, rapidement et précisément. L'utilisation d'un système de conditionnement automatique nous a précédemment permis d'étudier les mécanismes précis par lesquels ces chunks sont formés et réorganisés durant l'apprentissage de séquences. Dix-huit babouins de Guinée (Papio papio) ont répété la même séquence fixe de neuf mouvements durant 1000 essais lors d'une tâche de pointage d'une cible mouvante sur écran tactile. Nous avons constaté que les patterns de *chunking* sont réorganisés au cours de l'apprentissage, les chunks devenant progressivement moins nombreux et plus longs. Nous avons également identifié deux formes de réorganisation du pattern de chunking : la recombinaison de chunks préexistants et la concaténation de deux chunks distincts en un seul. Pour comprendre les conditions dans lesquelles ces réorganisations se produisent, nous étudions ici comment la stabilité d'un chunk et la stabilité des frontières entre chunks sont liées à ces réorganisations. Nos analyses montrent que les chunks et les frontières moins stables sont les plus susceptibles de produire des réorganisations. Ces résultats apportent de nouvelles informations sur la dynamique fine des mécanismes de chunking au cours de l'apprentissage de séquences.

Mots-clés : apprentissage de séquences ; apprentissage associatif ; chunking

Introduction

As individuals in constant interaction with the environment, primates evolve in a continuous stream of stimulations that trigger behavioral responses. Most behaviors are produced sequentially and learning rapidly and efficiently long sequences of actions represents an evolutionary challenge. This is the case for humans, especially for language processing and production (Conway & Christiansen, 2001; Lashley, 1951; Petkov & Ten Cate, 2020), but more broadly in all primate communication systems, where sequences can be long and complex (Aychet, Blois-Heulin & Lemasson, 2021; Habib-Dassetto, Montant & Reboul, this issue; Ouattara, Lemasson & Zuberbülher, 2009).

An important constraint rendering the learning of long sequences difficult is the natural limits of short-term memory (Cowan, 1988, 2017). To bypass these limits, a core cognitive mechanism allowing the compression of information, and increasing short term memory capacity, is the formation of chunks (Mathy & Feldman, 2012; Miller, 1956). Indeed, chunking is usually defined as the process of associating and grouping several items together into a single processing unit (Gobet & al, 2001; Gobet, Lloyd-Kelly and Lane, 2016).

To understand the general learning mechanisms shared by primates and involved in sequence learning and chunking, motor sequence learning tasks have been widely used in comparative psychology, where motor sequence learning is defined as the process by which a specific sequence of movements is executed with increased speed and accuracy (Willingham, 1998). In this field, chunking is widely considered as the main motor sequence integration mechanism (Diedrichsen & Kornysheva, 2015; Wymbs et al., 2012), and is commonly believed to be rooted in elementary associative processes (i.e., Perruchet & Vinter, 2002; Rey et al., 2019). Indeed, several primate species 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, *Homo sapiens*, Abrahamse et al., 2013; Bottary et al., 2016; in rhesus monkeys, *Macaca mulatta*, Scarf et al., 2018, Terrace, 2002; in baboons, *Papio papio*, Tosatto et al., 2022).

Furthermore, as the input's representation might evolve during learning, some studies were also interested in the temporal aspect of chunking and how chunking patterns change 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 is the concatenation of chunks (Verwey, 2001; Wright et al., 2010), i.e., 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).

We have recently conducted a study on Guinea baboons (*Papio papio*) on the role of extended practice in the formation and the evolution of chunks (Tosatto et al. 2022). 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. In accordance with the literature, this study found an increase in chunks size throughout the repeated production of the sequence. However, we also observed two (instead of one) forms of reorganizations of the chunking pattern. Indeed, as in previous studies, we observed *concatenations*, but we also observed another mechanism, *recombinations*, i.e., the emergence of a new segmentation pattern – such as two chunks of 3 items becoming a chunk of 4 items followed by a chunk of 2 items. Thus, recombinations seem to also lead to an increase in chunk size but necessitate a previous chunk to be resegmented. These findings show that linear associations between adjacent elements or a

hierarchical organization of the sequence do not seem to be the only mechanisms at work during sequence learning, and that chunks may be more flexible than previously thought (Diedrichsen & Kornysheva, 2015; Rosenbaum et al., 1983; Sakai et al., 2003; Fonollosa et al., 2015).

To explain this variability in the types of reorganizations observed, we hypothesized the role of two main parameters: (1) the internal stability of chunks; (2) the stability of chunk boundaries. Indeed, stable chunks might be less likely to be resegmented from one block to another and survive throughout the task, whereas a less stable chunk might be more likely to disappear (see the Results Section for an operational definition of chunk stability and chunk boundary stability). Similarly, a stable chunk boundary might be less likely to disappear throughout the task than a less stable one.

In this study, we propose to enrich our understanding of these reorganization phenomena by suggesting a method to assess the internal stability of a chunk and the stability of a boundary between two chunks. Considering the large dataset provided by Tosatto et al. (2022) and the many occurrences of chunk reorganizations it contains, using dedicated posthoc analyses, we attempt at shedding light on the link between these parameters and the evolutions of the chunking pattern throughout this experiment.

Method

Fully detailed method and materials can be found in Tosatto and al. (2022).

Participants

Thirteen female and five male Guinea baboons (*Papio papio*, age range 2.8–23.7 years) from the CNRS primate facility in Rousset (France), living in a social group of 25 individuals, were tested in this study. For practical reasons, we stopped the experiment after 18 monkeys completed all scheduled trials.

Materials

This experiment was conducted with a computer-learning device based on the voluntary participation of baboons (for details, see Fagot & Bonté, 2010). Baboons had free access to operant conditioning learning devices equipped with touch screens. The screen was divided into nine equidistant predetermined locations represented by white crosses on a black background, virtually labeled as position 1 to 9 (see Figure 1).

<insert Figure 1 here>

A trial began with the presentation of a yellow fixation cross at the bottom 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 red circle then replaced the next position in the sequence until it was touched, and a new position was displayed. Reward was provided at the end of a sequence of nine touches. The time elapsed between the appearance of the red circle and the baboon's touch on this circle was recorded as the RT.

Procedure

Baboons were either presented with a single sequence (each baboon was either trained on Sequence 1, N=8, or Sequence 2, N=10, and never received the other sequence) and had to produce it for 1000 successive trials. RTs for each position of the sequence were recorded for all the trials.

Results

Previous results summary

To observe the chunking pattern at different stages of learning, RTs for each of the nine positions and for the 1,000 trials were divided into 10 Blocks of 100 trials, and we identified the chunking pattern for each baboon at each block by computing mean RTs per

CHUNK STABILITY IN BABOONS

position over each block of 100 trials. The identification of chunks relied on identifying chunk boundaries by isolating significant increases in the successive responses to each position in the sequence. Practically, for each block of 100 trials, the mean RT for Position n and n+1 were computed and if the mean RT for Position n+1 was significantly higher than the mean RT for Position n, then this difference was taken as marking a boundary between two chunks. More details about this procedure can be found in Tosatto et al. (2022). Figure 2 illustrates the chunking pattern of a single baboon (Ewine) and its evolution throughout the task.

<insert Figure 2 here>

Three main findings were obtained in this previous study. First, in line with the literature, baboons spontaneously segmented the long sequences into short chunks at the beginning of the task. Second, with extended practice, chunks became longer and fewer. Third, the number of chunks and the increase in chunks' size was due to two types of reorganizations: the recombination of several preexisting chunks and the concatenation of two distinct chunks into a single one. For instance, in Figure 2, at Block 2, Positions 6 to 9 are grouped into two chunks of two items each (6-7/8-9). However, at Block 3, a new segmentation pattern has emerged: Position 6 is no longer grouped with Position 7, as the mean RT for the latter has significantly increased. Position 7 and 8 are now grouped into a chunk, while the mean RT for Position 9 has increased and it is no longer grouped with Position 8. The change in chunking pattern for these Positions between Blocks 2 and 3 is an example of recombination. An example of concatenation can be found on the same figure between Blocks 9 and 10 for Positions 1 to 5. During Block 9, these positions are grouped as two distinct chunks of respectively three and two items. At Block 10, the mean RTs for Positions 4 and 5 decrease, making the boundary between Positions 3 and 4 disappear and leading to a single chunk of five items. Finally, these evolutions of the chunking pattern were accompanied by a

significant decrease of the mean response time in all baboons. This result suggests that the formation of chunks and their modification accelerated sequence production, confirming that chunking fosters learning and increases performance fluency.

Post-hoc analyses

Proxies for inferring chunk and boundary stability

Our main goal here is to acquire a better understanding of chunks reorganizations and why chunks either survive from block to block or are reorganized. We hypothesize that the stability of a chunk plays a key role in its survival. One way of looking at the stability of a chunk is to consider the decrease in RT between the successive positions within this chunk. Indeed, if we observe a strong decrease in the successive response times within a chunk, we can qualify this chunk as very stable. For example, if we look at the performance of the baboon Ewine in Block 4 (Figure 2), it appears that in the first chunk (grouping Positions 1-3), the decrease in RTs from one position to the next is relatively strong while the decrease in RTs for the second chunk (grouping Positions 4 and 5) is lower. Following our reasoning, the probability of the first chunk being reorganized would therefore be lower than for the second chunk.

Practically, the large difference in milliseconds between each response time within a chunk will result in a large standard deviation among all RTs. We thus propose to take the within standard deviation (WSD) of responses belonging to the same chunk as a proxy of its stability and assess the link between this value and the survival of the corresponding chunk throughout the blocks of trials. Similarly, we hypothesize that the stability of a boundary between two chunks strongly depends on the difference between the mean RT on the last position of the first chunk and the mean RT on the first position of the next chunk. The larger

the difference, the stronger the stability of the boundary and the greater the probability the boundary will survive from Block to Block.

Figure 3 provides a schematic illustration of these propositions for a sequence of nine positions. Here the sequence is artificially segmented into three chunks of three positions. The first chunk includes Positions 1-3 and due to the large differences in RTs between each of these positions, the resulting WSD is also quite large, suggesting that the chunk is rather stable. Similarly, the difference between the mean RT in Position 3 (last position of the first chunk) and the mean RT in Position 4 (first position of the second chunk) is large indicating that the chunk boundary is quite stable. Due to smaller WSDs, the second and third chunks are certainly less stable and the same goes for their boundary with a smaller difference between Positions 6 and 7. We therefore predict that the last two chunks should give rise to reorganizations, while the first chunk should not change over the course of repetitions.

<insert Figure 3 here>

Chunk stability

To quantify the survival of a chunk from one block to the next, we used the following method: if a chunk is present in Block n, it is considered as surviving in Block n+1 if either the chunk is exactly the same in Block n+1 or it belongs to a larger chunk. We assessed the effect of WSD on chunk survival using a logistic binomial regression model in which chunk survival is coded 1 and 0 otherwise. Chunks composed of only one position were excluded from this analysis considering they necessarily have a WSD of 0 and a 100% chance of surviving from one block to the next.

The logistic regression was highly significant $X^2(1, N = 421) = 20.8$, p< .001 and indicated that the likelihood of chunk survival increased with stability, and that each millisecond added

to a chunk's WSD increased its chances of survival in the next block by 3% (OR=1.030; 95% CI [1.015, 1.045], see Figure 4A).

Boundary stability

Here again, we propose that the stability of a chunk boundary is simply reflected by the difference between the mean RT for the last position of the first chunk and the mean RT for the first position of the second chunk. The greater the difference, the greater the probability of survival of the boundary in the next Block should be. To quantify the boundary survivals from one block to the next, we simply assessed for each boundary present at Block n whether it was still marking a chunk boundary at Block n+1.

We used a second logistic regression to assess the relationship between the stability of the chunk boundary and its survival (survival=1; 0 otherwise) in the next block of trial. The logistic regression was highly significant $X^2(1, N=407) = 70.4$, p< .001 and indicated that likelihood of boundary survival increased with its stability, and that each millisecond added to the size of the boundary increased its chances of survival in the next block by 5.7% (OR=1.057; 95% CI [1.038, 1.076], see Figure 4B).

<insert Figure 4 here>

Discussion

There were two main findings in the present study. First, we found that there is a strong link between the internal stability of a chunk and its survival over different stages of learning. Indeed, very stable chunks, as evidenced by their large within standard deviation, are more likely to survive from block to block during a sequence learning task. Conversely, less stable chunks are more likely to be reorganized differently from block to block. Second, we found that the stability of a boundary between two chunks is also strongly linked with its survival. Similarly to chunk stability, very stable boundaries, as evidenced by their larger size,

CHUNK STABILITY IN BABOONS

are more likely to survive from block to block. Therefore, both the internal stability of chunks and the stability of chunk boundaries likely determine the survival of a chunking pattern or its reorganization.

These results, although arising from post-hoc analyses, suggest that the role of these parameters – chunk stability and boundary stability – need to be studied further to understand the complex dynamics underlying the evolution of chunking patterns during sequence learning. However, we are not yet able to precisely link these reorganizations – recombination or concatenation - to the variations of these parameters. Indeed, for instance, chunk stability can predict chunk survival, but a chunk can survive (e.g., not being segmented) while still being concatenated with another chunk. Therefore, chunk survival does not indicate the absence of reorganization. Similarly, a boundary can disappear between two chunks and lead to a concatenation, but a new boundary can appear simultaneously on the same chunk and a recombination will be observed. This is the case in Figure 2, between Blocks 2 and 3, where the disappearance of the boundary between Positions 7 and 8 would have led to a concatenation, but two new boundaries have appeared between Positions 6 and 7 and Positions 8 and 9. Therefore, our predicted outcomes (chunk survival and boundary survival) are not themselves predictors of a particular type of reorganization. Understanding what determines either type of reorganizations most likely requires studying the interaction between these parameters (chunk and boundary stability), which we were not able to do on this limited dataset.

Although these parameters seem to clearly play a role in the evolution of the chunking pattern, modeling the evolution of this dynamical system still remains to be done. One way to further explore the role of these parameters and their interaction would be to design an experiment where chunk stability and boundary stability would be manipulated. We could

CHUNK STABILITY IN BABOONS

test, for example, a situation where two successive chunks have a strong internal stability and are separated by a stable or less stable boundary. As the realization of the second chunk would become more efficient, leading to a lower difference between the last RT of the first chunk and the first RT of the second chunk, we would then predict a higher probability for these chunks to concatenate into a single one, depending on the boundary stability.

Additionally, it is important to note that, despite a variability of the chunking patterns across subjects (see Tosatto et al., 2022), we have identified a central common feature driving the reorganizations of chunks during sequence learning. Furthermore, we argue that these results, obtained with Guinea baboons, can confidently be generalized to many primate species. Indeed, as stated before, chunking mechanisms appear to be shared across primate species and rely on common associative mechanisms, and the precise dynamics of chunk evolution, including concatenations and recombinations, appear to be very similar even between humans and baboons (Tosatto, Fagot & Rey, 2023).

Note that, as the sequence is mastered, RTs may decrease to a floor performance which should lead to less possibilities for reorganizations. Floor performance for RTs was not reached in the present study but reaching floor performances indeed affect the chunking pattern and its reorganizations. In another experiment, we trained baboons over a longer period of 4,000 trials on a single repeated sequence composed of 5 positions (Tosatto et al., under review). We observed that baboons reached a plateau in terms of mean sequence production speed and, concurrently, a plateau was reached in the growth of chunk size, necessarily decreasing the number of recombinations and concatenations. The same effect was observed in humans, although they needed a shorter training period to reach this plateau (Tosatto et al., 2023). These results suggest that as practice increases, the chunking pattern seems to stabilize and the number of reorganizations decreases.

Finally, the fact that chunking patterns appear flexible and dependent on the stability of associations makes sense from an evolutionary point of view. Indeed, it is important that, during sequence learning and especially motor sequence learning, the cognitive system can maintain a balance between a stable representation of the sequence, to identify or produce it efficiently, and possibilities to reorganize said sequence in memory, to optimize performance and accommodate the behavior to the potential presence of interference (i.e., the presence of an event interrupting the sequence). Likewise, the analyses carried out in this study provide new constraints for modeling the nature and dynamics of fundamental chunking mechanisms with ever greater precision.

Acknowledgements

This work was supported by the Institut Convergence ILCB (ANR-16-CONV-0002) and the HEBBIAN ANR project (#ANR-23-CE28-0008). The funders had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript.

Open Practices Statements

Data from the experiment are available on Open Science Framework at https://osf.io/xcw95/.

Conflict of Interest

The authors declare that they have no conflict of interest.

Animal rights

This research adhered to the applicable French rules for ethical treatment of research animals and received ethical approval from the French Ministry of Education (approval APAFIS#2717-2015111708173794 10 v3).

References

- Abrahamse EL, Ruitenberg MFL, de Kleine E, Verwey WB, 2013. Control of automated behavior: Insights from the discrete sequence production task. *Frontiers in Human Neuroscience* 7.
- Acuna DE, Wymbs NF, Reynolds CA, et al. 2014. Multifaceted aspects of chunking enable robust algorithms. *Journal of Neurophysiology* 112: 1849-1856.
- Aychet J, Blois-Heulin C, Lemasson A. 2021. Sequential and network analyses to describe multiple signal use in captive mangabeys. *Animal Behaviour* 182: 203-226.
- Bera K, Shukla A, Bapi RS. 2021. Motor Chunking in Internally Guided Sequencing. *Brain Sciences* 11: 292.
- Bottary R, Sonni A, Wright D, Spencer RMC. 2016. Insufficient chunk concatenation may underlie changes in sleep-dependent consolidation of motor sequence learning in older adults. *Learning & Memory* 23: 455-459.
- Conway CM, Christiansen MH. 2001. Sequential learning in non-human primates. *Trends in Cognitive Sciences* 5: 539-546.
- Cowan N. 1988. Evolving conceptions of memory storage, selective attention, and their mutual constraints within the human information-processing system. *Psychological Bulletin* 104: 163-191.
- Cowan N. 2017. The many faces of working memory and short-term storage. *Psychonomic Bulletin & Review* 24: 1158-1170.
- Diedrichsen J, Kornysheva K. 2015. Motor skill learning between selection and execution. *Trends in Cognitive Sciences* 19: 227-233.

- Fagot J, Bonté E. 2010. Automated testing of cognitive performance in monkeys: Use of a battery of computerized test systems by a troop of semi-free-ranging baboons (Papio papio). *Behavior Research Methods* 42: 507-516.
- Fonollosa J, Neftci E, Rabinovich M. 2015. Learning of Chunking Sequences in Cognition and Behavior. *PLOS Computational Biology* 11.

Gobet F, Lane P, Croker S, Cheng P, Jones G, Oliver I, Pine J. 2001. Chunking mechanisms in human learning. *Trends in Cognitive Sciences* 5: 236-243.

Gobet F, Lloyd-Kelly M, Lane PCR. 2016. What's in a Name? The Multiple Meanings of "Chunk" and "Chunking". *Frontiers in Psychology* 7.

Lashley KS. 1951. The Problem of Serial Order in Behavior. New York, Wiley.

- Mathy F, Feldman J. 2012. What's magic about magic numbers? Chunking and data compression in short-term memory. *Cognition* 122: 346-362.
- Miller GA. 1956. The Magical Number Seven, Plus or Minus Two: Some Limits on Our Capacity for Processing Information. *Psychol Rev* 63: 81-97.
- Ouattara K, Lemasson A, Zuberbühler K. 2009. Campbell's monkeys concatenate vocalizations into context-specific call sequences. *Proceedings of the National Academy of Sciences* 106: 22026-22031.
- Perruchet P, Vinter A. 2002. The self-organizing consciousness as an alternative model of the mind. *Behavioral and Brain Sciences* 25: 360-380.
- Petkov CI, ten Cate C. 2020. Structured Sequence Learning: Animal Abilities, Cognitive Operations, and Language Evolution. *Topics in Cognitive Science* 12: 828-842.
- Ramkumar P, Acuna DE, Berniker M, Grafton ST, Turner RS, Kording KP. 2016. Chunking as the result of an efficiency computation trade-off. *Nature Communications*, 7.

- Rey A, Minier L, Malassis R, Bogaerts L, Fagot J. 2019. Regularity Extraction Across Species: Associative Learning Mechanisms Shared by Human and Non-Human Primates. *Topics in Cognitive Science* 11: 573-586.
- Rosenbaum DA, Kenny SB, Derr MA. 1983. Hierarchical control of rapid movement sequences. Journal of Experimental Psychology: Human Perception and Performance 9: 86-102.
- Sakai K, Kitaguchi K, Hikosaka O. 2003. Chunking during human visuomotor sequence learning. *Experimental Brain Research* 152: 229-242.
- Scarf D, Smith C, Jaswal V, Magnuson J, Terrace HS. (2018). Chunky Monkey? The spontaneous temporal chunking of simultaneous chains by Humans (*Homo Sapiens*) and rhesus monkeys (*Macaca mulatta*). In A.I. Contreras, B.H. Godinez (Eds), *Studies of Rhesus Monkeys and their Behaviors* (pp. 39-58). Nova Science Publishers, Hauppauge, NY.
- Terrace HS. 2002. The Comparative Psychology of Chunking. In S.B. Fountain, M.D. Bunsey, J.H. Danks, & M.K. McBeath (Eds), *Animal Cognition and Sequential Behavior* (pp. 23-55). Springer, Boston, MA.
- Tosatto L, Fagot J, Nemeth D, Rey A. 2022. The Evolution of Chunks in Sequence Learning. *Cognitive Science* 46.
- Tosatto L, Fagot J, Rey A. 2023. The dynamics of chunking in humans (*Homo sapiens*) and Guinea baboons (*Papio papio*). *Journal of Comparative Psychology* 137: 191–199.
- Verwey WB. 2001. Concatenating familiar movement sequences: The versatile cognitive processor. *Acta Psychologica* 106: 69-95.
- Willingham DB. 1998. A neuropsychological theory of motor skill learning. *Psychological Review* 105: 558-584.
- Wright DL, Rhee JH, Vaculin A. 2010. Offline Improvement during Motor Sequence Learning Is Not Restricted to Developing Motor Chunks. *Journal of Motor Behavior* 42: 317-324.

Wymbs NF, Bassett DS, Mucha PJ, Porter MA, Grafton ST. 2012. Differential Recruitment of the Sensorimotor Putamen and Frontoparietal Cortex during Motor Chunking in Humans. *Neuron* 74: 936-946.

CHUNK STABILITY IN BABOONS

Figure 1

Experimental display and stimuli presentation

Affichage et présentation des stimuli

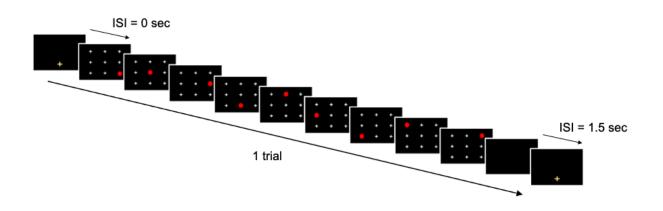
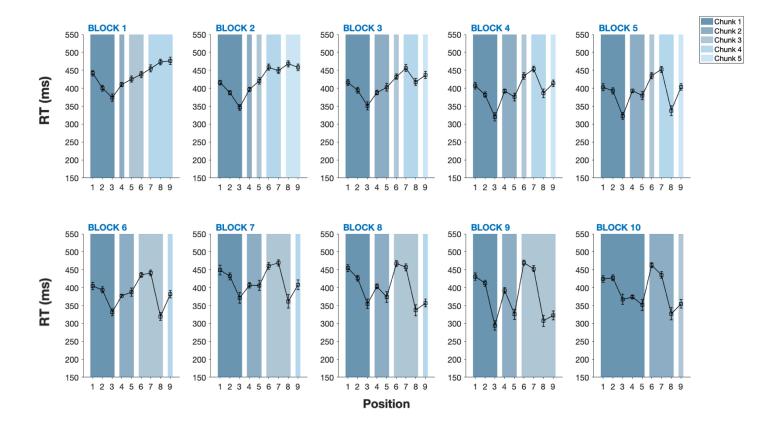


Figure 2

Evolution of the chunking pattern for one baboon – Ewine



Évolution du pattern de chunking pour un babouin – Ewine

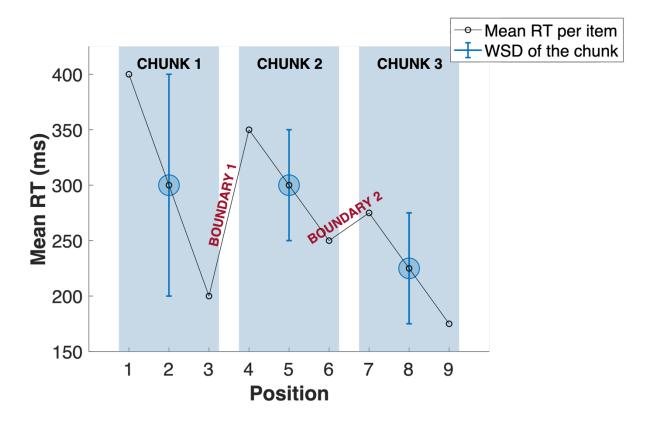
Note. A. Mean RT per position across the 10 blocks of trials for one baboon (Ewine) showing the evolution of the chunking pattern (error bars represent 95% confidence intervals). Similar figures can be found for all baboons in Tosatto et al. (2022) as supplementary materials.

Note. A. Temps de réponse moyen par position sur les 10 blocs d'essais pour un babouin (Ewine) montrant l'évolution du *pattern* de *chunking* (les barres d'erreur représentent les intervalles de confiance à 95 %). Des figures similaires peuvent être trouvées pour tous les babouins dans Tosatto et al. (2022) en matériel supplémentaire.

Figure 3

Example of the variability in chunk stability and boundary stability

Example de variabilité associée à la stabilité des chunks et frontières de chunks



Note. The mean RTs and chunking pattern displayed here are an example adapted from existing chunking patterns observed in baboons. Chunk 1 is considered as very stable as there is a strong decrease in successive RTs within this chunk, which is reflected by a high WSD (WSD_{C1}=100ms, in blue). Chunks 2 and 3 are considered less stable as evidenced by the smaller decrease in successive RTs within each chunk, resulting in a lower WSD (WSD_{C2}= WSD_{C3}=50ms). Boundary 1 is an example of a stable boundary, as the time elapsed between Position 3 and 4 is large (Size_{B1}=150ms), and Boundary 2 is less stable as the time elapsed between Position 6 and 7 is smaller (Size_{B2}=25ms).

Note. Les TRs moyens et le *pattern* de *chunking* présentés ici sont un exemple tiré de *pattern* de *chunking* existants observés chez les babouins. Le *chunk* 1 est considéré comme très stable

car il y a une forte diminution des TRs successifs dans ce *chunk*, ce qui est reflété par un *WSD* élevé (WSD_{C1}=100ms, en bleu). Les *chunks* 2 et 3 sont considérés comme moins stables, comme le montre la diminution plus faible des TR successifs dans chaque *chunk*, ce qui se traduit par un *WSD* plus faible (WSD_{C2}= WSD_{C3}=50ms). La frontière de *chunk* 1 est un exemple de frontière stable, car le temps écoulé entre les positions 3 et 4 est important (Size_{B1}=150ms), et la frontière 2 est moins stable, car le temps écoulé entre les positions 6 et 7 est plus petit (Size_{B2}=25ms).

Figure 4

Logistic regressions predicting (A) the survival of a chunk as a function of the chunk Within Standard Deviation (WSD) and (B) the survival of a boundary as a function of the boundary size.

Régressions logistiques prédisant (A) la survie d'un chunk en fonction de la déviation standard interne (WSD) et (B) la survie d'une frontière de chunk en fonction de sa taille (Size).

