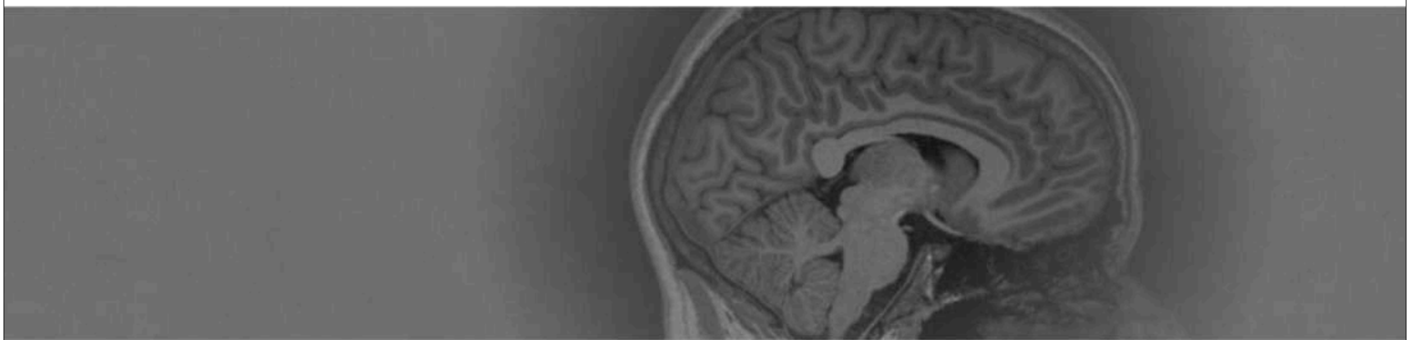
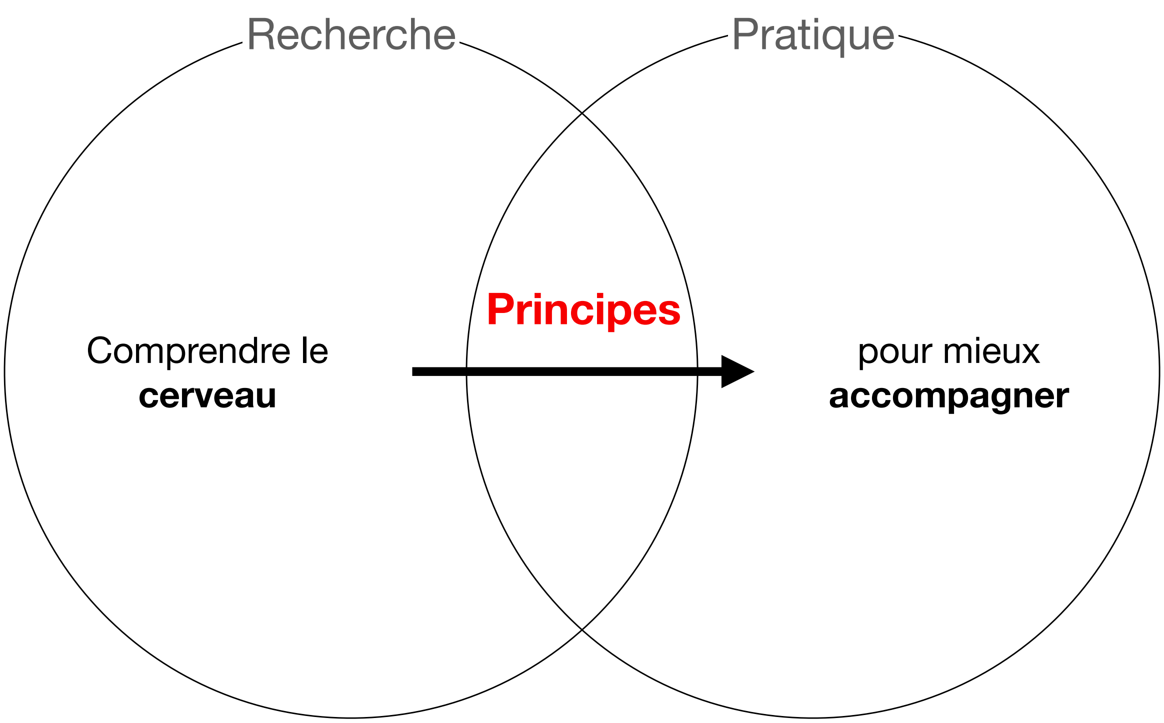
labneuroeducation.org youtube.com/stevemasson facebook.com/profstevemasson x.com/stevemasson



Comprendre le cerveau pour mieux accompagner l’apprentissage de la lecture et le développement de la littératie

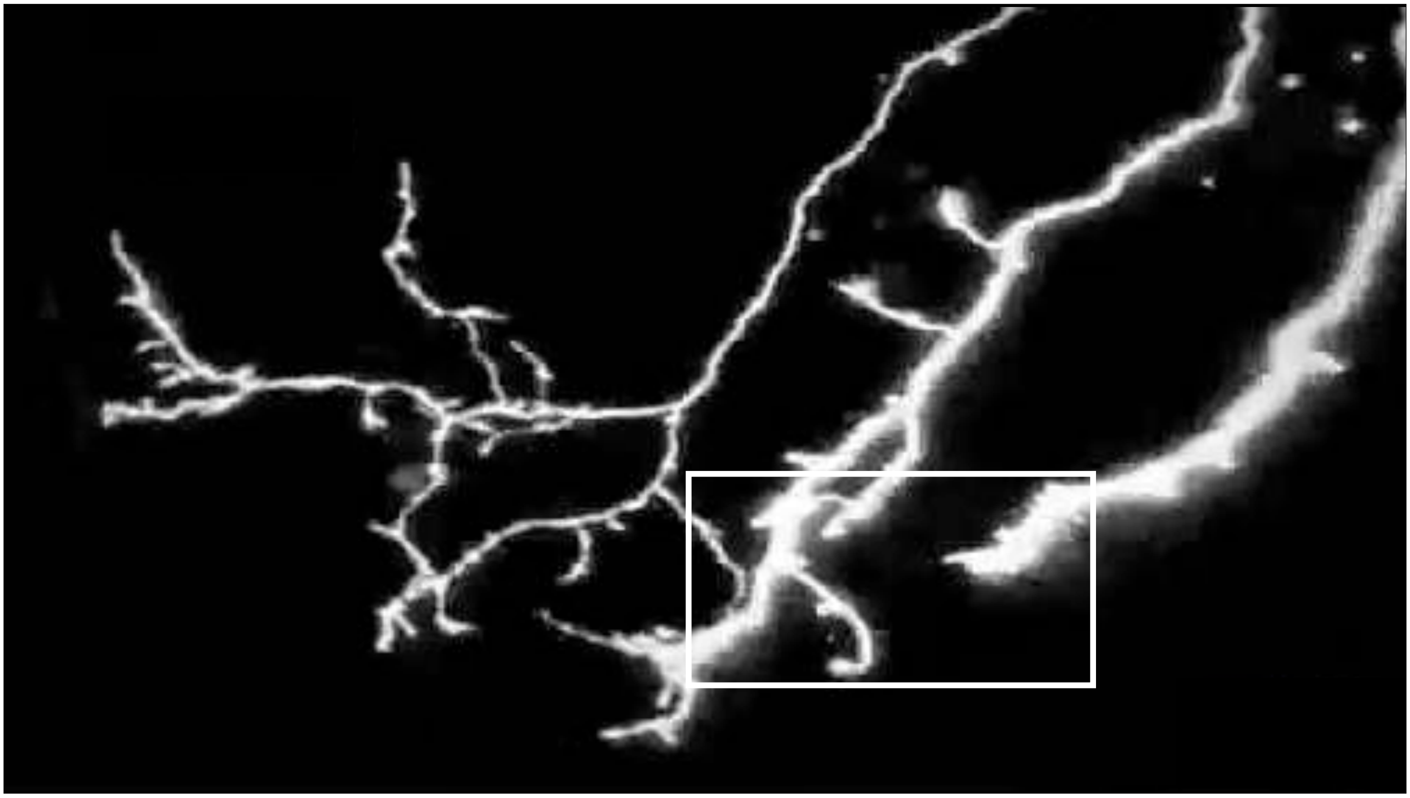
Conférence d’ouverture - Colloque AuTour de la lecture du TREM - 10 déc. 2024

Steve Masson, professeur à l’Université du Québec à Montréal



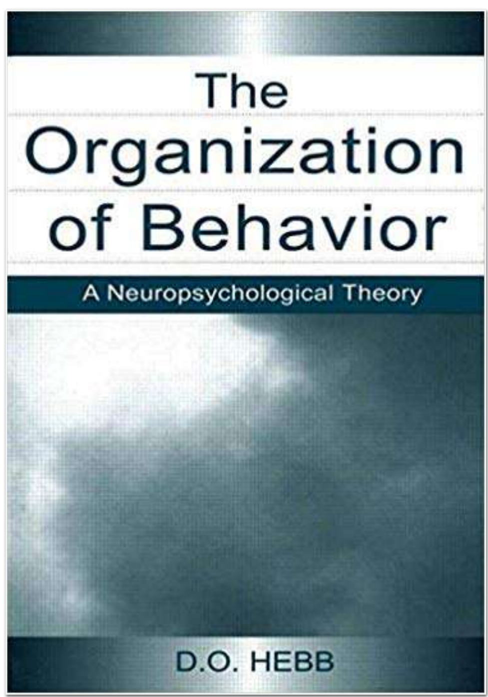
Principe 1

Apprendre, c'est changer
son **cerveau**.



Livre de

Hebb

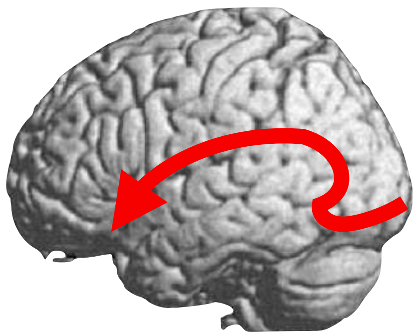


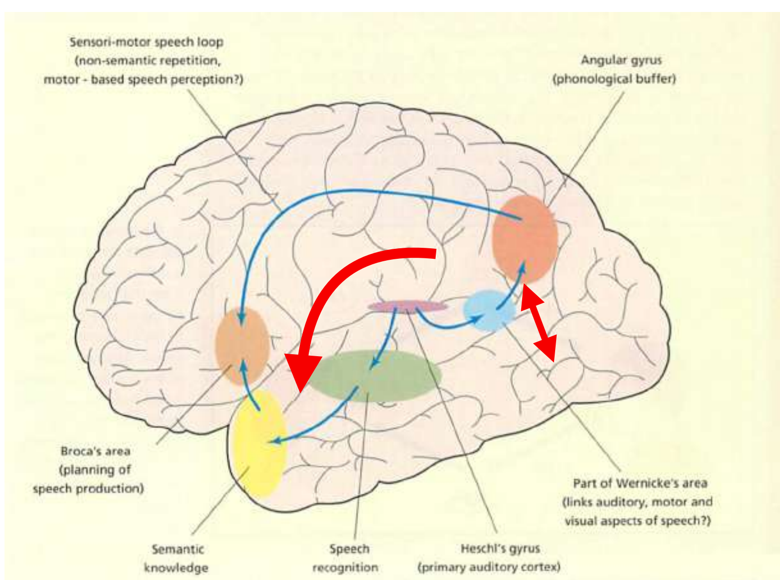
Mécanisme de modification de connexions

Les neurones qui s’**activent** ensemble se **connectent** ensemble.

Analogie de la forêt

Apprendre à **lire**,
c'est construire des **chemins** dans son cerveau.





Principe 1

Activer les neurones à plusieurs reprises

Comment ?

Vocabulaire

Correspondances lettres-sons

Stratégie 1

Planifier plusieurs moments d'activation

Étude de Koedinger et al.

PNAS RESEARCH ARTICLE | PSYCHOLOGICAL AND COGNITIVE SCIENCES OPEN ACCESS

An astonishing regularity in student learning rate

Leveraging a scientific infrastructure for exploring how students learn, we have developed cognitive and statistical models of skill acquisition and used them to understand fundamental similarities and differences across learners. Our primary question was why do some students learn faster than others? Or, do they? We model data from student performance on groups of tasks that assess the same skill component and that provide follow-up instruction on student errors. Our models estimate, for both students and skills, initial correctness and learning rate, that is, the increase in correctness after each practice opportunity. We applied our models to 1.3 million observations across 27 datasets of student interactions with online practice systems in the context of elementary to college courses in math, science, and language. Despite the availability of up-front verbal instruction, like lectures and readings, students demonstrate modest initial prepractice performance, at about 65% accuracy. Despite being in the same course, students' initial performance varies substantially from about 55% correct for those in the lower half to 75% for those in the upper half. In contrast, and much to our surprise, we found students to be astonishingly similar in estimated learning rate, typically increasing by about 0.1 log odds or 2.5% in accuracy per opportunity. These findings pose a challenge for theories of learning to explain the odd combination of large variation in student initial performance and striking regularity in student learning rate.

Significance

Prior research, often using self-report data, hypothesizes that the path to expertise requires extensive practice and that different learners acquire competence at different rates. Fitting cognitive and statistical growth models to 27 datasets involving observations of learning and performance in academic settings, we find evidence for the first hypothesis and against the second. Students do need extensive practice, about seven opportunities per component of knowledge. Students do not show substantial differences in their rate of learning. These results provide a challenge for learning theory to explain this striking similarity in student learning rate. They also suggest that educational achievement gaps come from differences in learning opportunities and that better access to such opportunities can help close those gaps.

Humans are capable of a wide and flexible variety of learning adaptation. This adaptability is particularly apparent in the development of expertise associated with high-profile careers, like technology innovation or music composition, but also in the wide variety of academic subject matter, reading, writing, math, science, second language, etc., humans master. Better understanding of how human learning works in the context of academic courses is of scientific interest because academic learning is particularly distinct to the human species. It is also of practical interest because such understanding can be used to develop more effective education. New technologies have often made better science possible. Such is the case for educational technologies which, in this century, have been increasingly providing unprecedented volumes of detailed data on academic learning. With center-level funding from the National Science Foundation to LearnLab (learnlab.org), we developed a social-technical infrastructure to systematically acquire such data and use it both to optimize interactive learning technologies and to pursue scientific questions about student learning.

LearnLab's early goals were to identify the mental units of learning in academic courses, to use these insights to design and demonstrate improved instruction in randomized controlled experiments embedded in courses, and to build models of learners that may reveal significant similarities and differences across learners. Past research produced methods for discovering and validating improved cognitive models of the mental units students acquire in academic courses (e.g., ref. 1). These improved cognitive models were used to redesign course units, and random assignment field experiments comparing student use of the redesign (treatment) with the original design (control) demonstrated enhanced learning outcomes (e.g., refs. 2 and 3). A key theoretical hypothesis of these cognitive models is that a decomposition of learning into discrete units, or knowledge components, produces predictions that can be tested against student performance data across different contexts and at different times. Investigations across multiple datasets support this knowledge component hypothesis (e.g., refs. 1 and 4).

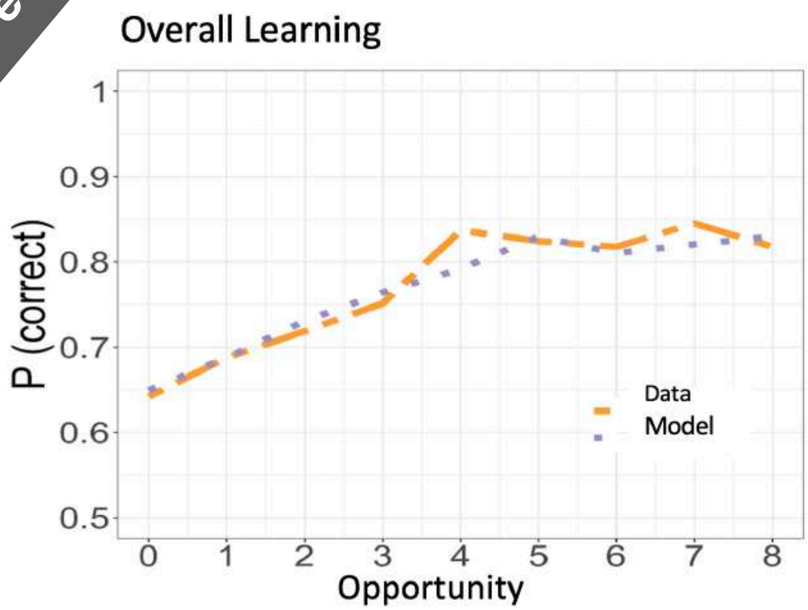
In this paper, we combine these cognitive models with statistical growth models to explore significant similarities and differences across academic learners. Our research questions are:

1. Practice needed: How many practice opportunities do students need to reach a mastery level of 80% correctness?
2. Initial performance variation: How much do students vary in their initial performance?
3. Learning-rate variation: How much do students vary in their learning rate?

PNAS 2023 Vol. 120 No. 13 e2221311120 https://doi.org/10.1073/pnas.2221311120 1 of 11

Taux d'apprentissage en fonction du **nombre d'activations**

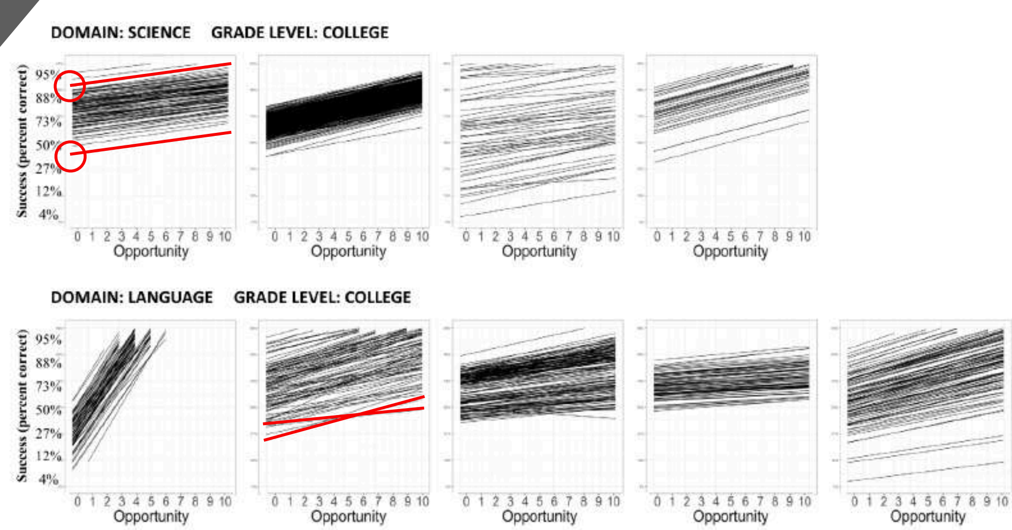
Étude de Koedinger et al.



+ 2,5 % par activation

~7 activations

Étude de Koedinger et al.



Taux d'apprentissage très similaires

Principe 1
Activer les neurones à plusieurs reprises

Comment ?

Stratégie 1
Planifier plusieurs moments d'activation

Stratégie 2
Entraîner la récupération en mémoire

Étude de Zaromb et al.

Memory & Cognition
2010, 38 (8), 995-1008

The testing effect in free recall is associated with enhanced organizational processes

Franklin M. Zaromb and Henry L. Roediger III
Washington University, St. Louis, Missouri

In two experiments with categorized lists, we asked whether the testing effect in free recall is related to enhancements in organizational processing. During a first phase in Experiment 1, subjects studied one list over eight consecutive trials, they studied another list six times while taking two interspersed recall tests, and they learned a third list in four alternating study and test trials. On a test 2 days later, recall was directly related to the number of tests and inversely related to the number of study trials. In addition, increased testing enhanced both the number of categories accessed and the number of items recalled from within those categories. One measure of organization also increased with the number of tests. In a second experiment, different groups of subjects studied a list either once or twice before a final criterial test, or they studied the list once and took an initial recall test before the final test. Prior testing again enhanced recall, relative to studying on the final test a day later, and also improved category clustering. The results suggest that the benefit of testing in free recall learning arises because testing creates retrieval schemas that guide recall.

A robust finding is that testing a person's memory for previously learned material enhances long-term retention, relative to restudying the material for an equivalent amount of time (e.g., Carrier & Pashler, 1992; for a review, see Roediger & Karpicke, 2006a). This finding, known as the *testing effect*, has been demonstrated using a wide range of study materials and types of tests, in both laboratory and classroom settings and in various subject populations (e.g., Butler & Roediger, 2007; Gates, 1917; Kang, McDermott, & Roediger, 2007; McDaniel, Anderson, Derbish, & Morrisette, 2007; Roediger & Karpicke, 2006b; Spitzer, 1939; Tse, Balota, & Roediger, in press). Recent years have seen renewed interest among researchers investigating the potential benefits of testing for learning as a means to improving learning in educational settings (McDaniel, Roediger, & McDermott, 2007; Pashler, Rohrer, Cepeda, & Carpenter, 2007).

One limitation with this work is that testing effects typically report improvements in learners' retention of discrete facts (e.g., foreign vocabulary words) without necessarily demonstrating a better understanding of the subject matter through testing (Daniel & Poole, 2009). However, a growing body of research has shown that testing can serve as a versatile learning tool by enhancing the long-term retention of nontested information that is conceptually related to previously retrieved information (Chan, 2009; Chan, McDermott, & Roediger, 2006), by stimulating the subsequent learning of new information (Izawa, 1970; Karpicke, 2009; Szpunar, McDermott, & Roediger, 2008; Tulving & Watkins, 1974) and by permitting better transfer to new questions (Butler, 2010; Johnson & Mayer, 2009; Rohrer, Taylor, & Sholar, 2010). In the present research, we further examine the potential benefits of testing by asking whether testing can improve individuals' learning and retention of the conceptual organization of study materials, relative to studying the materials alone—a question not yet addressed in the literature.

Psychologists have long grappled with questions of how the processes involved in mentally organizing information influence learning and retention (e.g., Ausubel, 1963; Bartlett, 1932; Katona, 1940). One theoretical assumption that has guided much of the cognitive research examining organization and learning was Miller's (1956) conception of recoding, or *chunking*, in which he argued that the key to learning and retaining large quantities of information was to mentally repackage, or *chunk*, the study materials into smaller units. Evidence for chunking has come primarily from studies using serial recall and free recall paradigms in which subjects often study and attempt to recall verbal materials such as lists of words over multiple alternating study and test trials (e.g., Bower & Springston, 1970; Tulving, 1962), but it has also come from other techniques (e.g., Mandler, 1967).

In support of the chunking hypothesis, researchers have pointed to the finding that when people study lists of words coming from different conceptual categories in a randomized order, they tend to recall them in an organized fashion by clustering conceptually related responses together (W. A. Bousfield, 1953; W. A. Bousfield, Cohen, & Whitmarsh, 1958). Furthermore, response clustering is often associated with greater retention (Mulligan, 2005; Puff, 1979). Similarly, Tulving (1962) found that when students learned

F. M. Zaromb, fzaromb@ets.org

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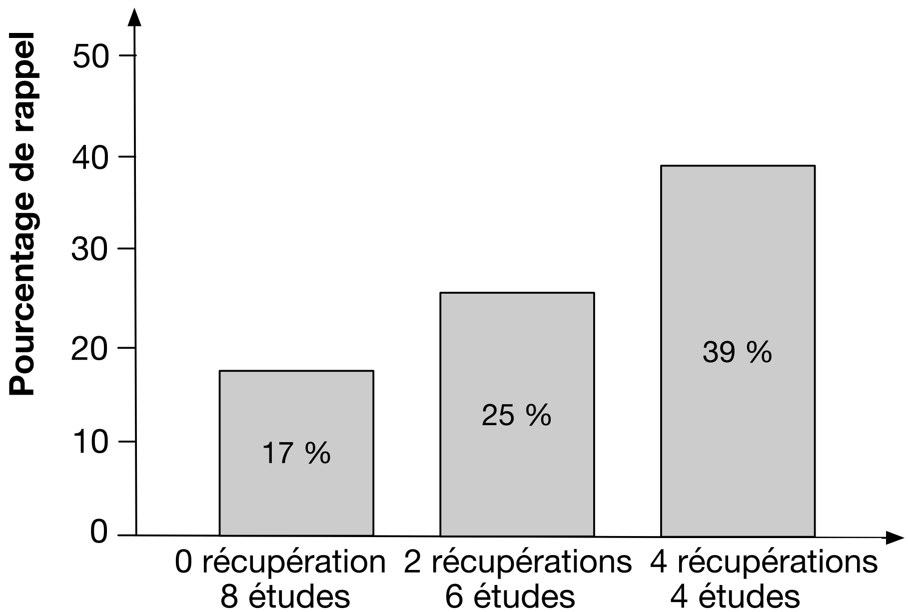
Effets de l'entraînement à la **récupération** en mémoire vs **étude**

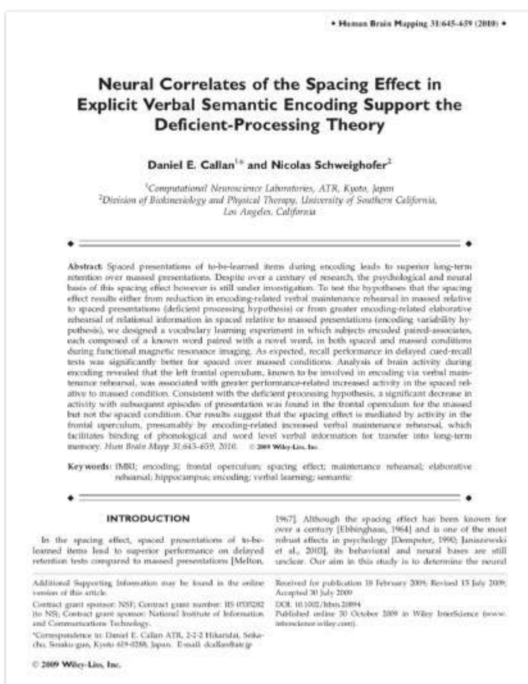
Étude de Zaromb et al.



Principe 2

Activation 1 | Activation 2 | Activation 3

Étude de Callan et al.



• Human Brain Mapping 31:645–659 (2010) •

Neural Correlates of the Spacing Effect in Explicit Verbal Semantic Encoding Support the Deficient-Processing Theory

Daniel E. Callan[1*] and Nicolas Schweighofer[2]

[1]Computational Neuroscience Laboratories, ATR, Kyoto, Japan
[2]Division of Biokinesiology and Physical Therapy, University of Southern California, Los Angeles, California

Abstract: Spaced presentations of to-be-learned items during encoding leads to superior long-term retention over massed presentations. Despite over a century of research, the psychological and neural basis of this spacing effect however is still under investigation. To test the hypotheses that the spacing effect results either from reduction in encoding-related verbal maintenance rehearsal in massed relative to spaced presentations (deficient processing hypothesis) or from greater encoding-related elaborative rehearsal of relational information in spaced relative to massed presentations (encoding variability hypothesis), we designed a vocabulary learning experiment in which subjects encoded paired-associates, each composed of a known word paired with a novel word, in both spaced and massed conditions during functional magnetic resonance imaging. As expected, recall performance in delayed cued-recall tests was significantly better for spaced over massed conditions. Analysis of brain activity during encoding revealed that the left frontal operculum, known to be involved in encoding via verbal maintenance rehearsal, was associated with greater performance-related increased activity in the spaced relative to massed condition. Consistent with the deficient processing hypothesis, a significant decrease in activity with subsequent episodes of presentation was found in the frontal operculum for the massed but not the spaced condition. Our results suggest that the spacing effect is mediated by activity in the frontal operculum, presumably by encoding-related increased verbal maintenance rehearsal, which facilitates binding of phonological and word level verbal information for transfer into long-term memory. *Hum Brain Mapp* 31:645–659, 2010. © 2009 Wiley-Liss, Inc.

Key words: fMRI; encoding; frontal operculum; spacing effect; maintenance rehearsal; elaborative rehearsal; hippocampus encoding; verbal learning; semantic

INTRODUCTION

In the spacing effect, spaced presentations of to-be-learned items lead to superior performance on delayed retention tests compared to massed presentations [Melton, 1967]. Although the spacing effect has been known for over a century [Ebbinghaus, 1964] and is one of the most robust effects in psychology [Dempster, 1990; Janiszewski et al., 2003], its behavioral and neural bases are still unclear. Our aim in this study is to determine the neural

Additional Supporting Information may be found in the online version of this article.
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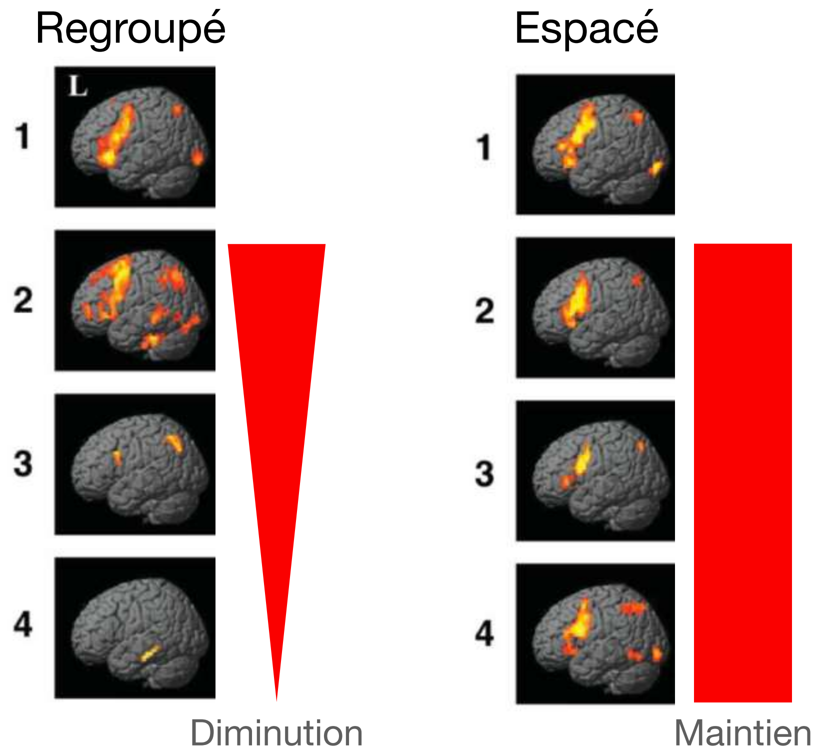
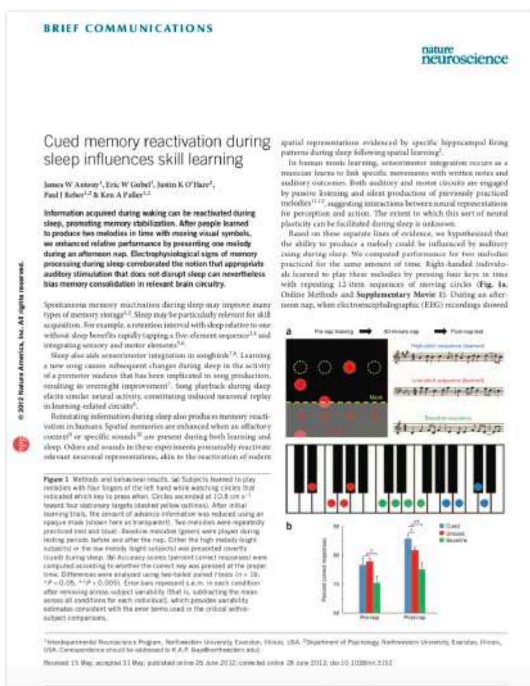
Received for publication 18 February 2009; Revised 15 July 2009; Accepted 30 July 2009
DOI: 10.1002/hbm.20894
Published online 30 October 2009 in Wiley InterScience (www.interscience.wiley.com).

Effets de l'**espacement** sur l'activité cérébrale

Étude de Callan et al.



Étude de Antony et al.


BRIEF COMMUNICATIONS

nature neuroscience

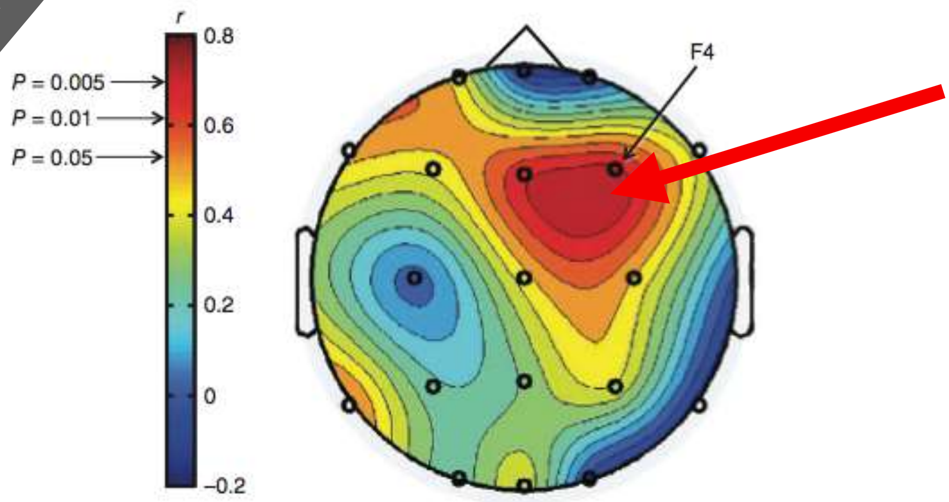
Cued memory reactivation during sleep influences skill learning

James W Antony[1], Eric W Gobel[1], Justin K O'Hare[2], Paul J Reber[1,2] & Ken A Paller[1,2]

Information acquired during waking can be reactivated during sleep, promoting memory stabilization. After people learned to produce two melodies in time with moving visual symbols, we enhanced relative performance by presenting one melody during an afternoon nap. Electrophysiological signs of memory processing during sleep corroborated the notion that appropriate auditory stimulation that does not disrupt sleep can nevertheless bias memory consolidation in relevant brain circuitry.

Effets du **sommeil** sur l'apprentissage et l'activité cérébrale

Étude de Antony et al.



Cortex prémoteur lié à la main utilisée

Étude de Kornell et al.

APPLIED COGNITIVE PSYCHOLOGY
Appl. Cognit. Psychol. **23**: 1297–1317 (2009)
Published online 19 January 2009 in Wiley InterScience
(www.interscience.wiley.com) DOI: 10.1002/acp.1537

Optimising Learning Using Flashcards: Spacing Is More Effective Than Cramming

NATE KORNELL*

Department of Psychology, University of California, Los Angeles, USA

SUMMARY

The spacing effect—that is, the benefit of spacing learning events apart rather than massing them together—has been demonstrated in hundreds of experiments, but is not well known to educators or learners. I investigated the spacing effect in the realistic context of flashcard use. Learners often divide flashcards into relatively small stacks, but compared to a large stack, small stacks decrease the spacing between study trials. In three experiments, participants used a web-based study programme to learn GRE-type word pairs. Studying one large stack of flashcards (i.e. spacing) was more effective than studying four smaller stacks of flashcards separately (i.e. massing). Spacing was also more effective than cramming—that is, massing study on the last day before the test. Across experiments, spacing was more effective than massing for 90% of the participants, yet after the first study session, 72% of the participants believed that massing had been more effective than spacing. Copyright © 2009 John Wiley & Sons, Ltd.

The spacing effect—that is, the fact that spacing learning events apart results in more long-term learning than massing them together—is a robust phenomenon that has been demonstrated in hundreds of experiments (Cepeda, Pashler, Vul, Wixted, & Rohrer, 2006; Dempster, 1996; Hintzman, 1974; Glenberg, 1979) dating back to Ebbinghaus (1885/1964). Learners would profit from taking advantage of the spacing effect, both in classrooms and during unsupervised learning (e.g. Bahrick, Bahrick, Bahrick, & Bahrick, 1993)—and doing so seems feasible from a practical perspective because spacing does not take more time than massing, it simply involves a different distribution of time (Rohrer & Pashler, 2007). Yet the spacing effect has been called 'a case study in the failure to apply the results of psychological research' (Dempster, 1988, p. 627). One reason for this failure is that spacing has seldom been investigated using procedures that are directly applicable in educational settings (although there are exceptions, e.g. Rohrer & Taylor, 2006, 2007; Smith & Rothkopf, 1984). For example, in spacing experiments, a spaced condition is often compared to a pure massing condition, in which the same item (e.g. a word pair) is presented twice in a row with no intervening items. Pure massing is ineffective, but it is also often unrealistic (Seabrook, Brown, & Solity, 2005). The goals of the present experiments were twofold: First, to investigate the spacing effect in a realistic study situation, and second, to examine students' attitudes towards spacing as a study strategy. The research was also intended to provide learners with practical information about how to study.

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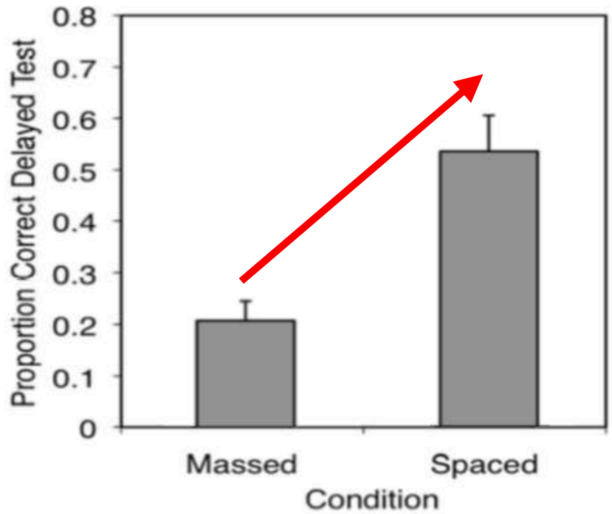
Effets de l'**espacement** sur l'apprentissage

Étude de Kornell



Principe 2
Espacer les activités d'apprentissage

Comment ?

Stratégie 1
Distribuer l'apprentissage

Regroupé

Activation 1 | Activation 2 | Activation 3

Distribué

Activation 1 Activation 2 Activation 3

Plus souvent moins longtemps

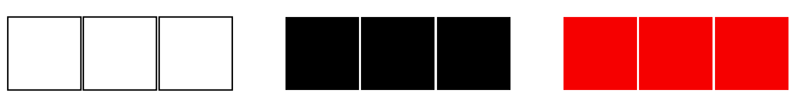
Principe 2
Espacer les activités d'apprentissage

Comment ?

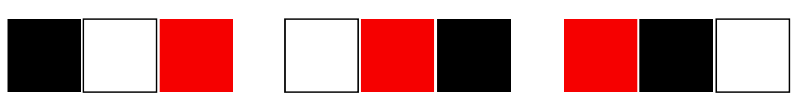
Stratégie 1
Distribuer l'apprentissage

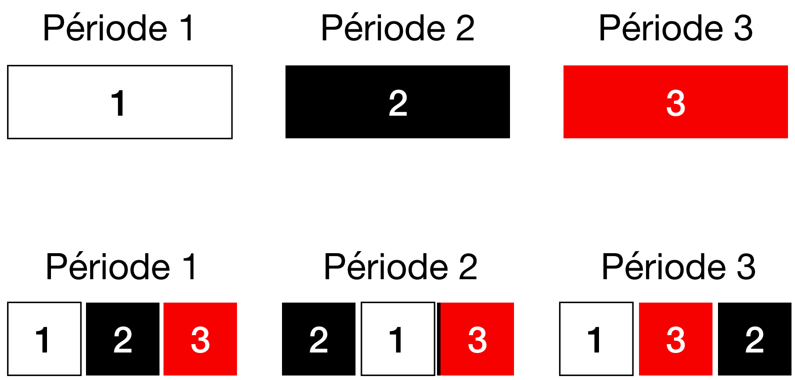
Stratégie 2
Entrelacer les apprentissages

Regroupé



Entrelacé





31

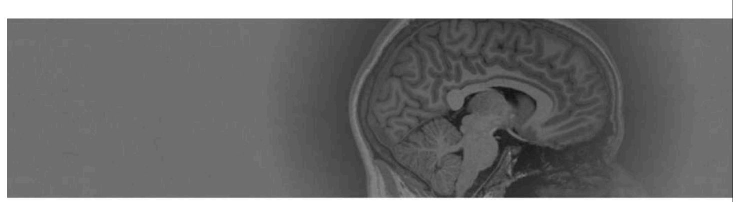
Cours 1	Cours 2
Objectif 1	**Objectif 1**
Objectif 1	Objectif 2
Objectif 1	Objectif 2
Objectif 1	Objectif 2
Objectif 2	Objectif 2

32

Regroupé	ON	ON	ON	ON
Entrelacé	ON	AU	ON	AU

Comment entrelacer ?

- Faire des **retours** sur des éléments vus plus tôt (capsule de révision)
- **Ajouter aux exercices** existants des questions portant sur du contenu antérieur
- **Conserver** une partie des exercices pour plus tard



Principe 3

État d'esprit

Dynamique

Croire qu'on peut s'améliorer

Fixe

Ne pas y croire.

Étude de

Moser et al.

Research Report

Psychological Science
22(12) 1484–1489
SAGE

Mind Your Errors: Evidence for a Neural Mechanism Linking Growth Mind-Set to Adaptive Posterror Adjustments

Jason S. Moser[1], Hans S. Schroder[1], Carrie Heeter[2], Tim P. Moran[1], and Yu-Hao Lee[2]
[1]Department of Psychology and [2]Department of Telecommunications, Information Studies, and Media, Michigan State University

Abstract
How well people bounce back from mistakes depends on their beliefs about learning and intelligence. For individuals with a growth mind-set, who believe intelligence develops through effort, mistakes are seen as opportunities to learn and improve. For individuals with a fixed mind-set, who believe intelligence is a stable characteristic, mistakes indicate lack of ability. We examined performance-monitoring event-related potentials (ERPs) to probe the neural mechanisms underlying these different reactions to mistakes. Findings revealed that a growth mind-set was associated with enhancement of the error positivity component (Pe), which reflects awareness of and allocation of attention to mistakes. More growth-minded individuals also showed superior accuracy after mistakes compared with individuals endorsing a more fixed mind-set. It is critical to note that Pe amplitude mediated the relationship between mind-set and posterror accuracy. These results suggest that neural mechanisms indexing on-line awareness of and attention to mistakes are intimately involved in growth-minded individuals' ability to rebound from mistakes.

Keywords
individual differences, electrophysiology, cognitive processes

Received 2/22/11; Revision accepted 7/11/11

Whether you think you can or think you can't—you are right. (popularly attributed to Henry Ford)

Decades of research by Dweck and her colleagues indicate that academic and occupational success depend not only on cognitive ability, but also on beliefs about learning and intelligence (e.g., Dweck, 2006). Dweck's model of implicit theories of intelligence (TOIs) distinguishes people who believe intelligence is unchangeable (i.e., those who have a *fixed mind-set*) from people who believe intelligence is malleable and can be developed through learning (i.e., those who have a *growth mind-set*). It is critical to note that these mind-sets are associated with different reactions to failure. Fixed-minded individuals view failure as evidence of their own immutable lack of ability and disengage from tasks when they err; growth-minded individuals view failure as potentially instructive feedback and are more likely to learn from their mistakes (Dweck, 1999; Utman, 1997).

Despite years of work examining the self-report and behavioral correlates of these different mind-sets, little is known about the neural mechanisms that underlie them—only one study has examined the neural underpinnings of mind-set. In that study, Mangels, Butterfield, Lamb, Good, and Dweck (2006) measured event-related potentials (ERPs)—electrical brain signals elicited by external or internal events—in college students endorsing a fixed or growth mind-set while they performed a difficult general knowledge test. They found that compared with fixed-minded individuals, growth-minded individuals allocated more attentional resources to corrective information following error feedback and were more likely to correct their mistakes on a surprise retest.

Although Mangels et al. (2006) found differences between individuals with fixed versus growth mind-sets in neural and behavioral responses to corrective information, they demonstrated these effects on a task in which performance accuracy was ambiguous. Participants became aware of their mistakes only when they were signaled by external feedback. This task was also quite difficult (success rates were kept at ~40%), which may have exaggerated differences between the groups

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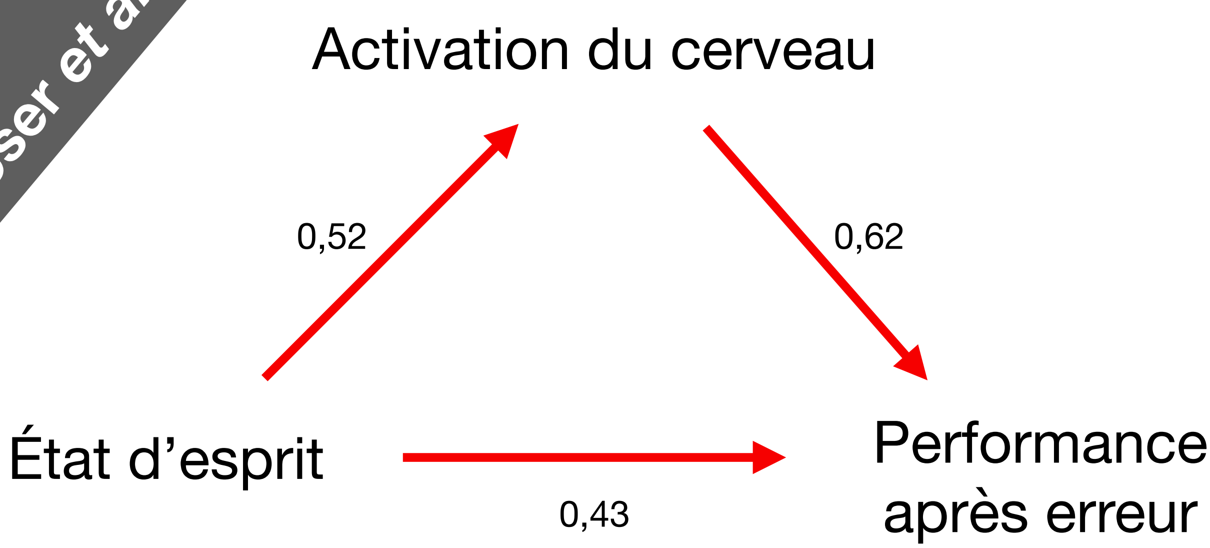
Effet de l'**état d'esprit** sur l'**activité** du cerveau

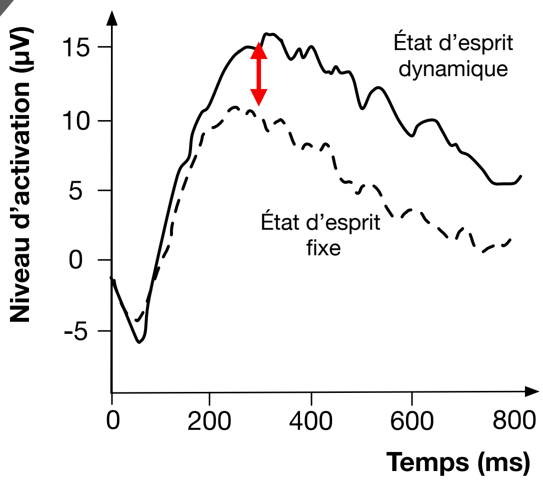
Étude de

Moser et al.



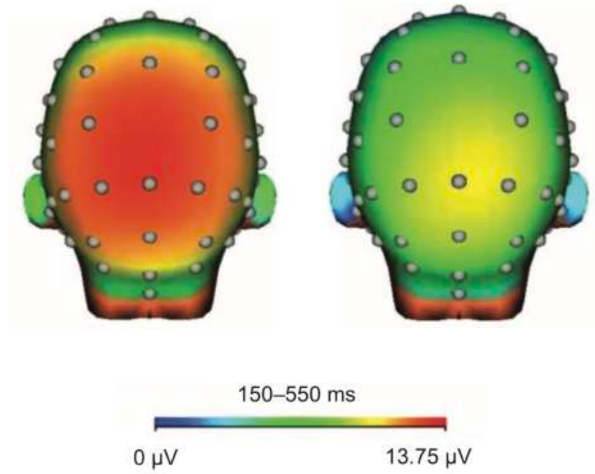
Étude de Moser et al.

Après erreur

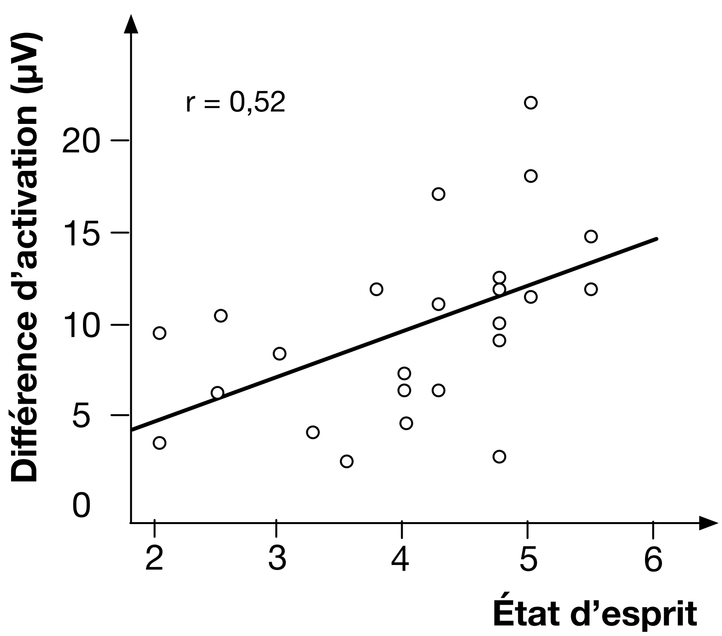


État d'esprit **dynamique**

État d'esprit **fixe**



Étude de Moser et al.



Étude de Schroder et al.

Biological Psychology 101 (2014) 21–37

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journal homepage: www.elsevier.com/locate/biopsycho

Mindset induction effects on cognitive control: A neurobehavioral investigation

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Post-error adjustments

ABSTRACT

Messages about how much our abilities can change – or "mindset" messages – affect learning, achievement, and performance interpretations. However, the neurocognitive mechanisms responsible for these effects remain unexplored. To address this gap, we assessed how a mindset induction influenced cognitive control brain activity. Participants were randomly assigned to read that intelligence was either malleable (growth-mindset condition) or immutable (fixed-mindset condition) before completing a reaction-time task while electroencephalogram was recorded. Findings revealed that inducing a growth mindset resulted in enhanced attention to task-relevant stimuli, whereas inducing a fixed mindset enhanced attention to responses. Despite enhanced attention to responses in the fixed mindset group, this attention allocation was unrelated to adaptive performance adjustments. In contrast, the growth mindset induction produced a relatively strong coupling between error-related attention allocation and adaptive post-error performance. These results suggest that growth- and fixed-mindset messages have differential effects on the neural dynamics underlying cognitive control.

1. Introduction

Individuals are exposed to different messages about the nature of abilities on an everyday basis, from the teacher comforting a student ("It's OK, not everyone can be a math person"), to the parent praising a child ("You really are a smart boy"), to the sports announcer commenting on a player's skill ("Wow, what a natural!"). These kinds of messages convey implicit assumptions about the malleability of different abilities and may contribute to the attitudes individuals hold about the nature of their abilities – or "mindsets" as they are called in contemporary psychological research. Decades of research suggest that mindsets substantially influence learning, motivation, and achievement (Dweck, 1999, 2006; Gunderson et al., 2013; Mueller & Dweck, 1998; Rattan, Good, & Dweck, 2012). A consistent finding is that a belief in the malleability of self-attributes – a growth mindset – is associated with better performance and perseverance, especially when individuals are faced with challenging tasks. Although the psychological and motivational outcomes associated with mindsets are well understood, researchers know relatively little about the neurocognitive processes that mediate the impact of mindsets on achievement outcomes. In this study, we examined how standard mindset inductions (messages about abilities) influence cognitive control.

1.1. Mindsets/implicit theories

People generally hold one of two beliefs (or "mindsets")[2] about the malleability of self-attributes such as intelligence: the "growth mindset" construes intelligence as malleable and improvable; the "fixed mindset" understands intelligence as an absolute entity that cannot be changed (Dweck, Chiu, & Hong, 1995). A large body of literature has documented that these different mindsets lead to different attributions, goals, and experiences of performance situations (see Burnette, O'Boyle, VanEpps, Pollack, & Finkel, 2013 for a review). For instance, individuals who hold the growth mindset believe that successful performance is largely driven by effort, whereas fixed-minded individuals believe success is determined mostly by natural ability (Dweck, 2006). These basic assumptions of where ability comes from are thought to bias individuals' goals for achievement. Whereas growth-minded individuals typically focus on learning to master a given task,

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[2] Note that we consider the terms "mindsets" and "implicit theories" as interchangeable. A growth mindset corresponds to an "incremental theory" whereas a fixed mindset corresponds to an "entity theory".

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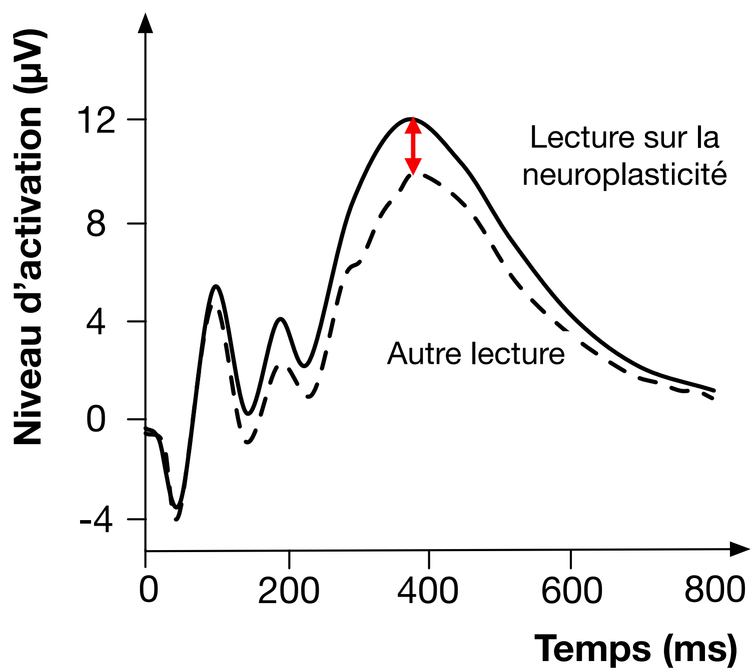
Effet de la lecture d'un **texte** (dynamique vs fixe) sur l'activité du cerveau

Étude de Schroder et al.



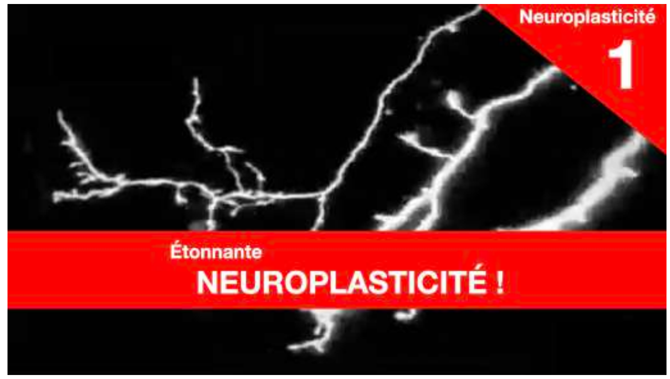
Principe 3

Cultiver un état d'esprit dynamique

Comment ?

Stratégie 1

Connaître la notion de neuroplasticité



http://www.labneuroeducation.org/cerveau

https://youtu.be/36IA8Y8mRgE?

Principe 3
Cultiver un état d'esprit dynamique

Comment ?

Stratégie 1
Connaître la notion de neuroplasticité

Stratégie 2
Fournir des encouragements compatibles avec un état d'esprit dynamique

Quoi dire ?

Succès = **processus** (impliquant effort **et** stratégies)

« L'objectif, ce n'est pas de tout réussir d'un coup. L'objectif est de développer ta compréhension étape par étape. Que peux-tu essayer d'autre ? »

« Bravo pour ton excellent résultat. Tu as travaillé fort, tu as amélioré tes stratégies d'étude et, depuis, tu ne cessez de t'améliorer ! »

Inspiré de Dweck (2015)

Réussite ⇒ rétroaction positive ↑ ⇒ striatum ↑ ⇒ dopamine ↑ ⇒ sentiment de plaisir/satisfaction ↑ ⇒ **motivation**

Réussite ⇒ **motivation**

Synthèse

Principe 1
Activer les neurones à plusieurs reprises

Principe 2
Espacer les activités d'apprentissage

Principe 3
Cultiver un état d'esprit dynamique