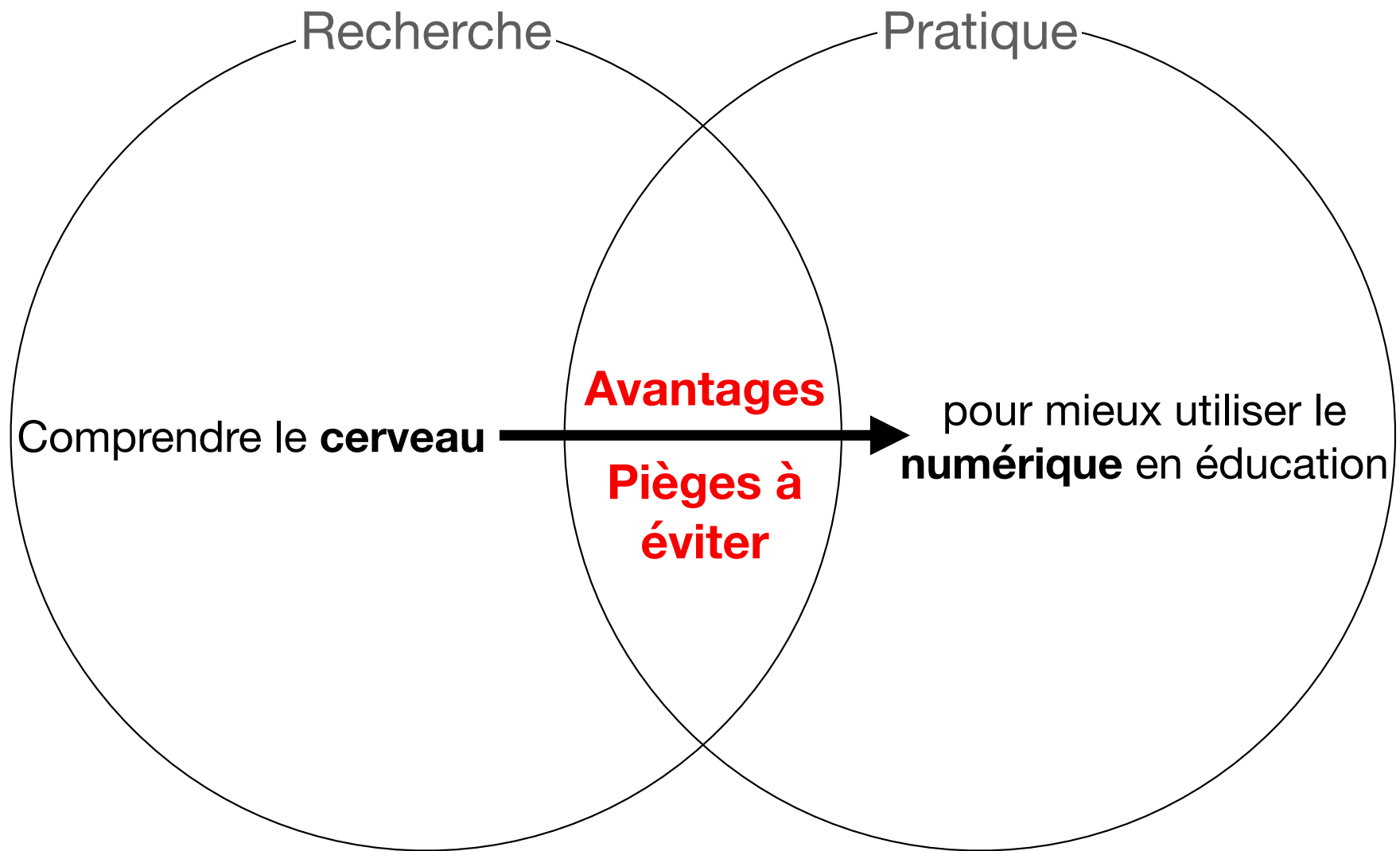


Comprendre le cerveau pour mieux utiliser le numérique en éducation

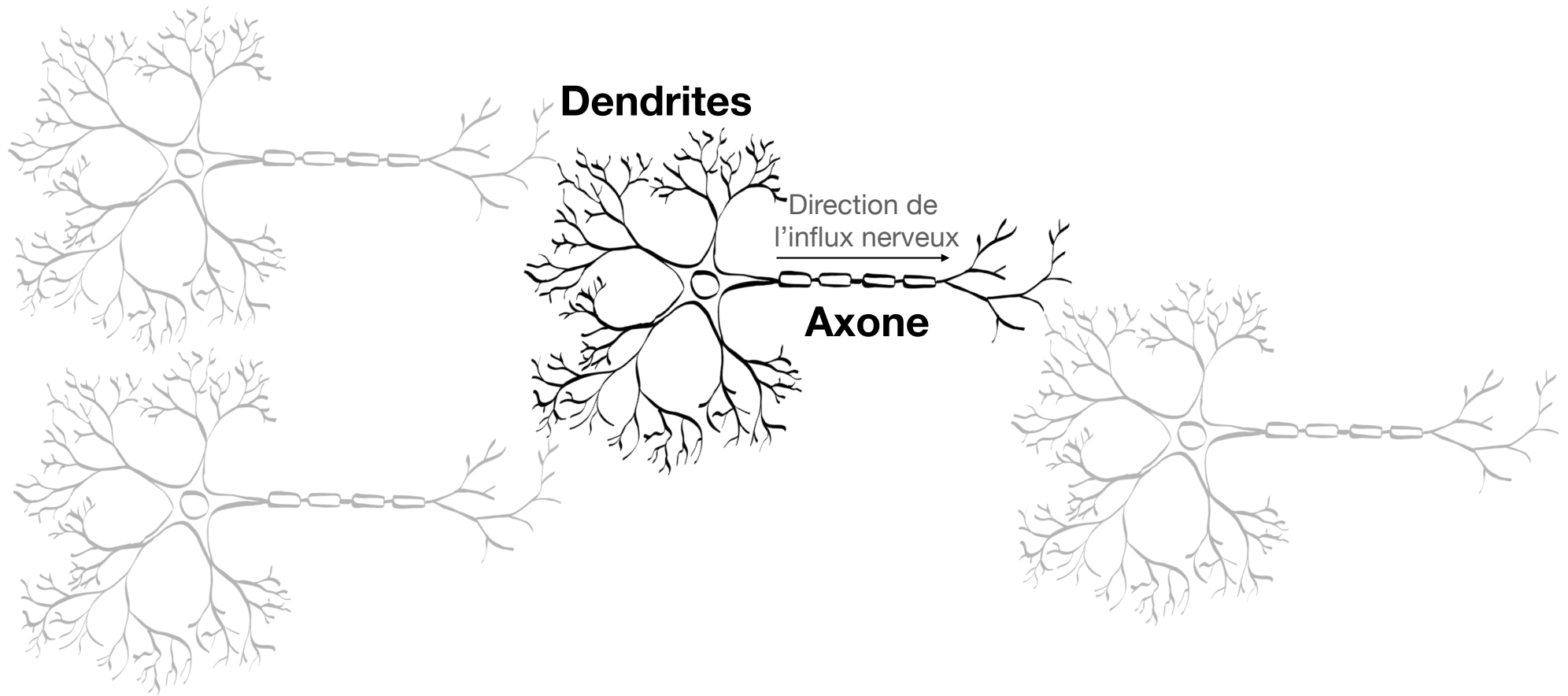
Centre collégial de soutien à l'intégration - 11 mars 2025 - Université Laval
Steve Masson, professeur à l'Université du Québec à Montréal

Numérique en éducation
ni bon ni mauvais
dépend de l'utilisation



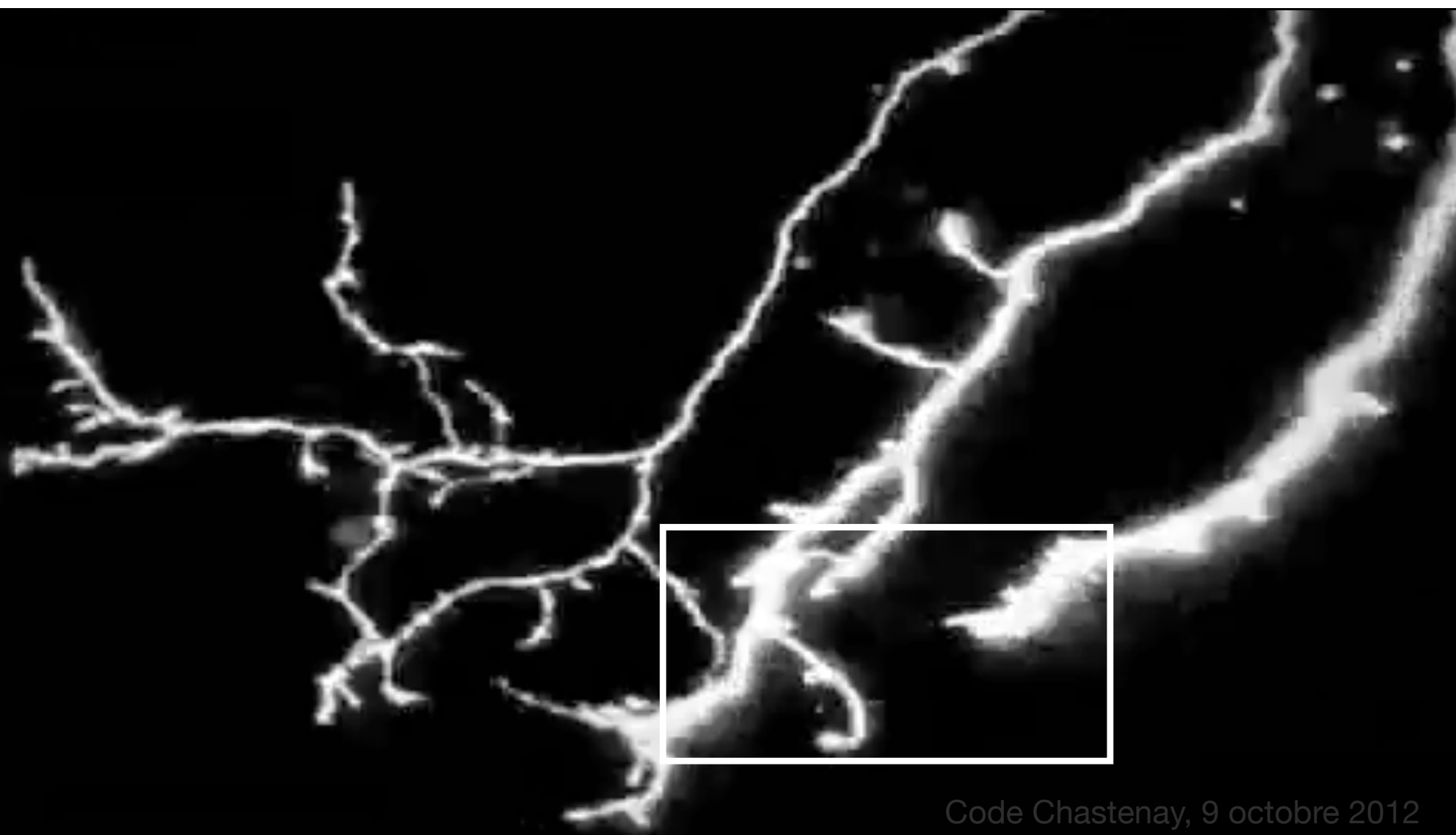
Partie 1

Comprendre le cerveau



**Apprendre, c'est changer
ses connexions neuronales.**

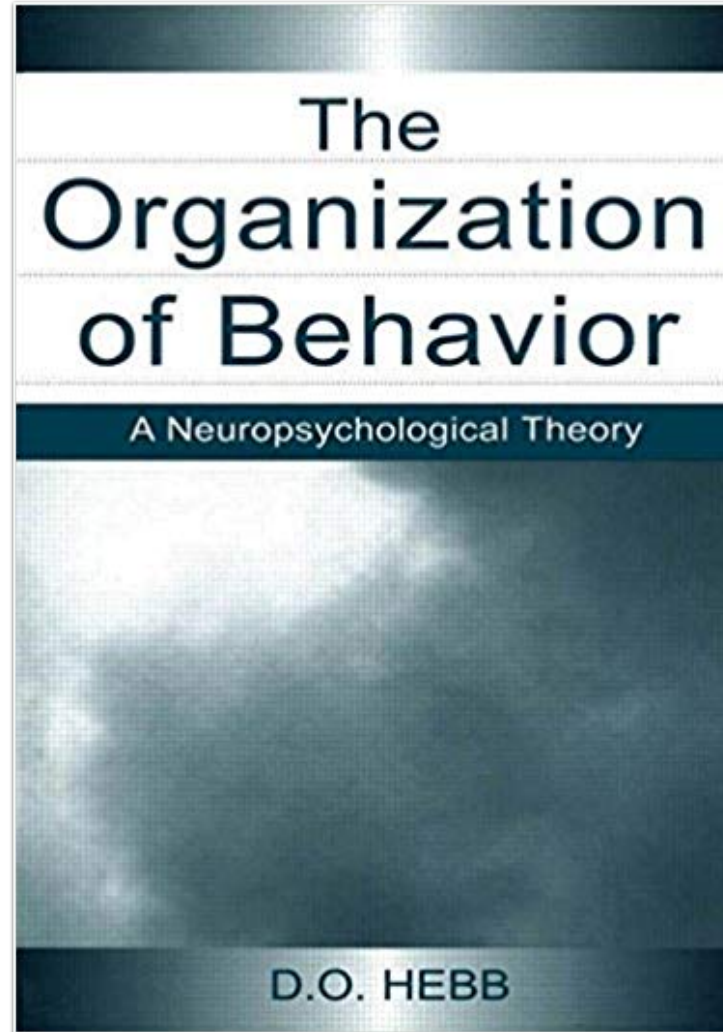
Neuroplasticité



Code Chastenay, 9 octobre 2012

Livre de

Hebb

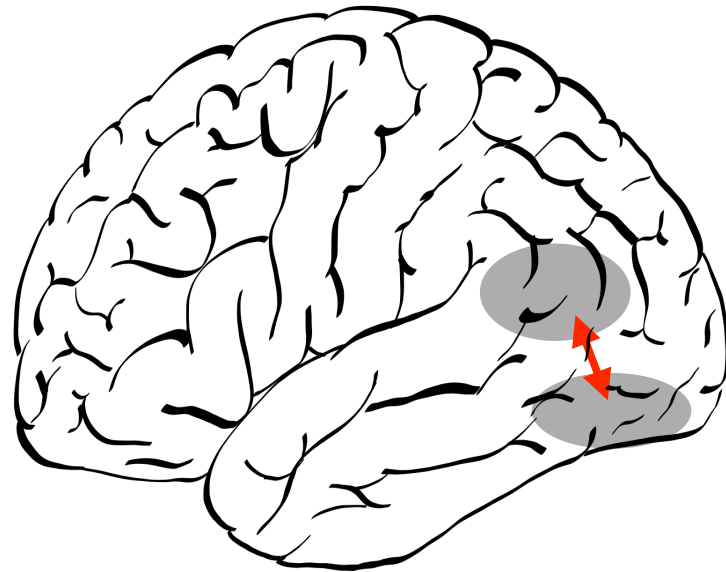


Mécanisme de modification de connexions

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

Analogie de la forêt





PNAS
RESEARCH ARTICLE
PSYCHOLOGICAL AND COGNITIVE SCIENCES
OPEN ACCESS

An astonishing regularity in student learning rate

Kenneth R. Koedinger¹, Paulo F. Carvalho², Ran Liu³, and Elizabeth A. McLaughlin⁴

Edited by Douglas Medin, Northwestern University, Evanston, IL; received December 25, 2022; accepted February 10, 2023

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.

learning rate | learning curves | deliberate practice | logistic regression growth modeling; educational equity

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?

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.

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Author contributions: K.R.K., P.F.C., and R.L. designed research; K.R.K., P.F.C., and R.L. performed research; K.R.K., P.F.C., and R.L. analyzed data; and K.R.K., P.F.C., and E.A.M. wrote the paper.

The authors declare no competing interest.

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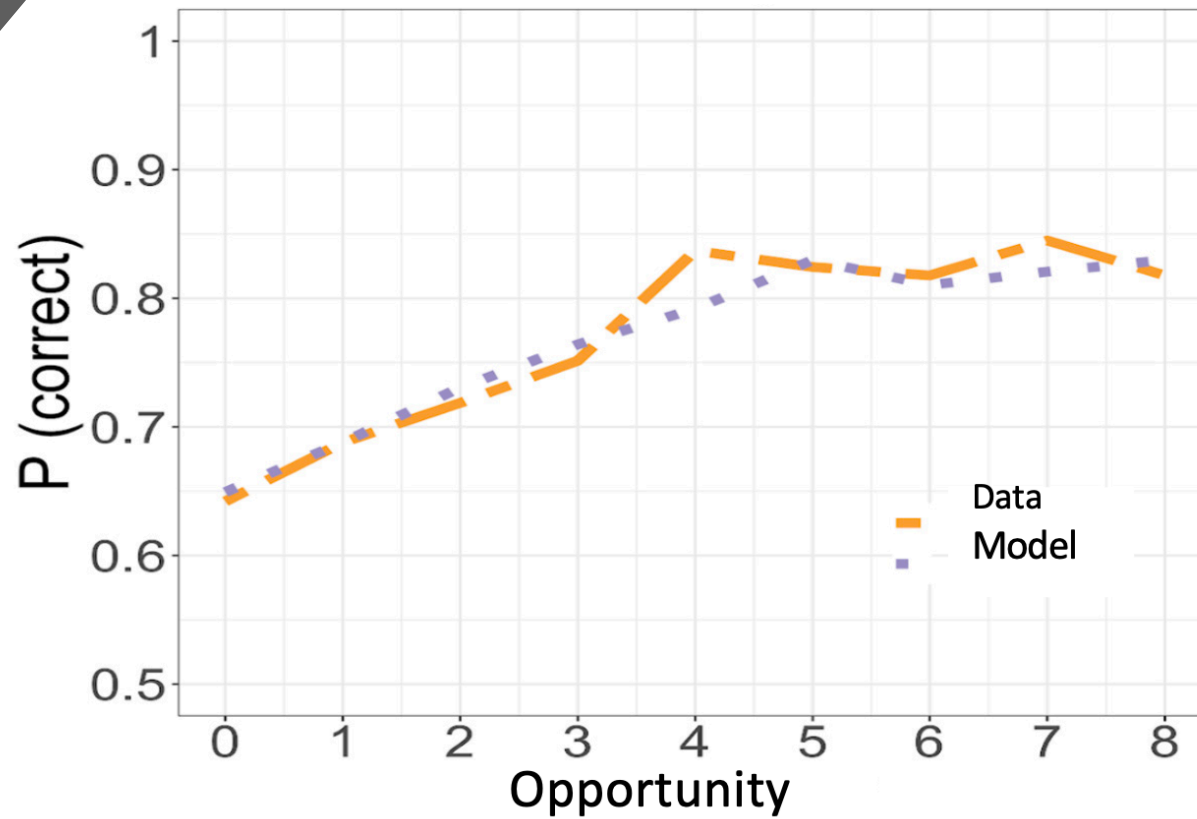
This article contains supporting information online at <https://www.pnas.org/lookup/suppl/doi:10.1073/pnas.2221311120/-DCSupplemental>.

Published March 20, 2023.

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

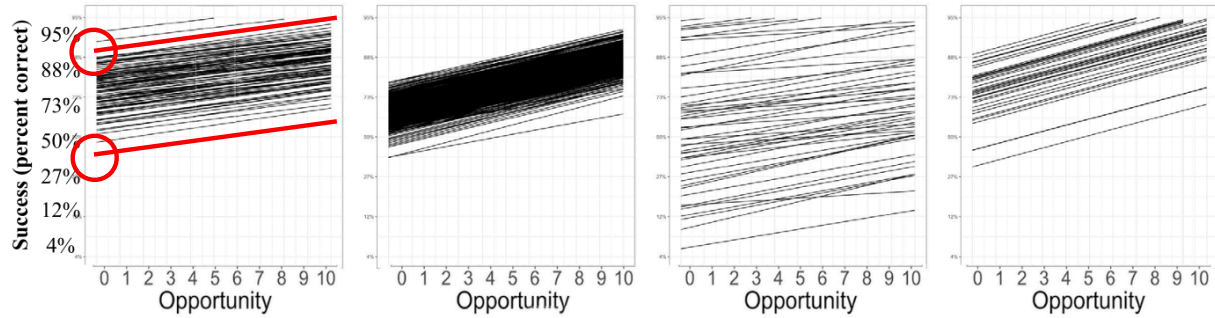
Overall Learning



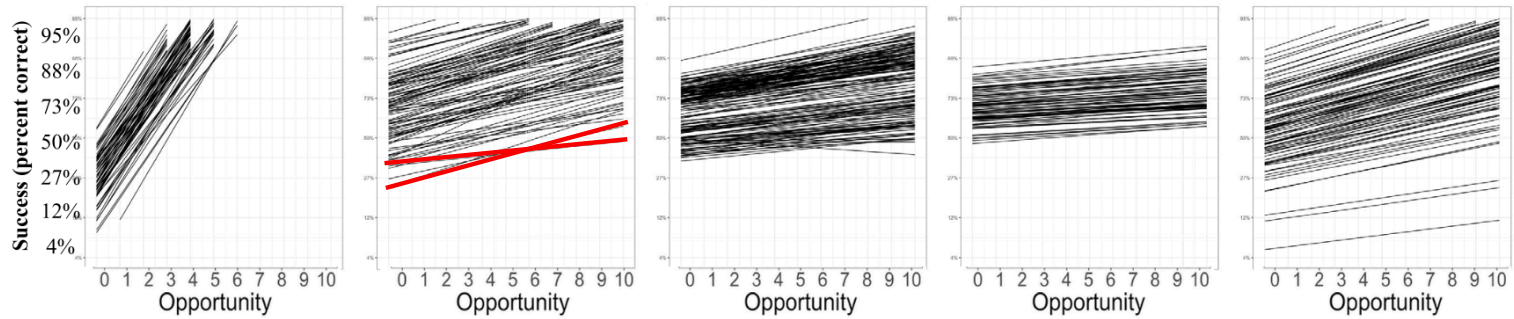
+ 2,5 % par activation

~7 activations

DOMAIN: SCIENCE GRADE LEVEL: COLLEGE

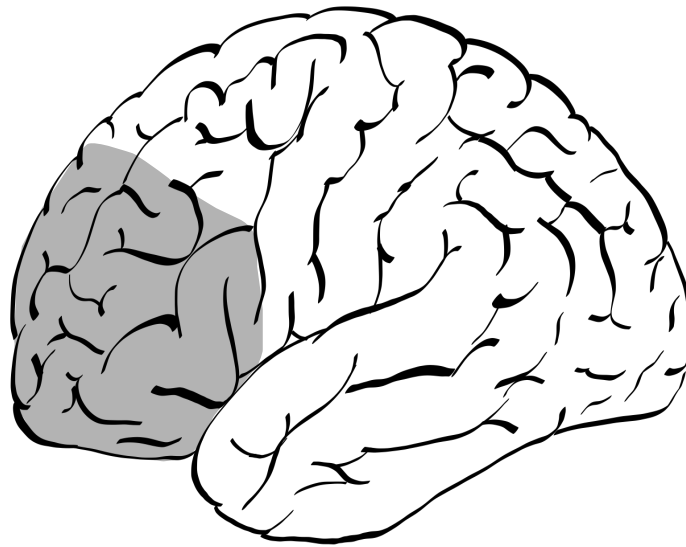


DOMAIN: LANGUAGE GRADE LEVEL: COLLEGE



Taux d'apprentissage très similaires

Cortex préfrontal ↓



Partie 2

Avantages

Avantage 1

Mémoire à
long terme

Récupération



Mémoire
de travail

Récupération = Réactivation

Memory & Cognition
2010, 38 (5), 995–1008
doi:10.3758/MC.38.5.995

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.

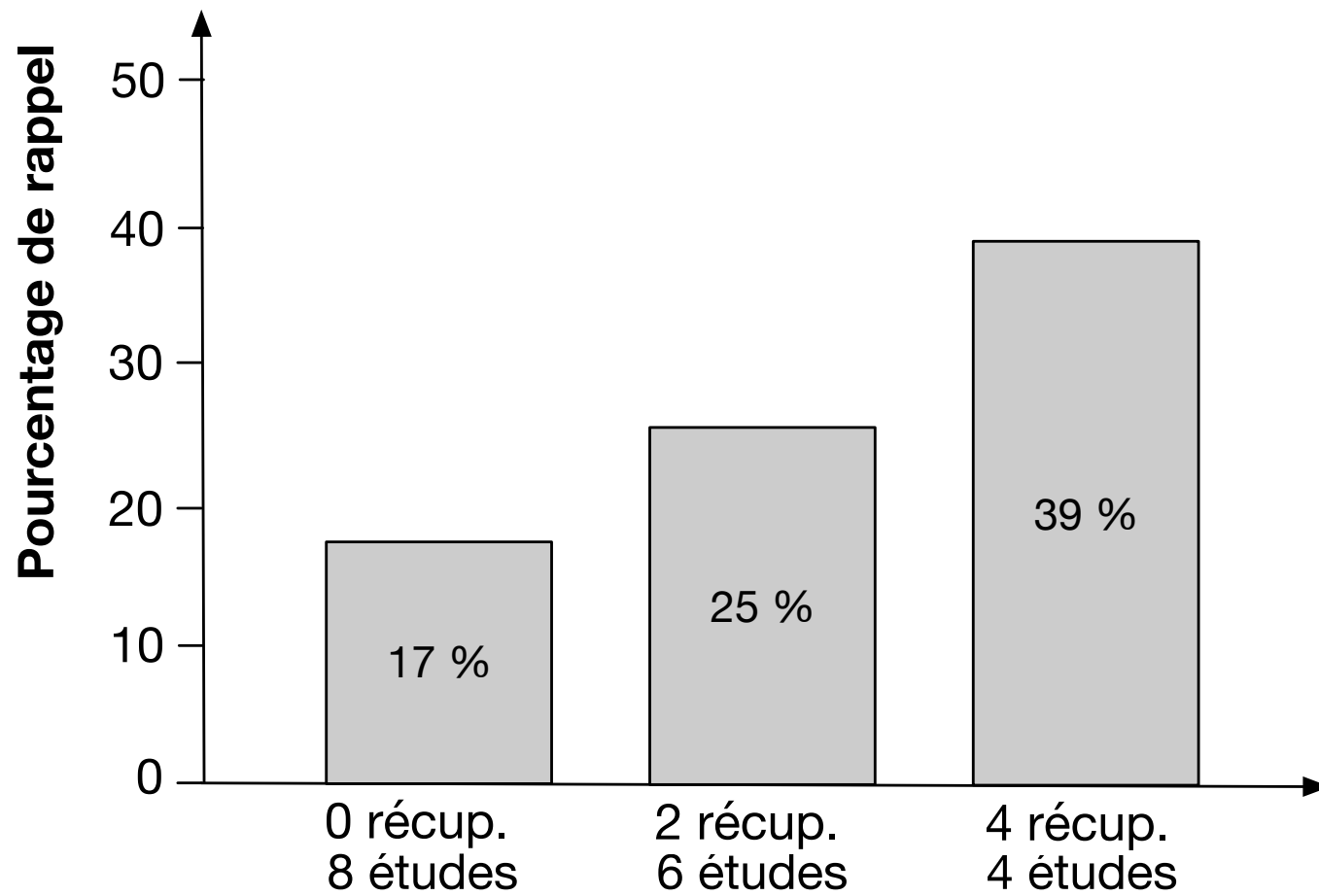
Psychologists have long grappled with questions of how the processes involved in mentally organizing information influence learning and retention (e.g., Ausubel, 1963; Bartlett, 1932; Katona, 1940). One theoretical assumption that has guided much of the cognitive research examining organization and learning 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 repackaging, 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

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

Étude de
Zaromb et al.



Avantage 1

Faciliter l'entraînement à la récupération en mémoire

Comment en profiter ?

Stratégie 1

Questions en ligne
(Wooflash, Kahoot, etc.)

Stratégie 2

Génération automatique de
questions grâce à
l'intelligence artificielle

Stratégie 3

Étude avec une autre
personne par visioconférence

Stratégie 4

Espacement de la
récupération en mémoire

Activation 1

Activation 2

Activation 3

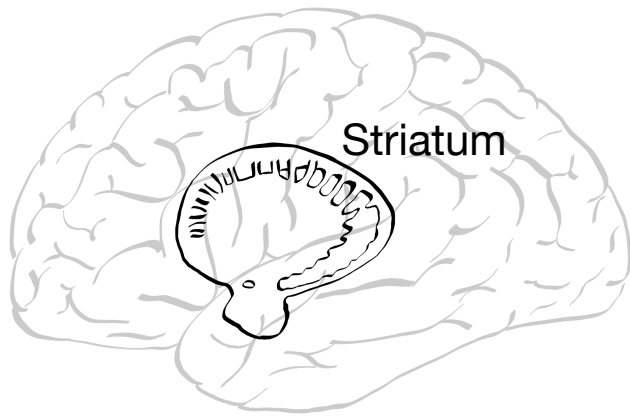
Avantage 2

Rétroaction

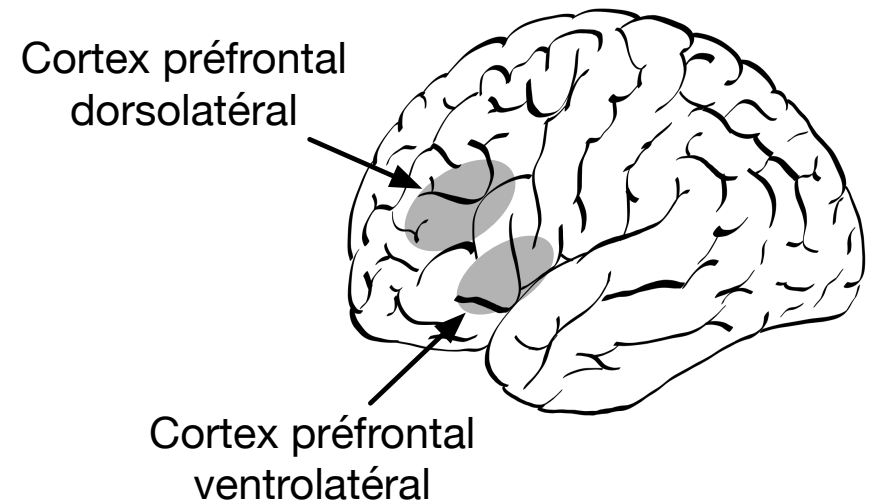
Retour d'information survenant à la suite d'une **action**

Effets de la rétroaction

Rétroaction **positive** ⇒
système de récompenses



Rétroaction **négative** ⇒
système de correction d'erreurs



Avantage 2

Aider à maximiser la rétroaction

Comment en profiter ?

Stratégie 1

Plus de rétroactions grâce
aux questions en ligne avec
correction automatique

Stratégie 2

Plus de rétroactions grâce à
l'intelligence artificielle

Stratégie 3

Rétroactions plus immédiates
grâce aux questions en ligne
et l'intelligence artificielle

Review of Educational Research
December 2015, Vol. 85, No. 4, pp. 475–511
DOI: 10.3102/0034654314564881
© 2015 AERA. <http://rer.aera.net>

Effects of Feedback in a Computer-Based Learning Environment on Students' Learning Outcomes: A Meta-Analysis

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Cito Institute for Educational Measurement and University of Twente

Remco C. W. Feskens

Cito Institute for Educational Measurement

Theo J. H. M. Eggen

*Cito Institute for Educational Measurement and
University of Twente*

In this meta-analysis, we investigated the effects of methods for providing item-based feedback in a computer-based environment on students' learning outcomes. From 40 studies, 70 effect sizes were computed, which ranged from -0.78 to 2.29 . A mixed model was used for the data analysis. The results show that elaborated feedback (EF; e.g., providing an explanation) produced larger effect sizes (0.49) than feedback regarding the correctness of the answer (KR; 0.05) or providing the correct answer (KCR; 0.32). EF was particularly more effective than KR and KCR for higher order learning outcomes. Effect sizes were positively affected by EF feedback, and larger effect sizes were found for mathematics compared with social sciences, science, and languages. Effect sizes were negatively affected by delayed feedback timing and by primary and high school. Although the results suggested that immediate feedback was more effective for lower order learning than delayed feedback and vice versa, no significant interaction was found.

KEYWORDS: feedback, computers, learning, meta-analysis

The importance of assessment in the learning process is widely acknowledged, especially with the growing popularity of the assessment for learning approach (Assessment Reform Group [ARG], 1999; Stobart, 2008). The role of assessment in the learning process is crucial. "It is only through assessment that we can find out whether a particular sequence of instructional activities has resulted in the intended learning outcomes" (Wiliam, 2011, p. 3). Many researchers currently claim that formative assessment can have a positive effect on the learning outcomes of students. However, these claims are not very well grounded, an issue that

475

Méta-analyse sur l'effet de la rétroaction

Facteur	Ampleur de l'effet
Moment de la rétroaction	
Rétroaction immédiate	0,46
Rétroaction différée	0,22

Avantage 2

Aider à maximiser la rétroaction

Comment en profiter ?

Stratégie 1

Plus de rétroactions grâce
aux questions en ligne avec
correction automatique

Stratégie 2


Plus de rétroactions grâce à
l'intelligence artificielle

Stratégie 3

Rétroactions plus immédiates
grâce aux questions en ligne
et l'intelligence artificielle

Stratégie 4

Rétroactions plus élaborées
grâce aux questions en ligne
et l'intelligence artificielle

Facteur		Ampleur de l'effet
Type de rétroaction		
	Rétroaction élaborée <i>(Fournir une explication)</i>	0,49
	Rétroaction fournissant la réponse correcte <i>(Dire qu'il y a une erreur et fournir la bonne réponse)</i>	0,32
	Rétroaction ne fournissant pas la réponse correcte <i>(Dire qu'il y a une erreur, mais sans donner la bonne réponse)</i>	0,05



Dylan Wiliam
@dylanwiliam

...

Google's Gemini is extraordinary: arxiv.org/abs/2312.11805

Prompt

Here's a solution to a Physics problem by a student.

23. A skier slides down the frictionless slope as shown. What is the skier's speed at the bottom?

Start
H=40 m
Finish
L=80 m

Solution:

The conservation of energy means that the energy of the skier is same at the beginning and at the end.

Start: $E = mgL$

End: $E = \frac{1}{2}mv^2$

$\Rightarrow mgL = \frac{1}{2}mv^2$

$\Rightarrow v = \sqrt{2gL} = \sqrt{2 \times 9.81 \times 80} = 39.6 \text{ m.s}^{-1}$

Try to reason about the question step by step.

Did the student get the correct answer? If the solution is wrong, please explain what is wrong and solve the problem.

The student did not get the correct answer. The student made a mistake in the calculation of the potential energy at the start of the slope. The potential energy at the start of the slope is given by mgh , where m is the mass of the skier, g is the acceleration due to gravity, and h is the height of the slope. The student used the length of the slope, L , instead of the height, H , in the calculation of the potential energy.

The correct solution is:

The conservation of energy means that the total energy of the skier is the same at the beginning and at the end of the slope.

At the start of the slope, the skier has only potential energy, which is given by mgh .

At the end of the slope, the skier has only kinetic energy, which is given by $\frac{1}{2}mv^2$

Therefore, we can write:

$$mgh = \frac{1}{2}mv^2$$

Canceling out the mass m on both sides, we get:

$$gh = \frac{1}{2}v^2$$

Solving for v , we get:

$$v = \sqrt{2gh}$$

Substituting the given values, we get:

10:41 AM · 14 févr. 2024 · 51,3 k vues

<https://twitter.com/dylanwiliam/status/1757792298639728983>

Partie 3

Pièges à éviter

Piège à éviter 1

Piège à éviter 1

Éviter que le numérique devienne une source de distractions

Comment l'éviter ?

Stratégie 1

Ranger son téléphone

Brain Drain: The Mere Presence of One's Own Smartphone Reduces Available Cognitive Capacity

ADRIAN F. WARD, KRISTEN DUKE, AYELET GNEEZY, AND MAARTEN W. BOS

ABSTRACT Our smartphones enable—and encourage—constant connection to information, entertainment, and each other. They put the world at our fingertips, and rarely leave our sides. Although these devices have immense potential to improve welfare, their persistent presence may come at a cognitive cost. In this research, we test the “brain drain” hypothesis that the mere presence of one’s own smartphone may occupy limited-capacity cognitive resources, thereby leaving fewer resources available for other tasks and undercutting cognitive performance. Results from two experiments indicate that even when people are successful at maintaining sustained attention—as when avoiding the temptation to check their phones—the mere presence of these devices reduces available cognitive capacity. Moreover, these cognitive costs are highest for those highest in smartphone dependence. We conclude by discussing the practical implications of this smartphone-induced brain drain for consumer decision-making and consumer welfare.

We all understand the joys of our always-wired world—the connections, the validations, the laughs . . . the info. . . . But we are only beginning to get our minds around the costs.

—Andrew Sullivan (2016)

The proliferation of smartphones has ushered in an era of unprecedented connectivity. Consumers around the globe are now constantly connected to faraway friends, endless entertainment, and virtually unlimited information. With smartphones in hand, they check the weather from bed, trade stocks—and gossip—while stuck in traffic, browse potential romantic partners between appointments, make online purchases while standing in-store, and live-stream each others’ experiences, in real time, from opposite sides of the globe. Just a decade ago, this state of constant connection would have been inconceivable; today, it is seemingly indispensable.¹ Smartphone owners interact with their phones an average of 85 times a day, including immediately upon waking up, just before going to sleep, and even in the middle of the night (Perlow 2012; Andrews et al. 2015; dscout 2016). Ninety-one percent report that

they never leave home without their phones (Deutsche Telekom 2012), and 46% say that they couldn’t live without them (Pew Research Center 2015). These revolutionary devices enable on-demand access to friends, family, colleagues, companies, brands, retailers, cat videos, and much more. They represent all that the connected world has to offer, condensed into a device that fits in the palm of one’s hand—and almost never leaves one’s side.

The sharp penetration of smartphones, both across global markets and into consumers’ everyday lives, represents a phenomenon high in “meaning and mattering” (e.g., Kernan 1979; Mick 2006)—one that has the potential to affect the welfare of billions of consumers worldwide. As individuals increasingly turn to smartphone screens for managing and enhancing their daily lives, we must ask how dependence on these devices affects the ability to

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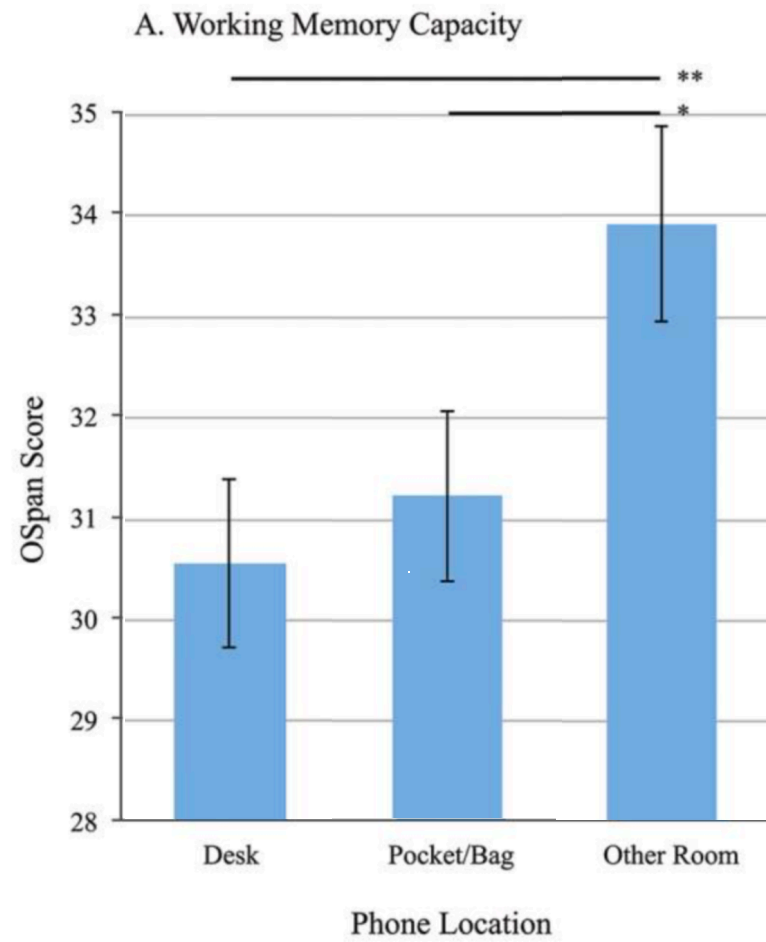
1. In 2007, only 4% of American adults owned smartphones (Radwanick 2012). As of January 2017, 77% of American adults—and 92% of those under the age of 35—own smartphones (Pew Research Center 2017). Penetration is similarly high in most Western nations, and even higher in several Middle Eastern and Asian countries. South Korea, for example, has a national smartphone ownership rate of 88%, including 100% of those under 35 (Pew Research Center 2016).

JACR, volume 2, number 2. Published online April 3, 2017. <http://dx.doi.org/10.1086/691462>
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Effet négatif de la présence de son téléphone

Étude de
Ward et al.





Piège à éviter 1

Éviter que le numérique devienne une source de distractions

Comment l'éviter ?

Stratégie 1

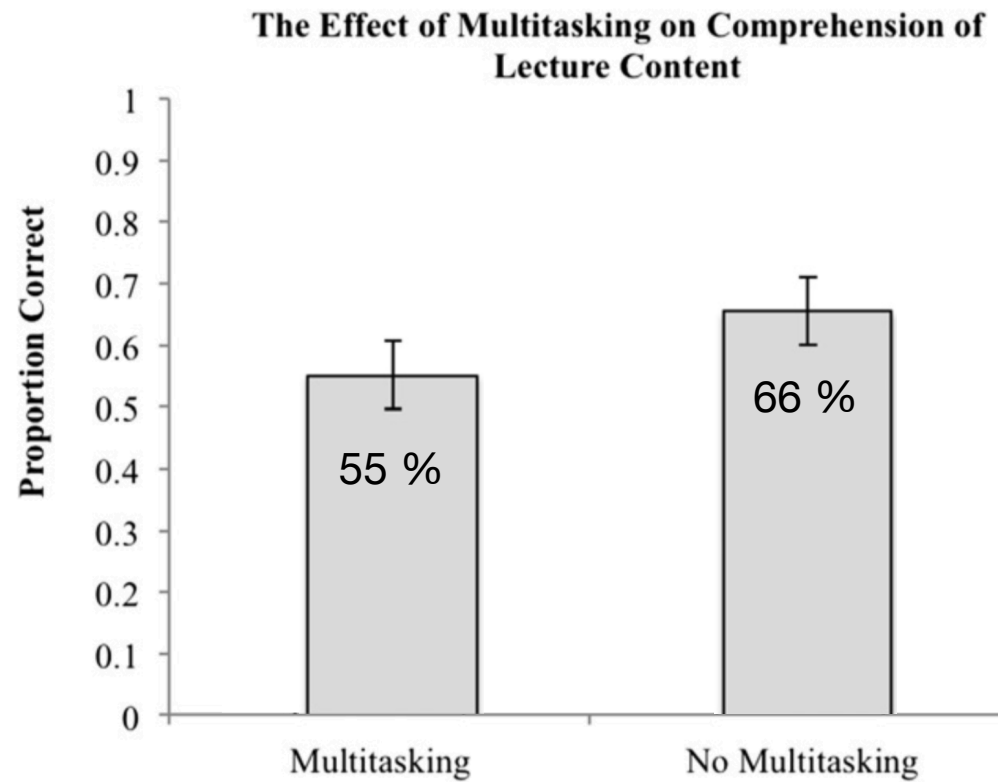
Ranger son téléphone

Stratégie 2

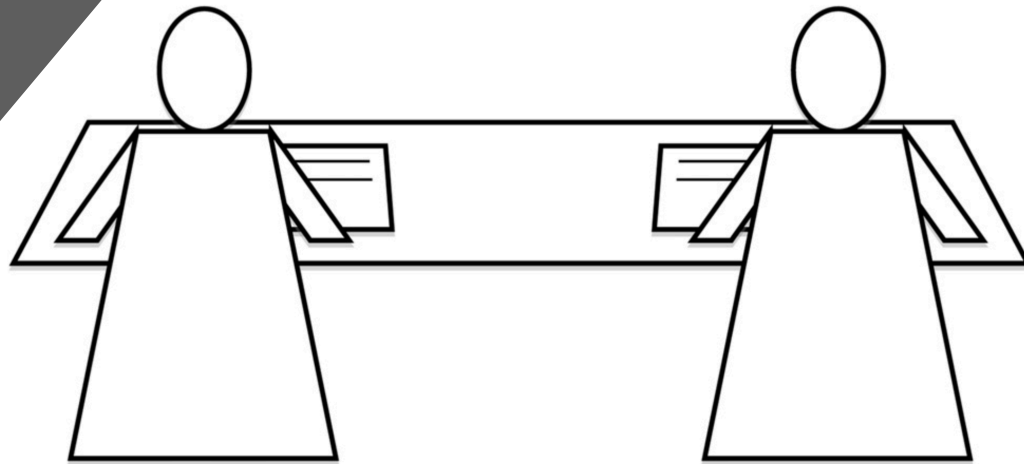
Éviter le multitâche



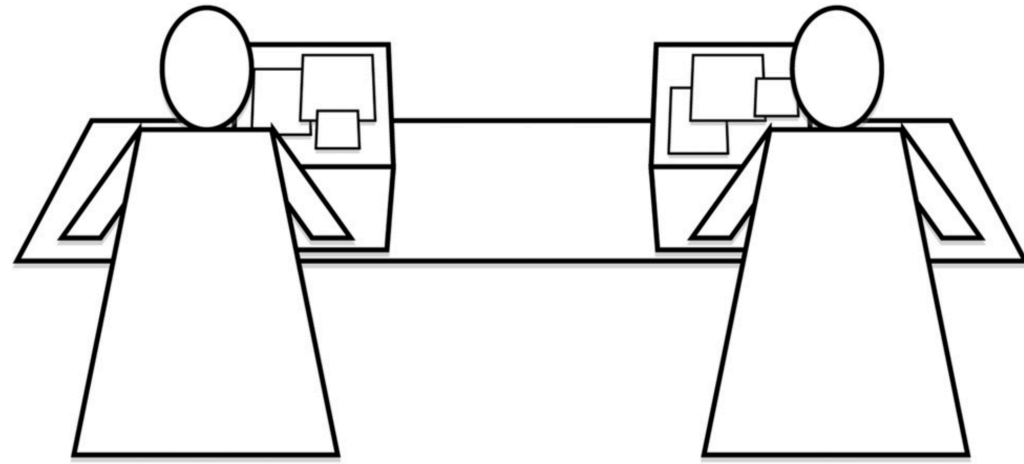
Effet négatif du **multitâche** et des **médias sociaux** (ordinateur en classe)

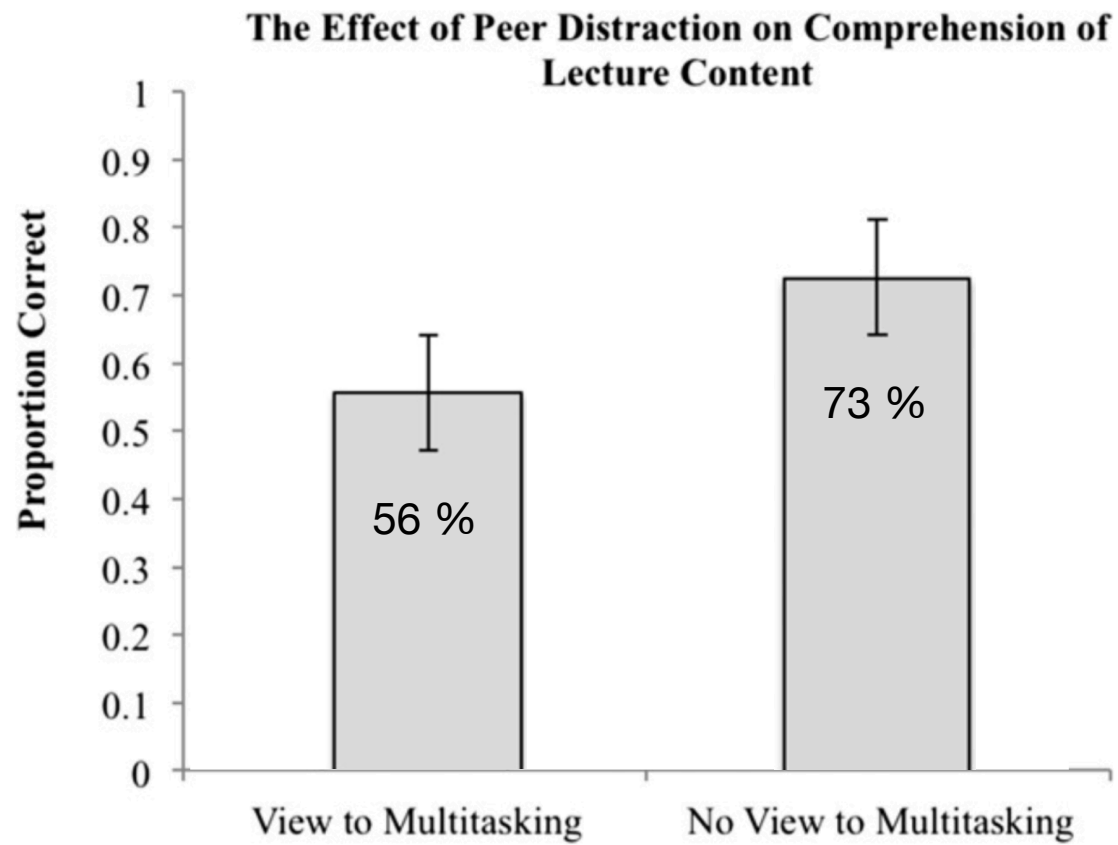


Not in view of a multitasking peer



In view of a multitasking peer





Piège à éviter 2

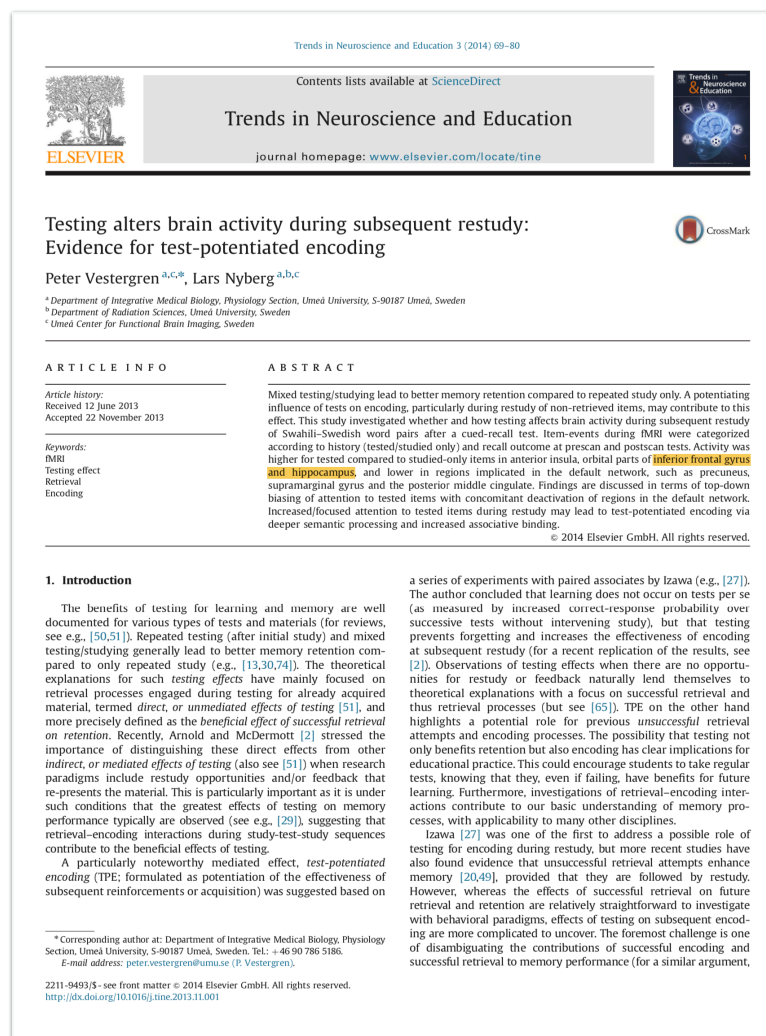
Piège à éviter 2

Éviter que le numérique devienne une raison de ne plus activer/mémoriser

Comment l'éviter ?

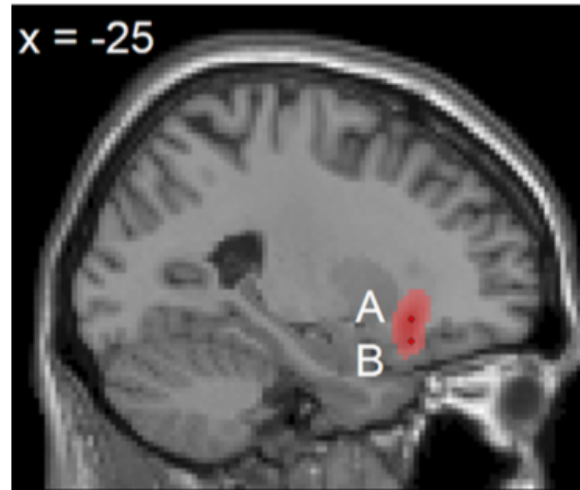
Stratégie 1

Éviter de chercher l'info sur Internet plutôt que de récupérer en mémoire

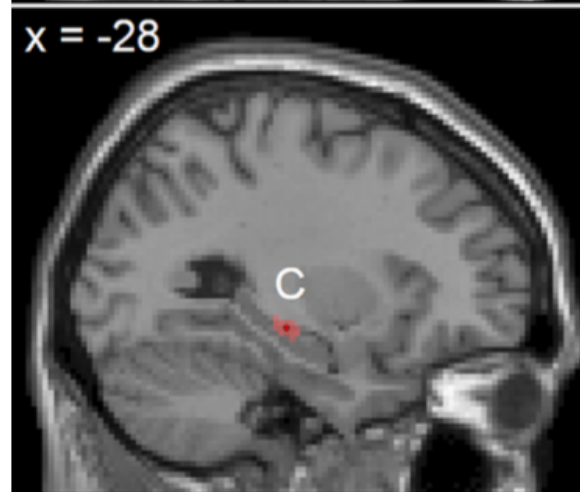


Effets de la récupération en mémoire vs lecture

Étude de
Vestergren et Nyberg



Cortex préfrontal
ventro-latéral



Hippocampe

Mémorisation

Récupération > lecture

Piège à éviter 2

Éviter que le numérique devienne une raison de ne plus activer/mémoriser

Comment l'éviter ?

Stratégie 1

Éviter de chercher l'info sur Internet plutôt que de récupérer en mémoire

Stratégie 2

Éviter de ne plus mémoriser, car tout se trouve sur Internet

Mémoriser

Pour être capable de **chercher** des informations

Pour être capable d'**esprit critique**

Pour être capable de **créativité**

Pour être capable de **comprendre**

Pour **ne pas surcharger** le cerveau

Pour être capable de **réfléchir**

Synthèse

Utilisation du numérique en éducation

Avantages

Avantage 1

Faciliter l'entraînement à la récupération en mémoire

Avantage 2

Aider à maximiser la rétroaction

Pièges

Piège à éviter 1

Éviter que le numérique devienne une source de distractions

Piège à éviter 2

Éviter que le numérique devienne une raison de ne plus activer/mémoriser