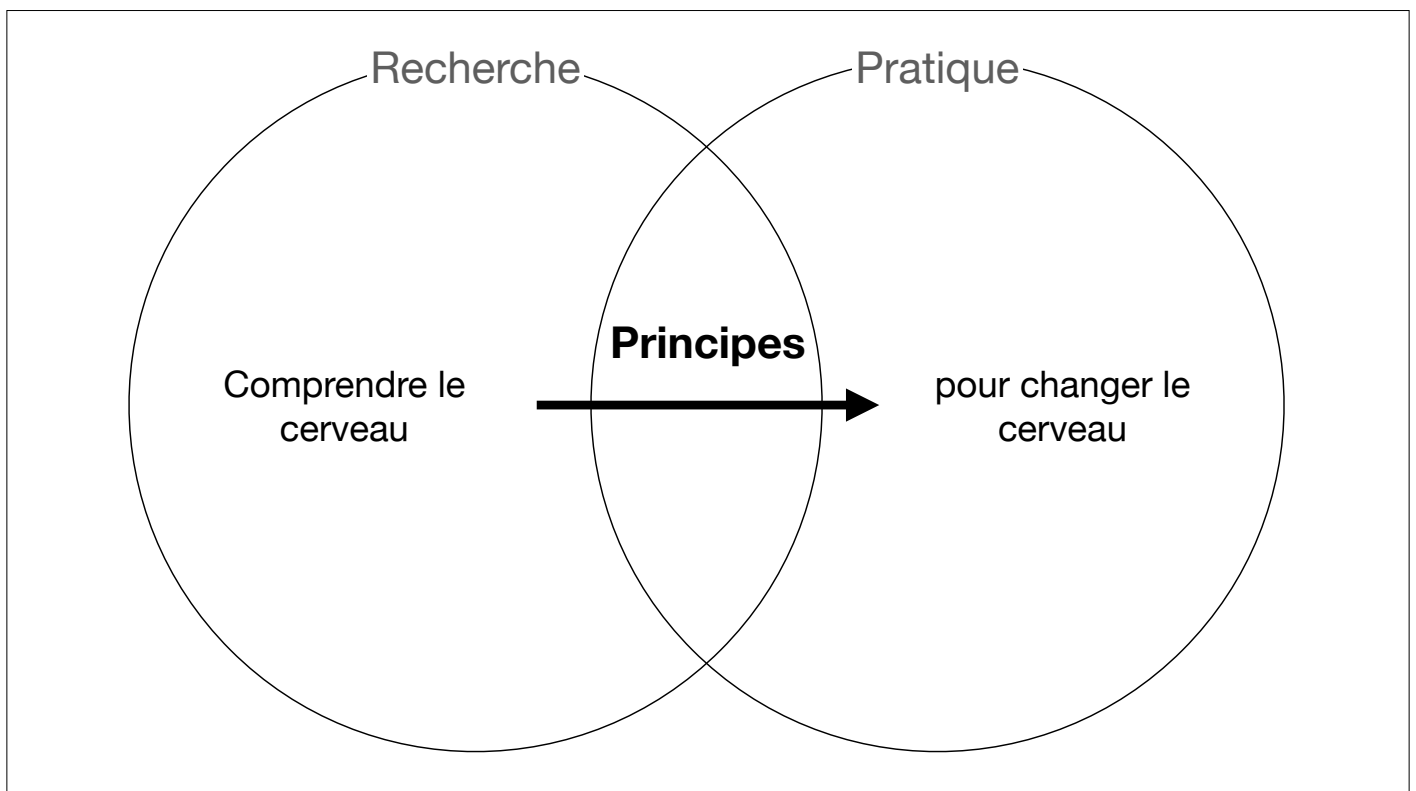


Enseigner change le cerveau !

Colloque pédagogique du Collège Ahuntsic 2024 - 10 janvier 2024
Steve Masson, professeur à l'Université du Québec à Montréal

1



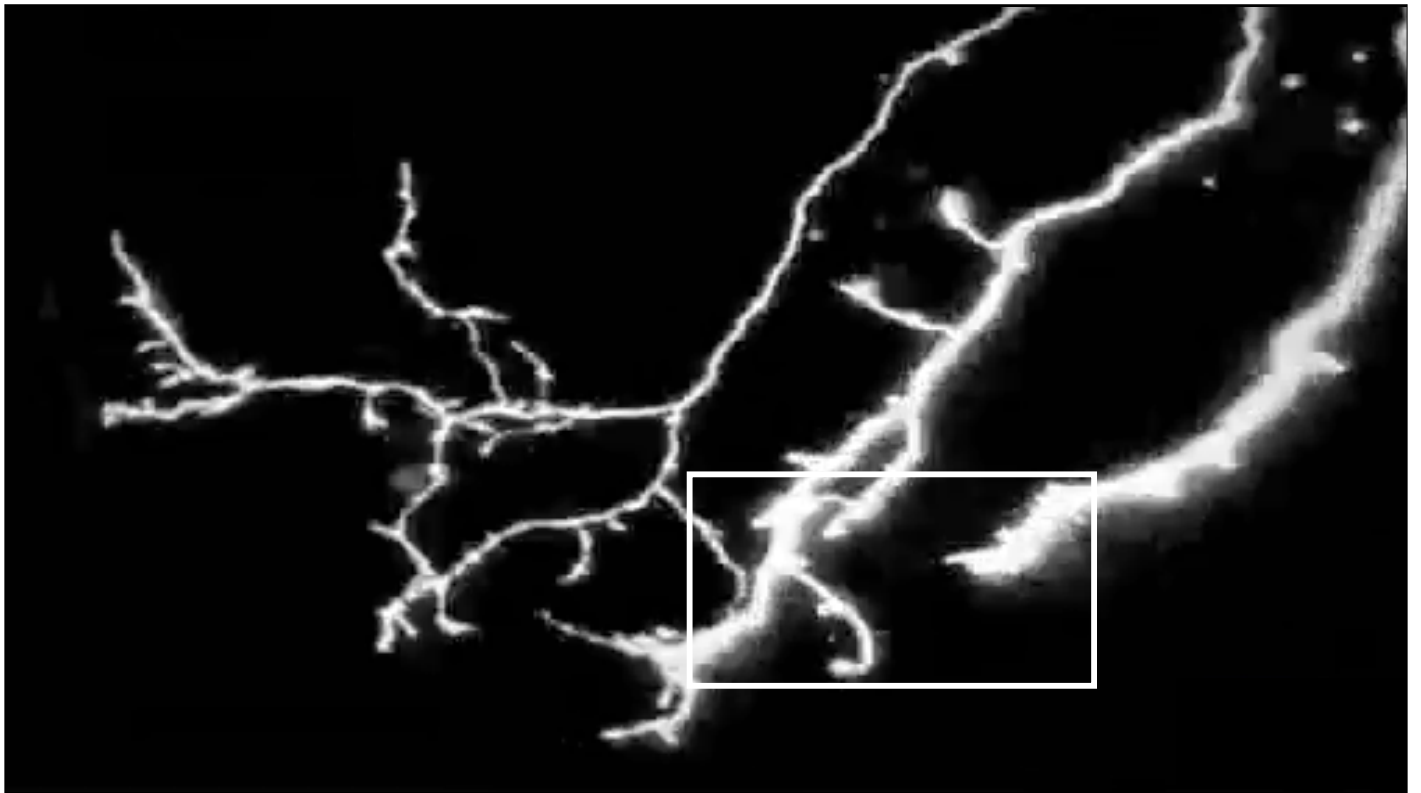
2

Principe 1

3

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

4



5

Livre de
Hebb

The
**Organization
of Behavior**

A Neuropsychological Theory

D.O. HEBB

Mécanisme de modification de connexions

6

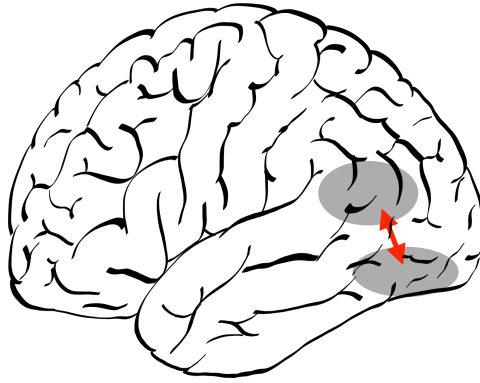
Les neurones qui s'**activent** ensemble
se **connectent** ensemble.

7

Analogie de la forêt



8



9

Principe 1

Activer à plusieurs reprises

Comment ?

Stratégie 1

Planifier plusieurs moments
d'activation

10

Étude de Koedinger et al.

PNAS
RESEARCH ARTICLE | PSYCHOLOGICAL AND COGNITIVE SCIENCES

An astonishing regularity in student learning rate

Kenneth H. Koedinger¹, Paulo F. Carvalho², Ran Lu³, and Elizabeth A. McLaughlin¹
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 5% 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](https://www.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.

Author affiliations: ¹Human-Computer Interaction Institute, Carnegie Mellon University, Pittsburgh, PA 15213, and ²Engineering, Anna Learning, Seattle, WA 98101

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

The authors declare no competing interest.

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To whom correspondence may be addressed. Email: koedinger@cmu.edu.

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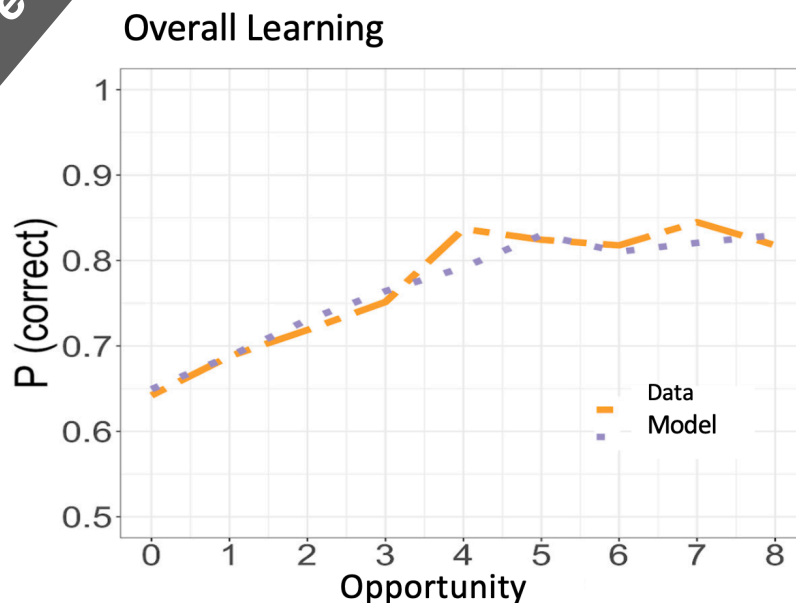
Published March 20, 2023.

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

11

Étude de Koedinger et al.



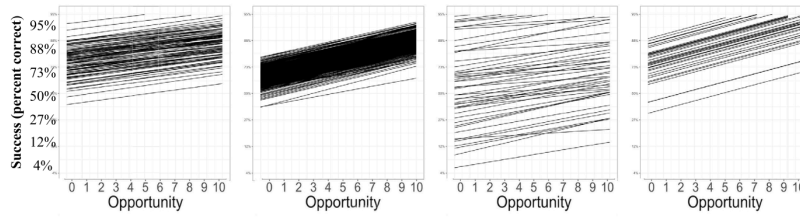
+ 2,5 % par activation
~7 activations

12

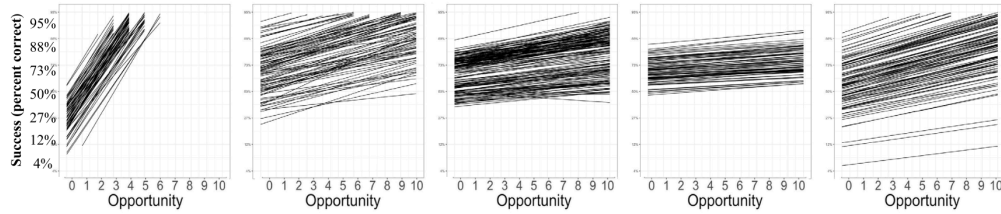
Étude de

Koedinger et al.

DOMAIN: SCIENCE GRADE LEVEL: COLLEGE



DOMAIN: LANGUAGE GRADE LEVEL: COLLEGE



Taux d'apprentissage très similaires

13

Principe 1

Activer à plusieurs reprises

Comment ?

Stratégie 1

Planifier plusieurs moments d'activation

Stratégie 2

Utiliser fréquemment des approches actives

14

Approches
actives



Produire

Approches
passives



Écouter / Lire

15

Étude de
Freeman et al.

Active learning increases student performance in science, engineering, and mathematics

Scott Freeman¹*, Sarah L. Eddy², Miles McDonough³, Michelle K. Smith⁴, Nnadozie Okoroafor⁵, Hannah Jordt⁶, and Mary Pat Wenderoth¹

¹Department of Biology, University of Washington, Seattle, WA 98195; and ²School of Biology and Ecology, University of Maine, Orono, ME 04469

Editorial by Bruce Alberts, University of California, San Francisco, CA, and approved April 15, 2014 (received for review October 8, 2013)

To test the hypothesis that lecturing maximizes learning and course performance, we metaanalyzed 225 studies that reported data on examination scores or failure rates when comparing student performance in undergraduate science, technology, engineering, and mathematics (STEM) courses under traditional lecturing versus active learning. The effect sizes indicate that on average, student performance on examinations and concept inventories **improved by 0.47 SDs under active learning** ($n = 158$ studies), and that the odds ratio for failing was 1.95 under traditional lecturing ($n = 67$ studies). These results indicate that average examination scores improved by about 6% in active learning sections, and that students in classes with traditional lecturing were 1.5 times more likely to fail than were students in classes with active learning. Heterogeneity analyses indicated that both results hold across the STEM disciplines, that active learning increases scores on concept inventories more than on course examinations, and that active learning appears effective across all class sizes—although the greatest effects are in small ($n < 50$) classes. Trim and fill analyses and fail-safe n calculations suggest that the results are not due to publication bias. The results also appear robust to variation in the methodological rigor of the included studies, based on the quality of controls over student quality and instructor identity. This is the largest and most comprehensive metaanalysis of undergraduate STEM education published to date. The results raise questions about the continued use of traditional lecturing as a control in research studies, and support active learning as the preferred, empirically validated teaching practice in regular classrooms.

construction | undergraduate education | evidence-based teaching | scientific teaching

Lecturing has been the predominant mode of instruction since universities were founded in Western Europe over 900 y ago (1). Although theories of learning that emphasize the need for students to construct their own understanding have challenged the theoretical underpinnings of the traditional, instructor-focused, “teaching by telling” approach (2, 3), to date there has been no quantitative analysis of how constructivist versus exposition-centered methods impact student performance in undergraduate courses across the sciences, technology, engineering, and mathematics (STEM) disciplines. In the STEM classroom, should we ask or should we tell? Addressing this question is essential if scientists are committed to teaching based on evidence rather than tradition (4). The answer could also be part of a solution to the “pipeline problem” that some countries are experiencing in STEM education: For example, the observation that less than 60% of US students who enter university with an interest in STEM, and just 20% of STEM-attending underrepresented minority students, finish with a STEM degree (5).

To test the efficacy of constructivist versus exposition-centered course designs, we focused on the design of class activities—as opposed to laboratories, homework assignments, or other exercises. More specifically, we compared the results of experiments that documented student performance in courses with at least some active learning versus traditional lecturing, by metaanalyzing

225 studies in the published and unpublished literature. The active learning interventions varied widely in intensity and implementation, and included approaches as diverse as occasional group problem-solving, worksheets or tutorials completed during class, use of personal response systems with or without peer instruction, and studio or workshop course designs. We followed guidelines for best practice in quantitative reviews (32 *Methods and Materials*), and evaluated student performance using two outcome variables: (i) scores on identical or formally equivalent examinations, concept inventories, or other assessments; or (ii) failure rates, usually measured as the percentage of students receiving a D or F grade or withdrawing from the course in question (DFW rate).

The analyses, then, focused on two related questions: Does active learning boost examination scores? Does it lower failure rates?

Results

The overall mean effect size for performance on identical or equivalent examinations, concept inventories, and other assessments was a weighted standardized mean difference of 0.47 ($Z = 9.78$; $P < 0.001$), meaning that on average, student performance increased by just under half a SD with active learning compared with lecturing. The overall mean effect size for failure rate was an odds ratio of 1.95 ($Z = 10.4$; $P < 0.001$). This odds ratio is equivalent to a risk ratio of 1.5, meaning that on average, students in traditional lecture courses are 1.5 times more likely to fail than students in courses with active learning. Average failure rates were 23.8% under active learning but 33.8% under traditional lecturing—a difference that represents a 55% increase (Fig. 1 and Fig. S1).

Significance

The President's Council of Advisors on Science and Technology has called for a 25% increase in the number of science, technology, engineering, and mathematics (STEM) bachelor's degrees completed per year and recommended adoption of empirically validated teaching practices as critical to achieving that goal. The studies analyzed here document that active learning leads to increases in examination performance that would raise average grades by a half a letter, and that failure rates under traditional lecturing increase by 55% over the rates observed under active learning. The analysis supports theory claiming that calls to increase the number of students enrolling in STEM degrees could be answered, at least in part, by abandoning traditional lecturing in favor of active learning.

Author contributions: S.F. and M.P.W. designed research; S.F., M.M., M.S., N.O., H.J., and M.P.W. performed research; S.F. and S.L.E. analyzed data; and S.F., S.L.E., M.M., M.S., N.O., H.J., and M.P.W. wrote the paper.

The authors declare no conflict of interest.

*To whom correspondence should be addressed. E-mail: sfreem@u.washington.edu.

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See Commentary on page 8178.

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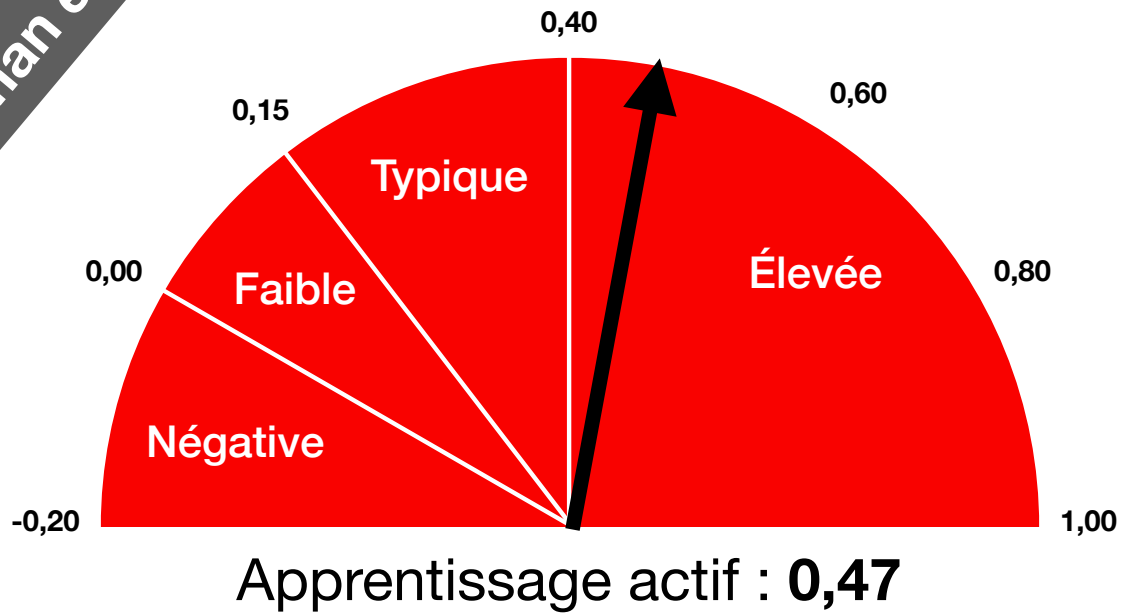
0410-9451 | PNAS | June 10, 2014 | vol. 111 | no. 23

www.pnas.org/doi/10.1073/pnas.1310030111

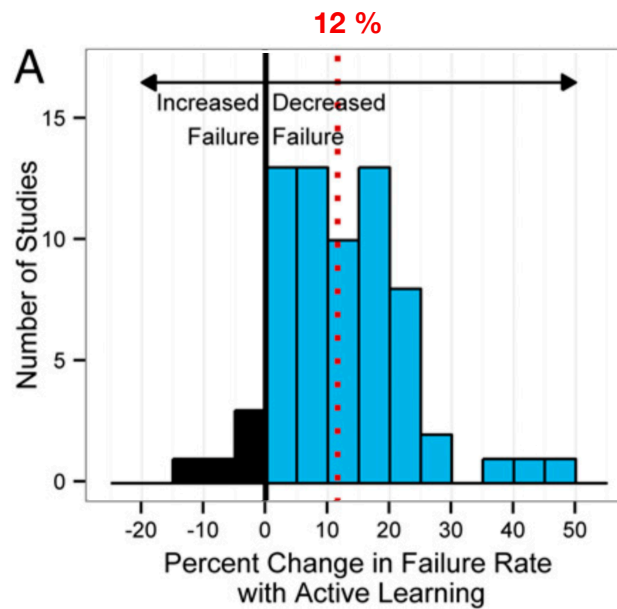
Méta-analyse sur l'efficacité de l'apprentissage actif (vs enseignement magistral)

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Taille de l'effet



17



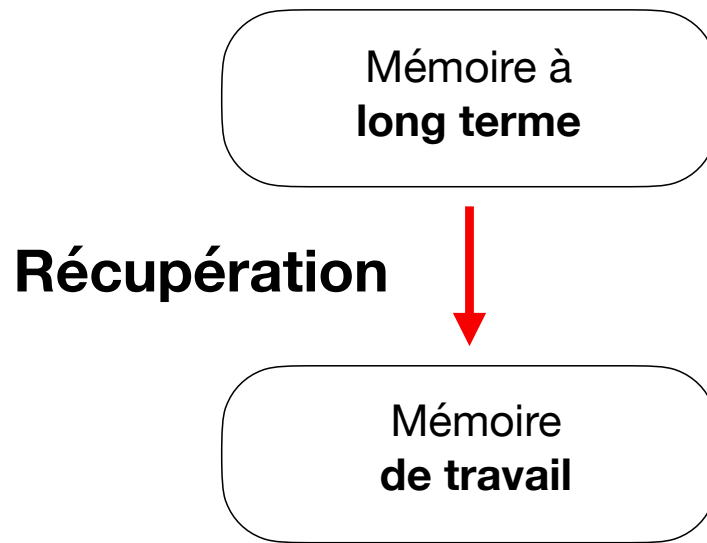
18

Quelles sont les **approches actives**
les plus **efficaces** ?

19

Principe 2

20



21

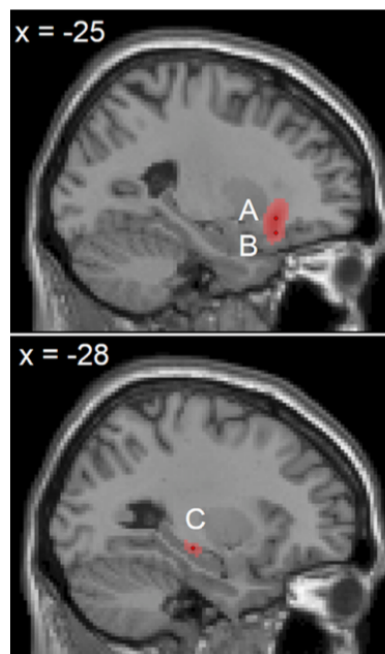
Récupérer = Réactiver

22



Effets de la récupération en mémoire (tests) vs étude

23



Cortex préfrontal
ventrolatéral

Hippocampe

Mémorisation

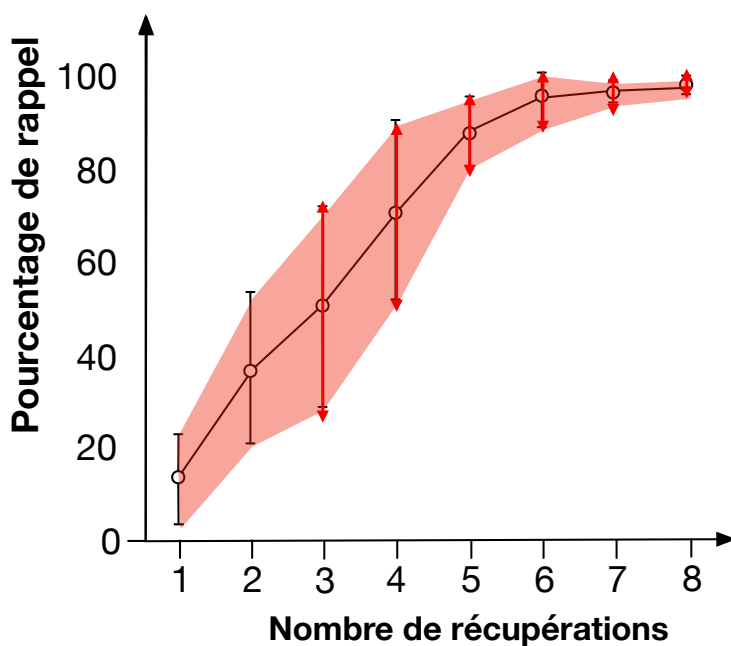
Récupération > étude

24



Effets de la **récupération** en mémoire sur l'apprentissage

25



Apprentissage ↑

Variabilité ↓

Étude de Zaromb et al.

Memory & Cognition
2010, 38 (3), 995-1000
doi:10.3758/MC.38.3.995

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, Detrich, & 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, Roher, 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; Szepura, McDermott, & Roediger, 2008; Tulving & Watkins, 1974) and by permitting better transfer to new questions (Butler, 2010; Johnson &

Mayer, 2009; Roher, 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@wustl.edu

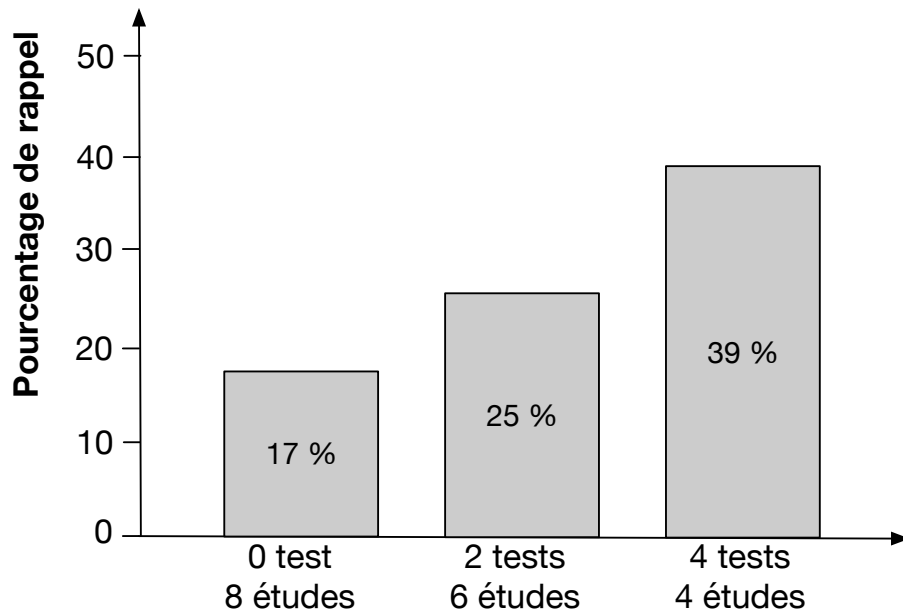
995

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Effets des tests vs étude

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Étude de Zaromb et al.



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Rethinking the Use of Tests: A Meta-Analysis of Practice Testing

Olusola O. Adesope
Washington State University
Dominic A. Trevisan
Simon Fraser University, Canada
Narayankripa Sundararajan
Washington State University

The testing effect is a well-known concept referring to gains in learning and retention that can occur when students take a practice test on studied material before taking a final test on the same material. Research demonstrates that students who take practice tests often outperform students in nontesting learning conditions such as restudying, practice, filler activities, or no presentation of the material. However, evidence-based meta-analysis is needed to develop a comprehensive understanding of the conditions under which practice tests enhance or inhibit learning. This meta-analysis fills this gap by examining the effects of practice tests versus nontesting learning conditions. Results reveal that practice tests are more beneficial for learning than restudying and all other comparison conditions. Mean effect sizes were moderated by the features of practice tests, participant and study characteristics, outcome constructs, and methodological features of the studies. Findings may guide the use of practice tests to advance student learning, and inform students, teachers, researchers, and policymakers. This article concludes with the theoretical and practical implications of the meta-analysis.

KEYWORDS: practice test, testing effect, retrieval practice, meta-analysis, systematic review

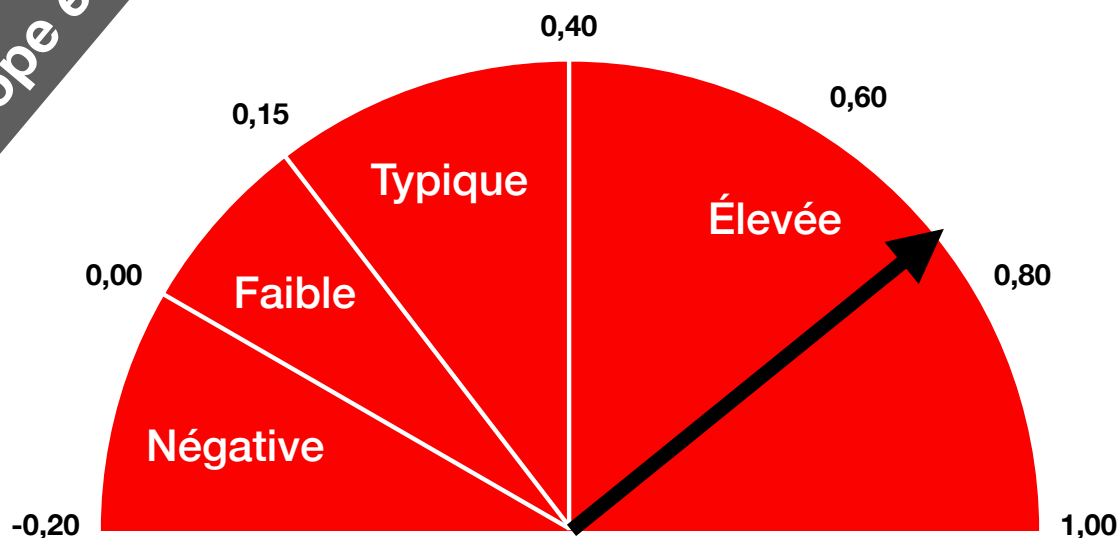
Johnny comes home from school exhausted. He's scheduled to take five tests within the next few days (American literature, C++ programming, U.S. and Global Economics, Calculus, and Forensic Science), and results will determine whether he can graduate. Despite spending hours each night preparing for exams, he becomes overwhelmed grappling with complex topics. "Why do we have tests?" Johnny exclaims to his parents. "How do I study for these tests? I don't know!" Johnny's parents notice his frustration and are concerned that he's considering dropping out of high school, since he struggled to make it to Grade 12.

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Méta-analyse sur l'effet de la récupération en mémoire

29

Taille de l'effet



Récupération en mémoire : 0,74

30

Principe 2

Récupérer en mémoire

Comment ?

Stratégie 1

Faire fréquemment des tests

Stratégie 2

Répondre souvent à des questions

Stratégie 3

Laisser du temps pour récupérer en mémoire

Stratégie 4

Donner des indices

Principe 3

Élaborer = Réactiver

33

Élaborer = recupérer en mémoire + établir des liens

34

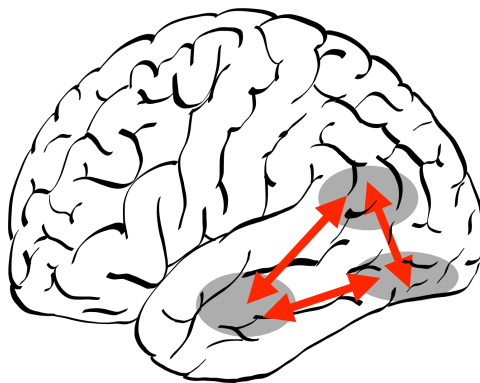
Élaborer =

activer des **neurones**
liés à l'apprentissage **visé**

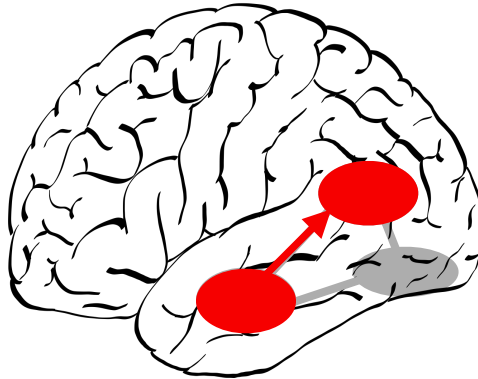
+

activer d'**autres neurones**
(notions reliées, connaissances antérieures, etc.)


35



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Étude de
Moss et al.



NeuroImage

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



The neural correlates of strategic reading comprehension: Cognitive control and discourse comprehension

Jarrod Moss ^{a,*}, Christian D. Schunn ^b, Walter Schneider ^b, Danielle S. McNamara ^c, Kurt VanLehn ^d

^a Department of Psychology, Mississippi State University, USA
^b Learning Research and Development Center, University of Pittsburgh, USA
^c Department of Psychology, University of Memphis, USA
^d School of Computing, Arizona State University, USA

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ABSTRACT

Neuroimaging studies of text comprehension conducted thus far have shed little light on the brain mechanisms underlying strategic learning from text. Thus, the present study was designed to answer the question of which brain areas are active during performance of complex reading strategies. Reading comprehension strategies are designed to improve a reader's comprehension of a text. For example, self-explanation is a complex reading strategy that enhances existing comprehension processes. It was hypothesized that reading strategies would involve areas of the brain that are normally involved in reading comprehension along with areas that are involved in strategic control processes because the readers are intentionally using a complex reading strategy. Subjects were asked to reread, paraphrase, and self-explain three different texts in a block design fMRI study. Activation was found in both executive control and comprehension areas, and furthermore, learning from text was associated with activation in the anterior prefrontal cortex (APFC). The authors speculate that the APFC may play a role in coordinating the internal and external nodes of thought that are necessary for integrating new knowledge from texts with prior knowledge.

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Introduction

The importance and difficulty of comprehending expository text is evident to anyone who has attempted to learn about a new field of science by reading a textbook. Comprehension is not a simple process of accessing word meanings and then combining them. The process of comprehension involves the construction of a mental representation of a text, which is referred to as a situation model (e.g., Kintsch, 1988; Zwaan and Radvansky, 1998). The construction of a situation model requires lexical processes to access word meanings, memory retrieval to elaborate on the text and form connections to prior knowledge, and inference processes to help integrate the current sentence with prior sentences and knowledge.

The complexity of text comprehension processes results in large individual differences in the strategies that students utilize to understand texts as well as what students learn from texts (e.g., Chi et al., 1988; Just and Carpenter, 1992; McNamara, 2004). Although there have been neuroimaging studies of text comprehension (e.g., Ferstl and von Cramon, 2001; Xu et al., 2005; Yaloust et al., 2008a, 2008b), these studies have not examined the differences in brain

activity associated with different reading strategies. Understanding the neural correlates of different types of strategic reading comprehension processes should help us to better understand the brain mechanisms underlying comprehension.

Strategic reading comprehension

There are a number of theoretical frameworks that describe the cognitive processes underlying text comprehension (Kintsch, 1988, 1998; McNamara and Magliano, 2009; Zwaan et al., 1995). Many of these theories propose that the reader constructs a situation model that is a representation of text content that abstracts away from the written form of the sentences composing the text and includes knowledge not contained directly in the text. Constructing a coherent situation model requires that the reader form a textbase on the basis of the propositions contained directly in the text itself, and elaborate on this information by using prior knowledge through inference processes (Kintsch, 1988, 1998; Zwaan, 1999; Zwaan and Radvansky, 1998).

The quality of the situation model depends on how successful the reader is at representing the propositions of the text, providing information missing from the text from prior domain-general and domain-specific knowledge, and forming coherent representations by drawing inferences across phrases in the text (Kintsch, 1988,

Effet de l'auto-explication vs relecture

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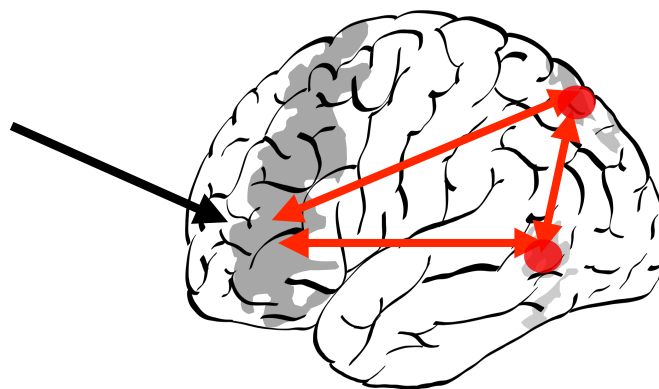
Étude de
Moss et al.

51 % de rétention vs 41 %

39

Étude de
Moss et al.

Cortex
préfrontal

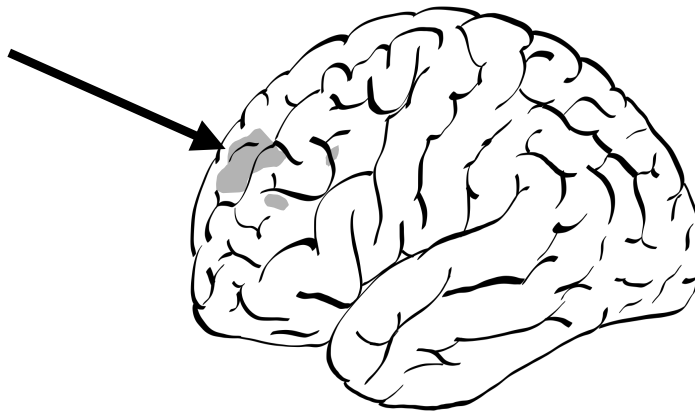


Auto-explication > relecture

40

Étude de
Moss et al.

Cortex
préfrontal
antérieur



Corrélation :
activité lors de l'auto-explication ↑ ⇒ gain d'apprentissage ↑

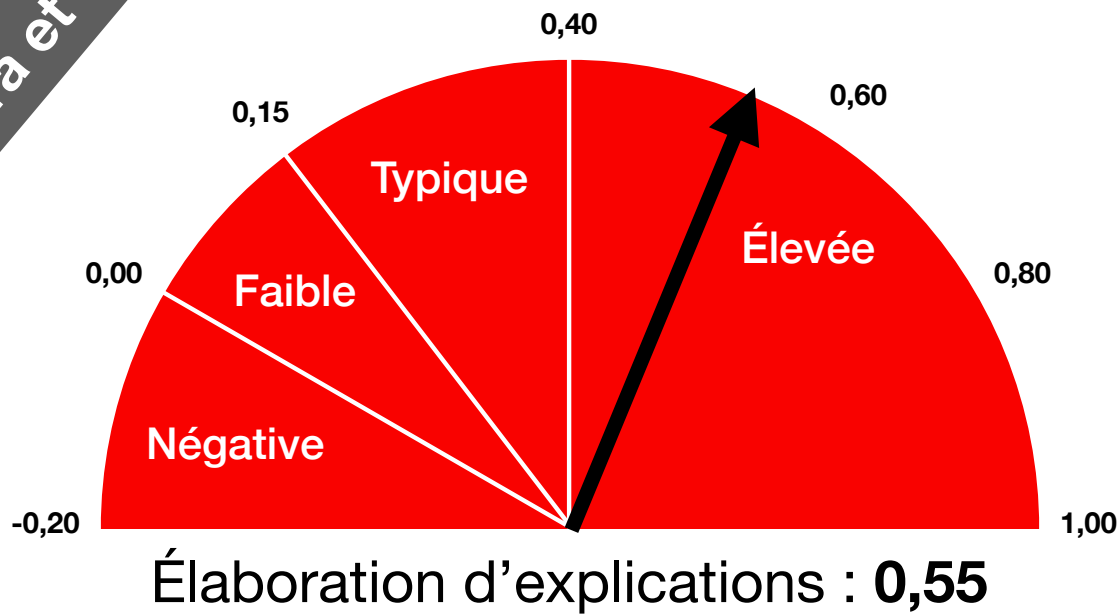
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Étude de
Bisra et al.



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Taille de l'effet



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Principe 3

Élaborer des explications

Comment ?

Stratégie 1

Questionner pour élaborer
des explications

Stratégie 2

S'auto-expliquer

44

Synthèse

45



Principe 1

Activer à plusieurs reprises



Principe 2

Récupérer en mémoire



Principe 3

Élaborer des explications

46