Active math and grammar learning engages overlapping brain networks

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Edited by Marcus E. Raichle, Washington University in St. Louis, St. Louis, MO, and approved October 8, 2021 (received for review April 11, 2021)

We here demonstrate common neurocognitive long-term memory effects of active learning that generalize over course subjects (mathematics and vocabulary) by the use of fMRI. One week after active learning, relative to more passive learning, performance and fronto-parietal brain activity was significantly higher during retesting, possibly related to the formation and reactivation of semantic representations. These observations indicate that active learning conditions stimulate common processes that become part of the representations and can be reactivated during retrieval to support performance. Our findings are of broad interest and educational significance related to the emerging consensus of active learning as critical in promoting good long-term retention.

active vs. passive learning | memory | neurocognitive | evidence-based teaching

There is an emerging consensus on the virtues of active learning methods for improving student performance (1). Such learning methods can be any instruction or technique that requires students to actively engage in the learning process, as compared to more traditional, passive ways of learning (1, 2).

One form of active learning is retrieval practice (RP), where the activity of including test sessions while acquiring new information has been shown to markedly boost long-term retention (2, 3). While not a new insight, the effectiveness of RP has attracted much interest recently and has been shown to be effective for various forms of learning contexts, populations, and topics (2, 3). In fact, RP is one of few learning methods considered to have high utility for improving students' learning (2). Learning conditions that require students to be actively engaged have also been emphasized in the context of learning mathematics (4, 5). Instead of imitating a provided algorithmic solution (algorithmic reasoning [AR]), more effective mathematical learning is accomplished if students are required to generate the solution (creative mathematical reasoning [CMR]; e.g., refs. 4, 5).

The apparent benefits of active learning, regardless of course subject, could result from the recruitment of overlapping learning processes and networks in the brain. For instance, deeper information processing activates left prefrontal cortex (PFC) brain regions and leads to superior retention in a variety of learning situations (6, 7). Alternatively, different forms of active learning could strengthen long-term retention via nonoverlapping brain systems (8). Here, using a within-subject design, we tested the hypothesis of a common brain basis of learning effects following active vs. more passive learning methods for two separate course subjects, vocabulary and mathematics.

Results

In experiment (Exp.) 1 ($n = 86$), the participants learned foreign language vocabulary by a more passive strategy (study [S]) and by active RP. In Exp. 2, a subsample ($n = 72$) of the participants from Exp. 1 were required to actively generate the mathematical solution (CMR) (e.g., refs. 4, 5) or more passively imitate a provided algorithmic solution (AR) (Fig. 1 *A–D*). Commonalities in brain activity for the active learning methods were assessed in a conjunction analysis (RP > S ∩ CMR > AR) (9) of functional MRI (fMRI) data acquired about 1 wk after initial learning. After this retention interval, several major consolidation processes have occurred (10) and the performance should largely reflect long-term memory. In both experiments, performance was higher after active than passive learning [Exp. 1: RP = 40%; S = 25% (11); Exp. 2: CMR = 49%; AR = 44% (12)].

For both active learning methods, relative to passive learning, higher brain activity was found in a number of cortical regions when participants were tested on the same questions 1 wk later, notably in the left hemisphere (Fig. 2 *A* and *B*). The regions included the inferior frontal gyrus (IFG) ($x, y, z = -42, 44, 8; -36, 52, 12$), precuneus ($x, y, z = -8, 72, 42$) inferior parietal/angular gyrus ($x, y, z = -44, -58, 52; -34, -58, 38$), frontal superior medial ($x, y, z = -8, 16, 44; -6, 30, 36$), the posterior cingulum ($x, y, z = -2, -30, 32$), and a smaller cluster within the IFG ($x, y, z = -34, 16, 32$). Despite the observation that regions C1–C6 had higher brain activity when learning with active methods, there were two regions that had disproportionally higher activity when learning math (Fig. 2*B*, C1 and C3). Next, to verify that the results were not driven by the higher performance rate following active learning, we reran the imaging analysis and statistically controlled for performance differences between active and passive learning. The results remained virtually identical, suggesting that the observed differences predominantly reflected qualitative active learning processes and not merely quantitative performance differences. Reversing the contrast (i.e., S > RP ∩ AR > CMR) revealed no common brain activity that was stronger for the two passive vs. active learning methods.

Discussion

Our findings provide support for the hypothesis of engagement of a shared brain network at retrieval after active compared to more passive learning. Specifically, 1 wk after learning, despite identical retrieval conditions, higher functional brain activity was evident after active compared to more passive initial learning of vocabulary and mathematics in several left-lateralized brain regions, notably in the precuneus, the inferior parietal cortex/angular gyrus, and the left lateral and medial PFC.

Author contributions: C.G., J.L., B.J., L.N., and C.W.-H. designed research; C.W.-H. performed research; S.S., M.A., and C.W.-H. analyzed data; and S.S., L.K.W., M.A., C.G., J.L., B.J., L.N., and C.W.-H. wrote the paper.

The authors declare no competing interest.

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This article contains supporting information online at http://www.pnas.org/lookup/suppl/doi:10.1073/pnas.2106520118/-/DCSupplemental.

Published November 8, 2021.

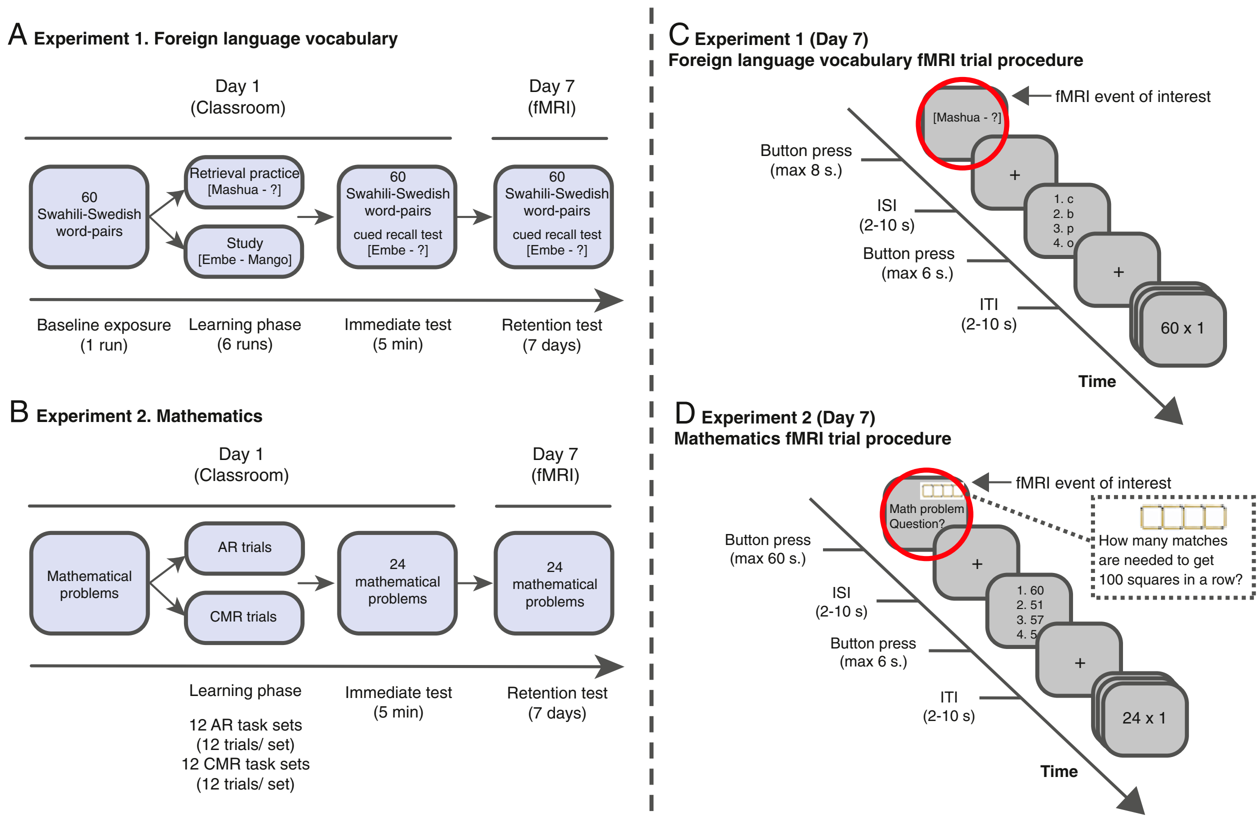

Fig. 1. Overview of the experimental designs in Exp. 1 (*A*) and Exp. 2 (*B*). (*C*) The fMRI trial procedure in the foreign language vocabulary task (Swahili–Swedish word pairs), and (*D*) the fMRI trial procedure in the mathematics task. The red circle in *C* and *D* represents the fMRI event of interest.

The observed overlap in brain activity during retrieval of vocabulary and mathematics may reflect reactivation of common active learning processes. Such processes could be reactivation of semantic representations by the left PFC (7), reactivation of contextually linked information in the precuneus (13, 14), and fact retrieval and attention processes for the angular gyrus (15). Of note, as the two course subjects likely differ to some degree in the cognitive demands involved in performing the task at hand, it cannot be ruled out that some of the overlap reflects curriculum-specific processes (15). With this caveat, consistent with a constructivistic perspective, our findings suggest that active learning of vocabulary and mathematics stimulate common processes that become part of the representations and can be reactivated during retrieval to support performance.

In conclusion, our results support the hypothesis of a common brain basis of learning effects following active vs. more passive learning of two separate course subjects, vocabulary and mathematics. These results are of importance for educators as well as the broader society (1–3), as they provide mechanistic insights into how activity improves student performance via differential brain engagement during learning.

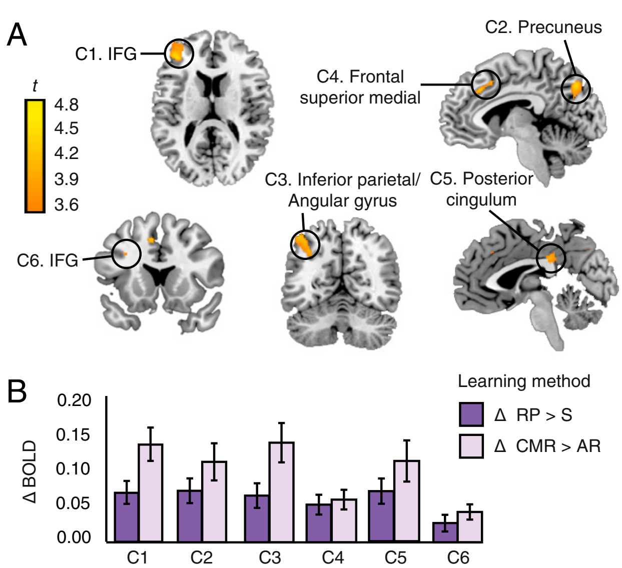

Fig. 2. (*A*) Brain regions showing higher activity following active learning vs. passive learning (RP > S ∩ CMR > AR). (*B*) The bar graph shows the difference (indicated by Δ) in blood-oxygen-level–dependent (BOLD) activity when contrasting active > passive learning for each brain region (C1–C6) and course subject (dark purple bars = Δ RP-S; light purple bars = Δ CMR-AR). S is study (passive); RP is retrieval practice (active); AR is algorithmic reasoning (passive); CMR is creative mathematical reasoning (active). Error bars display ±1 SE mean.

Materials and Methods

The same upper-secondary school pupils participated in Exps. 1 and 2 (M_{age} = 18.2 y). In experiment 1, the pupils learned foreign language vocabulary (word pairs), by means of RP (active) and by means of study (S, passive). In experiment 2, the pupils learned to solve mathematical problems by means of CMR (no solution formula was provided, active; 4, 5) or through AR (a solution formula was provided, passive; 4, 5). One week later, participants returned to take a subsequent memory test of all of the previously learned materials in the MR scanner (Fig. 1 *C* and *D*). In both experiments, each student saw a random order of questions and whether a question was learned through active or passive methods was also random.

A conjunction analysis investigated whether the two active learning conditions engaged common brain regions (11) (i.e., the "conjunction null" hypothesis; see *SI Appendix*). For each experiment, respectively, the minimum of the t values in each voxel was calculated (Exp. 1: RP > S, Exp. 2: CMR > AR). The statistical threshold was set to $t > 3.5$ at the voxel level, and $k > 10$ at the cluster level. An extended materials and methods section can be found in *SI Appendix*.

Data Availability. The anonymized data (fMRI) that support the results from the current study have been deposited in XNAT Central [https://central.xnat.org; project ID ActiveMathGram (16)].

ACKNOWLEDGMENTS. We are grateful to the staff at Umeå Center for Functional Brain Imaging. Funding was received from the Swedish Research Council (B.J., L.N., V.R., grant no. 721-2014-2099), Knut and Alice Wallenberg's Foundation (L.N., grant/award no. 2015.0277), and Umeå School of Education (C.W.-H.).

1. S. Freeman *et al.*, Active learning increases student performance in science, engineering, and mathematics. *Proc. Natl. Acad. Sci. U.S.A.* **111**, 8410–8415 (2014).
2. J. Dunlosky, K. A. Rawson, E. J. Marsh, M. J. Nathan, D. T. Willingham, Improving students' learning with effective learning techniques: Promising directions from cognitive and educational psychology. *Psychol. Sci. Public Interest* **14**, 4–58 (2013).
3. H. L. Roediger, III, A. C. Butler, The critical role of retrieval practice in long-term retention. *Trends Cogn. Sci.* **15**, 20–27 (2011).
4. J. Lithner, A research framework for creative and imitative reasoning. *Educ. Stud. Math.* **67**, 255–276 (2008).
5. J. Lithner, Principles for designing mathematical tasks that enhance imitative and creative reasoning. *ZDM Math. Educ.* **49**, 937–949 (2017).
6. F. I. M. Craik, R. S. Lockhart, Levels of processing: A framework for memory research. *J Verb Learn Verb Be* **11**, 671–684 (1972).
7. J. R. Binder, R. H. Desai, The neurobiology of semantic memory. *Trends Cogn. Sci.* **15**, 527–536 (2011).
8. M.-H. Sohn *et al.*, Behavioral equivalence, but not neural equivalence—neural evidence of alternative strategies in mathematical thinking. *Nat. Neurosci.* **7**, 1193–1194 (2004).
9. T. Nichols, M. Brett, J. Andersson, T. Wager, J.-B. Poline, Valid conjunction inference with the minimum statistic. *Neuroimage* **25**, 653–660 (2005).
10. Y. Dudai, A. Karni, J. Born, The consolidation and transformation of memory. *Neuron* **88**, 20–32 (2015).
11. B. Jonsson, C. Wiklund-Hörnqvist, T. Stenlund, M. Andersson, L. Nyberg, A learning method for all: The testing effect is independent of cognitive ability. *J. Educ. Psychol.* **113**, 972–985 (2020).
12. L. Karlsson Wirebring *et al.*, Effects on brain activity after creative mathematical reasoning when considering individual differences in cognitive ability. *bioRxiv* [Preprint] (2021). https://biorxiv.org/cgi/content/short/2021.03.30.437492v1 (30 March 2021).
13. M. Hebscher, J. A. Meltzer, A. Gilboa, A causal role for the precuneus in network-wide theta and gamma oscillatory activity during complex memory retrieval. *eLife* **8**, e43114 (2019).
14. T. R. Jonker, H. Dimsdale-Zucker, M. Ritchey, A. Clarke, C. Ranganath, Neural reactivation in parietal cortex enhances memory for episodically linked information. *Proc. Natl. Acad. Sci. U.S.A.* **115**, 11084–11089 (2018).
15. M. L. Seghier, The angular gyrus: Multiple functions and multiple subdivisions. *Neuroscientist* **19**, 43–61 (2013).
16. S. Stillesjö *et al.*, Task fMRI related to learning mathematical problems and grammar with active vs. passive methods. XNAT Central. https://central.xnat.org/data/projects/ActiveMathGram. Deposited 6 October 2021.