Learning to read does not compete with face and object recognition

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Abstract

Human cultural inventions, such as written language, are far too recent for dedicated neural infrastructure to have evolved in its service. Culturally newly acquired skills (e.g. reading) thus ‘recycle’ evolutionarily older circuits that originally evolved for different, but similar functions (e.g. visual object recognition). The destructive competition hypothesis predicts that this neuronal recycling has detrimental effects on the cognitive functions a cortical network originally evolved for. The converse possibility is that learning to read fine-tunes general object recognition mechanisms, resulting in improved recognition across categories. In a large-scale behavioral study with literate, low-literate, and illiterate participants from the same socioeconomic background we find that even after adjusting for cognitive ability and test-taking familiarity, literacy is associated with an increase, rather than a decrease, in object recognition abilities across object categories. These results are incompatible with the claim that neuronal recycling results in destructive competition.

Introduction

Learning to read has a profound impact on people's lives, changing not just their socioeconomic perspectives, but how they relate to the world around them. The broad significance of literacy has led researchers to investigate the cognitive (e.g. ¹⁻⁷) and neural⁸⁻¹⁴ processes that underlie the acquisition of this culturally transmitted, evolutionarily very recent skill. A hallmark finding is that in literates, but not illiterates, processing written language activates a surprisingly consistent cortical location in the left occipito-temporal lobe. This region, which appears to become specialized for processing of the visual forms of words^{15,16} has hence been called the visual word form area (VWFA, for critical discussion see ¹⁷) and is located near parts of high-level visual cortical areas that respond selectively to other visual categories, such as faces and tools. Given that the latter categories have had considerable evolutionary relevance for our species for a long time, it is not surprising that the brain has evolved dedicated cortical networks to process them as effectively as possible. In the case of written language, however, this poses an interesting puzzle as human writing systems have only been invented over the last 6000 years, which is too recent for a dedicated cortical system to have evolved in its service.

To account for this phenomenon, researchers have invoked the notion of neuronal recycling, according to which acquiring cultural skills involves the repurposing of circuits related to evolutionarily older but similar functions¹⁸. There is strong experimental support for this general notion¹⁰⁻¹², the exact mechanisms of this repurposing of preexisting cortical mechanisms however are hotly debated (e.g. ^{12,19}).

According to the initial formulation of the neuronal recycling hypothesis, reading acquisition involves destructive competition in the form of an 'invasion' into neuronal space that was formerly specialized for the processing other visual

categories, such as faces or tools¹⁸. The idea is that different visual categories compete for limited neuronal resources and the acquisition of a new category encroaches upon populations of neurons that previously performed similar (and thus useful) computations. Indeed, Dehaene and colleagues¹¹ reported some evidence for this view in a seminal functional magnetic resonance imaging study comparing cortical responses to different visual categories in participants with varying levels of literacy (ranging from complete illiterates to highly literate people in Brazil and Portugal). In their study, orthographic representations appeared to expand in the ventral visual system interfering with the expansion of faces, houses, and tools, in line with the idea that learning to read competes with the processing of other visual categories. A recent well-controlled, high-powered replication and extension of the Dehaene et al.¹¹ study however casts doubt on destructive competition as an important mechanism of neuronal recycling by presenting evidence for the converse case, namely enhanced responses to other visual categories in the ventral visual system surrounding the VWFA¹². This suggests that learning to read fine-tunes object recognition mechanisms rather than inducing destructive literacy-related cortical competition.

If learning to read indeed leads to competition with visual categories whose processing involves similar computations, it is likely that literacy acquisition would entail a cost in the form of a detrimental *behavioral* effect due to suboptimal processing of such categories. Indeed, one of the four main predictions of the destructive competition version of neuronal recycling is that competition can entail “small losses in perceptual and cognitive abilities due to competition of the new cultural ability with the evolutionarily older function in relevant cortical regions”¹⁸. By contrast, the visual fine-tuning view¹² predicts that the additional training of low-

level visual circuits on complex visual stimuli that comes with learning to discriminate letters and words also benefits perception and recognition in other visual categories. Visual fine-tuning therefore predicts that acquisition of literacy should come with, if anything, *better* behavioral performance in tasks that involve other visual categories.

Relevant in this regard is that previous evidence suggests that learning to read requires "unlearning" of mirror invariance to not confuse the letters "b" and "d", for instance. In particular, literates but not illiterates were found to be worse at a same-different task when mirrored versions of objects were presented (i.e., "b" and "d" are the same shape, but literates perceived them as different) than when the same object was presented twice^{20,21} (cf. ³). However, this effect cannot tease apart the two opposing accounts of neuronal recycling for two reasons. First, outside the context of a same-different task with mirrored vs. identical object pairs, the effect can equally be characterized as a mirror discrimination advantage for literates²², that is, learning to read trains the ability to distinguish mirrored versions of the same object. Second, at the core of the destructive competition hypothesis¹⁸ is the idea that neuronal resources previously allocated to one function are used for a similar but different function. In the case of reduced mirror invariance however, it is not the case that neuronal resources responsible for mirror discrimination in one domain (e.g., faces) are re-allocated to perform mirror discrimination during reading. We know this because enhanced mirror discrimination in literates transfers to other categories, such as faces^{20,21}.

In the present study we conducted a crucial behavioral test to distinguish the destructive competition and fine-tuning of visual categories accounts. Specifically, we tested object recognition memory of different categories (faces, cars, and bicycles) of

illiterates, low-literates, and literates of Tamil script in Chennai, India. Hundreds of millions of people in India are illiterate due to poverty and other socioeconomic factors rather than any neurological or cognitive impairments. Previous research has found that literates outperform illiterates on most formal cognitive-behavioral tests^{23,24}. Here, we solve this issue by testing the behavioral consequences of literacy on object recognition by selecting participants with differing literacy from the same communities and socio-economic backgrounds and statistically correcting reading proficiency for cognitive ability and familiarity with formal test-taking settings. For this purpose, we collected word and pseudoword reading scores to assess the reliability of participants' self-reported literacy status, as well as measures of non-verbal intelligence (Raven's Progressive Matrices^{25,26}) and working memory (digit span) to enable us to statistically control for participants' general level of cognitive ability. Before correction, we find that reading is associated with an improvement in object recognition memory. After correction this association is less strong but still positive, reflecting evidence for fine-tuning of visual processing, rather than destructive competition.

Results

Object recognition memory was assessed in Tamil illiterates, low-literates and literates (see Fig. 1 for the relationship between self-reported literacy and reading scores) to test whether literacy acquisition comes with a cost for other visual categories, such as faces. Participants performed the Cambridge Face Memory Task²⁷, Cambridge Car Memory Task²⁸, and Cambridge Bicycle Memory Task²⁹, collectively referred to as the Cambridge Recognition Memory Tasks (CRMT). In these tasks, participants see arrays of six target items (faces, bicycles, cars, in separate blocks) and

are then presented with three items one of which appeared in the six-item arrays. Their task is to select that item. In the second half of the task, Gaussian noise is added to increase difficulty.

Figure 1. *Self-reported literacy and word and pseudoword reading performance. Self-reported Tamil illiterates scored lower than low-literates on the word reading test in both Tamil and English, literates scored better than either of the other groups. There were outliers in each self-report group, suggesting that participants' self-reported literacy status was not entirely reliable. We therefore use reading score, rather than self-reported literacy, as a measure of literacy in the statistical analyses reported below.*

Adjusting reading scores

As expected for different, but related measures of cognitive ability, participants' Raven's Progressive Matrices scores and digit span are moderately correlated ($\rho = .48$, see Figure 2). Both Raven's Progressive Matrices scores and digit span are also moderately correlated with Tamil word reading score ($\rho = .51$ for both measures, see Figure 2). These correlations indicate common variance between the three tasks. Previous research suggests that literacy is associated with increased verbal working memory^{2,7} and Raven's scores^{12,14,30}. However, despite poverty and other socioeconomic factors being the main reasons for illiteracy in India, it cannot be conclusively ruled out that 'literacy-unrelated' general cognitive ability and familiarity with formal test-taking settings underlie some of the common variance between Raven's, digit span, and reading scores. To solve this issue, and to achieve a strong test of our experimental hypothesis, we regress out common variance attributable to general cognitive ability and familiarity with test taking, whilst preserving the variance that is uniquely associated with literacy. To adjust the raw (contaminated) reading scores, we construct a Bayesian binomial (generalized linear) mixed-effects model to predict the proportion of correctly read words and pseudowords in the reading task from the proportion of correct responses in the Raven's Progressive Matrices task and the mean of forward and backward digit span. After fitting the model, we extract the modes of the posterior traces for the by-participant intercepts from this model for use as predictors in the statistical model for the Cambridge Recognition Memory Tasks. In line with our expectations, the new, adjusted reading score is no longer correlated with the cognitive ability measures ($\rho = .03$ for Raven's, $\rho = .02$ for digit span, see Figure 2) but still strongly correlated with the original, unadjusted reading score ($\rho = .72$).

Full details on the model fitting procedure and the construction of the Raven's and digit span predictors can be found in the Supplementary Materials.

Figure 2. *Heatmap of absolute correlations between uncorrected and literacy-corrected predictors.*

Effects of literacy on object recognition memory

For modeling the effect of literacy on the Cambridge Recognition Memory Tasks, we consider each trial as a Bernoulli trial, creating a Bayesian generalized linear model predicting the odds of successfully answering a given trial. We pool the data from all three tasks (bicycles, faces, and cars), creating dummy coded predictors for the faces and cars categories and treating the bicycles category as the reference. Similarly, we dummy code the visual noise condition, leaving no noise as the reference condition.

Based on model comparisons using Pareto-Smoothed Importance Sampling Leave-One-Out Information Criteria³¹ (PSIS-LOOIC), we select a model with the predictors *visual noise*, *object category*, and *adjusted reading score* and the interactions between *visual noise* and *object category*.

The main result is that higher reading scores are associated with higher recognition memory scores (see Fig. 3). Crucially, this is the case both for the raw and the adjusted reading scores; even when regressing out variance that can be attributed to general cognitive capacity and test-taking familiarity, there is no evidence for decreased object recognition abilities in literates. Rather, literacy is associated with slightly better object recognition; a result that contrasts with the central tenet of the destructive competition hypothesis that literacy acquisition has detrimental effects on other visual abilities such as face recognition¹⁸. This result is consistent with the visual fine-tuning account of neuronal recycling and with recent evidence for enhanced responses to visual stimuli around the VWFA and in early visual cortex¹². Because the model selection prefers a model with a single slope for literacy across all visual categories, we observe positive effects of literacy on object recognition memory observed for all visual categories (faces, bicycles, and cars; see Fig. 4).

Figure 3. *Posterior densities of model coefficients for the model with raw reading score as a predictor (in orange) and the model with adjusted reading score as a predictor (in green). Coefficients are presented as log-odds, on a linear scale, for ease of visual comparison. Object category and visual noise coefficients are highly similar in both models, whereas the adjusted reading score coefficient is markedly lower than the coefficient for the raw reading score. Crucially, both are positive; log-odds ratio for adjusted reading score is .05 (95% credible interval [.02, .08]).*

Besides these main results, there is strong evidence for a varying interaction between *object category* and *visual noise*, with bicycles and cars appearing slightly easier to recognize in the noise condition than in the no-noise condition (difference in log-odds ratio is .11 for bicycles, 95% CI [.00, .22]; .14 for cars, 95% CI [.03, .25]),

whilst for faces, the noise condition appeared much *more* difficult than the no-noise condition (difference in log-odds ratio is -.65, 95% CI [-.76, -.54]).

Figure 4. *Estimated effects (expressed in log-odds) per condition, shaded regions are 95% credible intervals. Note that word reading is presented on a scale from -1 standard deviation to +1 standard deviation, centered on the mean word reading score.*

Discussion

In order to understand how the human brain works it is crucial to find out how it repurposes circuits related to evolutionarily older but similar functions when processing culturally transmitted evolutionary recent skills. During reading acquisition, a new cultural skill has to be accommodated in a system that does not provide a dedicated processing pathway. Reading, both as a cognitive and a neural phenomenon, has to create its own niche by modifying pre-existing networks to make them suitable for the required computations. This basic aspect of the neuronal recycling hypothesis is uncontroversial and strongly supported by previous experimental work⁸⁻¹⁴.

The open question we addressed here concerns the mechanisms of neuronal recycling. Does learning to read involve a process of destructive competition^{11,18} or instead lead to fine-tuning of object recognition mechanisms¹²? The present results do not support the notion that acquiring literacy causes decreased recognition in any object category. Our findings are more in line with a *generalized visual enhancement* effect, where training to recognize word forms increases the overall performance in visual object recognition. This generalized visual enhancement effect is very unlikely to be due to general cognitive ability or familiarity with test taking, since in the present study we regress common variance associated with these traits out of the literacy predictor before modeling its association with visual recognition. Rather, we propose that during the course of reading acquisition enhanced responses to various visual stimuli in the visual cortex^{11,12,20} in combination with enhanced attentional and oculomotor capacities^{14,32–36} leads to increased sensitivity to visual stimuli. This suggests that cultural inventions, such as reading, can transform perceptual processing, resulting in structural and functional changes and, as we report here, even in measurable behavioral benefits.

An additional cultural effect on object recognition memory manifested itself in the relatively large difference in performance between the cars and bicycles categories. Improved recognition memory for bicycles compared to cars is likely largely due to the better familiarity of the participants with bicycles than with cars. Participants largely used bicycles and motorcycles for transportation in daily life, and even when they encountered cars, these cars were unlikely to be the early 90s models of cars sold in Western Europe that were used in the Cambridge Car Memory Test.

In conclusion, the positive effect of literacy on object recognition memory, including face recognition memory, observed in the present study in combination with

recent evidence of enhanced responses to various objects in the vicinity of the VWFA as well as in early visual cortex¹², casts serious doubts on the viability of the destructive competition hypothesis. Whereas the competition hypothesis views the brain as a system with finite processing resources that different functions are competing for, the present findings point to a remarkable capacity of the brain: it appears to be able to incorporate new functions in such a way that, if anything, related functions are enhanced rather than impaired. It will be a fascinating topic for future research to pinpoint the exact mechanisms that make such an effective re-organization of the visual processing stream possible.

Methods

Participants

97 participants were recruited through a nongovernmental organization (NGO) working to improve living conditions for people of lower socioeconomic status in Chennai, capital city of Tamil Nadu state, India. 35 participants were registered with the NGO as illiterate, 30 were registered as low-literate, and 32 were registered as literate. The groups were matched for age and socioeconomic status, but there was a marked difference in the average number of completed years of education between the three groups (see Table 1). The tests reported below were conducted as part of a larger battery of tests that took each participant approximately three hours to complete. Participants received 2400 INR (roughly equivalent to 30 Euro) as compensation for their participation, equivalent to about two months' pay at the mean salary in our sample.

Group	N	Mean age in years	Mean years of education	Mean yearly earnings in INR
Literates	32	37.4	11.8 (<i>SD</i> = 1.7)	10,857 (<i>SD</i> = 5,295)
Low-literates	30	36.2	6.6 (<i>SD</i> = 1.1)	10,420 (<i>SD</i> = 5,813)
Illiterates	35	36.0	0	7,933 (<i>SD</i> = 5,875)

Table 1. *Descriptive statistics for the literate, low-literate, and illiterate participant groups.*

Design and procedure

To ensure literate and illiterate participants received identical instructions in a format that they could understand, instructions for the tasks in this study were prerecorded in Tamil and played automatically for each participant.

Word reading. The word reading section of the test battery consisted of word and pseudoword reading. For both words and pseudowords, participants were given 60 seconds to read up to 100 items from a list. Responses were recorded and scored for number of words read correctly. A native speaker of Tamil designed the Tamil pseudowords used in this task to ensure all pseudowords were phonotactically legal. Response scoring was also performed by a native speaker.

Digit span. Forward and backward digit span tasks were conducted to assess the working memory capacity of the participants. For both forward and backward digit span, the participant heard a series of numbers sequences. The sequences increased in length from 2 numbers to 10 numbers for forward digit span and from 2 numbers to 8 numbers for backward digit span. Number sequences were recorded in Tamil by a native Tamil speaker. After each number sequence was presented,

participants repeated back the sequence in the original order (for forward digit span) or in reverse order (for backward digit span). Each task was stopped when participants made two mistakes consecutively. Responses for both forward and backward digit span were recorded and scored based on the longest sequence repeated correctly before the task was stopped.

Raven's Progressive Matrices. General cognitive ability was measured using the Raven's Standard Progressive Matrices task²⁵. Because of time constraints we used a shortened version constructed by Bilker and colleagues²⁶ by selecting two lists of nine items from the original, redundant list of 60 items using item-response theory to ensure that sensitivity is preserved. Our task consisted of both nine-item lists; each list was presented as a block of items in order of increasing difficulty. Raven's SPM items consist of a display of a visuospatial pattern from which a section is missing. Participants must select the section that best fits in the empty spot from a multiple choice (6 or 8 options) display of possible replacement sections. Answer options are traditionally numbered, with responses delivered using a keyboard or in writing. To adapt this paradigm for illiterate participants, we presented the answer options with colored labels that corresponded with colored keys on a keyboard.

Cambridge Recognition Memory Tasks. The Cambridge Face Memory Task²⁷, Cambridge Car Memory Task²⁸, and Cambridge Bicycle Memory Task²⁹, which we collectively refer to as the Cambridge Recognition Memory Tasks (CRMT), are a set of tasks meant to test object recognition memory. Participants are first familiarized with six different items (either faces, cars, or bicycles) through a series of practice questions in the following format:

1. A single target item is presented three times: Once rotated 30 degrees to the left, once head on, once rotated 30 degrees to the right. Each of these presentations lasts three seconds.

2. A display of three items is presented, one of which is the previously presented item. Participants are instructed to select the previously presented item with a keypress.

Step 2 is repeated three times per target item. The sequence is repeated six times with different items, so the participant is familiarized with six target items. Object recognition for these six target items is then tested using the following format:

1. A display of all six target items is presented for 20 seconds, with the instruction to memorize these items.

2. A display of three items is presented, one of which is an item presented in the memorization display. Participants are instructed to select the memorized item with a keypress.

Step 2 is repeated 30 times.

The test phase consists of two parts. In the first half the memorization display and test display images are drawn from the same set. In the second half, the procedure is repeated as described above, but Gaussian visual noise is added to the answer slide images to increase the recognition difficulty.

The usual format for the CRMT is to have written instructions presented on-screen and response options labeled with numbers that participants then press on a keyboard. Presenting written instructions and numerals to illiterate participants is not possible, so we adapted the task to illiterates by replacing the written instructions with prerecorded instructions in Tamil, replacing the on-screen response labels with

(primary) color swatches, and putting corresponding color patches on the physical response keys.

Statistical modeling. Statistical analyses were performed using Bayesian linear and logistic (where appropriate) mixed-effects regression implemented with the BAMBI³⁷ package for Python, using the PyMC3³⁸ backend. We placed moderately regularizing priors on both fixed and random effects, in the form of narrow ($\sigma = .2$ on a partial correlation scale) zero-centered normal distributions cf. Westfall³⁹. Models were fitted by Markov Chain Monte Carlo sampling, using the No-U-Turn Sampler⁴⁰ (NUTS). The starting point for the Markov Chains was obtained through Automatic Differentiation Variational Inference⁴¹ (ADVI). Four chains were run for 2500 tuning samples, after which 5000 posterior samples were obtained per chain, for 20000 posterior samples in total per model. For each experiment, we fitted models with various permutations of effects and performed model selection based on model fit. The nature of the predictor matrix for the models predicting CRMT scores (no items repeated across categories; adjusted reading score as a between-participants predictor) meant that the data did not support even a minimal random effects structure. For the CRMT scores we therefore fitted only various permutations of fixed effects and their interactions. In the interest of parsimony, model fit was computed using Leave-One-Out Information Criterion with Pareto-Smoothed Importance Sampling³¹ (PSIS-LOOIC), a Bayesian index of model fit that penalizes model complexity. Sampling diagnostics indicate no sampling problems for the selected model (*minimum* $n_{effective} > 8000$, $r_{hat} < 1.001$). Full details on model comparison and the full range of models considered can be found in the Supplementary Materials.

Data and code availability

Data and code for fully reproducing all analyses in this manuscript are available online at <https://doi.org/10.5281/zenodo.3543572>. Additionally, the behavioral test suite administered to participants in this study is also available online at <https://doi.org/10.5281/zenodo.3543296>.

Author contributions

JvP, MO, MA, and FH designed the study; MA collected data; JvP and MO analyzed results; JvP, MO, MA, and FH wrote the article.

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Competing interests

The authors declare no competing interests.

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Supplementary materials accompanying “Learning to read does not compete with face and object recognition

Supplementary Methods and Results

In this supplementary methods and results section we present figures related to the model selection and model sampling. These figures demonstrate model fit and fitness, but are not germane to the general point made in the main article text and are therefore presented here. Fully reproducible methods (data and code) can be found online at <https://doi.org/10.5281/zenodo.3543572>.

Construction of Raven’s Progressive Matrices predictor

The reduced Raven’s Progressive Matrices test used here consists of 18 trials of varying difficulty. To reduce each participant’s 18 correct/incorrect answers, we construct a generalized linear mixed effects model, modeling each trial as a Bernoulli trial with by-participant and by-item random intercepts. The posterior means of the by-participant intercepts are extracted and used as participants’ Raven’s scores.

Construction of digit span predictor

The digit span test consists of two component tasks: forward and backward digit span. To collapse these into a single digit span score, we construct a linear model with task as a fixed effect and by-participant random intercepts. The posterior means of the by-participant intercepts are extracted and used as participants’ digit span scores.

Supplementary Figure 1. *PSIS-LOOIC model comparison of reading score models. Models are identified using the commonly used GLM model syntax. Lower deviance indicates better model fit, after penalizing for model complexity. Horizontal black lines are error bars (SE of deviance), grey lines represent SE of the difference between each model and the best-fit model. The best-fit model included task (word versus pseudoword) Raven's Progressive Matrices score, and digit span score.*

Supplementary Figure 2. *Posterior traces of selected reading model, refit including by-participant intercepts. Note that while there is very mild autocorrelation in the by-subjects fixed and random effects, there are more than 1500 effective samples for every parameter.*

Supplementary Figure 3. *PSIS-LOOIC model comparison of object recognition memory models. Models are identified using the commonly used GLM model syntax (note that “type” stands for object type, a three level categorical predictor). Lower deviance indicates better model fit, after penalizing for model complexity. Horizontal black lines are error bars (SE of deviance), grey lines represent SE of the difference between each model and the best-fit model. Three models are within the SE of the difference with the best-fit model (i.e. the difference in fit with the best-fit model is statistically indistinguishable from noise). In the interest of parsimony, we pick the least-complex model of these four similar models: noise * object type + unadjusted reading score. We then compare this model to the same model, with adjusted reading score instead of unadjusted reading score (for comparison, see Figure 3 in main article text).*

Supplementary Figure 4. *Posterior traces of selected object recognition memory model, refit with adjusted reading score instead of unadjusted reading score.*

Supplementary Discussion

The following discussion is not germane to the central point of the main article text (that literacy acquisition does not compete with object recognition memory) but still of interest for object recognition memory in general, and is therefore presented here in this supplementary discussion:

Orthogonal to the effect of literacy there was markedly worse recognition of previously seen faces in the visual noise condition than in the no-noise condition.

While face recognition seems to have special status in the human visual system, the simplest explanation for the face-selective noise effect lies in the difference between visual features that participants use to recognize faces, cars, and bikes. Faces, much more than bicycles or cars, have highly similar outlines and can only be identified based on differences in luminance across their surface. Evidently, adding visual noise impaired the recognition of these more subtle contrasts much more than the recognition of car and bicycle outlines (which are characterized by much sharper contrast).

The small improvement in the visual noise condition over the no-noise condition seems counter-intuitive, but can be explained from the ordering of the blocks in the experiment: the no-noise condition was always presented first, followed by the visual noise condition. Participants seemingly exhibited task learning over the course of the experiment causing them to perform better in the later trials of each task. We could have controlled for this learning effect by counterbalancing the order of blocks across participants, but this would have meant altering the canonical Cambridge Recognition Memory paradigm. Since we were most interested in the opposite effect (lower odds of recognition in the visual noise condition) we decided to preserve the original (not counterbalanced) block order. Note that the task learning effect does not explain the

difference between bicycles and cars, since the block order for the categories was bicycles, faces, and then cars.