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Letter processing in upright bigrams predicts reading fluency variations in children

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Abstract

Fluent reading is an important milestone in education, but we lack a clear understanding of why children vary so widely in attaining this milestone. Language-related factors such as rapid automatized naming (RAN) and phonological awareness have been identified as important factors that explain reading fluency. However whether any aspects of visual orthographic processing also explain reading fluency beyond phonology is unclear. To investigate these issues, we tested primary school children (n = 68) on four tasks: two reading fluency tasks (word reading and passage reading), a RAN task to measure naming speed, and a visual search task using letters and bigrams. Bigram processing in visual search itself was accurately explained by single letter discrimination and error patterns were unrelated to fluency or bigram frequency, negating the possibility of specialized bigram detectors. As expected, the RAN score was strongly correlated with reading fluency. Importantly, there was a highly specific association between reading fluency and upright bigram processing in visual search. This association was specific to upright but not inverted bigrams, and to bigrams with normal but not large letter spacing. It was explained by increased letter discrimination across bigrams and reduced interactions between letters within bigrams. Thus, fluent reading is accompanied by specialized changes in letter processing within bigrams.

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Author Contributions

All authors contributed to the overall study design. AA, SPA & SN designed experiments, AA implemented the experiment and collected data, AA, SN & SPA analyzed and interpreted data and wrote the manuscript with inputs from KVSH.

Context of the Research

The study originated through informal discussions between SN & AA/SPA/KVSH regarding the possible study of visual processing changes due to reading. We plan to conduct a longer term study to characterize changes in visual processing longitudinally as well as in early readers that might facilitate early reading skills.

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Introduction

Learning to read fluently is an important milestone during development, but there is considerable individual variation in attainment. For alphabetic languages, this variation has been explained using two simpler cognitive tasks: phoneme awareness (PA, which measures the ability to manipulate phonemes in a word), and rapid automatized naming (RAN, which measures the speed of naming visually presented letters or objects) (Melby-Lervåg et al., 2012; Norton and Wolf, 2012). These abilities not only explain concurrent individual variation in reading fluency (Melby-Lervåg et al., 2012; Norton and Wolf, 2012), but also its longitudinal development (Parrila et al., 2004; Lervåg and Hulme, 2009; Landerl et al., 2018; Vander Stappen and Reybroeck, 2018).

The RAN measure has been hypothesized to capture efficiency in cross-modal print processing (Nag and Snowling, 2012). Other explanations for the robust RAN-reading association range from domain-general speed of processing (Kail et al., 1999), especially serial processing (Sideridis et al., 2016), to domain-specific speed to retrieve phonological codes (Vander Stappen and Reybroeck, 2018), discriminate component visual features (Stainthorp et al., 2010) and recognize whole visual items (Lervåg and Hulme, 2009). Thus, RAN arguably captures component processes that are both perceptual-lexical as well as attentional and memory-based (Sideridis et al., 2016).

Given that reading begins with vision, it stands to reason that fluent reading is associated with changes in visual processing as well as in phonological or naming abilities. However, most previous work has focused on attentional processes, particularly with respect to reading difficulties. Dyslexia is associated with a range of processing deficits in visuospatial attention (Goswami, 2015), attention span (Bosse et al., 2007), change detection (Rima et al., 2020) and visual search (Casco and Prunetti, 1996; Vidyasagar and Pammer, 1999). These deficits are worsened when there is crowding (Bouma and Legein, 1977; Martelli et al., 2009; Zorzi et al., 2012). Whether these deficits explain normal variation in reading skills is, however, not clear.

At a more basic level, it is also not clear whether visual representations of letters or strings themselves change with reading experience, and whether these changes predict reading fluency. For instance, it is widely believed that learning to read leads to the formation of specialized detectors for letter combinations (Grainger and Whitney, 2004; Dehaene et al., 2005). Evidence in favour of this account comes from the greater activation of the word form regions to strings containing frequent bigrams. However, recent evidence has challenged this possibility by showing that discrimination between longer strings can be explained using single letters (Agrawal et al., 2019, 2020), and that fluent readers experience weaker interactions between letters in a bigram (Agrawal et al., 2019). However this association between bigram processing and reading fluency may be explained by other perceptual-lexical factors like RAN, or by generic cognitive factors such as visuospatial attention that are required for both visual processing and reading tasks.

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Overview of this study

Here, we investigated the relation between reading fluency and visual processing by testing two specific hypotheses. First, we asked whether visual processing in fluent readers is consistent with the presence of specialized bigram detectors. Since reading involves extensive experience with upright letters, we hypothesized that learning to read would result in the formation of specialized detectors for upright bigrams but not inverted bigrams. This comparison avoids any confounds due to letter shape because both upright and inverted bigrams contain the same features except for an orientation difference. To detect the presence of bigram detectors, we formulated a quantitative “part-sum” model to predict visual search on bigrams using the constituent single letters. Since bigram detectors, by definition, are activated by the entire bigram but not by the constituent letters, their presence should lead to poor performance of the part-sum model. We therefore hypothesized that the presence of upright bigram detectors should lead to poor performance of the part-sum model for upright but not inverted bigrams.

Second, we hypothesized that reading fluency variations across children would be predicted by upright bigram processing during visual search, over and above the variation predicted by RAN tasks. If confirmed, this is a non-trivial outcome because it implies that changes in bigram processing are independent of the perceptual-lexical processes captured by RAN, and that both influence reading fluency. Alternatively, it could be that bigram processing does not predict reading fluency variations any more than RAN measures, suggesting that changes in visual processing might accompany changes in rapid naming but do not directly covary with reading fluency variations.

Comparing upright and inverted bigrams also avoids confounds due to shared cognitive factors. For instance, a correlation between visual search performance and reading fluency could simply be because both tasks require visuospatial attention (Franceschini et al., 2012). However, any specific difference between upright and inverted bigrams cannot be explained using such cognitive factors.

We tested children in grades 3-5 (7-11 years old) across two time points (separated by ~10 months). We chose this age range because large individual differences are observed in reading fluency at this age (Nag and Snowling, 2012; Brysbaert, 2019). All participants were from a school where English is the medium of instruction, and were tested on English. Each child was tested on two standardized measures of reading fluency (word and paragraph reading). To optimize testing time with children, we selected a RAN task over a phoneme awareness (PA) task because the former is a better predictor of reading in some alphabetic orthographies (Landerl et al., 2018; Vander Stappen and Reybroeck, 2018), and PA is prone to floor effects in India (the location of the present study) where literacy instruction privileges either the look-and-see method or the syllable units in a word (Nag, 2017). To measure visual processing, each child was tested on a visual search task involving both single letters as well as upright and inverted bigrams. We chose visual search because it is a natural, intuitive task for children; they commonly encounter the odd-one-out task in school lessons, puzzles and play. At the same time, visual search has an objective measure of performance (correctly finding the target), and it can yield insights into visual feature

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integration (Arun, 2012; Mohan and Arun, 2012; Pramod and Arun, 2016, 2018; Sunder and Arun, 2016), including for letter processing during reading (Agrawal et al., 2019, 2020).

Experiment 1: letter and bigram searches

In Experiment 1, participants performed three tasks related to reading skills: single word reading (Figure 1A), passage reading (Figure 1B), and rapid automatized naming (RAN). Participants also took a visual search task, where they had to identify an oddball target among multiple identical distractors. The visual search items were either single letters, upright bigrams or inverted bigrams (Figure 1D).

Methods

Participants—A total of 68 children (34 male, aged 9.5 ± 0.9 years; 23 from 3rd grade, 27 from 4th grade, 18 from 5th grade) were recruited for the study. We selected this age range because there is large individual variation in reading fluency at this age (Brysbaert, 2019; Rakhlin et al., 2019). One participant was excluded from the analyses due to the overall accuracy being less than 80%. All children and their parents/guardians gave informed consent to an experimental protocol approved by the Institutional Human Ethics Committee of Indian Institute of Science, University of Oxford and The Promise Foundation. All participants were multilingual, with English as the first school language but with multiple other home and community languages including Kannada, Hindi and Telugu. All participants had normal or corrected-to-normal vision. They performed two reading tasks (word reading and passage reading), a RAN task (Norton and Wolf, 2012) and a visual search task. Sample size was chosen based on previous studies in the literature (Melby-Lervåg et al., 2012; Agrawal et al., 2020), since a power analysis was not feasible as the effect size specific to bigram processing in the primary school age band was unknown before starting the study.

Reading & RAN tasks

Word reading task—This was the standardized sight word efficiency task (TOWRE) (Torgesen et al., 2012). In this 104-word list, words increased in difficulty level, from simple words like “up” and “cat” to difficult words like “information” and “boisterous”. The word reading score was calculated as the number of words read correctly in the first 45 seconds, converted into a words/minute score.

Passage reading task—Participants were asked to read aloud a five-line passage titled “Qasim’s kurta” describing the patterned dress of a stranger (Nag and Arulmani, 2015). The passage was edited to a word count of fifty. Participants were informed that they will have to answer two questions at the end of the passage and therefore had to read carefully. A discontinuation rule was applied after errors on eight words (an error rate of 15%). The passage reading score was calculated as the total number of words read correctly divided by the time taken up to the point attempted, in units of words/minute.

Rapid Automatized Naming (RAN)—A set of 40 digits arranged in a 5 x 8 grid was shown to the participant, which they had to read aloud. The RAN score was calculated as 40 divided by the time taken by participants to complete reading the digits.

Visual Search tasks

Stimuli—A total of 13 uppercase English letters (A, H, I, J, K, L, N, R, S, T, U, V, Y) were chosen for the single letter search task. These letters were chosen to contain similar and dissimilar letters. All letters were shown in the Arial Font with the exception of the letter 'I', for which horizontal bars were added at the top and bottom to improve its discriminability. The height of each letter was 1° in visual angle.

For the bigram task, 6 letters (A, L, R, S, T, and V) were combined in all possible manner (i.e. AA, AL, AR, AS, AT, AV, LA, LL, … etc) to form 36 bigrams. These letters were chosen because they were not symmetric along the horizontal axis. Inverted bigrams were created by rotating the upright bigrams by 180° along the horizontal axis.

Procedure—Participants were seated comfortably in front of a laptop monitor placed ~60 cm away. Participants were instructed to look at information appearing on the screen, identify which side of the screen had an odd-one-out, and indicate its location by pressing one of two answer buttons (key 'Z' of the keyboard when the odd-one-out was to the left of screen and 'M' for right of screen). To ensure familiarity with the answer buttons on the keyboard and to measure baseline motor speed, participants first performed a baseline block prior to visual search. In this block, a white circle appeared on either side of a vertical red line dividing the screen (10 trials) and participants had to indicate (using "M" or "Z" key press) the side on which the circle appeared. Next was a practice block of visual search using unrelated objects (20 trials) and then the main visual search block. In the practice and main visual search blocks, participants viewed 16 items on a screen always arranged in a 4x4 grid, containing one target and 15 identical distractors. A vertical red line divided the screen into two halves. The target location was randomized from trial to trial so that it appeared equally often on the left or right. The search array was displayed on the screen until a key press by the child. Error trials were repeated after a random number of other trials until the correct response was obtained. To break the monotony of the multiple trials, a gif cartoon was displayed after every 80 trials, and participants were encouraged to take longer breaks at this time, if they wished.

In the main visual search block, participants performed a total of 616 trials (${}^{13}C_2$ = 78 single letter searches + 115 upright bigram searches + 115 inverted bigram search, with 2 repeats of each search). In the search array, both the oddball and the distractors were either single letters, or upright bigrams or inverted bigrams, and were analysed separately. These search types were randomly interleaved for each participant. We selected 115 searches out of 630 (${}^{36}C_2$) possible searches to ensure a range of search difficulty. We selected a total of 15 bigram pairs where the first letter changed, 13 pairs where the second letter changed, and 87 pairs with both letters changed. These 115 search pairs were fixed across all participants. All trials were interleaved, and incorrect trials were repeated randomly later in the task. The reaction time from correct responses were considered for all subsequent analyses.

The MATLAB function “isoutlier” was used to remove any data points that were three scaled deviations away from the median. This was done to improve the split-half consistency of the data. This step removed ~7.2% of the data. We obtained qualitatively similar results without this step.

Part-sum model to explain bigram dissimilarities using single letters

For each of the 115 bigram searches, we calculated the average search time (averaged across correct trials and participants) and converted this into search dissimilarity by taking the reciprocal (1/RT). This was done because previous work has shown that the reciprocal of search time yields better models of visual search compared to models based directly on RT (Arun, 2012; Pramod and Arun, 2014,2016). According to the part-sum model, the net dissimilarity between two bigrams (e.g., AB & CD) is given by a sum of pairwise letter relations between letters at corresponding and opposite locations across bigrams and within-bigram relations. Specifically,

$$d(AB,CD)=C_{AC}+C_{BD}+X_{AD}+X_{BC}+W_{AB}+W_{CD}+\text{constant}$$

where C_{AC} & C_{BD} represent dissimilarity between letters at the corresponding locations of the two bigrams, X_{AD} & X_{BC} represent the dissimilarity between letters at opposite locations in the two bigrams, and W_{AB} & W_{CD} represent dissimilarity between letters within the two bigrams. This is a general model because it allows for potentially different single letter dissimilarities at corresponding, across and within-object locations. The part-sum model parameters can be estimated because a given letter pair at each location can occur repeatedly across multiple bigram pairs (e.g. letter pair A-C is present at the corresponding locations of the pairs **A**B-**C**D, **A**D-**C**D, B**A**-B**C** etc.). Since bigrams were made from 6 selected letters, there are $^6C_2$ (= 15) letter pairs for each of the corresponding, across, and within terms. This results in a 46-parameter model (15 letter pairs/term x 3 terms + 1 constant). Since we have 115 dissimilarities values and only 46 parameters, we can uniquely estimate all the parameters using linear regression. The resulting set of simultaneous equations can be represented as $\mathbf{y} = \mathbf{Xb}$, where $\mathbf{y}$ is a 115x1 vector of observed dissimilarities, $\mathbf{X}$ is a 115 x 46 matrix with entries of either 0, 1 or 2 depending on whether a particular pair is absent, present or repeated at each of the corresponding, across or within terms and $\mathbf{b}$ is a 46 x 1 vector of unknown weights.

To compare model parameters for upright and inverted bigrams (Figure 2), we fit a single model for both upright and inverted bigrams together with separate C, X, W terms for each orientation but a single constant term. To predict fluency scores for each participant (Figures 2), we fit the part-sum model to upright and inverted dissimilarities separately.

Modelling fluency scores

For each participant, we estimated factors that could potentially predict reading fluency: the RAN score, mean reaction time in the baseline block. From the visual search blocks we took the mean accuracy, mean single letter dissimilarities, part-sum model parameters for bigram dissimilarities, computed separately for upright and inverted bigram searches. To estimate the cross-validated fluency model fits, we trained each factor on word reading score and evaluated it against the passage reading score.

For each scalar factor, we fitted a linear model **y** = **Xb**, Here, **y** is a 67x1 vector of observed word reading score, **X** is a 67x2 matrix with entries containing one of the above mentioned factor along with a constant term, **b** is a 2x1 vector of unknown weights that are estimated after solving the linear regression (*regress* function in MATLAB). Next, we calculated the predicted reading score using the estimated weights i.e. $\hat{\boldsymbol{y}} = \boldsymbol{X}\boldsymbol{b}$ and correlated it with the passage reading score. The correlation coefficient quantifies the contribution of each factor in predicting reading fluency.

Since upright and inverted bigram factors contain multiple part-sum model parameters, we first averaged the estimated corresponding, across and within term interactions across all 15 letter pairs. This resulted in 4 parameters for each participant (including the constant term of the part-sum model). Next, we performed the same model fits as mentioned above to predict the fluency score as a linear combination of average model terms i.e. **y** = **Xb**. Here, **y** is a 67x1 vector of observed word reading score, **X** is a 67x5 matrix with entries containing the average model terms together with a constant term, and **b** is a 5x1 vector of unknown weights.

Partial correlation analyses

To estimate the unique contribution of each factor, we performed a partial correlation analysis. First, we took the predicted fluency score for each factor (as described above) and regressed out the net contribution of all the other factors. Specifically, we fit a linear model **y = Xb**, where **y** is a 67x1 vector of fluency score predictions using that factor, and **X** is a 67-row matrix containing all the other factors, and **b** is a vector of unknown weights. We then calculated the residuals of this model i.e. (y – Xb) which represent the predictions of that factor that are not explained by the other factors. Proceeding likewise, we regressed out the net contribution of all the factors from the passage fluency score. The partial correlation is the correlation between these two sets of residuals, and represents the correlation between reading fluency and a particular factor that remains even after removing the influence of all other confounding factors.

Results

To measure the reliability of fluency scores across participants, we compared the fluency scores between two reading tasks. As expected, fluency scores for passage reading and word reading were highly correlated with each other ($r = 0.91$, $p < 0.00005$) (Figure 1C).

Visual search for single letters

We first analysed the performance of the participants on single letter searches. An example search involving single letters is shown in Figure 1D. Participants were highly accurate in their performance (average accuracy across 78 single letter searches, mean ± std: 98% ± 2.4% across 68 children). They also made highly consistent responses, as evidenced by a strong and significant correlation between the average search times of odd and even-numbered participants (Figure 1E). We did not observe any significant correlation between mean single letter search time and passage reading score ($r = -0.2$, $p = 0.1$). Across search pairs, the mean letter frequency, estimated by averaging the letter frequency of target and distractor in each trial, was neither significantly correlated with mean search time ($r = -0.12$, $p = 0.31$), nor with mean accuracy ($r = 0.08$, $p = 0.51$).

Visual search for upright vs inverted bigrams

Next we sought to evaluate whether bigram processing is different for upright compared to inverted bigrams. Specifically, we reasoned that, if learning to read upright letters leads to the formation of upright bigram detectors, any model based on single letters would perform poorly on predicting upright but not inverted bigrams.

Participants performed oddball visual search in which both target and distractors were either upright or inverted bigrams (Figure 1D). As before, irrespective of fluency level, they were highly accurate in all conditions (average accuracy across 115 bigram searches, mean ± sem: 95.8% ± 0.5% for upright bigrams, 95% ± 0.7% for inverted bigrams) and also highly similar in their responses as evidenced by a strong split-half correlation between odd- and even-numbered participants (Figure 1E). Interestingly, there was a significant correlation in accuracy for the upright and inverted bigrams ($r = 0.58$, $p < 0.00005$). The bigrams with the least accuracy were typically bigrams with either transposed letters or with one letter in common (top 10 upright bigram pairs with least accuracy: (RR, RS), (TV,VT), (LV,VL), (AR,RA), (AT,TA), (LR,TR), (RS,RT), (RT,ST), (LL,RL), (LT,SL)). We did not observe any systematic trend in error patterns with age or across fluency levels (correlation between search accuracy across bigrams: $r = 0.48$, $p < 0.00005$ between young and old participants, upon dividing into two equal groups based on age; $r = 0.48$, $p < 0.00005$ between more and less fluent readers, upon dividing into two equal groups based on reading fluency).

Participants took longer to perform inverted searches (average response times, mean ± sem across participants: 1.96 ± 0.03 s for upright, 2.43 ± 0.05 s for inverted; $t(114) = -11.81$, $p < 0.00005$, Cohen's $d = 2.27$ paired t-test across 115 searches). Thus, familiarity with the upright orientation improved discrimination. However, familiarity did not qualitatively alter visual search performance across type of letter orientation, as evidenced by a strong and significant correlation between search dissimilarities in the upright and inverted conditions ($r = 0.92$ across 115 bigram searches, $p < 0.00005$).

As with single letter analysis, we correlated the mean search time with passage reading score. The association between reading fluency and visual search times was specific to upright but not inverted bigrams (correlation between passage reading score and mean bigram search time: $r = -0.32$, $p < 0.05$ for upright bigrams, and $r = -0.15$, $p = 0.24$ for inverted bigrams).

Finally, we asked whether the frequency of bigrams predicted search difficulty. We first calculated the frequency of occurrence of each bigram based on an English print corpus (Balota et al., 2007). Among the bigrams used here, AT, AL, RA, ST are frequent bigrams and SV, VT, VL, AA are infrequent bigrams. We then asked whether the mean bigram frequency of the target and distractors in a given search was correlated with the mean search times or accuracy of these searches. This revealed no significant correlation (correlation with search time: r = 0.12, p = 0.19 for upright bigrams, and r = 0.12, p = 0.19 for inverted bigrams; correlation with accuracy: r = -0.03, p = 0.79 for upright; r = -0.1, p = 0.29 for inverted bigrams).

Can bigram search be explained using single letter relations?

The above findings show that reading fluency is associated with upright bigram searches, but does not elucidate whether this is due to improved single letter representations or due to specialized bigram detectors. To investigate this issue, we devised a quantitative model to explain visual search for bigrams using the constituent single letters. In a series of previous studies, we have shown that the reciprocal of search time (1/RT) – which is a measure of dissimilarity – yields more accurate models for visual search, and that the dissimilarity between objects differing in multiple features can be explained using the constituent features.

In keeping with these findings, we devised a “part-sum” model (Figure 2A) in which the search dissimilarity (1/RT) between a pair of bigrams, say AB & CD, is a linear sum of dissimilarities between the constituent pairs of single letters A, B, C, D i.e. (A,B), (A,C), (A,D), (B,C), (B,D), and (C,D). To account for possible differences in position, we grouped these pairs based upon the type of comparison and computed corresponding, across and within-bigram dissimilarity terms: there were letter pairs at corresponding locations in the two bigrams (e.g. AC & BD), at opposite or across locations (e.g. AD & BC), and within a bigram (e.g. AB & CD). Thus, the search dissimilarity for bigrams AB & CD is given by:

$$d(AB,CD)=C_{AC}+C_{BD}+X_{AD}+X_{BC}+W_{AB}+W_{CD}+c$$

where C_{AC} & C_{BD} are relations between letters in the two bigrams at corresponding locations, X_{AD} & X_{BC} are relations between letters in the two bigrams at opposite locations, W_{AB} & W_{CD} are letter relations within each bigram and c is a constant term. The part-sum model parameters can be estimated because the same terms repeat across searches: for instance, the term C_{AC} is present in the equation for d(AE,CF) as well as d(AG,CH). Since bigrams were constructed using six possible letters, the corresponding-location letter terms are ${}^{6}C_{2}$ = 15 in number, and likewise there are 15 across-location letter terms and 15 within-bigram letter terms. These unknown part relations can then be estimated from the data using standard linear regression (see Methods).

The part-sum model yielded excellent fits to the observed bigram dissimilarities (model correlation: r = 0.92 for upright bigrams, r = 0.94 for inverted bigrams; Figure 2B). Model correlations were close to the split-half consistency between participants, suggesting that the model explains nearly all the explainable variance in the bigram dissimilarities. Importantly, model fits were not systematically different between upright and inverted searches as would be expected if there were upright bigram detectors (Figure 2B). This in turn suggests that the better discrimination of upright bigrams by participants must be driven by letter-level differences in the part-sum model parameters.

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A further investigation of the part-sum model parameters revealed several other interesting results. First, the single letter relations estimated by the part-sum model for the corresponding, across and within terms were correlated with the observed single letter dissimilarities in this experiment ($r = 0.76$, $p < 0.005$; $r = 0.84$, $p < 0.0005$ & -0.61, $p < 0.05$ for C, X & W terms, for the part-sum model fit to the average dissimilarities for upright bigrams across all participants). Second, the within-bigram terms are consistently negative (Figure 2C), suggesting that search is harder when bigrams contain dissimilar letters. We have observed this effect consistently in previous studies – it resembles the well-known finding that search is harder when distractors are heterogeneous (Duncan and Humphreys, 1989; Vighneshvel and Arun, 2013; Pramod and Arun, 2016). Third, the interaction between the letters (both across and within) were weaker for upright compared to inverted bigrams. This weaker interaction leads to improved search for upright letters by increasing their discriminability.

Relation between bigram searches and reading fluency

The above findings that fluent readers are faster at discriminating upright bigrams might also be predicted by other covarying factors such as their RAN score, motor speed, and executive functions such as inhibition control. To investigate these possibilities, we sought to predict the individual variation in reading fluency using a variety of possible factors. To avoid overfitting, we generated a predicted fluency score by training each factor on the word reading scores, and then compared this prediction with the passage reading score.

To characterize the effect of overall task performance for each participant, we included the motor speed (measured during a baseline motor block; see Methods) and overall accuracy (across all searches). Such factors index non-specific executive functions that could predict fluency variations. To characterize any effects due to discrimination of single letters, we calculated the average dissimilarity across all single letter searches. To characterize the influence of upright bigrams, we fit a part-sum model to the upright bigram dissimilarities for each participant, and calculated the average of the corresponding, across and within terms separately, and included the constant term. We did likewise for the inverted bigram searches. Finally, we used the RAN score of each participant as a possible factor. For each factor we asked how well the predicted reading score using that factor (learned based on the word reading score) correlated with the independently observed passage reading score.

The results of these analyses are summarized in Figure 2D. To establish an upper bound on model performance, we compared the word reading fluency and passage reading fluency scores, which were highly correlated ($r = 0.91$, $p < 0.0005$; Figure 1C). Among all the individual factors, the RAN score had the highest correlation with passage reading fluency ($r = 0.55$, $p < 0.00005$; Figure 2D), followed by the upright bigram terms ($r = 0.40$, $p < 0.0005$; Figure 2D). This correlations were strongest for the part-sum model terms, compared to other measures derived from the bigram searches (correlation of passage reading scores with average upright bigram dissimilarity of each participant: $r = 0.32$, $p < 0.05$; with the average difference between upright and inverted bigram dissimilarity: $r = 0.36$, $p < 0.005$). Thus, the part-sum model parameters seem to capture the essential aspects of bigram processing.

The above analysis shows that a number of factors are correlated with passage reading fluency, but there could be correlations between these factors. To assess the unique contribution of each factor, we performed a partial correlation analysis. Specifically, we asked whether the correlation between a given factor with the passage reading fluency score would continue to be significant after regressing out all other factors. This revealed only two factors with a significant partial correlation: upright bigram terms and RAN score (Figure 2E). Hence, we conclude that RAN and upright bigram terms uniquely predict reading fluency compared to all other factors.

Experiment 2: bigram Search with varying letter spacing

The above findings show that reading fluency is associated with upright but not inverted bigram processing, suggesting that familiarity with upright letter orientations leads to specific changes in visual processing. We therefore wondered whether this effect would also be specific to frequently encountered letter spacings. This is an important question by itself because changes in letter spacing affect reading speed and children with dyslexia have been shown to be particularly impacted by spacing features (Zorzi et al., 2012; van den Boer and Hakvoort, 2015; Hakvoort et al., 2017). In addition, by testing the same participants after ~10 months, we also asked whether improvements in reading fluency can be predicted from changes in bigram processing.

Methods

All details of Experiment 2 were identical to those in Experiment 1 except those outlined below.

Participants—A total of 65 children (31 male, aged 10.2 ± 0.9 years, 23 from 4th grade, 26 from 5th grade and 16 from 6th grade) were recruited 10 months later for this follow-up experiment. Of these 59 children had previously participated in Experiment 1.

Stimuli—A total of 3 letters (F, G, and R) were combined in all possible ways (i.e. FF, FG, FR, GF, … etc) to form a total of 9 bigrams. These letters were chosen because they were not symmetric along the horizontal axis. Letters were 1° in height, and were separated by either 0.18º (normal spacing) or 1.05° (large spacing). The normal spacing here approximates the spacing between letters in Arial font but with a fixed width between letters.

Task—Participants were again given the two reading tasks (word & passage reading), a RAN task, and a visual search task involving upright and inverted bigrams with normal or large spacing. Participants performed a total of 288 searches ($^9C_2$ = 36 bigrams x normal and large letter spacing x 2 configurations x 2 repeats). All bigram searches were randomly interleaved.

Part-sum model—Since there are only $^3C_2$ = 3 letter relations each for the corresponding, across and within term, the part-sum model had only 10 free parameters, which were estimated from a total of 36 bigram dissimilarities.

Results

Participants were highly accurate across all search types (accuracy, mean ± sem: 96% ± 0.5% for upright-normal spacing, 95% ± 0.5% for upright-large spacing; 95% ± 0.6% for inverted-normal spacing, 94% ± 0.7% for inverted-large spacing). They were also highly similar in their responses (split-half correlation between RT of odd- and even-numbered participants, for normal and large letter spacing: $r = 0.96$ & 0.95 for upright bigrams, $r = 0.96$ & 0.97 for inverted bigrams; all $p < 0.00005$). An example bigram search array using normal letter spacing is shown in Figure 3A, and the same search with large spacing is shown in Figure 3B. It can be seen that the search with the large letter spacing is harder but this effect is weaker if the arrays are inverted. This was indeed true in general as well. Participants responded significantly slower for upright bigrams with large spacing (average response times, mean ± sem across participants: 1.8 ± 0.03 s for normal spacing, 1.99 ± 0.04 s for large spacing; $F(1, 8095) = 101.0$, $\eta^2 = 0.01$, $p < 0.00005$ for main effect of spacing, ANOVA on RT with spacing & image pair as factors; $F(35, 8095) = 56.69$, $\eta^2 = 0.2$, $p < 0.00005$ for image-pair, $F(35, 8095) = 4.05$, $\eta^2 = 0.02$, $p < 0.00005$ for interaction effect; Figure 3C). This effect was present even for inverted bigrams (average response times, mean ± sem across participants: 2.06 ± 0.05 s for normal spacing, 2.17 ± 0.05 s for large spacing, $F(1, 8095) = 26.4$, $\eta^2 = 0.003$, $p < 0.00005$ for main effect of spacing, ANOVA on RT with spacing & image pair as factors; $F(35, 8095) = 64.12$, $\eta^2 = 0.22$, $p < 0.00005$ for image-pair, $F(35, 8095) = 2.05$, $\eta^2 = 0.009$, $p < 0.00005$ for interaction effect).

The normal spacing advantage was moderately larger for upright compared to inverted bigrams (average difference in RT between normal and large spacing searches, mean ± sem across participants: 0.19 ± 0.16 s for upright bigrams, 0.11 ± 0.17 s for inverted bigrams, $t(35) = 2.16$, $p < 0.05$ on a paired t-test across participant-wise differences; Cohen's $d = 0.36$). However, search dissimilarities were highly correlated with each other for both normal and large spacing searches ($r = 0.94$ for upright bigrams, $r = 0.95$ for inverted bigrams; $p < 0.00005$), as well as between upright and inverted conditions ($r = 0.95$ for normal spacing, $r = 0.96$ for large spacing; $p < 0.00005$). Thus, bigram dissimilarities are qualitatively similar across letter spacing and bigram orientation.

Can reading fluency be predicted by bigram processing at the familiar spacing?

Next, we fit the part-sum model to the observed search dissimilarities for each participant for each of the four search types (upright/inverted x normal/large spacing). We then performed a similar analysis as before to determine whether the passage reading score can be predicted by various factors. The correlation of each factor with passage reading score is shown in Figure 3D. Interestingly, only the part-sum model terms for upright bigrams with normal spacing predicted reading fluency, compared to model terms for large spacing and inverted bigram terms (Figure 3D). As before, this correlation was specific to the part-sum model terms, compared to other measures from the bigram searches: passage reading fluency was only weakly correlated with the average upright bigram dissimilarity of each participant ($r = 0.17$ & 0.11 for small and large spacing, $p = 0.19$ & 0.37 respectively) and with the average difference between upright and inverted bigram dissimilarity ($r = 0.02$ & 0.03 for small and large spacing, $p = 0.89$ & 0.84 respectively). Thus the part-sum model captured some essential underlying aspect of bigram processing relevant to reading fluency.

To assess the unique contribution of each factor towards explaining reading fluency, we performed a partial correlation as before. Only two factors showed a significant partial correlation with the passage reading score after regressing out all other factors: upright bigram terms for normal spacing and the RAN score (Figure 3E). Hence, we conclude that the effect of visual processing on reading fluency is highly specific both to the familiar (upright) orientation and familiar (normal) spacing.

Can bigram processing changes predict longitudinal changes in fluency?

Since the same participants were tested ~10 months apart in Experiments 1 (time 1) & Experiment 2 (time 2), we wondered whether growth in reading fluency can be predicted using changes in upright bigram processing.

To this end, we analysed the data from 59 participants common to both Experiments 1 & 2. To predict the growth in fluency score using the change in the average part-sum model parameters (averaged across ${}^{3}C_{2} = 3$ terms for corresponding, across, within terms, together with the constant term), we performed a linear regression to predict the change in fluency as a weighted sum of the part-sum model parameters. Specifically, we fitted a linear model $\mathbf{y} = \mathbf{Xb}$, where $\mathbf{y}$ is a 59x1 vector depicting difference in fluency score (i.e. time 2 – time 1 scores), $\mathbf{X}$ is a 59 x 5 matrix with rows containing the difference between each type of model term together with a global constant term, and $\mathbf{b}$ is a 5x1 vector of unknown weights that is estimated using standard linear regression (*regress* function in MATLAB).

We first compared the reading and RAN scores across time. As expected, all scores improved with time (Figure 4A). To assess whether growth in RAN and reading scores can be predicted using bigram processing changes, we took the difference in the average model term magnitudes of each type (corresponding, across, within, and constant terms) and asked whether each score change can be predicted using a linear sum of the change in the model parameters for upright or inverted bigrams. We found that changes in upright or inverted bigram terms did not predict RAN score changes ($r = 0.11$, $p = 0.43$ for upright, $r = 0.21$, $p = 0.12$ for inverted). Interestingly, changes in upright bigram processing were able to predict the growth in both word reading and passage reading scores ($r = 0.42$, $p < 0.005$ for word reading, $r = 0.29$, $p < 0.05$ for passage reading; Figure 4B). By contrast, changes in inverted bigram processing predicted word reading improvements only weakly ($r = 0.30$, $p < 0.05$; Figure 4B) and did not predict passage reading ($r = 0.15$, $p = 0.27$). However, there was no significant difference between these correlations for upright and inverted bigrams ($p > 0.4$ for both word reading and passage reading, Fisher's z-test comparing upright and inverted bigrams). The lack of significant differences could be due to comparing differences which are inherently noisier, or alternatively due to no real difference. We consider the latter unlikely given the robust difference between upright and inverted bigrams in predicting fluency variations (Figure 2E, 3E). Distinguishing between these possibilities will require sampling a larger number of participants which is beyond the scope of the present study.

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In sum, we conclude that longitudinal changes in reading fluency can be predicted using changes in bigram processing.

Discussion

Here we investigated whether reading fluency in children is associated with their performance on visual search tasks. Our main finding is that visual search for bigrams predicts individual variations in reading fluency. This association was highly specific: it was true for upright but not inverted bigrams, and for bigrams with normal but not large spacing. It predicted both cross-sectional inter-individual variations in reading fluency as well as longitudinal changes within individuals. Below we discuss these findings in relation to the existing literature.

We have found that reading fluency has a highly specific association with upright, normally spaced bigrams during visual search. This finding is consistent with both the crowding and serial position effects being different for letters compared to unfamiliar symbols (Grainger et al., 2010; Chanceaux and Grainger, 2012). It is also consistent with the processing deficits for letters but not symbols reported in dyslexic readers (Shovman and Ahissar, 2006). But the specificity of the association to bigrams in upright orientation with normal spacing is noteworthy, because such selective effects have not been reported previously. It suggests that visual representations for letters and bigrams undergo changes and these changes are specific to commonly encountered text orientation and spacing. It also indicates a possible resolution to conflicting evidence in the literature with regard to letter spacing. Some studies have found improved reading speed and accuracy with increased letter spacing (Zorzi et al., 2012; Hakvoort et al., 2017), whereas others have found that reading speed is optimal at the default spacing (Perea et al., 2011; van den Boer and Hakvoort, 2015). We speculate that these discrepancies could reflect differences in the statistics of letter characteristics (e.g., font, spacing, size) as experienced by sampled readers in different studies.

Our results also reveal how visual representations change with reading. We have found that bigram discrimination in visual search can be explained entirely using dissimilarities between letters, for both upright and inverted bigrams. These results challenge the widely held view that reading should lead to the formation of specialized bigram detectors (Grainger and Whitney, 2004; Dehaene et al., 2005). If bigram detectors were formed through exposure to upright letters, upright bigram discrimination should have been less predictable from single letters compared to inverted bigram discrimination, but we observed no such trend (Figure 2B). Rather, we found that upright bigrams are more discriminable because of weaker within-bigram interactions (Figure 2C). This is consistent with our previous studies showing weaker letter interactions for readers and non-readers of Indian languages (Agrawal et al., 2019) and for upright compared to inverted bigrams in English (Agrawal et al., 2020). However, the previous studies did not control for cognitive or language-related factors, leaving open the possibility that any association between reading fluency and visual processing could be driven by these shared factors. Our study therefore represents an important advance beyond the earlier studies because we show a highly specific association between upright, normally spaced bigrams and English reading fluency, which is present even after controlling for important factors like RAN, motor speed, overall

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accuracy, and visuospatial attention which cannot by themselves explain the highly specific changes observed here.

Consistent with earlier results, we found that RAN score explained unique components of variance in reading fluency (Figure 2E, 3E). We used a serial RAN task in this study as it is a better predictor of reading of longer sentences (de Jong, 2011). The underlying cognitive processes of RAN remain under debate– it is known to involve overtly attending to an item, covertly attending to other neighbouring items, enhancement or suppression of distractors based on context and recency (Mascheretti et al., 2018). These cognitive factors are also known to be associated with reading (Lervåg and Hulme, 2009). The theoretical accounts of RAN suggest that it captures domain-general speed of processing (Kail et al., 1999; Sideridis et al., 2016), domain specific speed of access to phonological codes (Vander Stappen and Reybroeck, 2018) and visual features (Stainthorp et al., 2010), and cross-modal print processing (Nag and Snowling, 2012). However, our results go further to show that there are additional factors that enable reading fluency, such as highly specific bigram-level changes in visual processing.

Given that visual search performance changes with age, it is worth considering whether our findings are driven by these changes. The motor and executive functions required for efficient visual search improve rapidly in children around the ages tested in our study (Hommel et al., 2004; Gil-Gómez de Liaño et al., 2020). In particular, children are more susceptible to distractors compared to older adults despite having similar response times. However, these differences are unlikely to explain the highly specific association we have found between upright bigrams and reading fluency, for several reasons. First, all our searches involved a single oddball target among identical distractors, whereas most age-related differences have been observed for conjunction searches with multiple types of distractors. Second, motor speed alone also could not uniquely explain reading fluency, suggesting that motor processing alone cannot account for fluent reading. Third, children were equally accurate on upright and inverted bigram searches, suggesting no difference in error processing or feedback. They were however, faster on upright bigram searches, suggesting that familiarity had a specific influence on searching. This is consistent with many previous studies demonstrating better discrimination of familiar objects during visual search (Wang et al., 1994; Malinowski and Hübner, 2001; Mruczek and Sheinberg, 2005; Kaiser et al., 2014). In particular, it has been observed that visual search is faster for objects in a familiar orientation (Wolfe et al., 1999; Malinowski and Hübner, 2001) and that such orientation effects occur relatively late (McCants et al., 2018). However, our results go further to show that familiarity with specific orientations does not lead to greater errors in part-based models, as might be expected if familiarity led to the formation of specialized whole object detectors. Rather, our results are consistent with the possibility that familiarity leads to sharpening and perceptual tuning of the parts, leading to more separable representations of the whole object (Glezer et al., 2015; Agrawal et al., 2020). We speculate that viewing familiar letters biases the preparation and selection stages of visual search by modifying the underlying feature representations (Eimer, 2014).

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Limitations of this study

Our findings show an association between upright bigram processing and fluent reading, but do not reveal the direction of causality: does fluent reading lead to better bigram processing, or does better bigram processing lead to fluent reading? This question can be resolved if early changes in bigram processing were observed to precede changes in fluent reading, but this will require an extensive longitudinal study starting when literacy is emergent, which is beyond the scope of this study. Recent evidence suggests a causal role of visual processing in predicting the reading fluency of children in early grades (Bertoni et al., 2019). They found that the error rate in a crowding task (with small spacing) in pre-literate children predicted their passage reading fluency at the end of grade 1 even after controlling for phonological processing and RAN scores. However, this association could be confounded by factors such as visuospatial attention, priming and memorability that could influence both reading fluency and performance on the demanding crowding tasks used in these studies. Therefore it would be interesting to map changes in letter and bigram representations longitudinally across different stages of reading acquisition starting in the pre-school years when variations in visual search performance are large (Carroll et al., 2016; Gil-Gómez de Liaño et al., 2020). We speculate that early differences between upright and inverted bigram processing could be associated with differences in early exposure to print, and become substantial as reading skills develop to the point of fluency.

Due to practical constraints on testing time, we could not measure a broader set of language and cognitive abilities such as phonological awareness, visuospatial attention and executive functions. Another important factor that we did not explicitly control for is bilingual language experience, which can potentially predict reading fluency variations (Lallier and Carreiras, 2018). It is quite possible that all these factors also predict unique variations in reading fluency.

Nonetheless our findings do suggest a possible component in an intervention, whereby visual search activities involving upright bigrams or longer strings could facilitate optimal letter processing prior to the conversion of letters and letter strings into sounds and eventually words and their meanings. The proposed approach might complement other intervention techniques on reading such as training on action-video games (Franceschini et al., 2013). Such training has been reported to reduce crowding and enable parallel processing of letters (Franceschini et al., 2017). Such games also improve other cognitive abilities such as attentional control and phonological decoding, especially in children with developmental dyslexia (Bertoni et al., 2021).

Conclusion

In sum, we propose that upright bigram processing in visual search captures key aspects of orthographic processing that are modified with reading. We propose that it can complement other reading-related measures (RAN, phoneme awareness) and cognitive measures (visuospatial attention and executive function) to track the development of typical or atypical reading skills (Franceschini et al., 2012; Norton and Wolf, 2012; Carroll et al., 2016; Bertoni et al., 2019).

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Some of these results were presented at the Annual Conference of Cognitive Science meeting in 2019.

Data Availability

All data and code required to reproduce the results are available publicly at https://osf.io/bvzh5/

References

Agrawal A, Hari K, Arun SP. A compositional neural code in high-level visual cortex can explain jumbled word reading. Elife. 2020; 9 e54846 [PubMed: 32369017]

Agrawal A, Hari KVS, Arun SP. Reading Increases the Compositionality of Visual Word Representations. Psychol Sci. 2019; 30: 1707–1723. [PubMed: 31697615]

Arun SP. Turning visual search time on its head. Vision Res. 2012; 74: 86–92. [PubMed: 22561524]

Balota DA, et al. The English Lexicon Project. Behav Res Methods. 2007; 39: 445–459. [PubMed: 17958156]

Bertoni S, Franceschini S, Puccio G, Mancarella M, Gori S, Facoetti A. Action Video Games Enhance Attentional Control and Phonological Decoding in Children with Developmental Dyslexia. Brain Sci. 2021; 11

Bertoni S, Franceschini S, Ronconi L, Gori S, Facoetti A. Is excessive visual crowding causally linked to developmental dyslexia? Neuropsychologia. 2019; 130: 107–117. [PubMed: 31077708]

Bosse M-L, Tainturier MJ, Valdois S. Developmental dyslexia: the visual attention span deficit hypothesis. Cognition. 2007; 104: 198–230. [PubMed: 16859667]

Bouma H, Legein CP. Foveal and parafoveal recognition of letters and words by dyslexics and by average readers. Neuropsychologia. 1977; 15: 69–80. [PubMed: 831155]

Brysbaert M. How many words do we read per minute? A review and meta-analysis of reading rate. J Mem Lang. 2019; 109 104047

Carroll JM, Solity J, Shapiro LR. Predicting dyslexia using prereading skills: the role of sensorimotor and cognitive abilities. J Child Psychol Psychiatry. 2016; 57: 750–758. [PubMed: 26662375]

Casco C, Prunetti E. Visual search of good and poor readers: effects with targets having single and combined features. Percept Mot Skills. 1996; 82: 1155–1167. [PubMed: 8823883]

Chanceaux M, Grainger J. Serial position effects in the identification of letters, digits, symbols, and shapes in peripheral vision. Acta Psychol (Amst). 2012; 141: 149–158. [PubMed: 22964055]

de Jong PF. What Discrete and Serial Rapid Automatized Naming Can Reveal About Reading. Sci Stud Read. 2011; 15: 314–337.

Dehaene S, Cohen L, Sigman M, Vinckier F. The neural code for written words: a proposal. Trends Cogn Sci. 2005; 9: 335–341. [PubMed: 15951224]

Duncan J, Humphreys GW. Visual search and stimulus similarity. Psychol Rev. 1989; 96: 433–458. [PubMed: 2756067]

Eimer M. The neural basis of attentional control in visual search. Trends Cogn Sci. 2014; 18: 526–535. [PubMed: 24930047]

Franceschini S, Bertoni S, Gianesini T, Gori S, Facoetti A. A different vision of dyslexia: Local precedence on global perception. Sci Rep. 2017; 7 17462 [PubMed: 29234050]

Franceschini S, Gori S, Ruffino M, Pedrolli K, Facoetti A. A causal link between visual spatial attention and reading acquisition. Curr Biol. 2012; 22: 814–819. [PubMed: 22483940]

Franceschini S, Gori S, Ruffino M, Viola S, Molteni M, Facoetti A. Action video games make dyslexic children read better. Curr Biol. 2013; 23: 462–466. [PubMed: 23453956]

Gil-Gómez de Liaño B, Quirós-Godoy M, Pérez-Hernández E, Wolfe JM. Efficiency and accuracy of visual search develop at different rates from early childhood through early adulthood. Psychon Bull Rev. 2020; 27: 504–511. [PubMed: 32043221]

Glezer LS, Kim J, Rule J, Jiang X, Riesenhuber M. Adding words to the brain's visual dictionary: novel word learning selectively sharpens orthographic representations in the VWFA. J Neurosci. 2015; 35: 4965–4972. [PubMed: 25810526]

Goswami U. Sensory theories of developmental dyslexia: three challenges for research. Nat Rev Neurosci. 2015; 16: 43–54. [PubMed: 25370786]

Grainger J, Tydgat I, Isselé J. Crowding affects letters and symbols differently. J Exp Psychol Hum Percept Perform. 2010; 36: 673–688. [PubMed: 20515197]

Grainger J, Whitney C. Does the huamn mnid raed wrods as a wlohe. Trends Cogn Sci. 2004; 8: 58–59. [PubMed: 15588808]

Hakvoort B, van den Boer M, Leenaars T, Bos P, Tijms J. Improvements in reading accuracy as a result of increased interletter spacing are not specific to children with dyslexia. J Exp Child Psychol. 2017; 164: 101–116. [PubMed: 28810134]

Hommel B, Li KZH, Li S-C. Visual search across the life span. Dev Psychol. 2004; 40: 545–558. [PubMed: 15238042]

Kail R, Hall LK, Caskey BJ. Processing speed, exposure to print, and naming speed. Appl Psycholinguist. 1999; 20: 303–314.

Kaiser D, Stein T, Peelen MV. Object grouping based on real-world regularities facilitates perception by reducing competitive interactions in visual cortex. Proc Natl Acad Sci. 2014; 111: 11217–11222. [PubMed: 25024190]

Lallier M, Carreiras M. Cross-linguistic transfer in bilinguals reading in two alphabetic orthographies: The grain size accommodation hypothesis. Psychon Bull Rev. 2018; 25: 386–401. [PubMed: 28405906]

Landerl K, Freudenthaler HH, Heene M, De Jong PF, Desrochers A, Manolitsis G, Parrila R, Georgiou GK. Phonological Awareness and Rapid Automatized Naming as Longitudinal Predictors of Reading in Five Alphabetic Orthographies with Varying Degrees of Consistency. Sci Stud Read. 2018; 00: 1–15.

Lervåg A, Hulme C. Rapid Automatized Naming (RAN) taps a mechanism that places constraints on the development of early reading fluency. Psychol Sci. 2009; 20: 1040–1048. [PubMed: 19619178]

Malinowski P, Hübner R. The effect of familiarity on visual-search performance: evidence for learned basic features. Percept Psychophys. 2001; 63: 458–463. [PubMed: 11414133]

Martelli M, Di Filippo G, Spinelli D, Zoccolotti P. Crowding, reading, and developmental dyslexia. J Vis. 2009; 9: 14.1–18.

Mascheretti S, Gori S, Trezzi V, Ruffino M, Facoetti A, Marino C. Visual motion and rapid auditory processing are solid endophenotypes of developmental dyslexia. Genes Brain Behav. 2018; 17: 70–81. [PubMed: 28834383]

McCants CW, Berggren N, Eimer M. The guidance of visual search by shape features and shape configurations. J Exp Psychol Hum Percept Perform. 2018.

Melby-Lervåg M, Lyster S-AH, Hulme C. Phonological skills and their role in learning to read: a meta-analytic review. Psychol Bull. 2012; 138: 322–352. [PubMed: 22250824]

Mohan K, Arun SP. Similarity relations in visual search predict rapid visual categorization. J Vis. 2012; 12: 19–19.

Mruczek REB, Sheinberg DL. Distractor familiarity leads to more efficient visual search for complex stimuli. Percept Psychophys. 2005; 67: 1016–1031. [PubMed: 16396010]

Nag, S. Theories of Reading Development. Cain, K, Compton, DL, RK, P, editors. John Benjamins Publishing Company; 2017. 75–98.

Nag S, Arulmani G. Books for Embedded Phonics. The Promise Foundation. 2015.

Nag S, Snowling MJ. Reading in an Alphasyllabary: Implications for a Language Universal Theory of Learning to Read. Sci Stud Read. 2012; 16: 404–423.

Norton ES, Wolf M. Rapid automatized naming (RAN) and reading fluency: implications for understanding and treatment of reading disabilities. Annu Rev Psychol. 2012; 63: 427–452. [PubMed: 21838545]

Parrila R, Kirby JR, McQuarrie L. Articulation rate, naming speed, verbal short-term memory, and phonological awareness: Longitudinal predictors of early reading development. Sci Stud Read. 2004; 8: 3–26.

Perea M, Moret-Tatay C, Gómez P. The effects of interletter spacing in visual-word recognition. Acta Psychol (Amst). 2011; 137: 345–351. [PubMed: 21545978]

Pramod RT, Arun SP. Features in visual search combine linearly. J Vis. 2014; 14: 1–20.

Pramod RT, Arun SP. Object attributes combine additively in visual search. J Vis. 2016; 16: 8.

Pramod RT, Arun SP. Symmetric Objects Become Special in Perception Because of Generic Computations in Neurons. Psychol Sci. 2018; 29: 95–109. [PubMed: 29219748]

Rakhlin NV, Mourgues C, Cardoso-Martins C, Kornev AN, Grigorenko EL. Orthographic processing is a key predictor of reading fluency in good and poor readers in a transparent orthography. Contemp Educ Psychol. 2019; 56: 250–261. [PubMed: 31798206]

Rima S, Kerbyson G, Jones E, Schmid MC. Advantage of detecting visual events in the right hemifield is affected by reading skill. Vision Res. 2020; 169: 41–48. [PubMed: 32172007]

Shovman MM, Ahissar M. Isolating the impact of visual perception on dyslexics' reading ability. Vision Res. 2006; 46: 3514–3525. [PubMed: 16828838]

Sideridis GD, Simos P, Mouzaki A, Stamovlasis D. Efficient word reading: Automaticity of print-related skills indexed by rapid automatized naming through cusp-catastrophe modeling. Sci Stud Read. 2016; 20: 6–19.

Stainthorp R, Stuart M, Powell D, Quinlan P, Garwood H. Visual Processing Deficits in Children With Slow RAN Performance. Sci Stud Read. 2010; 14: 266–292.

Sunder S, Arun SP. Look before you seek: Preview adds a fixed benefit to all searches. J Vis. 2016; 16: 3.

Torgesen, JK, Wagner, CA, Rashotte, C. Test of Word Reading Efficiency - Second Edition (TOWRE-2). Circle Pines, MN: AGS; 2012.

van den Boer M, Hakvoort BE. Default spacing is the optimal spacing for word reading. Q J Exp Psychol (Hove). 2015; 68: 697–709. [PubMed: 25210997]

Vander Stappen C, Van Reybroeck M. Phonological Awareness and Rapid Automatized Naming Are Independent Phonological Competencies With Specific Impacts on Word Reading and Spelling: An Intervention Study. Front Psychol. 2018; 9: 320. [PubMed: 29593618]

Vidyasagar TR, Pammer K. Impaired visual search in dyslexia relates to the role of the magnocellular pathway in attention. Neuroreport. 1999; 10: 1283–1287. [PubMed: 10363940]

Vighneshvel T, Arun SP. Does linear separability really matter? Complex visual search is explained by simple search. J Vis. 2013; 13: 1–24.

Wang Q, Cavanagh P, Green M. Familiarity and pop-out in visual search. Percept Psychophys. 1994; 56: 495–500. [PubMed: 7991347]

Wolfe JM, Klempen NL, Shulman EP. Which end is up? Two representations of orientation in visual search. Vision Res. 1999; 39: 2075–2086. [PubMed: 10343791]

Zorzi M, Barbiero C, Facoetti A, Lonciari I, Carrozzi M, Montico M, Bravar L, George F, Pech-Georgel C, Ziegler JC. Extra-large letter spacing improves reading in dyslexia. Proc Natl Acad Sci U S A. 2012; 109: 11455–11459. [PubMed: 22665803]

VisionLabIISc. childreading. 2021. May 31. Retrieved from https://osf.io/bvzh5/

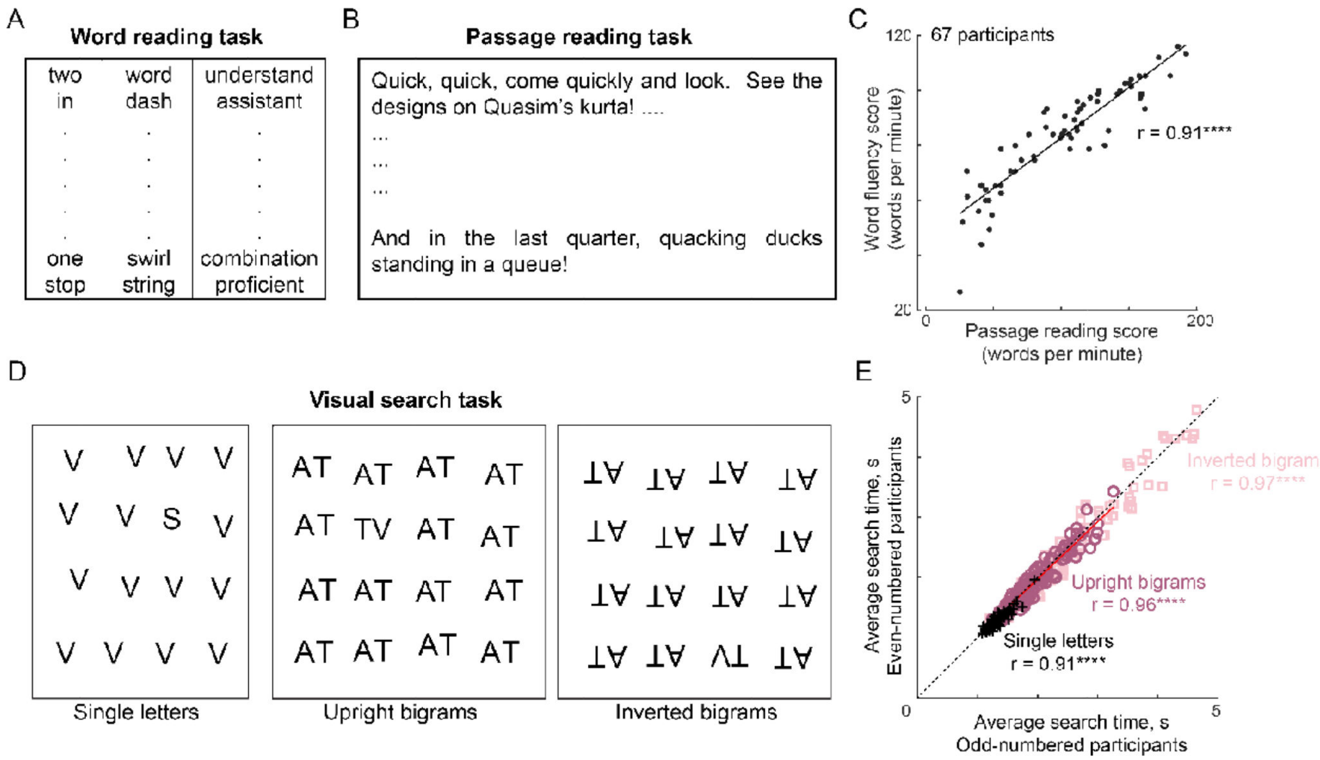

Figure 1. Reading fluency and visual processing tasks (Experiment 1)

(A) Example words equivalent to the sight word efficiency task (TOWRE).

(B) Example sentences from the passage reading task.

(C) Correlation between the fluency scores obtained from word reading task (A), and passage reading task (B). Each point represents one participant (n = 67) and asterisks indicate that the correlation is significant (**** is p < 0.00005).

(D) Example single letter and bigram search array from the visual search task.

(E) Search time in seconds (s) for even-numbered participants plotted against that of odd-numbered participants for letters (+), upright bigrams (o), and inverted bigrams (☐), indicating the reliability of the search data. The correlation between odd-numbered participants and even-numbered participants is indicated for each group.

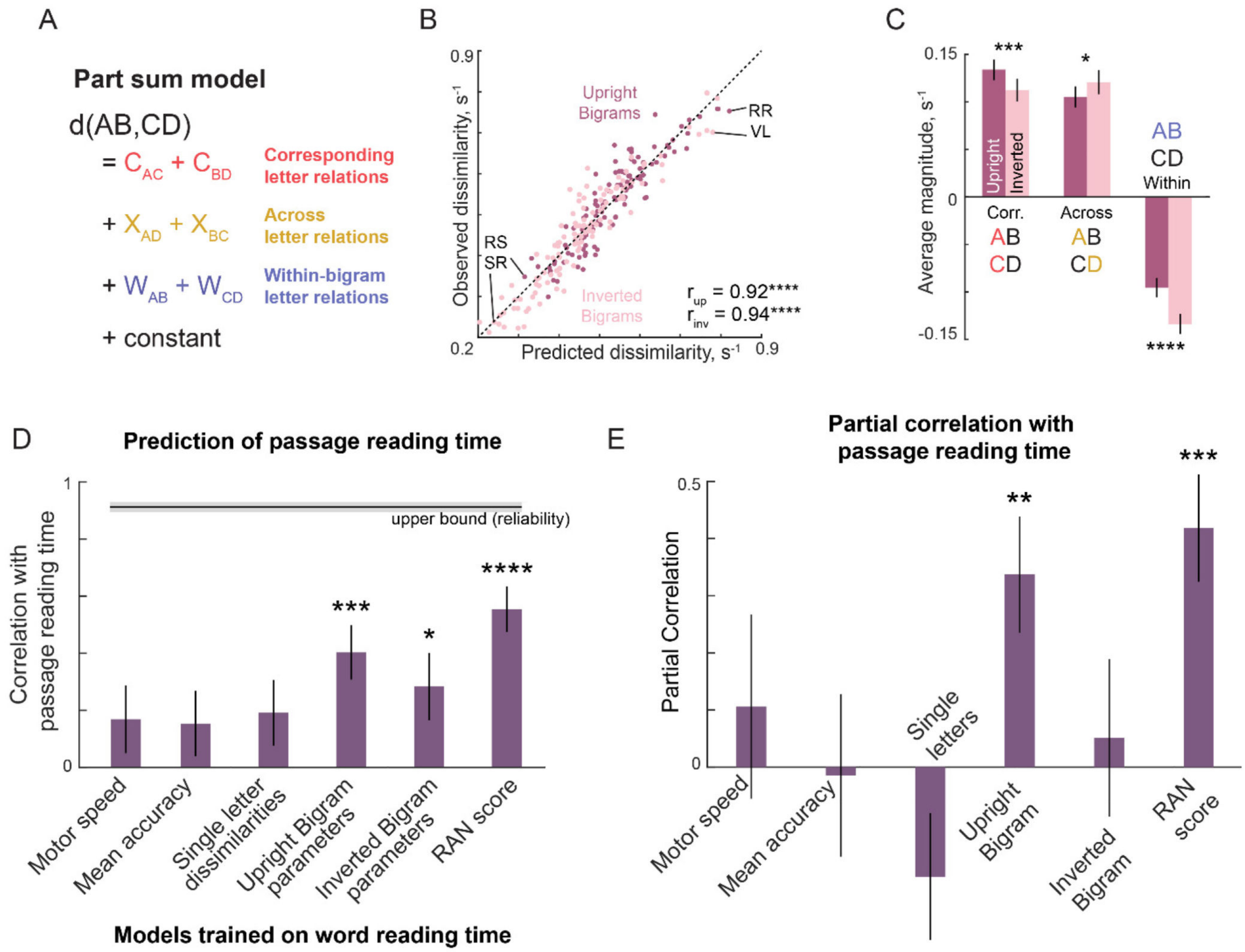

Figure 2. Upright bigram processing predicts reading fluency (Experiment 1)

(A) Schematic of the part-sum model, in which the net dissimilarity between two bigrams is a linear sum of single letter relations at corresponding locations across bigrams (C), opposite locations across bigrams (X) and letter relations within-bigrams (W).

(B) Observed bigram dissimilarity is plotted against predicted bigram dissimilarity from the part-sum model for both upright (*dark*) and inverted (*light*) bigram searches. Each point represents one search pair (n = 115 each). Example searches for two bigram pairs (RS,SR) & (RR,VL) are indicated for both upright and inverted conditions. Asterisks indicate that the model predictions were significantly correlated with the observed dissimilarities ($p < 0.00005$).

(C) Average model coefficients (mean ± sem) of each type for upright and inverted bigrams. Asterisks denote statistical significance obtained on a sign-rank test comparing 15 letter dissimilarities between upright and inverted conditions (* is $p < 0.05$, ** is $p < 0.005$, etc).

(D) Model correlation of each factor in predicting passage reading score. Error bars indicate ±1 s.d. using a bootstrap procedure (in which we repeatedly sampled 67 participants with replacement for a total of 1,000 times). All models were trained on word reading score, and tested on passage reading scores. Shaded error bars represent the noise ceiling i.e. correlation between word reading and passage reading score.

(E) Partial correlation of each factor with passage reading scores after regressing out all other factors. Asterisks denote significant correlation (* is $p < 0.05$, ** is $p < 0.005$, and so on). Error bars represent ± 1 s.d. of the correlation coefficient, calculated as in (D).

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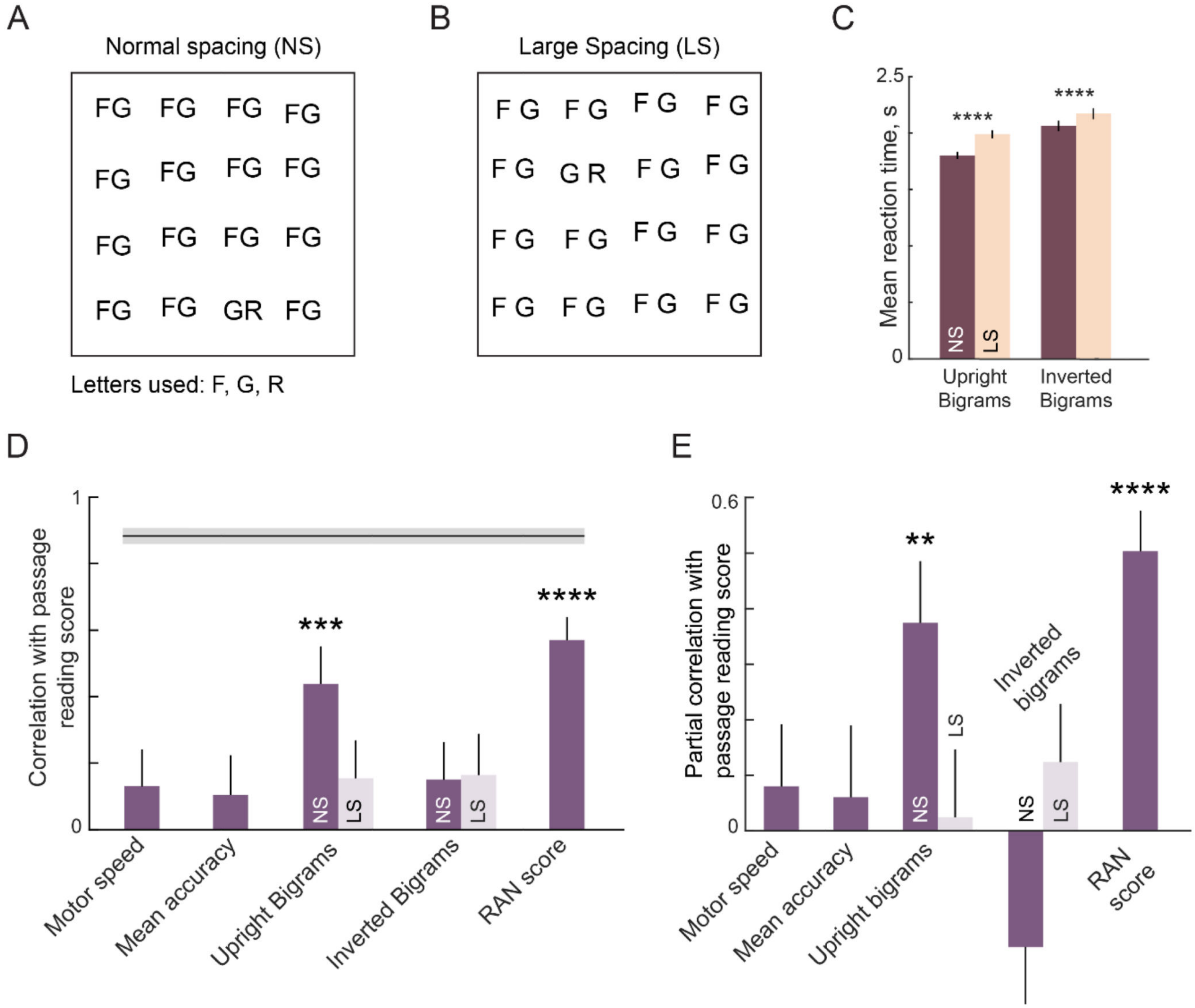

Figure 3. Effect of letter spacing on visual representation (Experiment 2)

(A) Example upright bigram search array with small letter spacing.

(B) Same as (A) but with large letter spacing. It can be seen that this search is slightly harder than the search in (A).

(C) Average search times (s = seconds) in the oddball search task for upright and inverted bigrams with normal and large spacing. Error bars indicate s.e.m. across participants. Asterisks denote statistical significance of the difference in means (**** is $p < 0.00005$, ANOVA – see text).

(D) Model correlation of each factor predicting passage reading score. Error bars indicate ±1 s.d. using a bootstrap procedure, whereby we repeatedly sampled 67 participants with replacement for a total of 1,000 times. Error bars on the top represents noise ceiling i.e. correlation between word reading and passage reading score.

(E) Partial correlation of each factor with passage reading scores after regressing out all other factors. Asterisks denote significant correlation (* is $p < 0.05$, ** is $p < 0.005$, and so on). Error bars represent ± 1 s.d. of the correlation coefficient, calculated as in (A).

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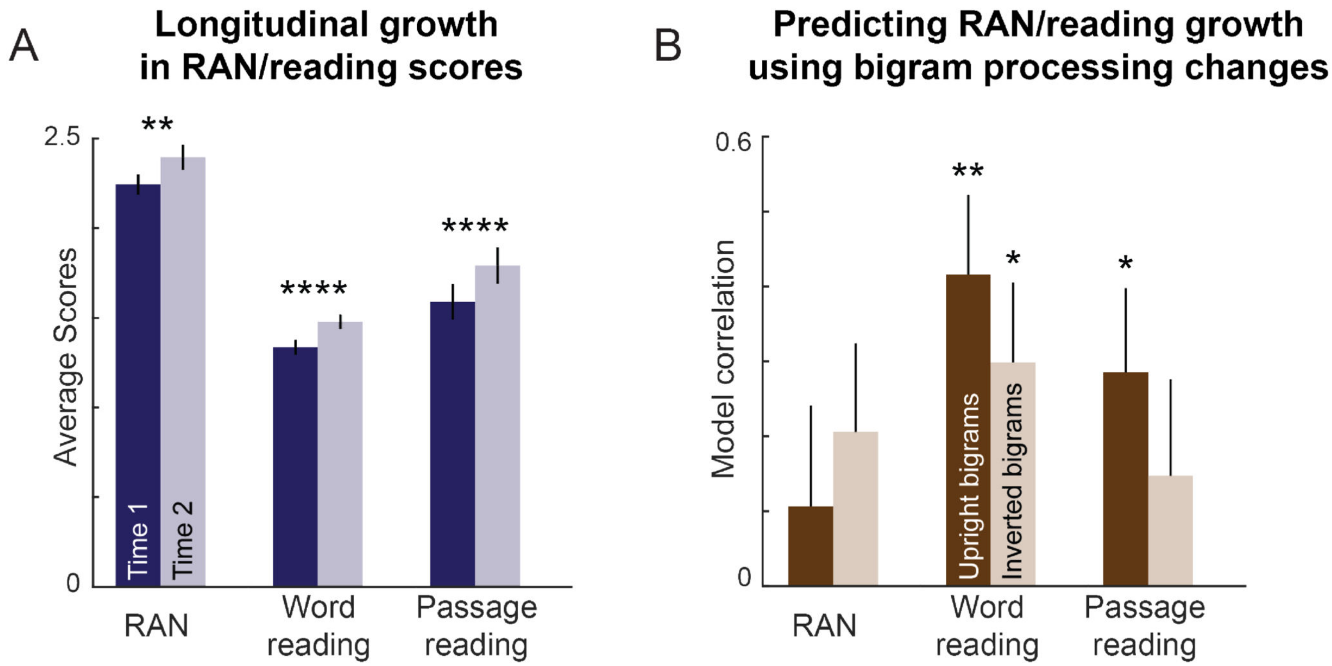

Figure 4. Longitudinal prediction of reading fluency using upright bigrams.

(A) Longitudinal growth in RAN and reading measures between Time 1 & Time 2 for individual participants. Asterisk represents statistical significance calculated using sign-rank test. Error bars represent s.e.m across participants.

(B) Prediction of RAN and reading score growth using upright (*dark*) and inverted (*light*) bigram processing changes. Error bars represent indicate ±1 s.d. obtained by a bootstrap procedure, whereby we repeatedly sampled 59 participants with replacement for a total of 1,000 times. Asterisks denote statistical significance of each correlation (* is $p < 0.05$, ** is $p < 0.005$, and so on).