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Exploring the relationships between reading instruction and individual differences in a computational model of reading

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Abstract

Studies have shown that individual differences in word reading can be observed for both skilled and novice readers. Several factors that could cause individual differences including reading experience, reading capacity, and oral language have been investigated. However, little is known about the influence of reading instruction on individual differences in reading. Given that early reading, training is critical to help children become proficient readers, the influence of reading instruction on subsequent reading behaviours should also be well understood. Thus, in this study, we investigated the relationships between reading instruction and individual differences in reading using computational models of reading. The model was exposed to a sound-focused, meaning-focused or balanced training scheme. We quantified the model's reliance on accessing semantics for reading, as an index of individual differences in semantic reliance (SR). The simulation results demonstrated that the degree of SR depended on reading instruction. Meaning-focused training resulted in higher SR, and that was followed by balanced training and then sound-focused. Moreover, SR was able to predict the model's word reading performance and interacted with other psycholinguistic reading factors including frequency, consistency, and orthographic neighbourhood size.

Keywords: reading instruction; individual differences; semantic reliance; computational modelling; word learning.

Introduction

Reading is a critical language skill allowing us to communicate with symbols and to spread knowledge widely. However, the process of training children (novice readers) to become skilled readers is nontrivial. That is because learning to read requires children to master mappings between orthographic (O), phonological (P), and semantic (S) forms of words. For decades, the issue concerning what is effective early reading instruction has been a hot topic in reading literature (e.g., Nation, 2009; Rayner et al., 2001; Taylor, Davis, & Rastle, 2017). For learning to read English words, there are two primary types of reading instruction. One is phonics-style training, in which children are instructed to learn intensively about the relationships between print and sound. The other one is meaning-focused training, in which children are instructed to learn intensively about the relationships between print and meaning.

The basis of phonics-style training originates from the nature of the English writing system. There are relatively systematic spelling-to-sound mappings than spelling-to-meaning mappings. Consequently, phonics-style training can help children exploit the systematicity of letters and sounds and is easier to learn. Various evidence from experimental, neuroimaging (Taylor, Davis, & Rastle, 2017), and computational studies (Chang et al. 2020) have shown that phonics-style training is superior to meaning-focused training. For instance, using an artificial word learning paradigm, Taylor et al. (2017) demonstrated that participants receiving orthography-to-phonology (OP) focused mappings achieved better accuracy and speed in reading compared to those participants receiving orthography-to-semantics (OS) focused mappings. The benefit of phonics training was not only observable in the reading-aloud task but also in the reading comprehension task. In a subsequent study using computational modelling, Chang et al. (2020) further demonstrated that oral language skills were critical to the transfer effect of phonics training in reading.

The advocate of meaning-focused training lays on the ultimate goal of reading, which is to access the meanings of words. Although spelling-to-meaning mappings are difficult to master, there are still some morphological regularities (e.g., *bake*, *baker*) in the mappings. Children are capable of learning semantic categories from orthography without the involvement of phonology (Nation & Cocksey, 2009). Thus, it might be better for children to acquire the OS relationships earlier rather than later during learning to read.

While substantial work has been done to investigate the effectiveness of different types of reading instruction, not enough is known about the influence of reading instruction on subsequent reading behaviours. Critically, whether the vestige of early reading instruction could be observed in mature reading or not and if so, how does it influence individuals' reading behaviours? These are the central issues that we would like to address in this study using computational models of reading.

Individual Differences in Reading

Multiple lines of studies have investigated variability in individuals' reading behaviours (Davies et al., 2013; Hoffman, Lambon Ralph, & Woollams, 2015; Woollams et al., 2016; Siegelman et al., 2020, 2022). Woollams et al. (2016) demonstrated individual differences in the degree of semantic reliance (SR) when reading words that have inconsistent spelling-to-sound mappings (e.g., *pint*). Adult readers with high SR tended to read slower than those with

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low SR, and the effect was moderated by consistency and imageability. These individual differences in reading are not only observed in adults but also in children. A recent study using a large cohort of children has demonstrated that children who showed higher sensitivity to OP regularities generally performed better in reading tasks than those with lower sensitivity to OP regularities (Siegelman et al., 2020). The sensitivity to OP or OS regularities is also crucial for the effectiveness of reading intervention. Children with high sensitivity to OP regularities and low sensitivity to OS regularities tend to receive better gains from phonologically-weighted intervention programs. (Siegelman et al., 2022).

So what might cause these variabilities in reading for adults and children? Several potential factors have been considered including reading experience (Andrews, 2015; Yap, Balota, Sibley, & Ratcliff, 2012), reading capacity (Dilkina, McClelland, & Plaut, 2008; Plaut, 1997), and oral language skills (Chang, 2023; Siegelman et al., 2020). Individuals who receive intensive reading experience, have abundant processing resources in the reading system, and have good oral language skills can generally develop high-quality orthographic, phonological, and semantic representations, and efficient reading pathways (mappings between representations). Thus, the development of representations and the use of reading pathways would seem to be key to driving individual differences in reading.

Within the connectionist view of reading (Seidenberg & McClelland, 1989; Harm & Seidenberg, 2004; Plaut et al. 1996), learning to read could be achieved via multiple pathways, depending on the division of labour along direct and indirect pathways to access phonology or semantics from orthography. Previous modelling work has shown that reading instruction could shift the division of labour of reading pathways in the system (Chang et al., 2020). However, it remains unknown whether the change in the division of labour resulting from reading instruction could be a potential source of individual differences in reading. Another relative and important question is what is the impact of reading instruction on subsequent reading behaviours.

Hence, the present study was designed to tackle the issues of individual differences in reading by systematically manipulating reading training and investigating its impact on subsequent reading behaviours in a computational model of reading. Specifically, we developed a fully implemented triangle model of reading and implemented three reading schemes with different focuses of reading instruction: OP focused, OS focused, and OPOS balanced. The OP focused model received three times as much training on the OP mappings, the OS focused model received three times as much training on the OS mappings, and the OPOS balanced model received an equal amount of training on the OP and OS mappings as a baseline model. Following Chang (2023), we derived SR based on the division of labour of OP and OS pathways as an index of individual differences in the model. We then investigated the relationships between the model's SR and different training regimes, and how it interacted with other psycholinguistic reading effects using a reading-aloud task.

Lastly, although computational modelling is an important tool for investigations of the mechanism underlying the reading process and functions, training a large-scale model such as a fully implemented triangle model of reading used here is often computationally expensive and time-consuming. That can also potentially limit the use of the model to simulate a large cohort of individuals, as in behavioural investigations (e.g., Siegelman et al., 2020). Therefore, to alleviate the training burden, in this study, we also utilised software optimisation techniques to speed up training processes. The details can be found in Method.

Method

Model Architecture

The model architecture, shown in Figure 1, was exactly the same as the one used in previous modelling work (Chang et al., 2020; Monaghan et al., 2017). It had three key processing layers: orthography (O), phonology (P), and semantics (S). There were 364 units in the orthographic layer, 200 units in the phonological layer, and 2446 units in the semantic layer. All three layers were connected to each other, but in between, they were connected with a hidden layer. Both hidden layers in the PS pathway and SP pathways had 300 units. Whereas both hidden layers in the OP and OS pathways had 500 units. There were additional attractor layers, consisting of 50 units, in phonology and semantics layers to enhance their phonological and semantic features respectively. Additionally, the semantic layer had a context layer, consisting of four units, to handle homophones. The hidden layer between them had ten units.

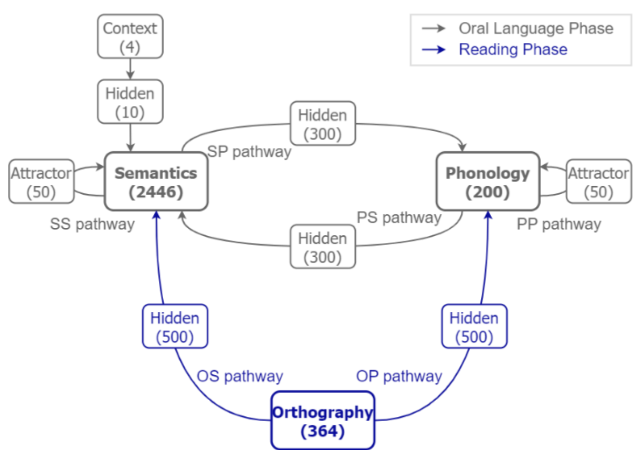

Figure 1: The architecture of the model.

Training Procedure

The model was trained on 6,229 English monosyllabic words. The training process included oral language training and reading training. The oral language training included four interleaving tasks: an oral vocabulary task (40% of trials), a meaning naming task (40% of trials), two tasks to develop a stable phonological attractor (10% of trials), and a semantic attractor (10% of trials) respectively. For the oral vocabulary task, the model was trained to map from phonological to semantic (PS) representations. During training, each phonological form of words was clamped for eight network times and then its semantic representation was generated by the model. For the meaning naming task, the model was trained to map from semantic to phonological (SP) representations. Each semantic form of words was clamped for eight network times and then its phonological representation was generated by the model. For the phonological attractor task, the model was trained to map between phonological to phonological representations (PP) to stabilise the representations. Each phonological representation was presented to the model for two network times and the model cycled the activation for the next six network times to recreate the input representation. The training procedure for the semantic attractor task was identical to that used for the phonological attractor task except that the model was trained to map semantic to semantic representations (SS).

After oral language training, all weights between the phonological and semantic layers were frozen. The model was continued to learn to read by learning the mappings between orthographic, phonological, and semantic representations for one million trials. A word was presented twelve network times in each trial. Importantly, the training process had three focused training: OP focused, OS focused, and OPOS balanced. For OP focused training, the model was trained under a 3:1 regime, where OP trials outnumbered OS trials by three times; for OS focused training, OS trials were three times more than OP trials. For OPOS-balanced training, the model was presented with the same number of OP and OS trials.

For both oral language training and reading training, the same training parameters were applied. For each training trial, a word was randomly selected according to its frequency (Marcus, Marcinkiewicz, & Santorini, 1993). The model's error (i.e., differences between target representations and output activations generated by the model) was calculated at the last network time. During training, backpropagation through time was used to optimise weights by reducing the differences. The learning rate was set to 0.05. To simulate variability in each reading training condition, ten versions of the OP focused models, the OS focused models, and the balanced models were trained with different initial weights.

Testing Procedure

During each training iteration, an error score was computed in terms of the Euclidean distance between the generated feature and the target feature. In the reading training phase, error scores were displayed per 5000 iterations and we exploited the scores at the end of training to discuss response times among models. High error scores in computational models resembled long response times (Seidenberg & McClelland, 1989).

For validating phonological output, the answer was considered correct only if its 8 phonological slots, which consisted of 200 units, were all exactly the same as the ones in target outputs. To test semantic output, we calculated the Euclidean distance of the generated output and the words in our corpus. The answer was deemed correct if the smallest distance found was the distance with the target word.

Model Training Acceleration

The MikeNet simulator (Harm & Seidenberg, 2004) has been widely deployed in the computational studies of reading (e.g., Chang et al., 2020; Harm & Seidenberg, 2004; Monaghan et al., 2017). MikeNet is written in the C programming language and is designed for large-scale neural networks. It is fast and can hold very large example files without taking up too much memory. The proposed model was developed in the MikeNet simulation environment. A training procedure for the target model with deep layers usually takes days or weeks due to the intensive computation requirement in computing backpropagation error scores and updating weight connections. To accelerate the training process, we leveraged two high-performance C libraries, Math Kernel Library (MKL) and Basic Linear Algebra Subprograms (BLIS), targeting the Intel and AMD processors respectively. Both libraries contained optimised math routines commonly used for software performance optimizations in the science, engineering, and financial applications on x86 microprocessors. We tuned the training performance by replacing the matrix-vector multiplication algorithms with the cblas_sgemv() API for machines with Intel CPUs and the bli_sgemv() API for those with AMD CPUs.

Table 1: Speedup ratios on Intel processors.

Iteration	Time Raw (sec)	Time Opt. (sec)	Ratio
100	1.22	0.34	3.62
1000	11.14	3.21	3.47
2000	22.18	6.40	3.47
3000	33.29	9.74	3.42
10000	113.16	32.36	3.50

Table 2: Speedup ratios on AMD processors.

Iteration	Time Raw (sec)	Time Opt. (sec)	Ratio
100	0.96	0.25	3.82
1000	9.01	2.32	3.89
2000	18.03	4.58	3.93
3000	27.22	6.87	3.96
10000	91.38	23.33	3.91

Table 1 illustrates the execution time of the simulation with software optimization using the Intel MKL library. The oral language phase of the proposed model was used as a benchmark to demonstrate the effectiveness of the software optimization. Training iterations ranged from a hundred to ten thousand. In Table 1, the column of Time Raw denotes the time required to finish training using the original MikeNet, while the column of Time Opt. records the time required with software optimization. Speedup ratios are calculated by dividing the times in the Time Raw column over those in the Time Opt. column. All ratios are greater than 3.4 among the different numbers of iterations. Similarly, Table 2 illustrates the execution time with software optimisation using the AMD BLIS. It shows an even more promising result with software optimization. All ratios are greater than 3.8.

Measuring SR based on the Division of Labour

Division of labour can help us understand how the model relies on each reading pathway in the system. Following Chang et al. (2020), a lesioning technique was adopted. To be specific, to isolate the contribution from the OP pathway, the OSP pathway was lesioned, and the Phonological sum squared error (SSE) was recorded. The reverse procedure was used to obtain the unique contribution from the OSP pathway. It is assumed that a large Phonological SSE indicates the lesioned pathway is critical (i.e., high contribution) while the intact pathway supports the function poorly (i.e., low contribution). Hence, the reciprocals of Phonological SSE obtained from the OP and OSP pathways were computed to indicate the proportion of contribution across the pathways. The identical procedure was used to obtain the contribution across the OS and OPS pathways except that Semantic SSE was computed instead. The SR was quantified by dividing the contribution of the OS pathway by the sum of the OP and OS pathways.

Results

At the end of oral language training, the model achieved an accuracy rate of 96.4% on the meaning naming task and an accuracy rate of 93.7% on the oral vocabulary task. At the end of reading training, the OP focused model, the OS focused model and the OPOS balanced model were able to accurately produce 99.84%, 99.32%, and 99.8% of phonological representations and 92.74%, 98.81%, 97.21% of semantic representations on the reading task, respectively.

The relationship between reading instruction and SR

The procedure for generating SR in the model was done for each of the 30 simulations with different approaches to reading instruction (OP focused, OS focused, or balanced). The result showed that SR ranged from 0.022 and 0.192 (M = 0.072, SD = 0.041). The relationship between reading instruction and SR was investigated by using a simple regression analysis with training focus as a predictor and with SR as a dependent variable. The simple regression model produced an R^2 value of 19.1% (Adjusted R^2 = 13.1%), p = .058. The SR generated from the OP model (M=0.053) was not significantly different from that generated from the balanced model (M = 0.067), p = 0.43. The SR difference between the balanced model and the OS model (0.096) was marginally significant, $\beta = 0.003$, $p = 0.1$. However, there was a significant SR difference between the OP and the OS focused models, $\beta = 0.043$, $p < 0.05$.

Exploring SR effects in the model

In the model, reading aloud was simulated by mappings of OP representations (Plaut et al., 1996; Harm & Seidenberg, 2004). To examine SR effects, a series of linear mixed-effect models (LMM) was conducted. LMMs were fitted using the *lme4* package in R (version 4.2.1, 2022). The SSE for words correctly pronounced by the model was used as a proxy for behavioural response times (RTs). For the LMM analysis, a set of psycholinguistic variables including word frequency (WF), orthographic neighbourhood size (ONS) (Coltheart et al., 1977), rime consistency (RC) (Glushko, 1979), concreteness (CON) (Brysbaert, Warriner, & Kuperman, 2014) and SR were included as predictors. Phonological SSE was included as a dependent variable. Outliers including words that the model misread, and SSE greater than three standard deviations from the mean were discarded. Furthermore, words without measures for all psycholinguistic variables were not considered. The data preprocessing procedures removed 0.242% of the observation points, leaving 157,428 observation points for analysis. Phonological SSE was log-transformed because the distribution was right-skewed. All the variables were scaled in order to obtain standardised coefficients in LMM.

As a baseline model, WF, ONS, RC, and CON were first included as fixed factors to predict Log Phonological SSE. Adding SR to the baseline model as a full model resulted in a significant improvement of model fit, $\chi^2(2) = 17.29$, $p < .001$, compared to the baseline model. The result is shown in Table 3. The effects of WF, ONS, RC, and CON were consistent with behavioural findings reported in several mega studies of word reading (Balota et al. 2004; Cortese & Khanna, 2007). Words were responded to more quickly if they were higher in frequency, higher in concreteness, had more consistent spelling-to-sound mappings, and had more orthographic neighbourhood size. Critically, larger SR was associated with more phonological SSE, $\beta = 0.109$, $t = 4.84$, conceiving as *slower* RTs, which is consistent with behavioural studies (Siegelman et al. 2020; Woollams et al., 2016).

Four interactions were conducted to investigate the influence of SR on the reading effects in the model. SR by WF, ONS, RC, or CON was added into the full model separately as a fixed factor. Adding WF x SR to the model resulted in a significant improvement, $\chi^2(1) = 9.97$, $p < .01$. Adding ONS x SR resulted in a significant improvement, $\chi^2(1) = 8.55$, $p < .01$. Adding RC x SR also resulted in a significant improvement, $\chi^2(1) = 60.49$, $p < .001$. Adding CON x SR resulted in a marginally significant improvement, $\chi^2(1) = 2.74$, $p < .1$. Figure 2 illustrated the largest interaction effect for RC x SR.

Table 3: Linear mixed-effect model fitted to phonological SSE produced by the model. All predictors were scaled.

	β	*t*	95% Confidence Interval
WF	-0.21	-27.26	(-0.22, -0.19)
ONS	-0.17	-22.98	(-0.18, -0.16)
RC	-0.11	-14.26	(-0.12, -0.09)
CON	-0.04	-5.71	(-0.06, -0.03)
SR	**0.11**	**4.84**	**(0.06, 0.15)**

Note: An effect was considered significant at the $p < .05$ level if its t-value was greater than 1.96 (Baayen, 2008).

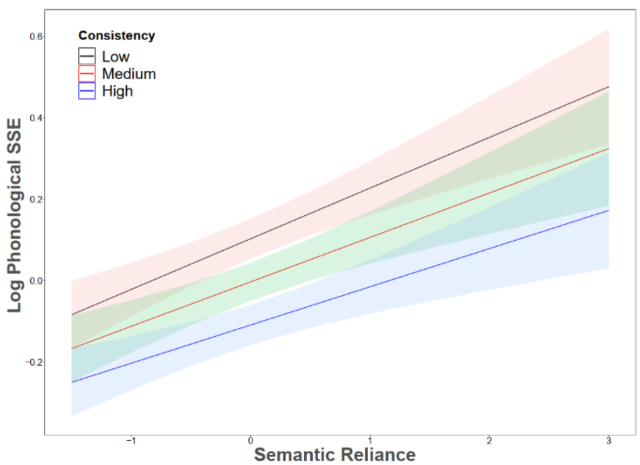

Figure 2. The interaction between rime consistency (RC) and semantic reliance (SR)

Discussion

Research in reading instruction generally focuses on investigating the (dis)advantages of using phonics-style or meaning-focused training for reading acquisition (Davis, 2013; Taylor et al. 2017). In this study, we focused on investigating the impact of different types of reading instruction on individual differences in reading aloud. Specifically, we utilised triangle connectionist models of reading to investigate whether different approaches to reading instruction could lead to different degrees of reliance on the semantic pathway and its interactions with other psycholinguistic factors that have previously been shown to be critical for reading aloud.

The simulation results demonstrated that a model which focused on print-to-meaning (i.e., the OS focused training model) showed the greatest reliance on the semantic pathway for reading aloud, whereas a model which focused on print-to-sound (i.e., the OP focused training model) showed the least and a model trained with balanced OP and OS mappings (i.e., the OPOS balanced training model) was in between. In English, the OP mappings are broadly systematic while the OS mappings are relatively arbitrary. As the model can learn the regularities of OP mappings, the reliance on the phonological pathway is very effective, especially for the reading-aloud task. Even so, by manipulating different types of reading instruction, the use of OP and OS reading pathways could be shifted. The finding was consistent with previous modelling work (Chang et al., 2020). Here we further demonstrated that the shift of reading pathways could be reformulated into the degree of semantic reliance as a source of individual differences in reading.

By using LMM analyses, we demonstrated that the model replicated a range of standard reading effects including frequency, consistency, orthographic neighbourhood size, and concreteness as observed in behavioural studies (Balota et al. 2004; Cortese & Khanna, 2007). More importantly, the SR derived from varying different types of reading instruction was able to predict model performance on reading aloud. The result is consistent with recent behavioural (Siegelman et al. 2020; Woollams et al., 2016) and neuroimaging evidence (Hoffman et al., 2015). Models with higher SR produced more phonological SSE compared to those with lower SR. That was because the semantic pathway was less efficient for reading aloud. When the semantic pathway was used more (i.e., high SR) in the model, more errors were observed. The degree of SR also has an impact on reading behaviours in the model. We observed that SR interacted significantly with word frequency, consistency, orthographic neighbourhood size, and marginally with concreteness. In particular, as in Figure 2, the largest interaction effect was observed between SR and consistency, in which models with high SR showed stronger consistency effects than those with lower SR.

While the present study has demonstrated the relationships between reading instruction and SR, the effect was not particularly strong. It is likely that we have a relatively small sample of simulations compared to a large cohort of participants generally used in behavioural studies of individual differences in reading. Thus, the present study can be improved by training more samples of simulations. With our speed-up training process, it is possible to train hundreds of models at a similar scale of behavioural mega-studies (e.g., Siegelman et al. 2020) to generate a wider range of variations in SR and enhance statistical power. Another future work could be conducted to investigate the change in SR over the time course of learning to read.

In summary, our simulation results demonstrated that reading instruction could shift the division of labour between alternative reading pathways in the system, resulting in individual differences in reading behaviours.

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