Reading instruction and individual differences in a computational model of Chinese character reading

Ching-En Kuo (nm6114083@gs.ncku.edu.tw)
Ya-Ning Chang (yaningchang@gs.ncku.edu.tw)
Miin Wu School of Computing, National Cheng Kung University, Tainan, Taiwan

Abstract

Adopting effective reading instruction is vital for educators and novice readers. In modern Chinese, approximately 80% of the characters are phonetic-semantic compounds. Orthographic knowledge training is one of the efficient training methods among fluency, working memory, phonological, orthographic, and morphological training in literacy development. However, the comparative effectiveness of orthographic knowledge training within phonics-based versus meaning-based instruction has received limited attention. Such comparisons have been shown to be vital for understanding effective reading instruction and individual differences in English reading. By developing a series of triangle models of Chinese character reading, this study aimed to investigate the influence of instructional methods on individual differences in reading. Specifically, the models were trained with sound-focused, meaning-focused, or even (mixed) instructional schemes. We employed semantic reliance (SR), which measures the relative reliance on orthography-to-phonology and orthography-to-semantics pathways, to assess individual reading differences across various training conditions. The simulation results demonstrated that SR scores varied across instructional methods, with the highest scores observed in the meaning-focused condition, followed by the even condition, and then the sound-focused condition. Furthermore, across all instructional conditions, the orthography-to-phonology pathway played a greater role in the reading-aloud task. These simulation results align with findings from studies of English reading. While the models successfully captured a range of typical reading effects in Chinese reading-aloud tasks, the presence of radical consistency effects also depended on various instructional methods.

Keywords: computational modelling; reading instruction; individual differences; Chinese character reading; radical consistency

Introduction

Reading is a nontrivial skill to be acquired and serves as a tool in subsequent communication and knowledge acquisition. Therefore, identifying effective strategies for reading development and appropriate interventions is essential for optimizing reading performance. A triangle framework (Harm & Seidenberg, 2004), which posits that reading proficiency arose from the interplay of decoding and language comprehension skills, was introduced building on the Simple View of Reading (Gough & Tunmer, 1986). It conceptualizes reading as a dynamic interaction among orthography, semantics, and phonology, offering a foundation for modeling reading processes through connectionist approaches. Such an approach was used in precedent studies simulating reading acquisition and individual differences in English reading (Chang, 2023; Chang et al., 2024; Monaghan et al., 2017). Building upon these reading frameworks, the study extended research by applying modeling approaches to investigate the impact of reading instruction and individual differences in Chinese character reading.

Reading Instruction in Chinese

Research on Chinese word acquisition has identified the efficacy of multiple training and intervention methods (Ruan et al., 2024). Within the domain of word reading, fluency training encompasses methods such as accelerated reading, where words or sentences are presented incrementally at increasing speeds, and repeated reading, which involves rereading the same material. Accelerated reading has been shown to improve silent reading (Dai et al., 2016). The characteristics of the Chinese language, particularly the prevalence of homophones and homographs, underscore the importance of working memory for retaining and retrieving morphemes. Indeed, training in visuospatial and visual-verbal working memory has been found to enhance performance in visual rhyming and reading fluency tasks (Luo et al., 2013). Another approach is morphological training, which focuses on morpheme-based retrieval of word information, with studies reporting improvements in word reading (Wang & McBride, 2017; Wu et al., 2009).

In addition to these methods, phonological training aims to associate the pronunciation and the print of the word. This can be implemented with or without phonetic scripts such as Zhuyin and Pinyin. However, studies indicate that interventions relying on phonetic scripts improve only script-specific performance, without significant transfer to word reading (Chen et al., 2016; Wang & McBride, 2017). In contrast, direct orthography-to-phonology training without phonetic scripts has demonstrated broader intervention gains, including improvements in character reading and rapid naming (Wang, 2017).

This study focuses particularly on orthographic training, which emphasizes character structure, particularly the role and positioning of components. Radical awareness training, which focuses on the semantic and phonetic roles of radicals in phonetic-semantic compound characters, is a common approach. However, few studies have continued exploring the efficacy of this method (Hu, 2001, 2003).

Critically, approximately 80% of contemporary Chinese

In D. Barner, N.R. Bramley, A. Ruggeri and C.M. Walker (Eds.), *Proceedings of the 47th Annual Conference of the Cognitive Science Society*

characters are phonetic-semantic compounds, consisting of a phonetic radical and a semantic radical. A degree of systematicity exists between phonetic radicals and the pronunciations of the whole characters, and between semantic radicals and the meanings of whole characters, paralleling the mappings of orthography and phonology (OP) and orthography and semantics (OS) in English (Chang et al. 2016; Cheng and Chang, 2024). Given this systematicity, these radicals have been utilized to form the basis for various instructional methods.

For instance, the intensive learning of characters approach teaches groups of characters sharing the same phonetic or semantic radical, allowing students to acquire multiple characters efficiently in a short period (Lam, 2011). Alternatively, the general orthographic knowledge approach emphasizes understanding the information and combinability of radicals that can significantly facilitate literacy acquisition. (Chen, 1998; Chin & Sheu, 2000; Packard et al., 2006).

However, a key question arises: how should instruction balance exposure to phonetic and semantic radicals to optimize character literacy acquisition? The varied approaches to reading instruction in different regions highlight the complexity of this question. In regions such as Hong Kong and Macau, students learn to read through in a whole-word manner, as neither Zhuyin nor Pinyin is employed (McBride et al., 2018). By contrast, in Taiwan, instructional approaches vary significantly (Chen & Hsuan, 2022; Wang, 2012), with no government-standardized methods.

Individual Differences

Several factors have been shown to affect individual reading behaviors, including oral language skills (Chang, 2023; Siegelman et al., 2020), reading capacity (Dilkina et al., 2008; Plaut, 2005), reading experience (Andrews, 2015; Yap et al., 2012), and reading instruction (Chang et al., 2024). Moreover, readers' sensitivity to the OP and OS regularities influences reading performance among individuals (Chang, 2023; Hoffman et al., 2015; Siegelman et al., 2020, 2022; Woollams et al., 2016). For example, Woollams et al. (2016) demonstrated that readers with high semantic reliance (SR) named more slowly than those with low SR. Similarly, children with high OP sensitivity had better reading performance in English as reported by Siegelman et al. (2020). These variations in OP and OS sensitivity are also reflected in the different intervention outcomes. Specifically, children with higher OP sensitivity had greater intervention gains under an OP-focused remedy (Siegelman et al., 2022). However, neither of these investigations has been conducted using Chinese words. Moreover, Yang et al. (2009) demonstrated that Chinese character orthography was likely more consistent with semantics than phonology, which showed drastic OP/OS regularity differences in English reading. We thus expect to see a similar pattern in our simulation.

In summary, to investigate the effectiveness of orthographic knowledge training in phonics-based versus meaning-based instruction, this study developed a series of computational modeling of Chinese character reading to investigate the impact of these reading strategies and their relationship to variations in individual reading behaviors. For comparison with the relevant studies in English (Chang, 2023; Chang et al., 2024; Kuo et al., 2023; Siegelman et al., 2020, 2022; Woollams et al., 2016), this study focused on reading-aloud tasks.

Method

Model Architecture

Following the triangle framework of English reading (Harm & Seidenberg, 2004), we developed a computational model of Chinese character reading using the optimized MikeNet simulator (Chang et al., 2024; Harm & Seidenberg, 2004; Kuo et al., 2023). As illustrated in Figure 1, the model comprised three key components: the vision (V), semantics (S), and phonology (P) layers. Critically, unlike Harm and Seidenberg's (2004) model, the process began with visual rather than orthographic (O) processing, allowing the model to learn the visual patterns of input characters naturally and emphasizing the combinability of two radicals. The V, S, and P layers contained 800, 600, and 105 neurons, respectively. A hidden layer of 364 neurons served as the O layer, connecting the V layer to the S and P layers through intermediate hidden layers. Specifically, the V layer was connected to the O layer through a hidden layer of 50 units, and then to both the P and S layers separately through hidden layers of 500 units each. Moreover, the P and S layers were mutually connected through two separate hidden layers of 1200 units each. To simulate the self-feedback mechanisms observed in neural processes, attraction layers of 50 neurons each were connected to both the S and P layers. Additionally, a context (C) layer of 134 neurons, connected to the S layers through a hidden layer of 120 neurons, provided contextual information to handle homophones. The sizes of hidden layers were all determined through pilot runs to ensure model trainability. The sizes of the V, S, P, and C layers were determined to accommodate their respective representations, as described in the following section.

Corpus and Representations

The training corpus was derived from a combined dataset of Chang, Welbourne, and Lee (2016) (3,621 characters) and the Academia Sinica Balanced Corpus (103,997 words, including single- and multi-character words) in traditional Chinese. The corpus was filtered to include only single-character phonetic-semantic compounds with their corresponding visual, semantic, and phonetic representations, resulting in 2,171 Chinese characters.

Vision Each character was presented in two adjacent 20-pixel by 20-pixel grids, with phonetic and semantic radicals occupying separate regions. For vision input, each character was converted into an 800-unit one-dimensional vector. This vector was generated by sequentially traversing the grid from the bottom-left corner to the top and then moving to the right.

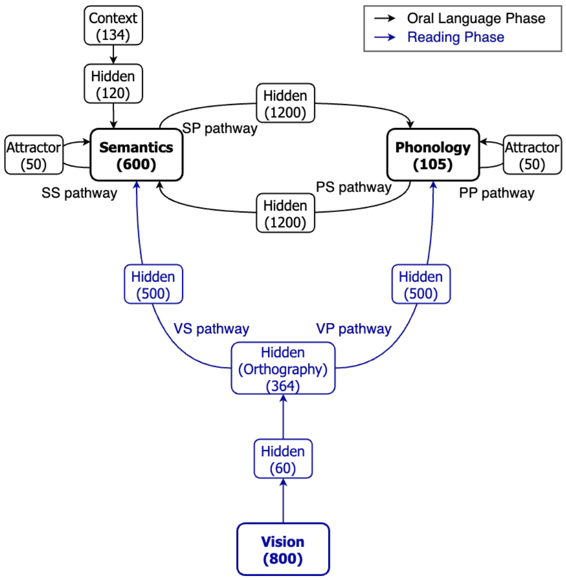

Figure 1: The architecture of the VSP model (vision, semantics, and phonology) in Chinese phonetic-semantic compound characters reading instruction

Each pixel value was binary, where a value of zero indicated an empty pixel.

Semantics The semantic features of each character were encoded as a 300-dimensional real-number vector, with values ranging from -1 to 1, generated using Word2Vec (Cheng & Chang, 2025). To binarize these vectors, negative values were appended to the end of the vector, creating a 600-dimensional vector. The non-zero values were coded as 1's in binarization. The resulting 600-dimensional binarized vector was then used as the semantic representation for each character.

Phonology The phonological representation of each character was based on a Romanized system previously used in Taiwan (Ministry of Education, Taiwan, 1986). The pronunciation of each character was decomposed into five phoneme attributes: initial consonant, medial, vowel, final consonant, and tone. Tone was encoded as a 5-dimensional binary vector (one dimension per tone). The other four attributes were each represented as 25-dimensional binary vectors encoding sound features (e.g., stop, voiced). These components together formed a 105-dimensional binary vector representing the phonological features of each character.

Context The context representation for each character was encoded as a 134-dimensional binary vector, randomly structured to enhance the model's ability to distinguish homophones by providing additional information. To be specific, the first 14 slots were one-hot encoded, each representing a homophone, while non-homophones were assigned vectors of zeros. The subsequent 120 slots were randomly activated with a 10% probability to increase representational distance between homophones (Rogers et al., 2004).

Training Procedure

The model was trained on 2,171 phonetic-semantic compound characters in a two-phase process: an oral language phase and a reading phase. The oral language training phase aimed to mimic children's oral language skills prior to learning to read. Critically, the reading training phase introduced three types of reading instruction: VP-focused, VS-focused, or evenly distributed VP-VS training schemes. In each trial, the model learned a character randomly selected based on its weighted frequency. A supervised learning approach was utilized, with weights updated via back-propagation through time (learning rate = 0.02). The sigmoid activation function and cross-entropy loss function were employed. Initially, 20 models were trained with different random seeds in the oral language phase. These models were then further trained in the reading phase under each of three instructional schemes (VP-focused, VS-focused, and even), resulting in 60 trained models (20 models $\times$ 3 schemes) for downstream evaluation.

Oral Language Phase The primary goal of the oral language phase was to train the models on speaking (SP pathway) and listening comprehension (PS pathway) tasks. During PS pathway training, the CS pathway (which provided contextual information to the semantic layer) was trained concurrently to provide content information required for disambiguating homophones. Self-feedback connections were also trained within the semantics (SS pathway) and phonology (PP pathway) layers. Stimuli were presented to the model for 12 timesteps during SP and PS trials, while for only one timestep during the SS and PP trials to encourage rapid attractor formation. The model was then asked to generate output from the six to the 12th timesteps. Each training iteration randomly selected one of the four pathways (PS, SP, SS, and PP), with probabilities of 40%, 40%, 10%, and 10%, respectively. The training of these pathways was interleaved. Two million iterations were conducted in this phase, with training stopped early when the model achieved over 90% accuracy on both the PS and SP tasks. Upon completing this phase, all weights, including those of the CS pathway, were frozen.

Reading Phase In the reading phase, models were divided into three groups, each receiving different reading instructions. Models were trained on reading comprehension (visual input to semantic output,V$\rightarrow$S) and reading aloud (visual input to phonological output, V$\rightarrow$P) tasks. Input-output pairs were provided for 12 timesteps per trial, with the model generating output between the 6th and the 12th timesteps. For VP-focused instruction, the training ratio of V$\rightarrow$S to V$\rightarrow$P was 1:3. For VS-focused instruction, the ratio of V$\rightarrow$S to V$\rightarrow$P was 3:1. For even instruction, the ratio of V$\rightarrow$S to V$\rightarrow$P was 1:1. Contextual information was provided during training. All weights, excluding those frozen weights from the oral language phase, were updated freely during training. The reading phase finished after one million iterations.

Testing Procedure

Correctness and Error Score After a forward pass for each input pattern, the model generated a pattern of real numbers at the output layer. The sum of squared errors (SSE) was calculated as the squared Euclidean distance between the model's output and the ground truth at both the phonological and semantic layers. For semantic accuracy, an output pattern at the semantics layer was classified as correct if it had the smallest Euclidean distance to the corresponding ground truth among all output-semantics pairs. For phonological accuracy, the output pattern at the phonological layer was converted into a five-slot phonology representation. The output was deemed correct if all five slots matched the ground truth.

Division of Labor and Semantic Reliance Following previous simulation work (Chang, 2023; Chang et al., 2024), semantic reliance in the model was measured using the division of labor (DOL) technique to assess individual differences. Specifically, for the reading-aloud task, the model underwent two separate inferences: one with the VP pathway lesioned and the other with the VSP pathway lesioned. Phonological SSE from the lesioned VP pathway reflected the importance of the VP pathway, while phonological SSE from the lesioned VSP pathway indicated the importance of the VSP pathway. Each pathway's DOL was determined by normalizing these values. We computed the SR scores for the models trained under three training schemes (VP-focused, VS-focused, and even). The relationships between the SR scores and reading instruction were then investigated.

Linear Mixed-effects Model Analysis

In behavioral studies, several psycholinguistic variables are shown to be important for explaining reaction times (RTs) in reading-aloud tasks (Chang, Hsu, et al., 2016; Cheng & Chang, 2025; Lee et al., 2005; Liu et al., 2007). To investigate whether the model could reproduce typical reading effects, a linear mixed-effects model (LMM) analysis was conducted. The psycholinguistic variables included as fixed factors were character frequency (CF), number of strokes (NS), phonetic combinability (PC), semantic combinability (SC), phonetic radical consistency (PRC), and semantic radical consistency (SRC). Phonological SSE was used as a proxy for behavioral RTs as the dependent variable. CF represented the occurrence rate of each character. NS was the total stroke count. PC represented the extent to which the phonetic radical could combine with other radicals to form existing characters, and SC represented the same for the semantic radical. PRC represented the degree to which the phonetic radical shared phonological information with the pronunciation of the whole character. All these variables were taken from Chang, Hsu, et al. (2016). SRC, taken from Cheng and Chang (2025), represented the degree to which the semantic radical contributed semantic information to the meaning of the whole character. To investigate the unique effect of SR, another LMM model was conducted, including all the aforementioned variables plus SR as an additional variable. To further explore the nature of the SR effect, we also investigated the interactions between SR and all the other variables. For data preprocessing, outliers exceeding three standard deviations from the mean of phonological SSE were excluded from the analysis.

Results

Accuracy At the end of the oral language phase, models achieved an accuracy of 97.87% in the speaking task (SP) and 91.07% in the listening comprehension task (PS). For the reading comprehension task (VS), the models achieved accuracies of 99.98%, 99.58%, and 99.57% under VP-focused, VS-focused, and even training schemes. For the reading-aloud task (VP), the models achieved 99.98%, 99.99%, and 99.98% accuracy under VP-focused, VS-focused, and even training schemes.

Relationships Between Reading Instruction and SR

The semantic reliance (SR) values across the three instructional schemes ranged from 0.028 to 0.163 ($M = 0.074$, $SD = 0.033$) for the reading-aloud task. Specifically, the mean SR was as follows: $M = 0.047$, $SD = 0.013$ under VP-focused instruction, $M = 0.108$, $SD = 0.028$ under VS-focused instruction, and $M = 0.067$, $SD = 0.020$ under even training scheme. To examine the relationship between reading instruction and SR, an ANOVA was conducted using the training scheme as the predictor for SR. The analysis revealed a significant effect, with $R^2 = 60.89\%$ (adjusted $R^2 = 59.51\%$), $p < .001$. Pairwise comparisons indicated significant differences in SR among the three instruction schemes: $t = 9.240$, $p < .001$ for VP v.s. VS; $t = 6.205$, $p < .001$ for VS v.s. even; $t = 3.035$, $p < .01$ for VP v.s. even.

Typical Reading Effects and SR Effects

The Reading Effects After filtering out 7.23% of data points due to outliers or incorrect responses, 120,496 data points remained for analysis. Because of positive skewness, Yeo-Johnson transformations were applied to CF, PC, SRC, and SSE. All factors were scaled. To begin with, a baseline LMM was employed to predict phonological SSE produced by all the models across three instructional schemes. Phonological SSE was used to simulate response times (RTs) in behavioral reading-aloud tasks (Chang, 2023; Monaghan et al., 2017). Model ID and character ID were included as random effects, and CF, NS, PC, SC, PRC, and SRC were included as fixed effects. As shown in Table 1, the LMM analysis revealed that low phonological SSE was associated with high CF, high SRC, and low NS. The PC, SC, and PRC effects were not significant. These results were broadly consistent with findings from the behavioral study in (Chang, Hsu, et al., 2016; Cheng & Chang, 2025) except the PRC effect.

The SR Effect We further investigated the unique effect of SR. Adding SR as a fixed-effect factor to the baseline LMM model significantly improved the model fit, $\chi^2(1) = 21.627, p < .001$. This full model indicated that higher SR was associated with higher phonological SSEs, consistent with behavioral studies in English (Siegelman et al., 2020; Woollams et al., 2016).

Table 1: LMM model fitted to phonological SSE

	β	t	95% Confidence Interval
CF	-0.23	-25.86	(-0.25, -0.21)
NS	0.05	5.92	(0.04, 0.07)
PC	0.00	0.01	(-0.02, 0.02)
SC	0.01	0.71	(-0.01, 0.02)
PRC	0.01	1.04	(-0.01, 0.04)
SRC	-0.03	-2.89	(-0.04, -0.01)
SR	0.10	5.02	(0.06, 0.14)

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

Interactions between SR and psycholinguistic variables The potential effects of interactions between SR and all the other psycholinguistic variables were explored. Among the six interaction terms tested, adding the interaction with SR resulted in significant improvement in model fit to different degrees. Adding SR × SRC to the full model resulted in a significant improvement, $\chi^2(1) = 15.76, p < .001$. Significant improvement was also observed for the interactions of SR with NS, $\chi^2(1) = 9.99, p < .01$; with CF, $\chi^2(1) = 6.31, p < .05$; with PRC $\chi^2(1) = 5.75, p < .05$; with PC, $\chi^2(1) = 19.686, p < .001$; and with SC, $\chi^2(1) = 13.347, p < .001$. Figure 2 demonstrates the interaction between SR and SRC, illustrating how semantic radical information interacts with SR.

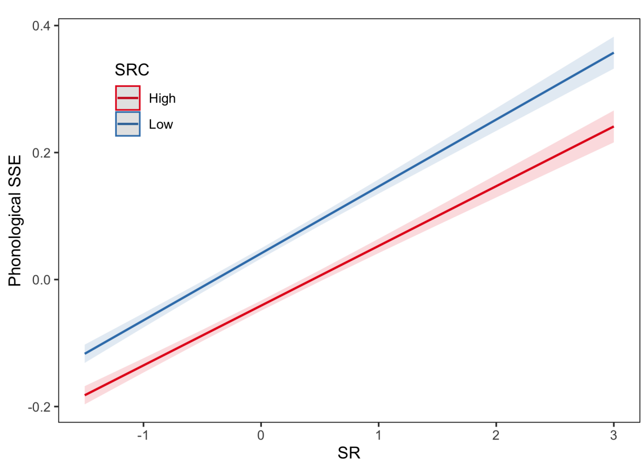

Figure 2: The interaction between SR and SRC (High: Above the mean of SRC; Low: Below the mean of SRC)

Analysis by Instruction Groups Lastly, our LMM results demonstrated reading effects consistent with previous behavioral findings (e.g., Cheng et al. 2025), except for the PRC effects. To further investigate this discrepancy, we conducted separate LMM analyses for the three instruction schemes: VP-focused, VS-focused, and even training. As before, all the psycholinguistic variables from the baseline model were included to predict phonological SSE. Due to space limitations, Table 2 only presents the PRC and SRC effects from the LMM analyses; the key patterns of other effects remained consistent. In the VP-focused analysis, the PRC effect was significant, with higher PRC scores correlating with smaller SSEs. However, the SRC effect was not significant in this analysis. Conversely, the event training analysis revealed a non-significant PRC effect but a significant SRC effect. Interestingly, the VS-focused analysis showed significant PRC and SRC effects, although the direction of the PRC effect contrasted with typical behavioral findings.

Table 2: LMM models fitted to phonological SSE by three instruction groups (only showing PRC and SRC)

	VP		Even		VS	
	β	p	β	p	β	p
PRC	-0.03	$< .01$	0.01	0.27	0.05	$< .001$
SRC	-0.01	0.20	-0.02	$< .05$	-0.04	$< .001$

Discussion

Most studies on Chinese character acquisition have focused on general orthographic knowledge rather than instructional implications of phonetic-semantic compound characters (Lam, 2011; Packard et al., 2006). Using computational modeling, this study investigated the impact of phonetic or semantic radical exposure on variations in individual reading behaviors. The models were trained under three instructional schemes - VP-focused, VS-focused, and even, marking the first application of computational modeling of this kind to Chinese character acquisition.

Our simulation results demonstrated that the degree of reliance on the semantic pathway in the model under different instructional methods differed significantly. Specifically, the model under VS-focused instruction had a higher SR compared to the model under even or VP-focused schemes. This result suggests that variations in individual differences in terms of SR can be directly linked to reading instruction. Moreover, although the Chinese written system is logographic, the DOL analysis revealed that reading aloud in the model relies more on the phonological pathway (i.e., all SRs smaller than 0.5) regardless of the type of reading instruction, differing only in the degree. These results are consistent with previous simulation work in English reading (Chang et al., 2020, 2024; Kuo et al., 2023), suggesting that VP mapping is also critical for reading Chinese characters aloud.

Regarding psycholinguistic effects, the simulation results showed that the model accounted for several key reading effects observed in the reading literature (Chang, Hsu, et al., 2016; Cheng & Chang, 2025; Liu et al., 2007), including CF, NS, PC, and SRC. Additionally, the SR scores derived from the models trained with different instructional methods contributed uniquely to explaining the models' phonological SSEs. Higher SR scores were associated with higher SSEs, indicating that the models named characters more slowly. The result aligns well with both behavioral (Siegelman et al., 2020; Woollams et al., 2016) and computational (Chang, 2023; Chang et al., 2024) investigations of individual differences in English reading.

One intriguing exception observed in the LMM results is the null effect of PRC. Further analysis, breaking down the models into three instructional groups, revealed that the PRC effect emerged only in models under phonetic-focused training, while its SRC effect was not observed. By contrast, the PRC effect was absent in models under even training and exhibited an opposite direction in models under semantic-focused training, while the SRC effect was present. The results suggest that the presence and correctness of the PRC and SRC effects may depend on the proportions of phonetic and semantic radical exposure during literacy development. Because the majority of studies in Chinese reading (Chang, Hsu, et al., 2016; Cheng & Chang, 2025; Lee et al., 2005; Liu et al., 2007) have demonstrated the PRC effect, this suggests that exhaustive training emphasizing print-to-sound mappings, or pronunciation, is necessary for the PRC effect to manifest in simulations. This interpretation aligns with educational practices in Taiwan, where children begin learning Zhuyin as early as kindergarten. Even after transitioning to character literacy training, Zhuyin remains concurrently provided until the fourth grade, enhancing phonological awareness despite being a visual representation of pronunciation (Ho, 2010). Similar benefits are observed with Pinyin in China (Wang et al., 2014). In Hong Kong, where neither Zhuyin nor Pinyin is used, children start learning to read as early as age three through look-and-say (Li & Rao, 2000). Future simulation studies can be developed to incorporate Zhuyin/Pinyin learning at the early stage of training to investigate its influence on subsequent reading behaviors (Chen et al., 2016; Wang, 2017; Wang & McBride, 2017).

In summary, this study represents the first application of computational modeling to Chinese character acquisition, with results corroborated by findings from multiple studies. Specifically, the simulations investigated the comparative effectiveness of orthographic knowledge training within phonics-based versus meaning-based instruction, and linked this with variations in individual reliance on alternative reading pathways when reading Chinese characters.

Acknowledgements

This research was supported by grants from the National Science and Technology Council (NSTC 113-2410-H-006-118 to YNC).

References

Andrews, S. (2015). Individual differences among skilled readers: The role of lexical quality. *The Oxford handbook of reading*, 129–148.

Baayen, R. H. (2008). *Analyzing linguistic data: A practical introduction to statistics using r*. Cambridge university press.

Chang, Y.-N. (2023). The influence of oral vocabulary knowledge on individual differences in a computational model of reading. *Scientific reports*, *13*(1), 1680.

Chang, Y.-N., Chang, T.-J., Lin, W.-F., Kuo, C.-E., Shi, Y.-T., & Lee, H.-W. (2024). Modelling individual differences in reading using an optimised mikenet simulator: The impact of reading instruction. *Frontiers in Human Neuroscience*, *18*, 1356483.

Chang, Y.-N., Hsu, C.-H., Tsai, J.-L., Chen, C.-L., & Lee, C.-Y. (2016). A psycholinguistic database for traditional chinese character naming. *Behavior Research Methods*, *48*, 112–122.

Chang, Y.-N., Taylor, J., Rastle, K., & Monaghan, P. (2020). The relationships between oral language and reading instruction: Evidence from a computational model of reading. *Cognitive Psychology*, *123*, 101336. https://doi.org/https://doi.org/10.1016/j.cogpsych.2020.101336

Chang, Y.-N., Welbourne, S., & Lee, C.-Y. (2016). Exploring orthographic neighborhood size effects in a computational model of chinese character naming. *Cognitive psychology*, *91*, 1–23.

Chen, H.-F. (1998). *The study of instruction of general orthographic knowledge of chinese characters on elementary students with word-recognition difficulties* [Master's Thesis]. National Taiwan Normal University [National Digital Library of Thesis and Dissertations in Taiwan]. https://hdl.handle.net/11296/76ebxt

Chen, S.-L., & Hsuan, C.-H. (2022). *Effective learning support teaching with every student* (2nd ed.). Psychological Publishing Co., Ltd.

Chen, S.-L., Tzeng, S.-J., Chu, S.-Y., & Chen, H.-Y. (2016). The impacts of remedial interventions on learning chinese for low-achieving first graders. *The Asia-Pacific Education Researcher*, *25*, 45–55.

Cheng, C.-F., & Chang, Y.-N. (2025). Investigating the effects of semantic radical consistency in chinese character naming with a corpus-based measure. *Journal of Experimental Psychology: Learning, Memory, and Cognition*. https://doi.org/10.1037/xlm0001425

Chin, L.-H., & Sheu, J.-J. (2000). A study of the effects of teaching phonetic-radical characters on second-grade normal students and students with learning disabilities. *Bulletin of special education*.

Dai, L., Zhang, C., & Liu, X. (2016). A special chinese reading acceleration training paradigm: To enhance the reading fluency and comprehension of chinese children with reading disabilities. *Frontiers in psychology*, *7*, 1937.

Dilkina, K., McClelland, J. L., & Plaut, D. C. (2008). A single-system account of semantic and lexical deficits in five semantic dementia patients. *Cognitive Neuropsychology*, *25*(2), 136–164.

Gough, P. B., & Tunmer, W. E. (1986). Decoding, reading, and reading disability. *Remedial and special education*, *7*(1), 6–10.

Harm, M. W., & Seidenberg, M. S. (2004). Computing the meanings of words in reading: Cooperative division of labor between visual and phonological processes. *Psychological review*, *111*(3), 662.

Ho, C. S.-H. (2010). Understanding reading disability in the chinese language: From basic research to intervention. *The Oxford handbook of Chinese psychology*, 109–121.

Hoffman, P., Lambon Ralph, M. A., & Woollams, A. M. (2015). Triangulation of the neurocomputational architecture underpinning reading aloud. *Proceedings of the National Academy of Sciences*, *112*(28), E3719–E3728.

Hu, Y.-C. (2001). A comparative study of the effectiveness of different instructional strategies of chinese characters on third-grade elementary students with reading disabilities. *Journal of Pingtung University of Education*, *14*.

Hu, Y.-C. (2003). The related variables in chiense characters learning and the effectiveness of different instructional strategies of chinese characters on fourth-grade elementary students with reading difficult. *Journal of Pingtung University of Education*, *19*.

Kuo, C.-E., Shi, Y.-T., Lin, W.-F., & Chang, Y.-N. (2023). Exploring the relationships between reading instruction and individual differences in a computational model of reading. *Proceedings of the Annual Meeting of the Cognitive Science Society*, *45*.

Lam, H. C. (2011). A critical analysis of the various ways of teaching chinese characters. *Electronic Journal of Foreign Language Teaching*, *8*(1).

Lee, C.-Y., Tsai, J.-L., Su, E. C.-I., Tzeng, O. J., Hung, D. L., et al. (2005). Consistency, regularity, and frequency effects in naming chinese characters. *LANGUAGE AND LINGUISTICS-TAIPEI*, *6*(1), 75.

Li, H., & Rao, N. (2000). Parental influences on chinese literacy development: A comparison of preschoolers in beijing, hong kong, and singapore. *International Journal of Behavioral Development*, *24*(1), 82–90.

Liu, Y., Shu, H., & Li, P. (2007). Word naming and psycholinguistic norms: Chinese. *Behavior research methods*, *39*(2), 192–198.

Luo, Y., Wang, J., Wu, H., Zhu, D., & Zhang, Y. (2013). Working-memory training improves developmental dyslexia in chinese children. *Neural regeneration research*, *8*(5), 452–460.

McBride, C., Wang, Y., & Cheang, L. M.-L. (2018). Dyslexia in chinese. *Current Developmental Disorders Reports*, *5*, 217–225.

Ministry of Education, Taiwan. (1986). *Mandarin phonetic symbols ii*. Ministry of Education.

Monaghan, P., Chang, Y.-N., Welbourne, S., & Brysbaert, M. (2017). Exploring the relations between word frequency, language exposure, and bilingualism in a computational model of reading. *Journal of Memory and Language*, *93*, 1–21.

Packard, J. L., Chen, X., Li, W., Wu, X., Gaffney, J. S., Li, H., & Anderson, R. C. (2006). Explicit instruction in orthographic structure and word morphology helps chinese children learn to write characters. *Reading and Writing*, *19*, 457–487.

Plaut, D. C. (2005). Connectionist approaches to reading. *The science of reading: A handbook*, 24–38.

Rogers, T. T., Lambon Ralph, M. A., Garrard, P., Bozeat, S., McClelland, J. L., Hodges, J. R., & Patterson, K. (2004). Structure and deterioration of semantic memory: A neuropsychological and computational investigation. *Psychological review*, *111*(1), 205.

Ruan, Y., Maurer, U., & McBride, C. (2024). Effectiveness of reading interventions on literacy skills for chinese children with and without dyslexia: A meta-analysis of randomized controlled trials. *Educational Psychology Review*, *36*(3), 80.

Siegelman, N., Rueckl, J. G., Steacy, L. M., Frost, S. J., van den Bunt, M., Zevin, J. D., Seidenberg, M. S., Pugh, K. R., Compton, D. L., & Morris, R. D. (2020). Individual differences in learning the regularities between orthography, phonology and semantics predict early reading skills. *Journal of memory and language*, *114*, 104145.

Siegelman, N., Rueckl, J. G., van den Bunt, M., Frijters, J. C., Zevin, J. D., Lovett, M. W., Seidenberg, M. S., Pugh, K. R., & Morris, R. D. (2022). How you read affects what you gain: Individual differences in the functional organization of the reading system predict intervention gains in children with reading disabilities. *Journal of educational psychology*, *114*(4), 855.

Wang, C.-C. (2012). Review of literature on character and vocabulary instruction studies in taiwan. *Bulletin of Educational Psychology*, *44*(2), 253–272.

Wang, L.-C. (2017). Effects of phonological training on the reading and reading-related abilities of hong kong children with dyslexia. *Frontiers in psychology*, *8*, 1904.

Wang, Y., Lam, S. S. Y., Mo, J., & McBride-Chang, C. (2014). Pinyin knowledge as a potentially important marker of early literacy. *Understanding developmental disorders of auditory processing, language and literacy across languages: International perspectives. IAP*, 189–206.

Wang, Y., & McBride, C. (2017). Beyond copying: A comparison of multi-component interventions on chinese early literacy skills. *International Journal of Behavioral Development*, *41*(3), 380–389.

Woollams, A. M., Lambon Ralph, M. A., Madrid, G., & Patterson, K. E. (2016). Do you read how i read? systemic individual differences in semantic reliance amongst normal readers. *Frontiers in psychology*, *7*, 1757.

Wu, X., Anderson, R. C., Li, W., Wu, X., Li, H., Zhang, J., Zheng, Q., Zhu, J., Shu, H., Jiang, W., et al. (2009). Morphological awareness and chinese children's literacy development: An intervention study. *Scientific Studies of Reading*, *13*(1), 26–52.

Yang, J., McCandliss, B. D., Shu, H., & Zevin, J. D. (2009). Simulating language-specific and language-general effects in a statistical learning model of chinese reading. *Journal of Memory and Language*, *61*(2), 238–257.

Yap, M. J., Balota, D. A., Sibley, D. E., & Ratcliff, R. (2012). Individual differences in visual word recognition: Insights from the english lexicon project. *Journal of Experimental Psychology: Human Perception and Performance*, *38*(1), 53.