Examining the Effects of Children's Word Specific Phonological Awareness on Word Reading Accuracy Within a Lexical Quality Theoretical Framework

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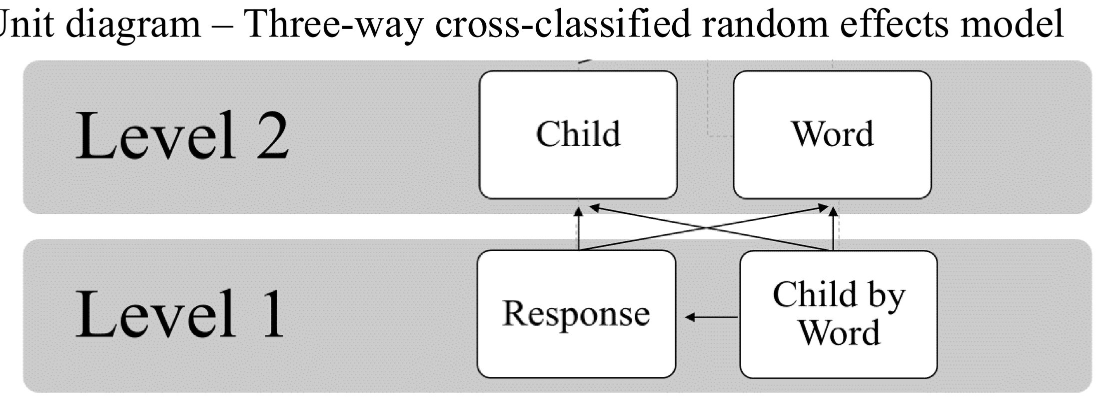
INTRODUCTION

The purpose of this study was to clarify the relationship between word reading accuracy and the quality of children's phonological representations utilizing Rasch-based Explanatory Item Response Models. These models are in line with theories and models of word learning that are item-based. That is, learning depends on the unique interaction between the skills a child brings to the task and the item/word characteristics. This results in continued changes to a child's word specific lexical representations (McClelland & Rumelhart, 1986; Nation & Castles, 2017; Rumelhart & Norman, 1978; Seidenberg & McClelland, 1989; Perfetti, 1991).

While previous work exploring child and word effect on children's word recognition abilities have incorporated an extensive set of child-level and word-level predictors of word reading and pseudoword decoding accuracy (e.g., Gilbert et al., 2011; Goodwin et al., 2014; Kearns et al., 2016; Steacy et al., 2022), to date there have been no investigations of phonological awareness at the child, word, and child-by-word level when predicting word reading accuracy. This study explored the simultaneous contribution of child-level, word-level, and child-by-word level predictors of word reading accuracy. Figure 1 depicts the cross-classified structure of the data.

Figure 1.
Unit diagram – Three-way cross-classified random effects model



RESEARCH QUESTIONS & MODELS

Q1. Does child-by-word phonological awareness (PAST PA) predict the probability of a child reading a given word accurately when controlling for child-by-word grapheme phoneme correspondence knowledge (GPCK) and familiarity (Fam)?
Model 1 Covariates. Level 1 (child-by-word): PAST PA, GPCK, Fam

Q2. After controlling for the effect of all other general child level predictors, how does a child's general phonological awareness affect the probability of correct word reading?
Model 2 Covariates. Level 1 (child-by-word): PAST PA, GPCK, Fam; Level 2 (child): Vocabulary (Voc), Matrix Reasoning (MatR), Rapid Letter Naming (RLN), Pseudoword Decoding Efficiency (PDE), Phonological Awareness Elision (PA)

Q3. Are there important word predictors (e.g., frequency, concreteness, number of phonemes [NPhon], spelling-to-pronunciation transparency rating [SPTR] and phonological Levenshtein Distance [PLD]) related to word reading accuracy?
Main Effects Model Covariates. Level 1 (child-by-word): PAST PA, GPCK, Fam; Level 2 (child): Voc, MatR, RLN, PDE, PA; Level 2 (word): Nphon, PLD, Frequency, Concreteness, SPTR

Q4. Is there an interaction between child decoding skill (PDE) and word transparency (SPTR)?
Interaction Model Covariates. Level 1 (child-by-word): PAST PA, GPCK, Fam; Level 1 (interaction) PDE*SPTR; Level 2 (child): Voc, MatR, RLN, PDE, PA; Level 2 (word): Nphon, PLD, Frequency, Concreteness, SPTR

METHOD

This study employed a short-term cross-sectional approach in children whose word reading was representative of a continuum of abilities.

Sample: A total of 82 second grade students attending one of seven classrooms across two Title-1 schools in North Florida participated in the study. Two students were excluded from analyses due to obtaining a standard score ≤ 70 on the 2-subtest WASI-2. The final sample of consisted of 80 students (mean age = 8.21 years, 48.8% female, 70% White, 17.5% Hispanic, 7.5% African American). According to teacher report, 60 (75%) had no disability classification, 14 (17.5%) had IEPs, 9 (11.3%) were retained 1-year, and 5 (6.2%) spoke English as a second language.

General Procedures:
- Children were assessed individually across two days, controlling for order effects of tasks using the same target words.
- Sessions were audio recorded for students with parental permission.
- Double scoring of student files was completed and disagreements addressed with a third scorer (46 out of 82 files double scored to date)
- REDCap was utilized for data entry (data will be double entered after double scoring).

Analyses: A logistic cross-classified random-effects model was utilized to estimate the probability of an individual correctly reading a specific word on the PAST. The lme4 package in the R system for statistical computing was be used to perform analyses (Bates et al., 2015).

PRELIMINARY RESULTS

Means, standard deviations and correlations for word-level predictors are presented in Table1, and those for raw scores of all child and child-by-word level predictors are presented in Table 2. Results for models 1 and 2 are presented in Table 3. Results for the Main Effects Model and Interaction Model are presented in Table 4.

Q1. At the child-by-word level, neither a child's word specific phonological awareness, GPCK, nor familiarity were significant predictors of word reading accuracy.
Q2. At the child-level, PDE and Voc were significant predictors of word reading accuracy.
Q3. At the word-level, SPTR, Frequency, Nphon, were significant predictors of a word being accurately read by an average child in our study.
- The predicted probability of an average child reading an average word in our study was 0.96
- Children with stronger definitional vocabulary and pseudoword decoding skills had a higher probability of correctly reading and average word in our study.
- Shorter, more frequently occurring and transparent words had a higher probability of being read accurately.

Q4. After controlling for the effects of child-by-word, child, and word-level predictors, the interaction of PDE and SPTR was not significant (z = 0.531, p = .596).

Table 1. Means, standard deviations, and correlations for word-level predictors

Variable	M	SD	1	2	3	4
Frequency	9.86	2.13				
PLD	1.61	0.78	-0.37**			
Nphon	4.15	1.63	-0.35*	0.90**		
Concreteness	3.69	1.03	-0.54**	0.09	0.07	
SPTR	2.26	2.60	-0.31*	0.07	0.07	-0.16

*M & SD represent mean and standard deviation, respectively. *p<.05 **p<.01*

Table 2. Means, standard deviations, and correlations for child and child-by-word level predictors

Variable	M	SD	1	2	3	4	5	6	7	8
PDE	22.07	9.83								
Voc	21.15	4.95	0.48**							
MatR	12.4	4.05	-0.01	0.24*						
PA	22.07	6.20	0.58**	0.46**	0.33**					
RLN	23.11	6.41	-0.38**	-0.29**	0.14	-0.28*				
PAST PA	40.10	8.47	0.58**	0.47**	0.26*	0.71**	-0.29**			
Fam	46.90	4.22	-0.20	0.14	-0.02	0.00	-0.13	0.03		
GPCK	40.35	4.76	0.55**	0.45**	0.24*	0.50**	-0.21	0.63**	0.05	
Word Read	44.70	9.29	0.66**	0.40**	-0.5	0.49**	-0.27*	0.65**	-0.08	0.63**

M & SD represent mean and standard deviation, respectively. *p<.05 **p<.01

Table 3. Results from the models addressing research questions 1 and 2, controlling for PDE

	Model 1			Model 2		
Parameter	logit	z-value	p-value	logit	z-value	p-value
Intercept	2.956	7.461	<0.001***	3.074	8.621	<0.001***
Child-by-Word Predictors						
PAST PA	0.133	0.895	0.371	0.089	0.568	0.558
GPCK	0.094	0.641	0.521	0.063	0.418	0.676
Fam	0.234	1.171	0.241	0.215	1.051	0.294
Child Level Predictors						
Vocabulary				0.085	2.163	0.031*
Matrix Reasoning				-0.054	-1.223	0.221
RLN				0.042	1.531	0.126
PA (elision)				0.058	1.664	0.096
PDE				0.146	6.428	<0.001***
Random Effects	Variance	% Var. Explained		Variance	% Var. Explained	
Person	4.142	3.58%		1.230	71.37%	
Word	1.805	5.15%		1.794	5.73%	

Table 4. Results from the unconditional model, main effects model, and interaction model controlling for PDE

	Unconditional Model			Main Effects Model			Interaction Model		
Parameter	logit	z-value	p-value	logit	z-value	p-value	logit	z-value	p-value
Intercept	3.342	10.44	<0.001***	3.063	9.330	<0.001***	3.057	9.246	<0.001***
Child-by-Word Predictors									
PAST PA				0.127	0.841	0.400	0.128	0.844	0.399
GPCK				0.030	0.203	0.839	0.029	0.199	0.842
Fam				0.214	1.053	0.292	0.214	1.052	0.293
Child Level Predictors									
Vocabulary				0.085	2.174	0.030*	0.085	2.174	0.030*
Matrix Reasoning				-0.054	-1.224	0.221	-0.054	-1.225	0.220
RLN				0.043	1.549	0.121	0.043	1.548	0.122
PA (elision)				0.057	1.653	0.098	0.057	1.653	0.098
PDE				0.147	6.446	<0.001***	0.146	6.278	<0.001***
Word Level Predictors									
Nphon				-0.465	-2.271	0.023*	-0.465	-2.271	0.023*
PLD				0.542	1.291	0.197	0.541	1.880	0.198
Frequency				0.213	2.450	0.014*	0.213	2.450	0.014*
Concreteness				0.237	1.419	0.156	0.238	1.421	0.155
SPTR				-1.122	-3.023	0.002**	-1.030	-2.750	0.006**
Interactions									
PDE x SPTR							0.003	0.129	0.897
Random Effects		Variance		Variance	% Var. Explained		Variance	% Var. Explained	
Person		4.296		1.228	71.42%		1.229	71.39%	
Word		1.903		0.828	56.51%		0.828	56.51%	

CONCLUSIONS

At the child-by-word level, results of this study suggest that the students in our sample had sufficiently redundant orthographic – O, phonological – P, and semantic – S, representations of the words in our study such that these words were already a part of each child's functional (if not autonomous) lexicon (Perfetti, 1991, 1992). Furthermore, the predicted probability of an average child reading an average word in this study was 0.96. As proposed by the Lexical Quality Hypothesis (Perfetti & Hart, 2002), this redundancy can facilitate word recognition in the absence of complete and precise word knowledge (Adlof et al., 2016). For the children and words in this study, the lack of significant child-by-word effects in our models may be representative of the important role precision and redundancy played in their word reading accuracy and the potential consequences of lexical quality (Perfetti, 2007).

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