Abstract Title Page

Title: A Multi-State Study Investigating the Generalizability of a Schema-Based Instructional Approach to Proportional Problem Solving

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Abstract Body

(Limit =1000 words, Current = 1052)

Background:

Ratio and proportional relationships, along with the interrelated topics of fractions, decimals, and percent provide a critical foundation for algebra (National Mathematics Advisory Panel, 2008). Solving even simple proportion problems is challenging for many children and adolescents (Adjiage & Pluvinage, 2007; Fujimura, 2001; Lamon, 2007; Lobato, Ellis, Charles, & Zbiek, 2010; Miyakawa & Winslow, 2009; Weinberg, 2002). A small number of studies have examined the efficacy of schema-based instruction (SBI), a multicomponent approach to teaching proportional problem solving. The studies of SBI, with roots in schema theory of cognitive psychology and cognitive models of mathematical problem solving, have provided evidence of its promise in improving student learning (Jitendra et al., 2009; Jitendra et al., 2015; Jitendra, Harwell, Karl, Simonson, & Slater, 2017; Jitendra, Harwell, Im, Karl, & Slater, 2017; Jitendra, Star, Rodriguez, Lindell, & Someki, 2011; Jitendra, Star, Dupuis, & Rodriguez, 2013). However all of these studies relied on data from the Upper Midwest of the U.S, and what is needed is evidence that the efficacy of SBI generalizes to a range of students and teachers located throughout the country. The ability to identify the populations of classrooms, teachers and students for which SBI can be used effectively will indicate the extent of the utility of implementing the SBI approach to proportional problem solving. The uniformity of three SBI studies by Jitendra et al. (2015, 2017a, 2017b) provides a unique opportunity to pool their data using Integrated Data Analysis (Curran & Hussong, 2009) to increase sample heterogeneity, resolve mixed findings from individual studies and mitigate the need for new studies, and better understand the classroom and student characteristics for which SBI is more or less effective.

Focus of Study:

Previously, SBI studies have focused on the impacts of SBI in proportional problem solving in focused geographic areas. The breadth of classrooms, teachers, and students for which SBI can be used effectively (replicate) will strengthen its utility. This speaks to generalizability, which can potentially be enhanced by pooling data from the individual SBI studies and performing essentially the same analyses appearing in the individual studies; findings based on the pooled data provide an empirical adjudication of results from individual studies and thus enhance generalizability.

We pooled data from the three SBI studies by Jitendra et al. (2015, 2017a, 2017b) and asked a single research question: Is SBI effective in improving students' proportional problem solving at posttest and nine to 11 weeks later at delayed posttest (PPS), and in improving general problem solving (GMADE posttest) and, if so, is it equally effective for classroom/teacher and student characteristics such as teacher gender, percentage of students receiving special education services in a classroom, years of teaching experience, and student race and gender across three U.S. states?

Setting and Population:

Students from seventh-grade classrooms in three U.S. states and their teachers participated in the study. The pooled dataset based on the studies of Jitendra et al. (2015, 2017a, 2017b) produced 3,714 students clustered within 154 classrooms. Because of missing student data 3,243 students appeared in most analyses. Table 1 summarizes the demographic variables for students and teachers in the pooled study.

Intervention:

A detailed description of SBI can be found in Jitendra et al. (2015).

Research Design and Data Collection:

All three studies employed a prospective randomized cluster (classroom/teacher) design in which classrooms were randomly assigned to a treatment (SBI) or control condition. Students in the control condition were taught the topics of ratio, proportion, and percent using their district-adopted textbooks in approximately the same 6-week time period as the treatment condition.

The three SBI studies by Jitendra et al. used the same two assessments. The first assessed students' proportional problem solving (PPS) on three different occasions (pre, post, and delayed posttest given nine to 11 weeks after the intervention). The PPS was constructed to include 22 multiple-choice questions and four short-response items using released items from NAEP and TIMSS. This assessment has been validated and used in prior studies (e.g. Jitendra et al., 2015). The second assessed students' general mathematics problem solving using scores on the Process and Application subtest of the Group Mathematics Assessment and Diagnostic Evaluation (GMADE, Pearson Education, 2004). We also collected data via videotaped lessons on the proportion problem solving instruction in the treatment (two observations per teacher) and control classes (one observation per teacher) to address the extent to which the SBI treatment was implemented with fidelity as well as to evaluate program differentiation and determine whether control teachers spontaneously provided instruction that was similar to the key elements of SBI.

Data Analysis and Results:

We used two-level (students nested within classrooms) hierarchical linear models fitted to each of the outcome variables (i.e., PPS posttest, PPS delayed posttest, GMADE posttest) to provide an assessment of the effect of the SBI treatment. The results (see Tables 2, 3, and 4) indicated statistically significant differences favoring SBI on the PPS posttest ($\gamma = 2.11$, $p < .001$), the PPS delayed posttest ($\gamma = 1.38$, $p < .001$), and the GMADE posttest ($\gamma = 0.68$, $p = .006$). Standardized effect sizes comparing the SBI and control conditions on the PPS posttest, PPS delayed posttest, and GMADE posttest were $g = 0.54$, 0.35, and 0.18 SDs, respectively. On the PPS posttest, years teaching mathematics and the percentage of students receiving FRL status were significant classroom predictors while both Hispanic and Black students scored significantly lower than White students, on average. On the PPS delayed posttest, the percentage of students receiving special education services was a significant classroom predictor and, again on average, Black students scored significantly lower than White students. On the GMADE posttest, years teaching mathematics, percentage of FRL students, and percentage of students receiving special education services were significant classroom predictors with Black and Hispanic students scoring significantly lower than White students, on average.

Conclusions:

The pooled data findings clarify that SBI improves students' mathematical problem solving, more so for proximal than distal measures. These findings also show Black and Hispanic students continue to lag behind White students, teachers with more experience tend to be associated with higher performing classrooms, and increasing concentrations of FRL and students receiving special education services are generally associated with weaker performances. These and other findings provide an empirical adjudication of results from individual studies and represent an opportunity to enhance generalizability of the effectiveness of SBI.

Appendix A. References

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Appendix B. Tables

Table 1.
Participant Demographic Information by Treatment

		SBI		Control	
		n	%	*n*	%
Student Information					
Age in years	*M* (*SD*)	12.71	(0.42)	12.68	(0.4)
Sex	Female	917	49.3	895	50.2
	Male	943	50.7	888	49.8
Race	Asian	92	5.0	111	6.2
	Black	213	11.5	157	8.8
	Hispanic	294	15.8	335	18.8
	Multiracial	32	1.7	25	1.4
	White	1226	66.0	1155	64.8
FRL	Yes	704	51.7	620	47.4
	No	657	48.3	688	52.6
ELL	Yes	164	8.8	149	8.4
	No	1693	91.2	1634	91.6
SpEd	Yes	183	9.9	138	7.7
	No	1674	90.1	1645	92.3
Teacher Information					
Sex	Female	53	70.7	57	73.1
	Male	22	29.3	21	26.9
Race	Asian	1	1.3	3	3.8
	Black	1	1.3	2	2.6
	Hispanic	5	6.6	0	0.0
	White	69	92.0	72	92.3
	Am Indian	0	0.0	1	1.3
Experience[a]	*M* (*SD*)	10.97	(6.71)	10.64	(8.03)
PD Hours in Math	*M* (*SD*)	22.14	(26.03)	23.18	(19.07)

Note. [a] = years experience teaching math; SBI = schema-based instruction; PD = professional development; FRL = students eligible for free or reduced priced lunch; ELL = English Language Learner; SpEd = students receiving special education services.

Table 2.
Multilevel results for MPS Posttest

Fixed Effects	*B*	*SE*	*t*	*df*	*p*
Between-Student Model					
Sex	0.02	0.13	0.17	3222	.867
Asian	0.26	0.30	0.88	3222	.378
Black	-0.99	0.25	-3.91	3222	<.001
Hispanic	-0.87	0.20	-4.35	3222	<.001
Multiracial	0.45	0.54	0.83	3222	.409
Pretest	0.66	0.02	41.09	3222	<.001
Between-Classroom Model					
Intercept	14.72	0.50	29.16	144	<.001
Treatment	2.11	0.26	8.09	144	<.001
Gender	0.50	0.29	1.73	144	.086
Yrs. experience	0.05	0.02	2.62	144	.01
PD hours	0.00	0.00	-0.30	144	.767
Special education	-0.25	0.12	-2.03	144	.044
ELL	-0.21	0.14	-1.47	144	.143
FRL	-0.46	0.17	-2.68	144	.008
Dummy 1	-0.34	0.34	-0.98	144	.329
Dummy 2	-0.04	0.43	-0.10	144	.918
Random Effects	VC	*SD*	χ^2	*df*	*p*
Classroom	1.85	1.36	590.24	144	<.001
Student	13.59	3.69			

Note. Special Education, ELL (English language learner), and FRL (eligible for free or reduced price lunch) expressed in quartiles; Yrs. experience = years of teaching experience; Dummy 1 and Dummy 2 are dummy predictors representing the three states; VC = variance component.

$\alpha = \frac{.15}{14} = .011$ for tests of the fixed effects.

Table 3.
Multilevel results for MPS Delayed Posttest

Fixed Effects	*B*	*SE*	*t*	*df*	*p*
Between-Student Model					
Sex	0.10	0.14	0.74	3103	0.459
Asian	0.07	0.31	0.23	3103	0.82
Black	-0.80	0.27	-3.00	3103	0.003
Hispanic	-0.53	0.21	-2.51	3103	0.012
Multiracial	0.53	0.55	0.96	3103	0.338
Pretest	0.68	0.02	40.07	3103	<0.001
Between-Classroom Model					
Intercept	14.00	0.50	28.10	142	<0.001
Treatment	1.38	0.26	5.38	142	<0.001
Gender	0.64	0.29	2.24	142	0.027
Yrs. experience	0.03	0.02	1.94	142	0.054
PD hours	0.00	0.00	-0.16	142	0.877
Special education	-0.34	0.12	-2.86	142	0.005
ELL	-0.06	0.14	-0.41	142	0.686
FRL	-0.38	0.17	-2.22	142	0.028
Dummy1	0.45	0.34	1.34	142	0.182
Dummy 2	-0.01	0.42	-0.03	142	0.977
Random Effects	VC	*SD*	χ^2	*df*	*p*
Classroom	1.69	1.30	498.86	142	<.001
Student	14.29	3.78			

Note. Special Education, ELL (English language learner), and FRL (eligible for free or reduced price lunch) expressed in quartiles; Yrs. experience = years of teaching experience; Dummy 1 and Dummy 2 are dummy predictors representing the three states; VC = variance component.

$\alpha = \frac{.15}{14} = .011$ for tests of the fixed effects.

Table 4.
Multilevel results for GMADE Posttest

Fixed Effects	*B*	*SE*	*t*	*df*	*p*
Between-Student Model					
Sex	0.04	0.12	0.31	3175	0.757
Asian	0.38	0.29	1.32	3175	0.188
Black	-0.73	0.24	-2.99	3175	0.003
Hispanic	-0.76	0.19	-3.92	3175	<0.001
Multiracial	-0.17	0.51	-0.34	3175	0.737
Pretest	0.49	0.02	29.03	3175	<0.001
Between-Classroom Model					
Intercept	13.92	0.48	29.20	144	<0.001
Treatment	0.68	0.25	2.77	144	0.006
Gender	0.45	0.27	1.62	144	0.106
Yrs. experience	0.05	0.02	2.96	144	0.004
PD hours	0.00	0.00	-0.77	144	0.446
Special education	-0.33	0.12	-2.87	144	0.005
ELL	0.02	0.13	0.16	144	0.87
FRL	-0.61	0.16	-3.74	144	<0.001
Dummy 1	0.04	0.32	0.12	144	0.907
Dummy 2	0.34	0.41	0.84	144	0.4
Random Effects	VC	*SD*	χ^2	*df*	*p*
Classroom	1.63	1.28	556.14	144	<.001
Student	12.33	3.51			

Note. Special Education, ELL (English language learner), and FRL (eligible for free or reduced price lunch) expressed in quartiles; Yrs. experience = years of teaching experience; Dummy 1 and Dummy 2 are dummy predictors representing the three states; VC = variance component.

$\alpha = \frac{.15}{14} = .011$ for tests of the fixed effects.