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The Relationship among Reading, Math and Science Achievement: Exploring the Growth Trajectories over Three Time Points

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Abstract: *Science, Technology, Engineering, and Math (STEM) education is considered critical and valid for the modern workforce which is strongly enveloped in technology. Therefore, it is imperative to reinforce science and math education and knowledge among students early in their educations. Despite this understanding, most research has focused on the importance of mathematics and emphasized its role in science education. Research highlights the relationships between math and science fluency in students' education at a specific point in time (Fleischman et al., 2010). Furthermore, reading has been strongly linked to success in math and also science achievement. However, few studies have examined the relationships among reading, math, and science simultaneously. Given that research identifies reading as a strong predictor for both math and science, it is necessary to explore how ability and achievement in these two subjects is influenced by reading in the early years of school.*

LITERATURE REVIEW

Research on math and science achievement has focused on different issues ranging from contextual factors relating to home, school and classroom environments (Heck and Hallinger, 2009), to changes in achievement over time (Clewell & Ginorio, 1996; Pianta, Belsky, Vandergrift, Houts, & Morrison, 2008), and how reading mainly impacts each of these two subjects. Positive attitudes toward science and positive attitudes toward mathematics have increased science achievement (Clewell & Ginorio, 1996), while growth in math achievement showed small positive relations with observed emotional interactions and exposure to math activities (Pianta et al., 2008). Additional studies have explored how different variables influence students' math and science growth trajectories. Heck and Hallinger (2009) examined distributed leadership using multilevel latent change analysis identifying significant direct effects of distributed leadership on change in the schools' academic capacity and indirect effects on student growth rates in math. In another study, educational investments were found to play a critical mediation role on socioeconomic and racial/ethnic disparities on children's math and reading growth (Cheadle, 2008).

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Math Achievement

Greenman, Bodovski and Reed (2011) investigated children's math achievement using ECLS-K data from grades K-5. They looked at parental practices and neighborhood characteristics and their associations with math achievement through the end of the 5th grade. They found children from disadvantaged neighborhoods had lower 5th-grade math achievement. Families living in high poverty, high unemployment, and low-education neighborhoods employed fewer education-oriented practices with their kindergarten-first grade children. These activities include such things as reading with children, visiting zoos and museums, or signing youngsters up for sports teams and music lessons. However, the positive effect of such parental practices on children's mathematics achievement was stronger for children who live in disadvantaged neighborhoods than for children from more advantaged neighborhoods.

Unfortunately, only 26 percent of U.S. 12th graders reach the threshold of proficiency in math on the National Assessment of Educational Progress (National Center for Education Statistics, 2010). Moreover, U.S. 8th graders' performance on the 2007 Trends in International Mathematics and Science Study was mediocre (Gonzales et al., 2008). In addition, they scored below average on the 2009 Programme for International Assessment (Fleischman, Hopstock, Pelczar, & Shelley, 2010). The need to improve mathematics learning in the United States has been a primary driver of education reform efforts, including the Common Core initiative (Schiller, Schmidt, Muller, & Houang, 2010). Consequently, given the emphasis on not only literacy but math and science related concepts, it is important to explore how these subjects interact in relation to student learning.

Science Achievement

Science achievement has also been researched in relation to similar subjects as math achievement. Contextual variables such as parental values and child-specific expectations influenced the students' interest and success in science hence better science achievement and even the possibility for future science careers (Kong, 2016; Taskinen, Dietrich, & Kracke, 2015). Gender differences have also been consistently identified as a major determinant for achievement and eventually science oriented careers (Han, & Buchmann, 2016; Reilly, Neumann, & Andrews, 2015). Moreover, disparities are identified in different kid's settings such as urban and rural schools with socioeconomic status playing a major role in influencing the differences in achievement (Kryst, Kotok, & Bodovski, 2015; Van Laere, & van Braak, 2015; Walker, 2015). Most importantly, science achievement has been largely associated with math achievement and literacy (Maerten-Rivera, Ahn, Lanier, Diaz, & Lee, 2016). Furthermore, it has been noted that gaps in science just like math achievement stem from early education and persist through the education journey of many students (Morgan, Farkas, Hillemeier, & Maczuga, 2016).

Problem Statement

Despite many studies focusing on achievement on specific factors for specific time points and age groups (Kim, & Chung, 2015; Patrick, & Mantzicopoulos, 2015) for different subjects, it is important to examine how interrelationships between subjects influence growth in achievement hence learning ability among students. Moreover, literacy is considered an important aspect for learning at any stage of the education process (Maerten-Rivera et al., 2016). Literacy is mainly measured through an individual's reading ability especially in the early years of schooling. Despite this knowledge research has extensively examined reading individually as a subject or in relation to mathematics or science. While research has identified reading as an important determinant of achievement in both math and science, there is scarce exploration of how these three subjects interrelate over time. Consequently, due to the emphasis on the relevance of STEM in many education forums, understanding the trajectories of students' reading ability, mathematics and science achievement concurrently over the course of their early school years is vital. A gap in the literature exists in the longitudinal development of reading, math, and science understanding for grades kindergarten through eight.

RATIONALE FOR LGCM AND DATA USED

Latent Growth Curve Modelling (LGCM) is mainly used to demonstrate change in specific behavior or factors over time (T. Duncan et al., 2013). In order to demonstrate the change in math and science achievement in relation to reading ability over time it is necessary to employ an appropriate LGCM procedure for the given longitudinal data.

Consequently, this study utilized the ECLS-K longitudinal data for math, science and reading achievement from third to eighth grade for the 1998-99 cohorts. Specifically, we focused on exploring the growth trajectories in math and science, in relation to reading during the 5th (3rd grade), 6th (5th grade), and 7th (8th grade) rounds of data collection in the ECLS-K longitudinal study. The choice for this period was dictated by the nature of teaching science in early education. Children are exposed to general science for their initial years in school before being introduced to science in their third grade of school. As a result, longitudinal analysis including science achievement can only be performed starting from third grade and beyond. Additionally, the achievement scores have been adjusted to IRT scores to account for the different assessments used during the different years of school in the same subject hence legitimizing the use of LGCM for analysis.

RESEARCH QUESTION AND HYPOTHESES FOR THE STUDY

The research question in this study will explore the growth trajectory for math, science, and reading achievement over three years. Since reading achievement has been explored in relation to both math and science, it will be considered as the reference group in a factor-of-curves LGM model. Specifically, the research questions will ask; (a) what are the forms of growth and the degree and pattern of associations among the intercepts and the growth parameters of math, science, and reading? And (b) to what extend can the relationships among the growth factors be explained by a higher order ability construct? Additionally, the differences between growth trajectories for math and science achievement over the period of the study will be explored. It is hypothesized that the intercepts and trajectories of achievement among the three subjects covary, specifically children who experience growth in achievement in one subject over time are also likely to experience growth in achievement in other subjects.

METHODS

DATA COLLECTION AND PARTICIPANTS

The Early Childhood Longitudinal Study, Kindergarten Class of 1998-99 (ECLS-K) data was utilized in this study. The data was accessed via the Education Data Analysis Tool (EDAT) from the National Center for Education and Statistics (NCES) website. The data was collected during the spring of 3rd grade (2002), 5th grade (2004), and 8th grade (2007). The base-year sample was nationally representative of children enrolled in kindergarten in the US during that year and consisted of 22,782 children from 944 schools. Participants were students enrolled in both public and private schools, and parents from diverse racial/ethnic and socioeconomic backgrounds drawn from a nationally representative sample. Analysis in this study will be is restricted to the final three rounds of data collection for reading, math, and science achievement. See Table 1

Number of children in the ECLS-K sample by response status and data collection round: School years 2001-02, 2003-04, and 2006-07.

Table 1
Number of children in the ECLS-K sample by response status and data collection round: School years 2001-02, 2003-04, and 2006-07

			Response status			
Data collection round	Unweighted sample size	Ineligibles	Unknown eligibility	Non-followed movers	Non-respondents	Respondents
Spring-third grade	21, 357	122	289	4, 117	1, 524	15,305
Spring-fifth grade	16, 143	39	210	3, 765	309	11, 820
Spring-eighth grade	12, 129	36	67	↟	2, 301	9, 725

Note: ↟ not applicable

INSTRUMENTS AND VARIABLES

INSTRUMENTS

Children were assessed on their mathematics, science, and reading ability using developmentally appropriate instruments developed by the Educational Testing Service (ETS). Assessments were direct cognitive tests designed to evaluate student's general knowledge and skill in the respective academic areas and were administered in paper and pencil format to students in small group timed settings. The assessments targeted appropriate subject level content across the three subjects as determined by ETS. The assessments were supervised by trained test administrators in each round and children were assessed with the same instrument regardless their grade level. Assessments comprised of cognitive and physical (i.e., height and weight) components and were administered alongside self-administered student questionnaires.

VARIABLES IN THE STUDY

The independent variables of interest were selected from the cognitive assessment achievement scores over the span of three years of interest in math, science, and reading. Given the differing nature of assessments from one grade to another as children moved through different grades, IRT scores will be used in this analysis. The IRT scores have been calibrated across grades to account for the variations in the assessments over the years of the study. Data coding included several variables for missing data including: (a) -9 = not ascertained; (b) -8 = don't know; (c) -7 = refused; and -1 = not applicable. These variables define different kinds of missing information for the achievement scores including the missing data for nonresponse. See Table 2.

Table 2
Description of observed (independent) variables used in this study as Item Response Theory (IRT) scale scores: School years 2001-02, 2003-04, and 2006-07

Variable	Description	Range of values	Weighted mean	Standard deviation
C5R4RSCL	C5 RC4 Reading IRT Scale Score	0-212	125.70	28.57
C6R4RSCL	C6 RC4 Reading IRT Scale Score	0-212	148.67	26.85
C7R4RSCL	C7 RC4 Reading IRT Scale Score	0-212	167.24	28.05
C5R4MSCL	C5 RC4 Math IRT Scale Score	0-174	98.77	24.96
C6R4MSCL	C6 RC4 Math IRT Scale Score	0-174	122.94	25.18
C7R4MSCL	C7 RC4 Math IRT Scale Score	0-174	139.28	23.10
C5SR2SSCL	C5 RC4 Science IRT Scale Score	0-111	49.91	15.29
C6SR2SSCL	C6 RC4 Science IRT Scale Score	0-111	63.87	15.73
C7SR2SSCL	C7 RC2 Science IRT Scale Score	0-111	82.72	17.07

DATA ANALYSIS AND PROCEDURES

DATA CLEANING AND PREPARATION

Variables were recoded to adjust the different values for missing to system missing in order to reflect the actual missingness in the data. Cases with missing values on all variables were deleted, and assumptions including normality and multicollinearity investigated. During analysis listwise deletion was used to exclude all cases with missing values. The final data consisted of 8,591 cases. In the first round of data collection, results in all three domains are normally distributed. In the second and third rounds, results become progressively more skewed to the left in all three domains.

RESULTS

Descriptive statistics for the ECLS-K data used in all models is presented with means, standard deviations, and correlations in **Error! Reference source not found.**Table 3

Descriptive Statistics. Statistical significance was evaluated at α = .05. Analysis was completed using IBM SPSS Amos 24 software.

Table 3
Descriptive Statistics

	Reading3	Math3	Science3	Reading5	Math5	Science5	Reading8	Math8	Science8
Reading3	1								
Math3	.723	1							
Science3	.739	.700	1						
Reading5	.845	.700	.723	1					
Math5	.682	.864	.673	.718	1				
Science5	.716	.696	.838	.760	.730	1			
Reading8	.732	.634	.671	.779	.662	.714	1		
Math8	.654	.788	.637	.689	.843	.691	.722	1	
Science8	.678	.688	.736	.720	.728	.790	.770	.773	1
M	130.25	101.94	52.22	153.65	126.28	66.45	101.94	143.03	85.35
SD	0.294	0.259	0.162	0.272	0.256	0.164	0.259	0.23	0.168

Note. Correlation matrix with means (M) and standard deviation (SD) at the bottom.

Two-Factor Models

Separate two-factor growth models with two factors representing the slope and intercept for each of the three academic domains were created. Factor loading for the slope factor were set at 0, 1, 2 to represent each data collection point of third grade (time 0), fifth grade (time 2), and eighth grade (time 5). Linear growth is suggested by a plot of the factor means against the observed times. Factor loadings for the intercept were all set to the constant of one. All parameter estimates with standard errors for the three models are presented in Table 4.

The three two-factor models all had 9 sample moments with 6 parameters. These models are over-identified; therefore model fit can be analyzed. With a large sample size such as this, statistically significant chi-square results are expected so the statistically significant chi-square results for the three models cannot be used as evidence that these models did not fit the sample in this study adequately. The RMSEA values for reading (.15), math (.23), and science (.20) were all above .05 which is an indication of inadequate fit. On the contrary, the CFI values for all three models were above .90 suggesting adequate model fit for the three models. We believe the increasing left skew of achievement scores in all three domains over the three measurement points is the reason for inadequate fit using the RMSEA statistic. However, with a large sample some extreme scores are to be expected (Tabachnick & Fidell, 2013). Since low outlying scores represent the achievement of actual students, the decision was made to leave outlying scores in the model. See Table 5 for model fit statistics for all models. Despite the effect of skewed data from the second and third round of testing, it was important to investigate the associative model based on the evidence of variability among the latent factors for these individual models.

Science

The two-factor science model is presented in Figure 1

Science Two-Factor Model, Standardized Estimates. Results for science show a model with χ^2 (N= 8591, df = 3) = 1031.48, p <.001. The unconditional two-factor model for science has a statistically significant mean intercept value of 51.44 (*SE* = .16) $p < .001$, and the mean slope value of M = 16.57 (*SE* = .06, $p < .001$). The significant mean slope suggests that children's science score increases by 16.57 units with each test period. The intercept variance for science scores is 191.72, $p < .001$ and the variance of the latent slope of science scores is 10.39, $p < .001$ are statistically significant indicating substantial variation among children in their science achievement at time one (third grade) and also in the rate of change (growth) in science. Error variances were constrained to be equal across the three time points, $E_{11,12,13} = 41.01$, $p < .001$. The relationship between slope and intercept is statistically significant, R = -7.89 (*SE* = 1, $p < .001$) indicating that children with higher initial science scores tend to change in science achievement more slowly than children with lower scores.

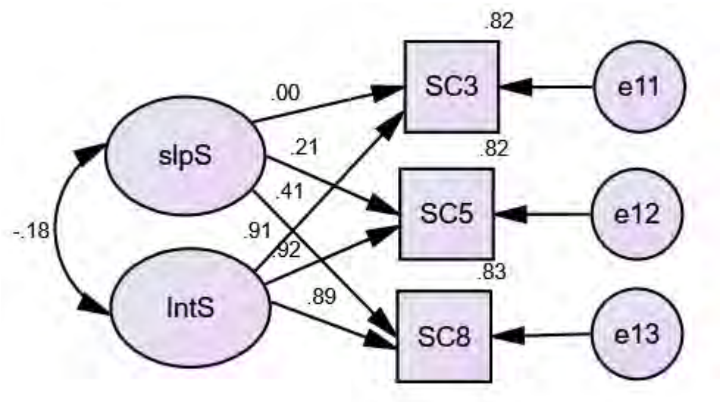
Table 4
Results of Two-Factor Models

	Science Mean		Reading Mean		Math Mean	
	Slope	Intercept	Slope	Intercept	Slope	Intercept
Effect	16.57	51.44	20.83	130.95	20.55	103.20
Standard Error	.06	.16	.11	.29	.08	.26
p-value	<.001	<.001	<.001	<.001	<.001	<.001
	Factor Variance		Factor Variance		Factor Variance	
Effect	10.39	191.72	43.18	628.79	16.86	523.96
Standard Error	.57	3.49	1.73	11.10	1.05	9.05
p-value	<.001	<.001	<.001	<.001	<.001	<.001
	Covariance		Covariance		Covariance	
Effect	-7.89		-53.76		-47.73	
Standard Error	1.00		3.22		2.26	
p-value	<.001		<.001		<.001	

Table 5
Model Fit, All Models

9591	N	Sample Moments	Parameters	χ^2 (d.f.)	RMSEA	CFI	AIC
Reading	8591	9	6	192.63 (3) $p < .001$	.15	.97	589.88
Math	8591	9	6	1335.59 (3) $p < .001$	.23	.94	1347.59
Science	8591	9	6	343.83 (3) $p < .001$	.20	.95	1043.48
Associative	8591	54	28	5529.69 (26) $p < .001$	.16	.94	5585.69

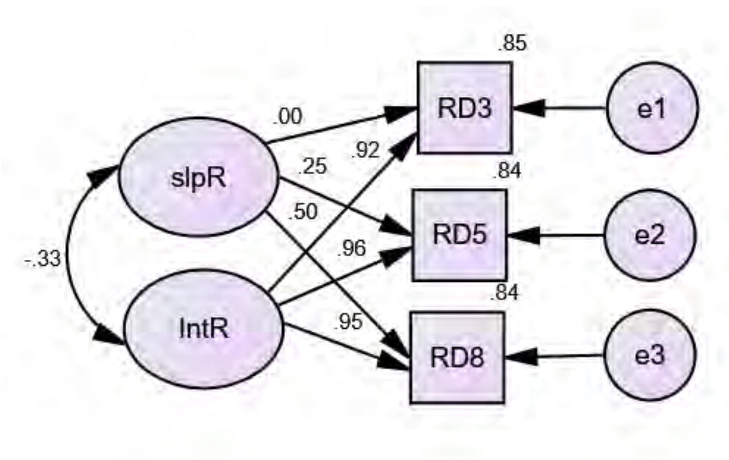
Figure 1
Science Two-Factor Model, Standardized Estimates



Reading

Results for reading show χ^2 $(N= 8591, df = 3) = 577.88$, $p <.001$. The unconditional two-factor model for reading has a statistically significant mean intercept value of 130.95 ($SE = .29$, $p < .001$) and mean slope value of M = 20.83, ($SE = .11$, $p < .001$). The significant mean slope suggests that children's reading increases by 20.83 units at every test point. The intercept variance for reading scores of 628.79 ($SE = 11.10$, $p < .001$) and the variance of the latent slope of reading of 43.18 ($SE = 1.73$, $p < .001$) are statistically significant indicating substantial variation among children's initial and rate of change (growth) in their reading ability. Error variances were constrained to be equal across the three time points, E = 110.98, $p < .001$ indicating significant intra-individual variation. The covariance between slope and intercept is statistically significant, R = -53.76 ($SE = 3.22$, $p < .001$) indicating that children with higher initial reading scores tend to change their reading more slowly than those with lower scores. See Figure 2.

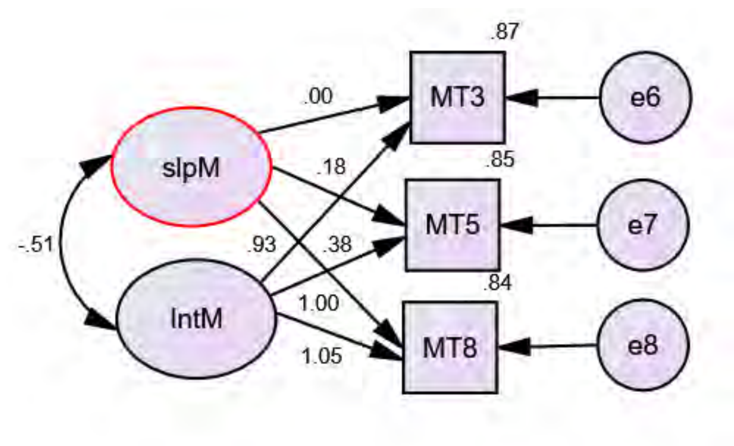
Figure 2
Reading Two-Factor Model, Standardized Estimates



Math

Results for math χ^2 (N= 8591, df = 3) = 1335.59, p <.001. The unconditional two-factor model for math has a statistically significant mean intercept value of 103.20 (*SE* = .26, *p < .001*) and the mean slope value of M = 20.55 (*SE* = .08, $p < .001$). The significant mean slope suggests that children's ability in math increases by 20.55 units at every test point. The statistically significant intercept variance for math scores is 523.96 (*SE* = 9.05, $p < .001$), indicating substantial variation among children in their math ability at third grade. In addition, the variance of the slope for math 103.20 (*SE* = .26, $p < .001$), suggests that there is substantial variation in growth of math ability among the children in this sample over the period of the study. Error variances were constrained to be equal across the three time points and are statistically significant, E = 78.69 (*SE* = 1.20, $p < .001$). The covariance between slope and intercept is statistically significant at -47.73 (*SE* = 2.26, $p < .001$), indicating that children with higher initial math scores tend to change their math more slowly than children with lower scores. See Figure 3.

Figure 3
Math Two-Factor Model, Standardized Estimates

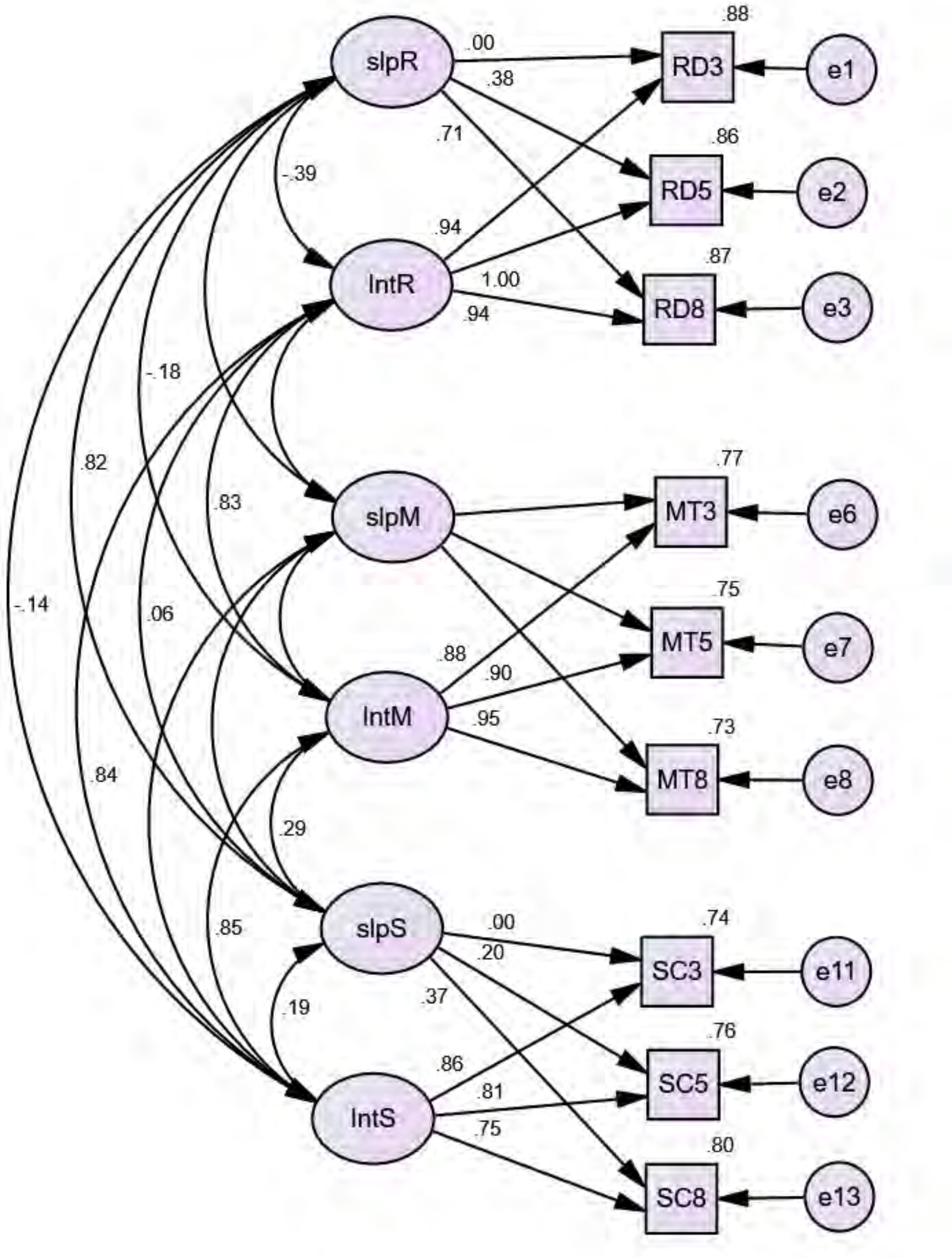


Looking at the three two-factor models as a group, we see that scores on reading are higher compared to math and science in third grade and the rate of change for reading is greater than for math or science. Math scores are initially higher than science scores but lower than reading and the rate of change of math is greater than science but less than reading. Science has the lowest initial scores with the lowest rate of change. All three models have statistically significant negative covariance between the slope and the intercept indicating that higher initial scores are associated with slower growth in achievement rates.

Associative Model

Next an associative model was estimated to simultaneously compare associations between the growth (slope) and starting point (intercept) for each of the three academic domains. See Figure 4. As before, factor loading were set with 0, 1, and 2 for the slope factors and intercept factors were fixed to one.

Figure 4
Associative Model, Standardized Estimates



This model connects the three two-factor models with estimated covariances which allow for the assessment of relationships among the different parameters of reading, math, and science achievement, as well as, the estimation of means and variances for the growth factors for each domain. Model fit indices for all models are summarized in Table . This model has χ^2 (N= 8591, df = 26) = 5529.69, p < .001, CFI = .94, AIC = 5585.70, and RMSEA = .16. While the RMSEA value indicates inadequate model fit, the CFI value indicates acceptable model fit. Estimates for means and variances are all statistically significant. Mean starting achievement for reading (IntR) = 20.83 (*SE* = .12, $p < .001$), for math (IntM) = 103.21 (*SE* = .24, $p < .001$), for science (IntS) = 51.44 (*SE* = .14) $p < .001$. Variances are IntR = 559.10 (*SE* = 8.82), IntM = 402.91 (*SE* = 7.06), and IntS = 118.37 (*SE* = 1.46) indicating significant variation in initial group scores in reading, math, and science. Error variances are also significant indicating inter-individual variation as well. All estimates for the associative model are presented in Table 7.

Table 7
Associative Model Mean & Variance Estimates

	Estimates				
	Means	*S.E.*	Variances	*S.E.*	*p*
slpR	20.83	.12	88.20	0.95	***
IntR	130.95	.27	559.07	8.83	***
slpM	20.55	.08	-1.84	1.12	.147
IntM	103.21	0.24	417.34	7.29	***
slpS	16.57	.06	3.34	0.11	***
IntS	51.44	0.14	144.87	1.71	***
e1	0		71.97	0.78	***
e2	0		71.97	0.78	***
e3	0		71.97	0.78	***
e6	0		144.87	1.71	***
e7	0		144.87	1.71	***
e8	0		144.87	1.71	***
e11	0		38.5	0.58	***
e12	0		38.5	0.58	***
e13	0		38.5	0.58	***

*All estimates are statistically significant at $p < .001$

Estimates for the significant mean growth factors are: reading (slpR) = 26.83 (*SE* = .12) $p < .001$, math (slpM) = 20.56 (*SE* = .08) $p < .001$, and science (slpS) =16.57, (*SE* = .06) $p < .001$. Significant variances of the slopes of achievement of math, reading, and science (V_{slpR} = 88.80, V_{slpM} = -1.8, V_{slpS} = 118.37, $p < .001$) are indication that significant individual variation exists in the development of the three domains. Significant intercept variations (V_{intR} = 559.07 V_{intM} = 402.92, V_{intS} = 118.37, $p < .001$)

Covariances are summarized in Table 8. Covariance between an intercept and a slope represents the relationship of achievement at the initial time of third grade with growth in achievement over the period of the study. A negative covariance indicates that higher than average achievement scores are paired with lower than average growth. It is interesting to note that all of the intercept-to-slope covariances are negative indicating that those with high initial achievement scores grow the most slowly over time.

Table 8
Associative Model Covariances

Covariance			Estimate	*SE*	*p*-value
Slope Science	<-->	Intercept Science	2.95	.80	***
Intercept Math	<-->	Slope Science	11.79	1.31	***
Intercept Math	<-->	Intercept Science	178.45	2.88	***
Slope Math	<-->	Intercept Math	-21.02	2.07	***
Slope Math	<-->	Slope Science	12.25	.47	***
Slope Math	<-->	Intercept Science	-17.80	1.02	***
Intercept Reading	<-->	Slope Math	-45.9	2.06	***
Intercept Reading	<-->	Intercept Math	377.13	6.72	***
Intercept Reading	<-->	Slope Science	-2.1	1.45	.147
Intercept Reading	<-->	Intercept Science	247.46	4.19	***
Slope Reading	<-->	Intercept Science	-13.62	1.55	***
Slope Reading	<-->	Slope Science	21.23	.69	***
Slope Reading	<-->	Intercept Reading	-92.25	2.92	***
Slope Reading	<-->	Slope Math	32.28	.94	***
Slope Reading	<-->	Intercept Math	-33.69	2.77	***

*** $p < .001$

Turning to the statistically significant intercept-to-intercept covariances, results indicate that high initial achievement scores in reading are associated with high initial achievement scores in science and math. Cov(IntR, IntM) = 377.13, cov(IntR, IntS) = 210.08, and cov(IntM, IntS) = 178.46 which leads to the conclusion that the association between initial achievement in reading and math is stronger than the initial achievement in reading and science, and that the initial achievement in math and science is associated less strongly than either subject with initial achievement in reading.

Finally turning to the associations between the statistically significant, growth factors we see that higher than average growth in one subject indicates higher than average growth in the other. Cov(slpM, slpS) = 12.25, cov(SlpR, SlpS) = 21.23, and cov(SlpR, SlpM) = 32.27. As with the slope-to-intercept covariance, the covariance between growth in reading and math is the highest, reading and science are less strongly associated with the association between growth in math and science being the weakest.

Discussion and Conclusions

Individual Subject Models

Results for the individual latent growth curve models for math, reading and science showed relatively high variabilities for both latent variables (constant and slope) for all three models. Additionally, there are negative correlations between starting values and change of growth rates. These findings provide evidence to investigate the trajectories using the associative model to examine correlations among the growth trajectories for the three constructs. Statistically significant correlations were found among the intercept and slope terms necessitating further exploration for associations of these three growth trajectories by building an associative model. Moreover based on the covariances between the slopes and intercepts for the three subjects, it was evident that children with higher initial achievement tend to change less in their ability over the period of the study.

ASSOCIATIVE MODEL

As expected, the correlations among the latent factors were all statistically significant for this model hence necessitating the exploration of the factor-of-curves model. Additionally, while the growth for reading was strongly associated with both math and science, math and science were less correlated. This finding strongly aligns with theoretical evidence for the relationship between reading and math or science. On the other hand, while many studies highlight the importance of math and science in STEM education, the low association in the growth for these two subjects reflects little emphasis on the integration of these subjects in elementary education. Finally the indication for higher growth in one subject relatively reflecting higher growth in another highlights the need to emphasize the teaching of the three subjects vigorously in early education.

LIMITATIONS AND DIRECTION FOR FUTURE STUDIES

In this study, science was first tested in third grade whereas math and reading were tested from kindergarten hence the initial point for achievement scores in this subject. The absence of science achievement scores is due to the later introduction of science in the school curriculum for children. Moreover, it is further described that at the time of data collection, there is no uniformity in the introduction of science to the students hence this impacts the achievement scores for students at the initial period and over time due to differences in concepts taught and those tested. Based on this knowledge, while in this study we were assigning a linear growth between the tested periods, this might not be the case thus causing unusually large correlations for the slopes of the three constructs. Consequently, while it is evident that there are commonalities among the three growth trajectories, the exact degree of growth trajectories for the individual subjects, especially science needs to be explored further. Moreover, studies might choose to focus on a specific set of schools with the same curriculum to study the relationships and commonalties among these constructs before extending to the information to larger studies. Also given the adoption of the Common Core state standards across the nation, a longitudinal study including these three subjects would be beneficial to inform the effectiveness of the curriculum over time.

The use of secondary data while advantageous to explore new areas within limited time is also inadequate. First we were limited to the number of time points that matched across the three subjects thus we could not explore earlier years for reading and math because science started during the third grade. Moreover, issues related to the context in which the data was collected given the time period cannot fully be used to explain the findings in the study currently.

Finally, research has mostly focused on comparing trajectories of math and reading or reading and science, with few discussing the commonalities among the three subjects despite the implicated relationships. The limited literature on the commonality among children's reading, math and science achievement trajectories compel us to explore the growth pattern before settling on the appropriate trends. The uncertainty and the lack of suggested model to some extent hurt the robustness of our model design hence the unusually large correlations for the growth factors in the FOC model. Future studies should extensively explore the trends for the three constructs through more recent longitudinal data or even simulation studies to provide more insight on this model. There is also need to explore how other variables such as gender, and home and school contextual variables could fit into this relationship. Literature identifies many of these variables as important in predicting achievement. Exploring such relationships might improve the model by reducing the higher than usual correlations.

IMPLICATIONS FOR THE FIELD

Despite the limitations addressed, it is evident from the findings that the factor-of-curves model provides useful information for the field in relation to reading, science, and math in elementary education. The finding that students with high initial achievement tend to grow less over time across the three subjects is strongly implicated in the education system where more emphasis is placed on improving learning ability for lower achieving student than on those that are high achieving. This presents a strong argument for the need for equality when addressing the diverse learning needs of students especially in relation to proponents of gifted education.

Given the emphasis on the importance of literacy, math and science in STEM education in both high school and higher education, this study provides important information for elementary education in relation to the curriculum where these subjects can be emphasized earlier on in order to foster better achievement. It also appears that the later introduction of science in the curriculum hurts the ability for students to perform better in this subject over time as compared to math and reading. Policy makers and educators would gain insight on reinforcing the emphasis on these three subjects especially given the Common Core state standards which emphasize the value and importance of STEM education in the learning of students.

Table 4 Parameter Settings

Parameters			Two-factor Models	Associative Model	Factor of Curves Model
Intercept	IncR	Mean	estimated	estimated	0
		Variance	estimated	estimated	NA
	IncM	Mean	estimated	estimated	estimated
		Variance	estimated	estimated	NA
	IncS	Mean	estimated	estimated	estimated
		Variance	estimated	estimated	NA
Slope	Slp R	Mean	estimated	estimated	0
		Variance	estimated	estimated	NA
	SlpM	Mean	estimated	estimated	estimated
		Variance	estimated	estimated	NA
	SlpS	Mean	estimated	estimated	estimated
		Variance	estimated	estimated	NA
Error variances		Means	Fixed at 0	Fixed at 0	Fixed at 0
		Error Variance, Reading	Constrained to be equal	Constrained to V1	Constrained to V1
		Error Variance, Math	Constrained to be equal	Constrained to V6	Constrained to V6
		Error Variance, Science	Constrained to be equal	Constrained to V11	Constrained to V11
Disturbance	$D_{int}X$*	Mean	NA	NA	Fixed at 0
		Variance	NA	NA	Constrained to Di
	$D_{slp}X$*	Mean	NA	NA	Fixed at 0
		Variance	NA	NA	Constrained to Ds
Covariances			estimated	Estimated	Estimated
Factor Loadings		IcpX*	Fixed at 1	Fixed at 1	Fixed at 1
		SlpX*	Fixed at 0, 1, 2	Fixed at 0, 1, 2	Fixed at 0, 1, 2

* X represents reading, math, or science.

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