Longitudinal Impact of Early Childhood Science Instruction on Middle Grades Literacy and Mathematics

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Nurtures

Networking **U**rban **R**esources with **T**eachers and **U**niversity to en**R**ich **E**arly Childhood **S**cience

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NURTURES
Uses the Complementary Learning Model

Increased academic achievement

+

Improved science comprehensio n

Nurtures

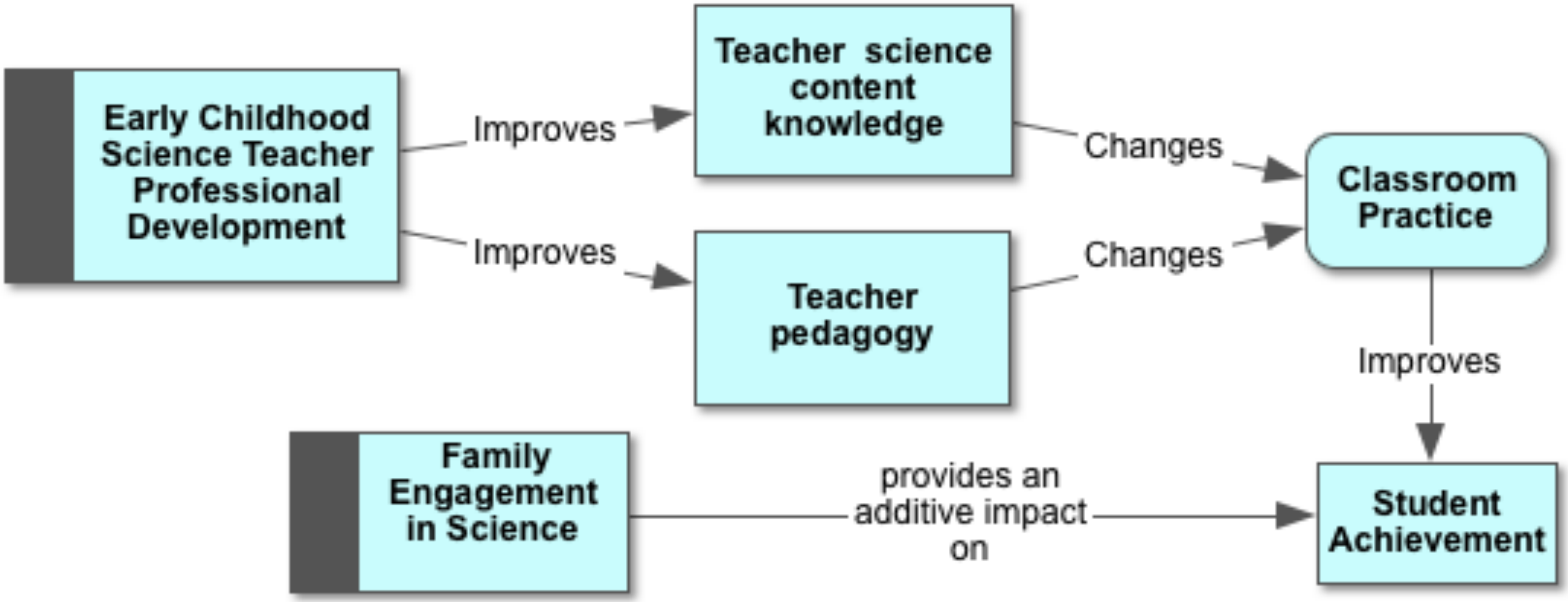
NURTURES Program

Teacher Professional Development

Classroom Extension Activities (Family Packs)

Community Sci-FUN Events and WGTE Learning Segments

NURTURES Theory of Action

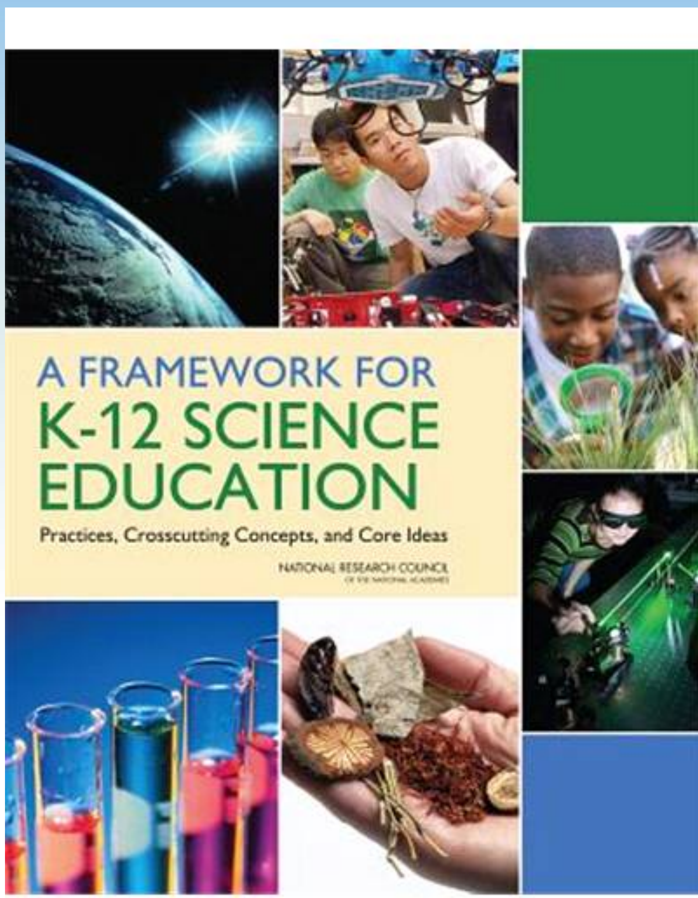


NURTURES Goals:

- increased science proficiency in PK-3 children
- align instructional practices of PK-3 teachers with K-12 Framework
- improve quality of family interactions while learning science together

Nurtures

State of Science Education Today



Framework for K-12 Science Education and the Next Generation Science Standards

- Scientific and Engineering Practices
- Cross-cutting Concepts
- Disciplinary Core Ideas

Nurtures

Aims of Study

- Key question: does having a NURTURES K through 3rd-grade teacher affect students' academic performance in subsequent elementary years in reading and mathematics?

- To answer: examine and describe the effect of NURTURES on students' academic performance at the district, grade band, and school level.

Sample Frame

Control and treatment students drawn from 41 out of 44 elementary schools in a large urban school district in the Midwest.

School district is characterized by high racial diversity and 64.8% of students receiving free and reduced lunch.

Nurtures

Participants

Treatment Students:

Had at least one NURTURES teacher during the 2012-'13, 2013-'14, 2014-'15, or 2015-'16 academic years.

MAP Assessment Year: Mid March 2018 based on 2015 normed data.

6759 – Reading study, grades: 2-5 (**2801** or **41.4 %** intervention)

6703 – Mathematics, grades: 2-5 (**2787** or **41.6%** in intervention)

Participants

- Intervention was defined as having a NURTURES teacher at any point in K-3.

  - For example, a student who was in 5th-grade in academic year 2017-’18 would have been in K-grade in 2012-’13, 1st-grade in 2013-’14, 2nd-grade in 2014-’15, 3rd-grade in 2015-’16, and therefore have more opportunities to have intervention teachers.

  - Most intervention students had only 1 intervention teacher. Only 7% of intervention students had 2 intervention teachers.

  - Multiple scenarios were possible due to retention of some students.

Demographic Characteristics of Participants in MAP Reading Group (N = 6759)

Characteristic	*n*	%
Grade		
2nd	1654	24.5
3rd	1837	27.2
4th	1595	23.6
5th	1673	24.8
Gender		
Female	3274	48.4
Male	3485	51.6
Ethnicity		
Asian	30	0.4
American Indian or Alaskan Native	11	0.2
African American	2714	40.2
Hispanic/Latino	771	11.4
Multiracial	639	9.5
Native Hawaiian or other Pacific Islander	4	0.1
White	2590	38.3
Retained in Grade		
Retained	663	9.8
Not retained	6096	90.2
Intervention		
Intervention teacher	2801	41.4
Non-intervention teacher	3958	58.6

Demographic Characteristics of Participants in MAP Mathematics Group (N = 6703)

Characteristic	*n*	%
Grade		
2nd	1634	24.4
3rd	1818	27.1
4th	1578	23.5
5th	1673	25.0
Gender		
Female	3254	48.5
Male	3449	51.5
Ethnicity		
Asian	29	0.4
American Indian or Alaskan Native	9	0.1
African American	2704	40.3
Hispanic/Latino	760	11.3
Multiracial	630	9.4
Native Hawaiian or other Pacific Islander	4	0.1
White	2567	38.3
Retained in Grade		
Retained	670	10.0
Not retained	6033	90.0
Intervention		
Intervention teacher	2787	41.6
Non-intervention teacher	3916	58.4

Baseline Equivalence – STAR EL Assessment as Covariate

- Fall scores for the **STAR Early Literacy** assessment for Kindergarteners in the study for 2013-’14, 2014-’15, and 2015-’16 was used as a **covariate**. The covariate was school-mean centered to enhance interpretation.

- The partner district does not offer STAR Mathematics in grades K-1, and only offers STAR Reading in grades K-1 to students who are already reading. EL assessment contains items foundational for later reading and mathematics skills.

- **STAR Early Literacy** - 27- items aligned to early literacy skills.

Three broad domains: Word Knowledge and Skills, Comprehension Strategies and Constructing Meaning, and Numbers and Operations.

HLM

- The hierarchical model adopted in this study is a two-level random-intercept hierarchical model, as implemented in R lme4. The technique is also known as multi-level analysis (M*plus*) or mixed regression models (STATA, SPSS).

- Models suitable for analysis of **grouped/nested** (e.g., students and teachers in schools) or **crossed** data structures (e.g., students or teachers changing schools over time), where the grouping/crossed factor is conceived as a random effect. The deviations and the amount of level-dependent random variation is estimated and incorporated in parameter estimates.

Bates, D., Maechler, M., Bolker, B., &, Walker, S. (2015). Fitting linear mixed-effects models using lme4. *Journal of Statistical Software, 67*(1), 1−48. doi:10.18637/jss.v067.i01.

HLM and Missing Data

- Multiple-data imputations were used due to a large number of missing pre-test (K-level STAR EL data). **32.7%** for reading sample and **32.8%** for mathematics sample.

- Joint-modeling chained approach was used to estimate missing values for all variables simultaneously

- Pan algorithm using Markov Chain Monte Carlo (MCMC) technique as implemented in the R pan package (Zhao & Schafer, 2018) was used for both samples separately. Burn-in and imputation stages were performed.

- The burn-in phase uses iterations to stabilize estimation parameters, and the imputation phase draws replacement for missing values into the desired number of imputed datasets (Grund, Lüdtke, & Robitzsch, 2016).

Grund, S., Lüdtke, O., & Robitzsch, A. (2016). Multiple imputation of multilevel missing data: An introduction to the R package pan. Sage Open, 6(4). Retrieved from https://doi.org/10.1177/2158244016668220.

Zhao, J. H., & Schafer, J. L. (2018). Package 'pan': Multiple imputation for multivariate panel or clustered data. R package version 1.6. Retrieved from https://cran.r-project.org/web/packages/pan/pan.pdf

HLM and Missing Data

- 50,000 burn-in iterations and 100 datasets were created.

- A separate procedure was used to combine all values (missing and non-missing) into separate datasets in the R mitml package (Grund, Robitzsch, & Lüdtke 2018).

- The following auxiliary variables were used in the imputation model: *post-test score*, *pre-test score*, *minority status*, *gender*, *student grade*, *retained status*, and *intervention*.

R Core Team (2018). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing, Vienna, Austria.URL: https://www.R-project.org

Grund, S., Robitzsch, A., & Luedtke, O. (2018). mitml: Tools for multiple imputation in multilevel modeling. R package version 0.3-6. Accessible from https://CRAN.R-project.org/package=mitml

Model – Level 1

- The predictor variables in both samples:

Student STAR **K-grade Early Literacy baseline measure**, **grade retention status** (levels: yes, no), **ethnicity** (levels: non-minority, minority), **gender** (male, female) and **Spring 2018 grade-level** (levels: 2, 3, 4, 5).

- The predictor variable of interest was **whether or not a student had a NURTURES program teacher** in 2012-13, 2013-14, 2014-15, and 2015-16 academic years (levels: yes, no).

- In practice students could have **more than one program teacher**, but this intervention variable was **dichotomized** to indicate either the presence or the absence of an intervention teacher.

Model – Level 2

- The **second-level** equations represented the effects of the schools (random intercepts only).

- No random slopes were modeled (e.g., it is difficult to assume that the gender or minority status effects are different across schools).

- Level-2 model was unconditional or did not include school-context variables. The consequence was that no cross-level interactions were considered.

Model

Level-1 Model

$$Post\text{-}test_{ij} = \beta_{0j} + \beta_{1j}*(school\text{-}centered\ baseline\ score_{ij}) + \beta_{2j}*(minority\ status_{ij}) + \beta_{3j}*(gender_{ij}) + \beta_{4j}*(\ school\text{-}centered\ grade\text{-}level_{ij}) + \beta_{5j}*(retained\ status) + \beta_{6j}*(intervention) + r_{ij}$$

Level-2 Model

$$\beta_{0j} = \gamma_{00} + \boldsymbol{u_{0j}}$$
$$\beta_{1j} = \gamma_{10}$$
$$\beta_{2j} = \gamma_{20}$$
$$\beta_{3j} = \gamma_{30}$$
$$\beta_{4j} = \gamma_{40}$$
$$\beta_{5j} = \gamma_{50}$$
$$\beta_{6j} = \gamma_{60}$$

Mixed Model

$$\begin{aligned}
&TESTRITS_{ij} = \gamma_{00} \\
&+ \gamma_{10}*school\text{-}centered\ baseline\ score_{iij} \\
&+ \gamma_{20}*minority\ status_{ij} \\
&+ \gamma_{30}*gender_{ij} \\
&+ \gamma_{40}*\ school\text{-}centered\ grade\text{-}level_{ij} \\
&+ \gamma_{50}*\ retained\ status\ _{ij} \\
&+ \gamma_{60}*\ intervention\ _{ij} \\
&+ \boldsymbol{u_{0j}} + r_{ij}
\end{aligned}$$

Figure 1. HLM2 random-intercept model specification for MAP Reading and Mathematics Ohio achievement data.

Reading Results

*Summary of Pooled Random-Intercept Model for MAP Reading Achievement Data (*N = *6759) across 100 Imputed Samples*

Fixed Effect	β	SE β	*t*-ratio	Approx. df	*p*
INTRCPT1, β_0					
INTRCPT2, γ_{00}	191.62	0.97	197.99	6311476	<.001
School-cent. baseline slope, β_1					
INTRCPT2, γ_{10}	0.07	0.00	27.55	1253	<.001
Minority status slope, β_2					
INTRCPT2, γ_{20}	2.19	0.37	5.94	15500	<.001
Gender slope, β_3					
INTRCPT2, γ_{30}	-1.30	0.33	-3.94	38649	<.001
School-cent. grade slope, β_4					
INTRCPT2, γ_{40}	7.03	0.15	45.77	10951	<.001
Retention status slope, β_5					
INTRCPT2, γ_{50}	-2.76	0.57	-4.88	28383	<.001
Intervention slope, β_6					
INTRCPT2, γ_{60}	2.35	0.34	6.90	74776	<.001

•The γ_{00} intercept of 191.63 represents a minority, non-intervention, average MAP Reading achievement in an average school between grades 3 and 4 (grade level was group- or school-centered) who was not retained in any grades between 2012-‘13 through 2015-‘16 academic years with an average STAR Early Literacy baseline measure (the baseline measure was group-centered).

Reading Results – Conditional Intra-Class Correlation (ICC)

	Estimate
Intercept~~Intercept|ID	34.602
Residual~~Residual	166.232
ICC|ID	0.172

Mathematics Results

Summary of Pooled Random-Intercept Model for MAP Mathematics Achievement Data (N = 6703) across 100 Imputed Samples

Fixed Effect	β	SE β	*t*-ratio	Approx. df	*p*
INTRCPT1, β_0					
INTRCPT2, γ_{00}	192.59	0.93	207.85	7398232	<.001
School-cent. baseline slope, β_1					
INTRCPT2, γ_{10}	0.07	0.00	33.95	1524	<.001
Minority status slope, β_2					
INTRCPT2, γ_{20}	2.44	0.32	7.67	17848	<.001
Gender slope, β_3					
INTRCPT2, γ_{30}	1.68	0.29	5.80	19274	<.001
School-cent. grade slope, β_4					
INTRCPT2, γ_{40}	8.19	0.13	61.05	7981	<.001
Retention status slope, β_5					
INTRCPT2, γ_{50}	-1.22	0.49	-2.46	18848	.014
Intervention slope, β_6					
INTRCPT2, γ_{60}	1.63	0.30	5.49	29722	<.001

•The γ_{00} intercept of 192.59 represents a minority, non-intervention, MAP Mathematics achievement of a student in an average school between grades 3 and 4 who was not retained in any grades between 2012-'13 through 2015-'16 academic year with an average STAR early literacy baseline measure.

Mathematics Results – Conditional Intra-Class Correlation (ICC)

	Estimate
Intercept~~Intercept|ID	32.341
Residual~~Residual	123.381
ICC|ID	0.208

Intervention Effect Sizes

- Reading: (Hedges' *g*) **.13** or SMALL

2.35 advantage points (β_6); given the annual (nine-month) growth of **7.03** points, this intervention advantage corresponded to approximately **3.0** months developmental advantage for the intervention students.

- Mathematics: (Hedges' *g*) **.10** or SMALL

1.63 advantage points (β_6); given the annual (nine-month) growth of **8.19** points, this intervention advantage corresponded to approximately **1.8** months developmental advantage for the intervention students.

Conclusions and Implications

- This study provided evidence for the efficacy of NURTURES in affecting student outcomes in early reading and mathematics in later grades when student level variables, namely gender, ethnicity and grade level were considered and the school context or between-schools variation properly accounted for.
- Overall, this study demonstrated that a *Framework*-aligned PD for early elementary educators can potentially lead to gains in student achievement in literacy, reading, and mathematics.
- Incorporating science inquiry instruction into early childhood classrooms may help to boost the reading and mathematics of young students.

Conclusions and Implications

- These results have implications for designers of science PD aimed at in-service early elementary educators.
- First, aligning science PD with the 3D *Framework* (NRC, 2012) may contribute to the gains seen in this study, as the science and engineering practices previously observed from NURTURES teachers (Tuttle, et al., 2016) align with the student gains measured in this study.
- This study suggests that achievement gaps in reading and mathematics can be addressed in part by providing *Framework*-aligned science instruction in early elementary classrooms.
- There are policy implications for teacher preparation, accreditation, and public funding for early childhood education.