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Title: Executive Function and Mathematics Achievement: Are Effects Construct- and Time-General or Specific?

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Abstract Body

Background / Context:

Executive function (EF) is considered a set of interrelated cognitive processes, including inhibitory control, working memory, and attentional shifting, that are connected to the development of the prefrontal cortex and contribute to children's problem solving skills and self-regulatory behavior (Best & Miller, 2010; Garon, Bryson, & Smith, 2008). EF skills are argued to be foundational for children to thrive in academic domains (Morrison, Cameron Ponitz, & McClelland, 2010), particularly for mathematics (Blair, Ursache, Greenberg, Veron-Feagans, & The Family Life Project Investigators, 2015). Consistent with this theory, EF measures are consistently found to correlate with children's mathematics achievement (Bull & Lee, 2014; Friso-van den Bos, van der Ven, Kroesbergen, & van Luit, 2013), and predict growth in mathematics using a variety of samples and analytic strategies (Blair et al., 2015; Fuhs, Nesbitt, Farran, & Dong, 2014; McClelland et al., 2014).

A recent meta-analysis, however, called the evidence for a causal effect of EF on later mathematics achievement into question (see Jacob & Parkinson, 2015, for review). Some correlational studies with strong sets of controls yield small estimates of the effect of EF on children's mathematics achievement (e.g., De Smedt et al., 2009; Duncan et al., 2007; Fitzpatrick & Pagani, 2012). Further, studies that have experimentally manipulated EF have found effects on children's mathematics achievement (e.g., Blair & Raver, 2014; Schmitt, McClelland, Tominey, & Acock, 2015), although some have not (e.g., Barnett et al., 2008). The skills targeted for manipulation in these interventions range from primarily EF-focused (e.g., Schmitt et al, 2014) to interventions that focus on EF skills and children's learning environments more broadly (Blair & Raver, 2014; Raver et al., 2011). Interventions with a broad scope may be a clinically useful strategy for enhancing children's EF and academic achievement. However, they make results theoretically difficult to interpret: treatment effects on achievement may be attributed to changes in EF, to changes to children's learning environments, or both (Jacob & Parkinson, 2015).

There are two potential reasons why prior work has yielded wide-ranging but consistent estimates of the effects of EF on children's mathematics achievement. First, studies have not fully addressed whether EF is related to mathematics through specific EF components (e.g., Friso-van den Bos et al., 2013; McClelland et al., 2014), a single underlying factor of EF (e.g., Fuhs et al., 2014; Wiebe, Espy, & Charak, 2008), or some combination. The current study attempts to unite previous research by examining if children's mathematics achievement is better predicted by a single underlying EF factor or specific EF tasks across four waves of data from the fall of prekindergarten to the spring of kindergarten. Compared to distinctions in EF components during later childhood and adulthood (Lee, Bull, & Ho, 2013; Miyake, Friedman, Emerson, Witzki, & Howerter, 2000), research primarily supports the existence of a single EF factor in early childhood (Allan & Lonigan, 2011; Fuhs et al., 2014; Wiebe et al., 2008). Second, some studies have used cross-lagged panel models that may not accurately account for all inter-individual differences, potentially resulting in overestimates of autoregressive and cross-lagged effects (Hamaker, Kuiper, & Grasman, 2015). This issue is relevant when interpreting the expected effects on mathematics achievement associated for boosting EF at specific time points. Thus, we examine if associations between EF and mathematics achievement are a function of time-general between person differences or time-specific variation. In other words, do factors influencing EF and mathematics achievement similarly across development account for EF and mathematics associations or do time-specific variations in EF predict subsequent changes in mathematics achievement?

Purpose / Objective / Research Question / Focus of Study:

The current study attempts to answer two complementary research questions to better understand associations between EF and mathematics in early childhood. First, the study examines whether children's mathematics scores are better predicted by a single EF factor or specific EF components (i.e., inhibitory control, working memory, attentional shifting). Given that EF tasks have been found to tap a single underlying EF factor in early childhood (e.g., Wiebe et al., 2008), we hypothesize that the EF factor will account for most of the task-specific EF associations with mathematics. Second, the study examines if associations between EF and mathematics are a function of time-general inter-individual differences or time-specific variation (i.e., cross-lagged effects). Large associations between EF and mathematics have been found (e.g., Fuhs et al., 2014); however, these estimates may be upwardly biased due to persistent inter-individual differences not fully statistically controlled in cross-lagged panel models (Hamaker et al., 2015). Prior work on children's mathematics achievement suggests that the factors that affect achievement similarly across development contribute more to the longitudinal stability of individual differences in children's mathematics achievement than the direct effects of children's previous achievement on their later learning (Bailey, Watts, Littlefield, & Geary, 2014). Thus, we hypothesize that the associations between EF and mathematics will be larger for the time-general factors than for cross-lagged, time-specific factors. That is, we expect factors that similarly effect performance across time in EF and mathematics to account for a large proportion of the stability in scores both within and across constructs.

Setting:

The current study uses data from a federally funded study in the Pacific Northwest region of the U.S. that focused on understanding the development of children's early cognitive and academic skills from preschool through kindergarten.

Population / Participants / Subjects:

In total, 435 children were recruited in the fall of preschool across two cohorts and followed through the spring of their kindergarten year (assessed in the fall and spring of prekindergarten and kindergarten year). Across the four waves, the sample was roughly 50% male, 50% low-income (i.e., enrolled in Head Start), 14% English language learners (ELL), and 35% non-White ethnicity (predominantly Latino or Pacific Islander). Children were approximately four and a half years old at wave one and just over six years old at wave four.

Intervention / Program / Practice:

Trained research assistants tested children over 2 – 3 sessions, lasting 10 – 15 minutes each on average. Children were tested in a quiet area in their school and the order of delivery of tasks was randomized to prevent order effects. A bilingual research assistant assessed children in Spanish if they were identified primarily as Spanish speakers (by the child's teacher).

Research Design:

Six EF tasks and a mathematics assessment were given to children at each wave. The Head-Toes-Knees-Shoulders (HTKS) task measures a combination of EF skills through gross motor responses (McClelland et al., 2014). The Card Sorting task, which is adapted from the more traditional Dimensional Change Card Sort, measures children's ability to shift attention and sort cards based on different rule sets (Blackwell, Cepeda, & Munakata, 2009). The Auditory Working Memory subtest from the Woodcock-Johnson III Tests of Cognitive Abilities (Woodcock, McGrew, & Mather, 2001b) measures verbal working memory. The Simon Says task measures children's ability to inhibit a dominant motor response and only respond when the tester says "[Insert Name] says…". The Day-Night Stroop task measures verbal inhibitory control, where children must suppress a dominant response for the opposite (Gerstadt, Hong, & Diamond, 1994). The Turtle task measures children's ability to draw slowly under instructions (versus a more natural motion; Kochanska, Murray, Jaques, Koenig, & Vandegeest, 1996). For mathematics, the Woodcock-Johnson Applied Problems subtest from the Woodcock Johnson Psycho-Educational Battery-III Tests of Achievement (Woodcock, McGrew, & Mathers, 2001a), measures early counting, addition, and subtraction skills, and escalates in difficulty to more complex multiplying, division, and geometry questions.

Data Collection and Analysis:

All data management and descriptive statistics were conducted using Stata 14 (StataCorp., 2015), and all structural equation modeling was conducted using M*plus* 7 (Muthen & Muthen, 2012). To answer the first research question of whether mathematics relations with EF are largely at the construct-general or construct-specific level, we examined the model fit indices for two sets of models that included the six EF tasks loading onto a general EF factor, but differed in the paths included to mathematics achievement. In the "EF Factor" models, we only include a regression path between the EF factor and mathematics. In the "Task-Specific EF" models, we include regression paths between the specific EF tasks and mathematics. Both sets of analyses were conducted for each of the four waves of data.

To answer the second research question regarding time-specific variations or time-general differences, we modeled the co-development of EF and mathematics achievement using a latent state-trait approach (Steyer, 1987). The model partitions variance into a time-general factor, which captures individual differences in EF and mathematics achievement that are similar across the four waves of data, and time-specific factors, which capture individual differences that are a function of the preceding time-point. Therefore, EF and mathematics at a specific wave are modeled as influenced by, (a) a time-general factor, (b) the preceding time-point for the same skill, (c) the preceding time-point for the other skill (i.e., a cross-lagged effect), and (d) unique sources of variance due to measurement error (Jackson, Sher, & Wood, 2000). We selected the EF task with the largest loading across waves from our previous analyses (i.e., the HTKS), rather than including all 6 tasks at each wave, to limit the number of parameters to be estimated in the model given our moderate sample size.

Findings / Results:

Descriptive statistics for the sample and measures at each wave are presented in Table 1. Overall, children's performance on the EF tasks and mathematics improved over time. Across the four waves, the EF tasks' correlations ranged in magnitude between rs = .12 – .56, with nearly all correlations significant at $p < .001$ (see Table 2).

(Insert Table 1)

(Insert Table 2)

Are children's mathematics scores better predicted by a EF factor or task-specific EF tasks across four waves of data? Our first set of analyses examined if the loadings of EF tasks onto a single EF factor tracked the bivariate correlations between EF tasks and mathematics (see Table 3). We found that this was the case, as the correlations between the task loadings and the task correlation with mathematics were rs = .76, .90, .95, and .78 across the four waves (n = 6 at each wave). These correlations support the hypothesis that the associations between EF tasks and mathematics achievement are related to how strongly EF tasks tap a single EF factor.

(Insert Table 3)

Our second set of analyses compared model fit indices between two sets of models that both included the specific EF tasks loading onto an EF factor (see Table 4). Across all four waves, the “EF Factor” model had the better BIC, more explained variance in mathematics (R^2 = .54 – .72), and a large, statistically significant coefficient between the EF factor and mathematics (*b* = .74*** – .85***). Furthermore, it shows good fit in terms of RMSEA, CFI, and TLI (Kline, 2005). However, the “Task-Specific EF” model had a better fit in terms of AIC, RMSEA, CFI, and TLI across all four waves. Furthermore, the χ^2 suggests statistically significant misfit for three of the four waves for the EF Factor model, but the Task-Specific EF model showed no significant misfit for any wave of data. Notably, the EF Factor model is statistically equivalent to estimating a single factor model, where children’s mathematics is an indicator of EF, along with the EF tasks. The loading of mathematics achievement on the EF factor is estimated to be .74, .81, .85, and .75 at each wave. Remarkably, this is higher than all of the specific EF task loadings at the third wave (Table 3), and higher than any of the specific EF task loadings other than the HTKS at all other waves. Taken together, the high (but non-unity; i.e., less than $r = 1$) correlations between general EF and mathematics, the good fit of both models, and the high loading of mathematics on the EF factor suggest that most, but not all, of the cross-sectional relations between EF task performance and mathematics achievement can be explained by an association between an EF factor and mathematics achievement.

(Insert Table 4)

Are associations between EF and mathematics a function of time-general inter-individual differences or a function of time-specific variation? The latent state-trait model including the co-development of EF and mathematics is shown in Figure 1. Model fit indices indicated excellent fit: $\chi^2(11) = 15.64$, $p = .16$, RMSEA = .032, CFI = .998, TFI = .994, and SRMR = .019. Overall, we find strong evidence of influences of time-general factors on EF and mathematics. For mathematics, we find the time-general factor loadings between .61*** – .83***, with time-specific autoregressive paths between .19 – .30***. For EF, we find the time-general factor loadings between .43*** – .68***, with time-specific autoregressive paths between .10 – .35***. We find a large significant correlation between the time-general factors of EF and mathematics, $r = .84$***, but no significant cross-lagged autoregressive paths between time-specific factors of EF and mathematics achievement (βs = -.057 – .092). This relation between EF and mathematics achievement may be due to children’s differences across development, which may include pre-existing differences in mathematics achievement, EF, other child characteristics, and/or stable external environmental influences on children’s development. It may also reflect an overlap in measurement between the EF measures and the math measure.

(Insert Figure 1)

Conclusions:

The current study suggests that the associations between EF and mathematics achievement may be a function of how well they tap a single underlying EF factor in early childhood (or an overlap in the measurement). Moreover, results support the hypothesis that the associations between EF and mathematics achievement are predominantly related to time-general inter-individual differences common to both constructs or measures, rather than time-specific variations. These findings fit within emerging theoretical and empirical evidence of the potential for EF interventions to transfer to mathematics achievement. In early childhood, children likely need interventions that are engaging and tap integrated aspects of EF (e.g., Schmitt et al., 2015), as well as persistent and sustained interventions over time (Diamond, 2012), and perhaps which directly integrate EF training and mathematics instruction, in order to find substantial and lasting transfer to academic domains.

Appendices

Appendix A. References

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Appendix B. Tables and Figures

Table 1
Descriptive Statistics for Demographics, EF tasks, and Math for Each Wave of Data

	N	Mean	SD	Range
Wave 1 Fall of Prekindergarten				
Male (% yes)	417	51.08		
Head Start (% yes)	417	54.92		
ELL (% yes)	417	14.39		
Non-White (% yes)	367	37.6		
Age	417	4.69	0.3	4.11 – 5.46
HTKS	400	17.56	17.28	0 – 58
Card Sort	406	13.69	6.68	1 – 23
Working Memory	399	2.85	3.14	0 – 17
Simon	408	0.711	1.42	0 – 5
Day-Night	406	23.95	8.78	0 – 32
Turtle	411	24.92	23.3	4.93 – 176.37
Math	401	410.17	23.3	301 – 467
Wave 2 Spring of Prekindergarten				
Male (% yes)	394	50.51		
Head Start (% yes)	394	54.31		
ELL (% yes)	394	15.23		
Non-White (% yes)	353	37.11		
Age	394	5.15	0.3	4.60 – 5.88
HTKS	385	25.18	18.37	0 – 60
Card Sort	387	16.51	5.93	2 – 23
Working Memory	385	4.22	4.12	0 – 18
Simon	387	1.47	1.9	0 – 5
Day-Night	386	26.84	7.24	0 – 32
Turtle	390	34.57	30.59	4.43 – 204.16
Math	391	419.83	23.11	301 – 481
Wave 3 Fall of Kindergarten				
Male (% yes)	308	50		
Head Start (% yes)	308	50.65		
ELL (% yes)	308	14.61		
Non-White (% yes)	291	36.43		
Age	307	5.67	0.3	5.10 – 6.52
HTKS	302	33.22	17.77	0 – 60
Card Sort	305	18.64	4.85	4 – 24
Working Memory	303	6.25	4.75	0 – 21
Simon	307	2.26	1.96	0 – 5
Day-Night	306	28.71	5.06	4 – 32
Turtle	306	46.97	47.19	5.03 – 486.95
Math	305	431.02	20.71	319 – 494
Wave 4 Spring of Kindergarten				
Male (% yes)	299	50.5		

Head Start (% yes)	299	50.84		
ELL (% yes)	299	14.05		
Non-White (% yes)	284	35.92		
Age	299	6.17	0.29	5.53 – 6.96
HTKS	295	39.24	16.03	0 – 60
Card Sort	295	19.79	3.89	6 – 24
Working Memory	294	8.58	5.26	0 – 25
Simon	293	2.73	1.88	0 – 5
Day-Night	296	29.4	4.43	4 – 32
Turtle	295	63.68	52.33	3.15 – 351.44
Math	295	442.09	19.29	363 – 507

Table 2
Correlations Between EF Tasks Across Four Waves

	1	2	3	4	5	6
Prekindergarten						
1. HTKS		0.53	0.39	0.50	0.33	0.37
2. Card Sort	0.48		0.33	0.34	0.26	0.34
3. WM[a]	0.34	0.27		0.37	0.25	0.27
4. Simon	0.40	0.31	0.34		0.18	0.24
5. Day-Night	0.36	0.30	0.17	0.25		0.20
6. Turtle	0.28	0.29	0.12[b]	0.22	0.17	
	1	2	3	4	5	6
Kindergarten						
1. HTKS		0.40	0.51	0.56	0.34	0.34
2. Card Sort	0.51		0.30	0.38	0.25	0.20
3. WM[a]	0.37	0.29		0.43	0.23	0.26
4. Simon	0.51	0.41	0.34		0.27	0.40
5. Day-Night	0.31	0.29	0.23	0.19		0.21
6. Turtle	0.34	0.23	0.20	0.27	0.15[b]	

Note. [a]Working Memory. Fall of the school year below the diagonal, spring of the school year above diagonal. [b]Significant at $p < .05$. All other correlations significant at $p < .001$.

Table 3
EF Tasks: Loadings onto underlying EF Factor, Bivariate Correlations with Math, and Reliabilities

	Loading on EF Factor	Correlation with Math	Cronbach's alpha
Wave 1 Fall of Prekindergarten (N = 417)			
HTKS	0.76	0.48	0.96
Card Sort	0.63	0.57	0.95
Working Memory	0.45	0.29	0.87
Simon	0.55	0.33	0.87
Day-Night	0.46	0.33	0.92
Turtle	0.40	0.34	0.72
Wave 2 Spring of Prekindergarten (N = 394)			
HTKS	0.81	0.60	0.96
Card Sort	0.64	0.61	0.93
Working Memory	0.52	0.41	0.89
Simon	0.59	0.45	0.89
Day-Night	0.40	0.33	0.91
Turtle	0.47	0.40	0.85
Wave 3 Fall of Kindergarten (N = 308)			
HTKS	0.79	0.62	0.96
Card Sort	0.64	0.60	0.91
Working Memory	0.48	0.46	0.88
Simon	0.64	0.50	0.85
Day-Night	0.38	0.33	0.86
Turtle	0.41	0.36	0.93
Wave 4 Spring of Kindergarten (N = 299)			
HTKS	0.79	0.59	0.95
Card Sort	0.50	0.51	0.88
Working Memory	0.62	0.47	0.87
Simon	0.72	0.45	0.82
Day-Night	0.41	0.30	0.85
Turtle	0.46	0.38	0.89

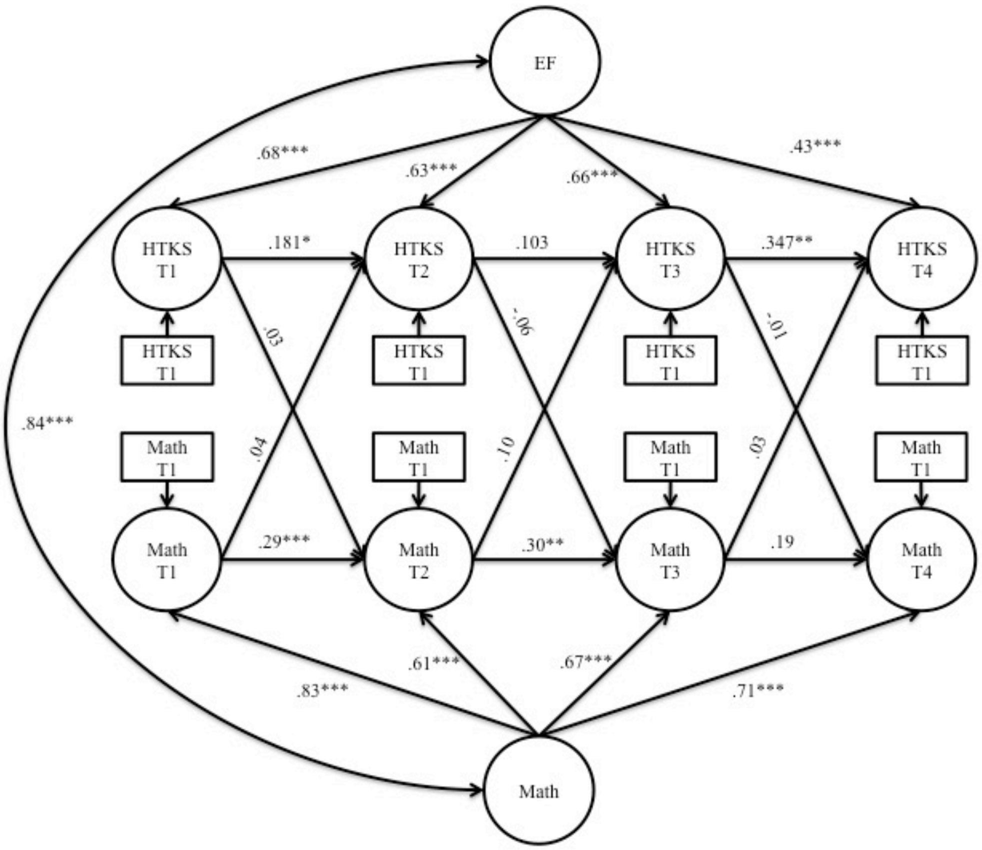
Note. All loadings and correlations significant at $p < .001$.

Table 4
Comparisons of underlying EF Factor Predicting Math and Task-Specific EF Predicting Math Across Four Waves

	EF Factor	Task-Specific EF
Time Point 1 (*N* = 417)		
Chi-square	32.19**	12.91
DF	14	9
RMSEA	0.056	0.032
CFI	0.968	0.993
TLI	0.953	0.984
AIC	19405.53	19396.26
BIC	19490.23	19501.12
R^2	0.543	0.427
Coef. Paths[a]	.74***	.17***, .37***, .08, .06, .11*, .15***
Time Point 2 (*N* = 394)		
Chi-square	24.98*	12.78
DF	14	9
RMSEA	0.045	0.033
CFI	0.985	0.995
TLI	0.977	0.988
AIC	18863.21	18861.01
BIC	18946.71	18964.39
R^2	0.657	0.526
Coef. Paths[a]	.81***	.24***, .34***, .11**, .13**, .09*, .12**
Time Point 3 (*N* = 308)		
Chi-square	14.35	6.63
DF	14	9
RMSEA	0.009	0.00
CFI	0.999	1.00
TLI	0.999	1.01
AIC	14769.24	14771.51
BIC	14847.57	14868.5
R^2	0.717	0.566
Coef. Paths[a]	.85***	.27***, .30***, .18***, .13**, .08*, .12**
Time Point 4 (*N* = 299)		
Chi-square	29.04*	7.77
DF	14	9
RMSEA	0.06	0.00
CFI	0.973	1.00
TLI	0.959	1.005
AIC	14092.31	14081.03
BIC	14170.01	14177.25
R^2	0.561	0.485
Coef. Paths[a]	.749***	.30***, .28***, .17**, .03, .05, .15**

Note. [a]For Task-Specific EF models, the coefficients are for the HTKS, Card Sort, Working Memory, Simon Says, Day-Night, and Turtle task, respectively. * $p < .05$; ** $p < .01$; *** $p < .001$.

Figure 1
Time-General versus Time-Specific Effects for EF and Math



Note. * $p < .05$; ** $p < .01$; *** $p < .001$.