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Moving beyond executive functions: Challenge preference as a predictor of academic achievement in elementary school

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Abstract
Intrinsic motivation and executive functions (EFs) have been independently studied as predictors of academic achievement in elementary school. The goal of this investigation was to understand how students' challenge preference (CP), an aspect of intrinsic motivation, is related to academic achievement while accounting for EFs as a confounding variable. Using data from a longitudinal study of 569 third-, fourth-, and fifth-graders (50% female), we tested students' self-reported CP as a predictor of mathematics and English language arts (ELA) achievement in multilevel models that controlled for school fixed effects and student demographic characteristics. CP was positively associated with mathematics and ELA over and above the set of covariates and EFs. While also controlling for prior achievement, CP continued to explain a small amount of unique variance in mathematics, but not in ELA. These results underscore the importance of including measures of students' intrinsic motivation, in addition to EFs, to obtain a comprehensive understanding of academic success.

Keywords: Challenge preference, Executive functions, Academic achievement, Elementary school, Longitudinal, Self-regulated learning

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Introduction

Executive functions (EFs), the higher-order cognitive skills that support goal-directed activities and self-regulation, have been extensively studied as predictors of academic achievement (Zelazo, Blair, & Willoughby, 2016). EFs are associated with learning-related classroom behaviors (Nelson et al., 2017) and have been identified as robust longitudinal predictors of academic achievement (Fuhs, Farran, & Nesbitt, 2015; Nguyen & Duncan, 2019). Yet research relating EFs to achievement has largely ignored the role of motivation (Howse, Lange, Farran, & Boyles, 2003), despite strong evidence that motivation plays a crucial role in student learning (Eccles & Wigfield, 2002). For example, intrinsic motivation— which refers to an individual's desire to participate in an activity because it is enjoyable in and of itself—underpins the pursuit of long-term goals (e.g., Wrzesniewski et al., 2014) and is positively related to academic achievement (Corpus & Wormington, 2014).

In this study, we focused on challenge preference (CP), an aspect of intrinsic motivation that refers to an individual's preference for challenging (as opposed to easy) activities (Harter, 1981). CP is a distinct construct that plays a crucial role in influential theories of learning and achievement. In Elliott and Dweck's (1988) achievement goal theory, challenge seeking (particularly in response to failure) is a key feature of learning goals that promote growth in achievement. Learning goals are characterized by a mastery orientation, in which individuals seek to increase their skills even if it means risking failure. In contrast, a performance orientation is characterized by an avoidance of challenging tasks, so as not to appear incompetent. Mastery orientation is positively associated with better learning outcomes (Huang, 2012).

Consistent with achievement goal theory, CP is positively associated with teachers' perceptions of elementary school students' learning-related classroom behaviors (Finch & Obradović, 2017). Moreover, previous research shows that students' self-reported CP (which has often been combined with other aspects of intrinsic motivation) has small to moderate associations with grade point average and standardized academic achievement test scores in elementary and middle school (Altermatt & Pomerantz, 2005; Broussard & Garrison, 2004; Goldberg & Cornell, 1998; Lepper, Corpus, & Iyengar, 2005; Soto, 1988).

However, longitudinal associations between CP and academic achievement have been understudied. We were able to identify a single empirical study investigating this relation, and that study was underpowered to detect the small effect sizes that are typical for predictors of change in academic achievement. In that study of 93 adolescents, self-reported CP was not significantly related to change in academic achievement between fifth and seventh grades (Bronstein, Ginsburg, & Herrera, 2005).

Moreover, no study has examined associations between CP and academic achievement while controlling for known associations between EFs and achievement. Consistent with the model of self-regulated learning, EFs and motivational processes are each believed to support academic learning (Zimmerman & Schunk, 2011). In other words, a student's ‘‘will" (motivation) and ‘‘skill" (EFs) independently contribute to learning-related classroom behaviors (McCombs & Marzano, 1990). To successfully learn new academic content, students must be ‘‘active participants" in their learning by engaging cognitively, motivationally, and behaviorally during classroom activities (Zimmerman, 1986, p. 308). CP motivates students to seek out opportunities to learn that extend beyond their current abilities, whereas EFs support students' abilities to stay on task, ignore distractions, control impulses, and shift flexibly between different ideas while engaging with learning-related challenges. Theoretically, students' CP supports *choosing* to engage in self-regulated behaviors that are crucial for classroom learning (McCombs & Marzano, 1990).

There is limited evidence that CP and other aspects of intrinsic motivation contribute to academic success *over and above* EFs. For example, we have previously reported unique effects of self-reported CP on teachers' reports of classroom behaviors (e.g., frustration tolerance, on-task behavior) while controlling for EFs in elementary school students (Finch & Obradović, 2017). Further, one study using a small sample of early elementary school students found that teachers' reports of student motivation contributed to reading achievement while controlling for an earlier measure of vocabulary and EFs (Howse et al., 2003). However, no study has examined how students' self-reported CP is linked to standardized assessments of academic achievement or has examined these constructs during middle childhood.

Third grade marks a significant change in children's schooling experiences, driven by the onset of standardized testing and a shift from basic reading instruction (''learning to read") to independent reading with a goal of learning content (''reading to learn"; Felton & Akos, 2011). Further, as children enter middle childhood, they are increasingly expected to regulate their behavior and monitor their progress on classroom tasks and assignments. Due to these new academic demands and behavioral expectations, many students struggle during the upper elementary school years and fall behind their peers academically (Annie E. Casey Foundation, 2010; Miles & Stipek, 2006). CP is particularly relevant during middle childhood, when children encounter more difficult schoolwork. Academic success and mastery goal orientation during the upper elementary school years are also associated with a positive transition to middle school (Anderman & Midgley, 1997; Tuominen-Soini, Salmela-Aro, & Niemivirta, 2012). This makes elementary school a particularly relevant developmental period for investigating prospective, longitudinal relations between CP and academic achievement. Given the high longitudinal stability of academic achievement, it is important to determine whether CP can predict changes in students' achievement and, thus, serve as a potential target for academic intervention.

The current study

We extended previous studies by testing the prospective longitudinal relations between student reports of CP and standardized achievement test scores in mathematics and English language arts (ELA). To understand unique associations of CP with academic achievement, we estimated a set of models that do not and do control for students' EFs. The purpose of these analyses was to reveal the strength of the relation between CP and achievement at a single point in time in elementary school and to show how much these relations are reduced when accounting for EFs, which are one of the most robust correlates of academic achievement. To understand the role that CP plays in predicting longitudinal change in achievement over a 2-year period, we estimated a second set of models in which we also controlled for prior achievement test scores.

Method

Participants and procedures

Participants in this study were 569 socioeconomically and ethnically diverse elementary school students (188 third-graders, 258 fourth-graders, and 123 fifth-graders) recruited from two public school districts (eight schools; 33 classrooms) in the San Francisco Bay Area on the U.S. West Coast. The percentage of students meeting or exceeding proficiency standards at these schools was 58% (*SD* = 19%) for mathematics and 69% (*SD* = 14%) for ELA. At these schools, a sizable percentage of students were eligible for free or reduced-price lunch (*M* = 42%, *SD* = 23%) and were classified as English language learners (*M* = 39%, *SD* = 19%). Student ages ranged from 8.00 to 12.29 years (*M* = 9.88 years, *SD* = 0.83), and 50% of the students were female. Racial/ethnic composition of the sample was as follows: 34% Asian/Pacific Islander, 31% Latinx/Hispanic, 23% White/Caucasian, 6% Black/African American, and 6% other/multiracial.

All study procedures were approved by the Stanford University Institutional Review Board and by the participating school districts. We obtained a waiver of consent for the classroom-based assessments and written parental informed consent to access administrative school records, which included achievement test data. Students were sampled at the classroom level within participating schools. Of the 813 students who were invited to participate in the study, 70% of parents gave informed consent for access to administrative school records. Data used in this longitudinal study were collected at three different times, each spaced approximately 1 year apart. First, initial standardized achievement tests were collected in the spring of 2013. Second, students' CP and EFs were assessed by the researchers in the spring of 2014. Third, follow-up standardized achievement tests were collected again in the spring of 2015.

Measures

Challenge preference

Students reported on their CP using a 5-question measure (Developmental Studies Center, n.d.). Each question asked students to choose between an easy scenario and a more challenging scenario (e.g., ‘‘I like a puzzle that is easy to solve” vs. ‘‘I like a puzzle that takes hard work to solve”) and was coded as a binary variable (0 = *easy,* 1 = *challenging*). The content of this scale included two items about puzzles, two items about games, and one item about a hard problem. In contrast to Harter’s (1981) challenge preference scale, none of the content was specific to an academic setting. We averaged the items for this scale to create a composite score, ordinal a = .83 (Gaderman, Guhn, & Zumbo, 2012). On average, students reported a preference for challenging activities (M = 0.73, SD = 0.29, range = 0–1).

Executive functions

We employed two independent measures of students’ EFs. Direct assessments are considered to be more objective than teachers’ reports, but they are less ecologically valid (Toplak, West, & Stanovich, 2013). In contrast, teachers’ reports can be biased by students’ demographic characteristics such as gender and race/ethnicity (Garcia, Sulik, & Obradović, 2019), but they have the advantage of capturing students’ EF behaviors as they occur in naturalistic learning contexts. The inclusion of both types of assessments provides a more comprehensive and robust way to capture students’ EF skills.

Direct assessments. Four widely used, developmentally appropriate tasks were used to directly assess students’ EF skills. Group-based assessments were used to minimize disruption for teachers and students. The tasks were simultaneously administered to all students in each classroom using tablet computers, which has been shown to be as valid and reliable as individual administration of the same tasks (Obradović et al. 2018). Relative to individual assessments, these group-based assessments may have greater ecological validity because they occur in a naturalistic classroom setting. The EF tasks were presented in a fixed order and included (a) the Multi-Source Interference Test (Bush & Shin, 2006; a = .81), a measure of inhibitory control; (b) Hearts & Flowers (Davidson, Amso, Anderson, & Diamond, 2006), a measure of inhibitory control and cognitive flexibility; (c) Flanker, also a measure of inhibitory control and cognitive flexibility (Zelazo et al., 2013); and (d) Digit Span Backward (Flanagan & Kaufman, 2009), a measure of working memory. Hearts & Flowers and Flanker each included two blocks of test trials. Cronbach's *a* values ranged from .58 (Digit Span Backward) to .81 (Multi-Source Interference Test). Based on results of confirmatory factor analysis (Sulik & Obradović, 2018), accuracy scores were first aggregated within the Hearts & Flowers task and within the Flanker task, and then scores were standardized and averaged across the four tasks to create an EF composite score (*a* = .67).

Teachers' reports. To obtain teachers' perceptions of student EFs, we asked each teacher to rank the students on the teacher's class roster based on how well they exemplified a vignette describing a student with good EF skills (see the Appendix; Sulik & Obradović, 2018). The statements that make up the vignette assess all three components of EFs—inhibitory control, cognitive flexibility, and working memory—and emphasize behaviors that can be easily observed by teachers and that are relevant to learning. We reversed the ranking scores so that high scores would indicate better EFs, and we converted the ranks to percentiles to adjust for differences in classroom size. We applied a probit transformation to the ranking scores to normalize their distribution.

Academic achievement

Students' mathematics and ELA achievement were measured using standardized achievement tests administered by the State of California. In the spring of 2013, the California Standards Test (CST) was used (Educational Testing Service, 2014). In the spring of 2015, following the adoption of the Common Core State Standards, the Smarter Balanced Assessment Consortium (SBAC, 2016) was used. Item response theory was used to score these tests. Reliability in the population of California students was excellent; depending on grade and content area, CST reliability (*a*) ranged from .93 to .95 and SBAC reliability (*q*) ranged from .91 to .93.

Covariates

Parental years of education, child gender, child race/ethnicity, and child age were obtained from school administrative data. Parental years of education was included as a covariate because of socioeconomic disparities in both EFs and achievement (Lawson, Hook, Hackman, & Farah, 2014; Reardon, 2011). Child gender and child race/ethnicity were included as covariates due to previous research demonstrating gender and racial/ethnic differences on teacher-reported EFs (Garcia et al., 2019). Finally, child age was included as a covariate because it is associated with better EFs (Lee, Bull, & Ho, 2013) and less CP (Lepper et al., 2005).

Subsample representativeness

To evaluate the representativeness of our subsample compared with the larger study sample, we tested whether there were differences on study variables that were not drawn from school records between students with (n = 569) and without (n = 244) consent for school records. We were not able to test for differences in achievement variables because these scores were available only for students with consent for school records. CP, gender, and age were not significantly associated with parental consent to access school records. There were two significant differences among the seven measures of EFs, namely that teacher-reported EFs, $t(759) = 4.90$, $d = 0.40$, and Digit Span Backward performance, $t(707) = 2.60$, $d = 0.22$, were better in the group with parental consent to access school records.

Missing data and attrition

Missing data percentages in our analytic subsample ranged from 0% for age and gender to 16% for parent educational attainment. A total of 37 students (7%) were missing academic achievement scores in 2013. Students were more likely to have missing achievement data in 2013 if they were African American/Black, $t(564) = 4.01$, $p < .001$, or other/multiracial, $t(564) = 3.56$, $p < .001$ (relative to White/Caucasian students); if they had higher math test scores, $t(483) = 3.83$, $p < .001$, and reading test scores, $t(482) = 3.37$, $p < .001$, in 2015; if they were rated by teachers as having worse EFs, $t(546) = 4.08$, $p < .001$; and if they had worse performance on Flanker incongruent trials, $t(508) = 3.00$, $p = .003$.

A total of 84 students (15%) were missing academic achievement test scores in 2015. Students were more likely to have missing achievement data in 2015 if they were Asian/Pacific Islander, $t(564) = 2.\ 04$,

p = .042 (relative to White/Caucasian); were female, $t(567) = 2.35$, p = .019; and were older, t (567) = 3.70, p < .001.

Analytic strategy

Multiple imputation using chained equations was used to address missing data (van Buuren, 2012). A total of 20 data sets were imputed using a single-level imputation model that included classroom fixed effects (Drechsler, 2015). Analyses were run on each imputed data set separately, and parameter estimates were pooled across imputations. We used multilevel modeling to test CP as a predictor of mathematics and ELA achievement. In all models, demographic covariates included age, gender, race/ethnicity, and parental educational attainment. We centered CP and EFs around each classroom's mean to rule out selection into classrooms as a potential confound. Effect sizes were quantified using the change in model R^2 (Nakagawa & Schielzeth, 2013).

Results

Bivariate associations

Correlations and descriptive statistics are presented in **Table 1**. CP was positively correlated with directly assessed EFs (r = .21, p < .001) and teacher-reported EFs (r = .09, p = .002). Directly assessed EFs and teacher-reported EFs were positively correlated with each other (r = .31, p < .001). CP and both measures of EFs were positively associated with all measures of achievement (rs ranged from .28 to .53, ps < .001). Older students reported greater levels of CP (r = .09, p = .002) and had better performance on direct assessments of EFs (r = .20, p < .001), earlier ELA achievement tests (r = .07. p = .014), and later mathematics and ELA achievement tests (rs = .20 and .27, respectively, ps < .001). Girls reported lower levels of CP than boys (r = .11, p < .001), were reported by teachers as having better EFs (r = .34, p < .001), and had slightly better ELA achievement test scores in 2013 and 2015 (rs = .09 and .12, p = .003 and p < .001, respectively). Finally, parental educational attainment was positively associated with CP (r = .18, p < .001), performance on

Table 1 Correlations and descriptive statistics.

	1	2	3	4	5	6	7	8	9	10
1. Challenge preference	—									
2. EFs, directly assessed	.21*	—								
3. EFs, teacher reported	.09*	.31*	—							
4. Mathematics (2013)	.28*	.43*	.38*	—						
5. English language arts (2013)	.30*	.47*	.39*	.75*	—					
6. Mathematics (2015)	.33*	.51*	.40*	.75*	.71*	—				
7. English language arts (2015)	.28*	.53*	.43*	.62*	.75*	.81*	—			
8. Child age (years)	.09*	.20*	.01	.02	.07*	.20*	.27*	—		
9. Female child	–.11*	.06*	.34*	–.01	.09*	–.01	.12*	–.10*	—	
10. Parent education (years)	.18*	.18*	.10*	.29*	.39*	.38*	.39*	.07*	–.04	—
Mean or %	0.73	0.00	0.10	409.20	365.17	2512.91	2502.94	9.88	50%	13.76
Standard deviation	0.29	1.00	0.96	91.85	69.06	88.26	95.77	0.83	–	3.44
Skewness	–0.87	–1.26	–0.07	0.22	0.20	0.01	–0.11	0.09	–	–0.48

EF: executive function.
* $p < .05$ using the Benjamini–Hochberg adjustment for multiple testing (Benjamini & Hochberg, 1995).

direct assessments of EFs ($r = .18$, $p < .001$), teacher-reported EFs ($r = .10$, $p = .001$), and academic achievement (*r*s ranged from .29 to .39, *p*s < .001).

Multilevel models for mathematics and English language arts

We used intraclass correlations (ICCs) to quantify the proportion of variance in academic achievement at the classroom level. ICCs were .23 for mathematics and .25 for ELA. EFs and CP were centered around each classroom's mean to obtain an unbiased estimate of the within-classroom (i.e., student-level) associations (Enders & Tofighi, 2007); this procedure is equivalent to the inclusion of classroom fixed effects and rules out selection effects because we are estimating only within-classroom effects, not between-classroom effects.

In our first set of models, we did not control for prior achievement. These models provide information about whether—and to what degree—CP was associated with students' academic achievement while controlling for the set of covariates. Model 1A included school fixed effects and the following demographic covariates: parents' educational attainment and students' gender, age, and race/ethnicity. Model 1B added student EFs (direct assessments and teachers' reports) to Model

1A. In our second set of models, we added controls for prior achievement to understand the role that CP plays in predicting change in achievement; Models 2A and 2B added prior achievement to Models 1A and 1B, respectively.

Predicting academic achievement

A baseline model (Model 1A) that included school fixed effects and demographic covariates explained 33.5% of the variance in mathematics and 35.2% of the variance in ELA. When CP was added to this model, it was positively associated with mathematics (β = .20, *SE* = .02, $p < .001$) and ELA (β = .15, *SE* = .03, $p < .001$). CP increased the model R^2 by 3.6% (to 37.1%) for mathematics and by 2.3% (to 37.4%) for ELA.

We estimated a second baseline model (Model 1B) that included student EFs in addition to school fixed effects and demographic covariates. This model explained 48.8% of the variance in mathematics and 52.0% of the variance in ELA. When CP was added to this model (see **Table 2**), it was positively associated with mathematics (β = .14, *SE* = .02, $p < .001$) and ELA (β = .09, *SE* = .02, $p < .001$). CP increased the model R^2 by 1.8% (to 50.6%) for mathematics and by 0.7% (to 52.7%) for ELA.

Table 2 Multilevel regression analyses predicting academic achievement without controls for prior achievement.

	Mathematics			English Language Arts		
	β	*(SE)*	*p*	*β*	*(SE)*	*p*
Intercept	0.16	(0.18)	.358	0.07	(0.17)	.680
Female child[a]	–0.19	(0.05)	<.001	0.09	(0.05)	.056
African American/Black[a,b]	–0.63	(0.11)	<.001	–0.60	(0.11)	<.001
Hispanic/Latino[a,b]	–0.42	(0.08)	<.001	–0.25	(0.08)	.001
Asian/Pacific Islander[a,b]	0.03	(0.08)	.709	–0.12	(0.08)	.104
Other/multiracial[a,b]	–0.19	(0.11)	.096	–0.18	(0.10)	.067
Child age (years)	0.09	(0.04)	.040	0.15	(0.04)	<.001
Parent education (years)	0.10	(0.03)	<.001	0.12	(0.03)	<.001
EFs, directly assessed	0.21	(0.03)	<.001	0.23	(0.03)	<.001
EFs, teacher reported	0.30	(0.03)	<.001	0.30	(0.03)	<.001
Challenge preference	0.14	(0.02)	<.001	0.09	(0.02)	<.001

EFs = executive functions. Models also control for school fixed effects.
a. Coefficients for dummy codes are standardized for the dependent variable only.
b. Reference category is "White/Caucasian."

Predicting change in academic achievement

For this analysis, our first baseline change model (Model 2A) included school fixed effects, demographic covariates, and prior achievement test scores. This model explained 62.8% of the variance in mathematics and 65.3% of the variance in ELA. While controlling for these covariates (see **Table 3**), CP was positively associated with change in mathematics (β = .07, *SE* = .02, *p* < .001) but was unrelated to change in ELA (β = .00, *SE* = .02, *p* = .977). Adding CP increased the model R^2 by 0.4% (to 63.2%) for mathematics.

We estimated a second baseline change model (Model 2B) that included student EFs in addition to school fixed effects, demographic covariates, and prior achievement test scores. This model explained 64.9% of the variance in mathematics and 67.3% of the variance in ELA. When CP was added to this model, it remained a significant predictor of change in mathematics achievement (β = .06, *SE* = .02, *p* = .002) and did not predict change in ELA achievement (β = .00, *SE* = .02, *p* = .910). For mathematics, CP increased the model R^2 by 0.3% (to 65.2%).

Table 3 Multilevel regression analyses predicting academic achievement with controls for prior achievement.

	Mathematics			English Language Arts		
	β	*(SE)*	*p*	*β*	*(SE)*	*p*
Intercept	0.00	(0.16)	.996	–0.06	(0.17)	.709
Prior Achievement	0.47	(0.02)	<.001	0.49	(0.02)	<.001
Female child[a]	–0.06	(0.05)	.224	0.09	(0.04)	.024
African American/Black[a,b]	–0.37	(0.10)	<.001	–0.51	(0.11)	<.001
Hispanic/Latino[a,b]	–0.22	(0.07)	<.001	–0.09	(0.06)	.175
Asian/Pacific Islander[a,b]	0.06	(0.06)	.360	–0.04	(0.06)	.554
Other/Multiracial[a,b]	–0.14	(0.10)	.148	–0.12	(0.09)	.156
Child age (years)	0.17	(0.04)	<.001	0.15	(0.04)	<.001
Parent education (years)	0.05	(0.03)	.086	0.06	(0.03)	.025
EFs directly assessed	0.10	(0.02)	<.001	0.09	(0.03)	<.001
EFs teacher reported	0.13	(0.03)	<.001	0.14	(0.03)	<.001
Challenge preference	0.06	(0.02)	.002	0.00	(0.02)	.910

EF, executive function. Models also control for school fixed effects.

a. Coefficients for dummy codes are standardized for the dependent variable only.

b. Reference category is "White/Caucasian."

Sensitivity analyses

We conducted two sets of sensitivity analyses (Duncan, Engel, Claessens, & Dowsett, 2014). First, we repeated the analyses without centering within classroom; our results were not substantively changed by the choice of centering method. Second, previous research suggests that the validity of questionnaire measures can be compromised for younger children (Borgers, de Leeuw, & Hox, 2000). Because CP was measured using 8- to 12-year-olds' self-reports, we tested age as a moderator of the relation between CP and academic achievement. This interaction was not related to ELA or mathematics achievement, indicating that the predictive validity of students' self-reported CP did not differ between younger and older students.

Discussion

The goal of this investigation was to understand the role of CP for elementary school students' academic achievement. Our findings are consistent with previous studies showing that students' self-reported CP (Altermatt & Pomerantz, 2005; Soto, 1988) and a broader intrinsic motivation construct that includes CP (Broussard & Garrison, 2004; Goldberg & Cornell, 1998; Lepper et al., 2005) are significantly related to academic outcomes. Extending this work, we showed that CP is a prospective longitudinal predictor of students' performance on standardized achievement tests. We also found that CP and EFs were independent predictors of academic achievement, supporting a theoretical model of self-regulated learning in which intrinsic motivation and cognitive skills jointly contribute to learning (McCombs & Marzano, 1990; Zimmerman & Schunk, 2011).

The unique contribution of challenge preference and executive functions

Intrinsic motivation and EFs have rarely been studied together, especially in upper elementary school grades. As a result, we lack even basic descriptive knowledge about the bivariate associations between CP and EFs during this developmental period. We found positive correlations between CP and EFs, which affirms the need to study these constructs together to understand their unique associations with achievement. Accounting for EFs as a potential confound reduced the associations between CP and academic achievement by 50% or more—but did not completely eliminate the unique effects of CP.

The inclusion of CP and multiple measures of EFs in the same model is also useful because it allows us to compare the relative effect sizes for each construct. This comparison revealed that unique effects were largest for teacher-reported EFs, followed by directly assessed EFs and CP. Although teacher-reported EFs are designed to measure students' EF-related behaviors in the classroom, they are also influenced by teacher–child relationships, students' demographic characteristics, and teachers' prior knowledge of students' academic achievement (Garcia et al., 2019). It is likely that teacher-reported EFs capture a variety of students' experiences in the classroom that contribute to academic achievement.

The importance of challenge preference for academic achievement

Our study showed that students' CP was uniquely related to their performance on both mathematics and ELA achievement tests over and above the significant contributions of students' age, gender, and race/ethnicity—as well as parents' educational attainment, teachers' reports of EF classroom behaviors, and direct assessment of EF skills. However, our CP measure significantly predicted 2-year longitudinal *change* only for mathematics test scores. This divergent finding between mathematics and ELA could be due to the content of our CP assessment. The CP scale that we used in this study was composed of items about students' preferences for challenging games, tasks, puzzles, and problems. It is possible that the content of our measure (e.g., puzzles) is more relevant to solving math problems than it is to ELA. One important direction for future research will be to understand whether CP is a unidimensional construct or whether there are meaningful distinctions among specific domains of CP (e.g., academic, sport, art) that can be linked to achievement in different areas. Understanding the underlying structure of CP would inform educators' efforts to promote it in school settings.

Further, there is a need to better understand how CP is related to other aspects of intrinsic motivation such as growth mindset—the belief that abilities are malleable rather than fixed. Persistence in the face of challenges has long been studied as an outcome in growth mindset experiments (Dweck, 1991). For example, growth mindset instructions have been shown to increase persistence in an educational game, particularly among struggling students (O'Rourke, Haimovitz, Ballweber, Dweck, & Popović, 2014). To our knowledge, researchers have not studied associations between CP and growth mindset in the absence of experimental manipulation and have not examined these two aspects of intrinsic motivation together in order to understand which one is a stronger predictor of academic achievement. Clarifying the degree to which CP and other aspects of motivation differentially promote positive student outcomes can both advance our understanding of the structure of the intrinsic motivation construct and guide approaches to fostering intrinsic motivation in elementary school students.

To contextualize the effect sizes for CP, we look to other motivational constructs that have been studied much more extensively. For example, meta-analyses indicate that the average bivariate correlation (r) with academic achievement (i.e., in the absence of any control variables) is only .10 (R^2 = 1.0%) for growth mindset (Sisk, Burgoyne, Sun, Butler, & Macnamara, 2018) and .13 (R^2 = 1.7%) for mastery goal orientation (Huang, 2012). For comparison, the correlations between CP and achievement in our study were substantially larger: .33 for math and .28 for ELA. The effect size for CP from the multilevel models is difficult to compare to previous research because of the unique set of covariates used in this study.

It is important to note, however, that the rigorous analytic approach used in this study provides a conservative estimate of the relations between CP and academic achievement. First, by using multilevel models that include school fixed effects and by centering the predictors within each classroom, we were able to rule out alternative explanations for the findings—such as selection effects. This is particularly important because sociodemographic characteristics such as income and race show strong clustering effects at the school level in the United States (Orfield, Ee, Frankenberg, & Siegal-Hawley, 2016; Owens, Reardon, & Jencks, 2016), where this study was conducted. Because of our analytic approach, CP could not explain any between-classroom variance. Second, obtaining increases in the model R^2 becomes progressively more difficult as the amount of variance explained by other predictors increases. Simply put, there is less unique variance in the dependent variable that is left to be explained by additional predictors. This is most notable for analyses in which we control for prior academic achievement because of the extremely strong longitudinal relations between achievement test scores (Adachi & Willoughby, 2015). Therefore, it is not surprising that CP explained a modest amount of unique variance in students' achievement score change over time.

Challenge preference: Measurement implications

Our measure of CP was short (i.e., five questions) and used a binary response scale. This approach was similar to other child surveys assessing mindsets (e.g., Cain & Dweck, 1995). This developmentally appropriate format helped to ensure that elementary school students understood the questions and could provide valid responses. Indeed, sensitivity analyses indicated that our results did not depend on age, suggesting that younger and older students understood the questions equally well. In contrast to our measures of EFs, which incorporated students' performance on four tasks as well as teachers' reports, our sole measure of CP was based on students' self-reported responses to hypothetical situations. It is possible that direct assessments of CP would have greater validity or would provide additional predictive utility.

There is a pressing need to develop and validate scalable direct assessments of intrinsic motivation. Extant direct assessments of CP—such as having children choose whether they would like to do a task that they know they can do (i.e. that makes them think a little) or a task that is more challenging (i.e. that makes them think a lot)—have previously been used only in preschool samples (Howse et al., 2003; Smiley & Dweck, 1994; Stipek & Ryan, 1997). These existing tasks use only one or two questions, and information about their reliability and validity is lacking. Adapting and expanding on these measures for use in elementary school and beyond would help to scale up research on the development of intrinsic motivation and its relation with academic achievement with larger and more representative samples. A multi-informant approach could also prove to be useful; currently, there are no validated teacher or parent report scales to measure child CP.

Challenge preference: Implications for classroom practice

Motivational characteristics—such as CP—are particularly attractive as intervention targets because treatment can be brief, inexpensive, and scalable (Lazowski & Hulleman, 2016; Paunesku et al., 2015). For example, interventions targeting students' mindsets can be effective in as little as a single session (Sisk et al., 2018). Prior research demonstrates that students display more CP and persistence when teachers praise students' effort rather than their intelligence (Mueller & Dweck, 1998). An experiment similarly showed that children exhibited significantly more persistence on a challenging puzzle task when they were provided with process praise (e.g., ''You must have tried really hard") compared with when they were provided with person praise (e.g., ''You're really good at this") (Kamins & Dweck, 1999). Therefore, teacher feedback focused on effort encourages students to persist when learning activities are difficult—which is particularly important during the upper elementary school years, when academic demands are significantly higher. Our results suggest that this kind of feedback could have benefits for students' achievement via increases in students' CP.

Furthermore, autonomy support in the classroom has been positively linked to children's intrinsic motivation, including CP (e.g., Bartholomew et al., 2018; Ciani, Middleton, Summers, & Sheldon, 2010). Autonomy support is a broad term encompassing teacher practices such as listening to student perspectives, providing rationale for teacher requests, and allowing students to give input and feedback on learning activities (Cheon, Reeve, Lee, & Lee, 2018). A meta-analysis of autonomy support interventions for teachers demonstrates that a relatively brief session (1–3 hours) focused on skill-based activities can significantly increase autonomy support in classrooms (Su & Reeve, 2011). Further, autonomy support interventions for teachers have been successful at improving students' intrinsic motivation (Guay, Valois, Falardeau, & Lessard, 2016; Hastie, Rudisill, & Wadsworth, 2013; Tessier, Sarrazin, & Ntoumanis, 2010). Changing classroom environments could help to mitigate documented declines in children's intrinsic motivation and CP as they age (Harter, 1981; Lepper et al., 2005) and support children's challenge seeking through the middle childhood years.

In comparison with interventions targeting students' mindsets (Paunesku et al., 2015), EF interventions tend to be more time and resource intensive (Diamond & Ling, 2016), suggesting that educational interventions targeting CP or other aspects of intrinsic motivation may have a more favorable cost–benefit ratio than EF interventions.

Limitations

In addition to measurement issues discussed above, the current study had several limitations. First, the measures of CP and directly assessed EFs had relatively low estimates of reliability. Measurement error could result in an underestimate of the effect size of the relations between CP and EFs as well as their associations with achievement. Conversely, measurement error could lead to overestimates of the *unique* associations between each construct and achievement because of inadequate statistical controls. In future work, a latent variable approach could mitigate the effects of measurement error. Second, because CP was measured only once, we were unable to test bidirectional relations between achievement and CP. Researchers have shown that academic achievement can predict intrinsic motivation (Bronstein et al., 2005; Garon-Carrier et al., 2016). One direction for future research will be to understand whether academic achievement is prospectively related to change in CP. Third, we examined EFs as a unitary construct because only four EF tasks were included in this study. Ideally, researchers would examine CP together with three EF skill domains (i.e., inhibitory control, cognitive flexibility, and working memory), especially because working memory is believed to be particularly important for math achievement (Friso-van den Bos, van der Ven, Kroesbergen, & van Luit, 2013).

Conclusion

Children who seek out challenges are believed to have more opportunities to learn and grow their skills (Elliott & Dweck, 1988). That view is supported by the findings from this prospective longitudinal study. Even while controlling for students' demographic characteristics and EFs, CP was associated with mathematics and ELA achievement, and it predicted change in mathematics achievement. The next steps for this line of research are to test whether interventions and teaching strategies that promote CP in elementary school students also benefit academic achievement.

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Appendix

Executive functioning vignette

Please read the following vignette and then rank your students. Put the student name who is best described by the vignette first and the student name who is most poorly described by the vignette last:

> This child easily adjusts to a new situation such as a change of teachers or class plans. S/he is also good at accepting new ways to solve a problem with schoolwork or friends. This child is good at remembering activities that include several steps and is able to finish them without being prompted or reminded. This child has good control over her/his actions—follows classroom rules (e.g., stays in assigned seat, raises hand), doesn't interrupt others, and knows how to take turns. This child is good at staying focused on a difficult or repetitive task. S/he is not easily distracted by irrelevant noises and sights. This child's backpack and desk are organized and s/he is good at keeping track of homework, permission slips, and lunch money. This child is careful and always checks work for mistakes.

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