Individual Differences in Learning v. Achievement: What self-regulation *really* predicts

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Submitted in partial fulfillment of the requirements for the degree of
Doctor of Philosophy
under the Executive Committee of the Graduate School of Arts and Sciences

COLUMBIA UNIVERSITY

2016

Abstract

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What makes some students more effective learners and better academic performers than others? Is the answer identical with respect to learning and academic achievement, or do the contributing factors differ? I examined two kinds of self-regulation – cognitive regulation and behavior regulation – as predictors of individual differences in middle-school students' learning and academic achievement. The type of learning investigated here is that of inductive learning, where knowledge must be discovered or constructed by the learner – the knowledge is not given to them, rather it is induced based on newly found evidence in light of preconceived beliefs.

Across two studies, one a pilot study with underachieving students of lower socioeconomic status (SES) (n=21) and the other a larger study with a wider range of lower to middle SES students (n=135), results were consistent. A measure of cognitive regulation, but not behavior regulation, predicted learning effectiveness on an inquiry learning task adapted for this study. Behavior regulation, but not cognitive regulation, predicted academic achievement (assessed by state-administered standardized achievement tests).

Longitudinal analyses were conducted to determine whether two distinct self-regulatory processes predicted change in academic performance. Cognitive regulation predicted improvement in math scores, while behavior regulation did not. Behavior regulation, however, showed little predictive power to English scores, and cognitive

regulation showed none. Finally, to better understand the directional associations of these variables, structural equation modeling was performed. Results suggested that it is indeed cognitive regulatory processes, not behavior regulation, that predict learning effectiveness, which in turn predict improvement on both Math and English standardized test scores.

These results support the conclusion that (a) learning and academic achievement are distinct constructs, and (b) cognitive regulation and behavior regulation are related, but distinct, processes of self-regulation, with cognitive regulation the more consequential as a long-term predictor of both learning and academic achievement.

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Acknowledgments

I wish to thank my doctoral advisor, Deanna Kuhn, for her guidance, patience, and unparalleled mentorship throughout my time at Columbia University. No doctoral student ever had a better advisor. Thank you for being exactly what I needed. Go bears.

Unconditional gratitude is expressed to my committee members Professors Jeanne Brooks-Gunn, Kimberly Noble, Tory Higgins, and Nim Tottenham, for their valuable feedback and commentary throughout my dissertation procedures. I give special thanks to Professor Anne Conway, who has generously given me so much of her time over the past years and for pushing my boundaries in quantitative work. I would also like to thank Professor Amanda Geller and Professor Irv Garfinkel for incorporating me into Columbia University's Population Research Center and the Fragile Families working group.

I thank my family for being so supportive throughout my entire career. Thanks to my mom, who has provided unconditional support.

My undergraduate advisors at UC Berkeley's Department of Psychology, Professors Joseph Campos, Dacher Keltner, and Alison Gopnik all introduced me to the world of research. I thank them for the wide range of experiences in their labs that truly led me to my doctoral studies in Developmental Psychology. Stephen Hinshaw: Thank you for everything; please don't ever change.

To my primary undergraduate advisor at the Goldman School, Bob Reich – words just won't do you justice. So, for you (as always) I'll keep it short: you made all the difference and I am eternally grateful. Thank you for giving everything meaning. No student ever had a better teacher. SMA: high five.

Finally, I would like to thank Willard Middle School in Oakland, California, for teaching me beyond what any textbook or degree could ever offer. I thank all the students I worked with there, and think of them all the time. They showed me exactly what I needed to know, what's worth knowing, and what questions I needed to ask.

◆

Moreover, I thank my father who, from the day I was born, to the day he passed, only wanted every opportunity to be available to me.

◆

for Courtney

CHAPTER I: Introduction & Literature Review

Why do some young adolescents learn more effectively than others or perform better in school? This twofold question addresses two arguably distinct processes in education – learning and academic performance. If school is intended to train students to perform well and score high on standardized tests, one can argue that our society has addressed, and moved toward, achieving exactly that intention. However, if education is aimed at more than just performance and is intended to foster learning and the development of learning skills, it is highly debatable, that schools are accomplishing this goal as well as they should be. What education should be, as Albert Einstein said, is not the learning of facts, but the training of the mind to think.

School achievement is a topic at the forefront of Americans' concern, as US students continue to perform poorly in international comparisons (Cutright & Fernquist, 2014). Particularly in urban underachieving classrooms, classroom atmosphere has been a focus, the idea being that high behavioral standards and expectations must be imposed and maintained if the classroom environment is to be conducive to students' learning. Ideally, once high behavioral standards are in place (Duckworth et. al., 2009), students gradually become able to regulate their own behavior and become more autonomous and effective learners.

It is in this respect that inquiry learning skills become central. As Plutarch said, "the mind is not a vessel to be filled but a fire to be kindled." Inquiry learning involves students directing their own acquisition of knowledge, ideally in a way that parallels the way scientists study the world (NRC, 1996). In the course of inquiry activities, students direct their own investigatory activity, in contrast to committing to memory information conveyed to them for later retrieval (de Jong & van Joolingen, 1998).

Inquiry Learning

Inquiry allows students to acquire new knowledge, but it also helps them to develop their own independent learning skills, so that as adults they will be able and disposed to acquire the further knowledge they will need. Students come to understand that they are able to acquire knowledge they desire, by initiating, managing, and executing knowledge acquisition on their own. This understanding is empowering.

Young adolescents are cognitively and developmentally more able than younger children to take on a high level of independence and personal control (Pintrich & Schunk, 2002). More often than not, however, sufficient opportunities to develop and exercise their autonomy within the classroom is lacking (Feldlaufer, Midgley, & Eccles, 1988). When students are given fewer choices about curriculum activities and are given fewer opportunities to assume personal responsibility, they may develop self-defeating motivational beliefs (Eccles et al., 1993).

Inquiry is a specific type of learning that gives priority to self-directed exploration and investigation, and to inferences justified by such evidence (Wilson et al., 2010). Teachers may hesitate to use inquiry in their classrooms due to confusion about the meaning of inquiry, the belief that inquiry instruction only works well with high-ability students, or a view of inquiry as difficult to manage (Welch et al., 1981). Teachers may assume that students already possess the cognitive skills that enable them to engage in inquiry learning activities in a way that is productive. Educators must work to overcome these false assumptions if students are to acquire the learning skills they need. Only with sustained practice will students develop skill in knowing *how* to know.

With such practice students also acquire a set of intellectual values — values that deem activities of this sort to be worthwhile in general and personally useful. Students who value intellectual inquiry believe: 1) they have the right (and the obligation) to understand things and make things work, 2) problems can be analyzed, 3) solutions often come from such analysis, and 4) they are capable of that analysis, (Resnick & Nelson-LeGall, 1997). Implementation of inquiry activity in the classroom provides students problem-analysis tools and understanding of when to use them, skill in knowing how to ask questions, in seeking help and enough information to solve problems, and finally, in being mindful of when to actively apply the tool kit of analysis skills (Resnick and Nelson-LeGall, 1997).

Inquiry and Multivariable Thinking

Children's causal knowledge changes over time (Bartsch & Wellman, 1995) and with new evidence (Slaughter, Jaakkola, & Carey, 1999). Concepts of causality play a fundamental role in cognition, not just in obtaining a high score on a test, but in understanding everyday phenomena, even though young children are unaware that their mental models implicitly evolve (Kuhn, 2012; Bullock, 1985). A mental model of interacting variables includes one or more antecedent (A) variables, and an outcome (O) variable, with A interpreted as a cause of O. Causal claims are often incorrectly based on a single co-occurrence of A and O even when additional covariates are present (Sloman, 2005; Kuhn, 2012; Fernbach, Macris, & Sobel, 2012). A multivariable mental model of causality, in which multiple causes contribute to an outcome is needed to adequately interpret and understand most phenomena.

Methods of scientific thinking that permit valid inferences of multivariable causality include, 1) construction of mental models of causality, and 2) conducting scientific investigation (essential in allowing for valid causal inferences) (Schunn & Anderson, 2008). How do students develop valid evidence-based inferences about how multiple variables collectively contribute to an outcome? How do they infer whether the causes they identify are additive or interactive? These are essential reasoning strategies involved in inquiry learning.

With appropriate experience and emerging from the curiosity and exploration of early childhood, strategies may become more formalized during the second decade of life (Zimmerman, 2007; Kuhn, 2011), not before. Thus, our focus is on junior high school students. Most students can develop these strategies, (Siler et al., 2010), but achieving them among vulnerable populations is far from assured (Kuhn, Pease, & Wirkala, 2009; Kuhn, Iordanou, Pease, & Wirkala, 2008; Siler, Klahr, Magaro, Willows, & Mowery, 2010; Strand-Cary & Klahr, 2008). Students must recognize that scientific investigation requires new knowledge and information to be gained, preceded by a question, and that the newly acquired input of information may conflict with one's initial understanding. More often than not, students in science classes treat "hands-on" activities as mere illustration of what they already regard as true (Kuhn & Pease, 2008).

When new information is assessed, it must be evaluated in the context of a question to be asked (i.e., How is one variable affected by the other?); otherwise students do not appreciate its purpose (Kuhn, Garcia-Mila, Zohar, & Andersen, 1995; Kuhn et al., 2008; Lehrer, Schauble, & Lucas, 2008; McElhaney & Linn, 2011). The student must come to understand that a variable being investigated must be varied and such resulting outcomes compared – observing a single instance is not informative (Kuhn et al., 2009). Most challenging, the ubiquitous problem of other covarying variables must be addressed. Such understanding does not come as a sudden insight. Instead over a prolonged period, valid and invalid strategies coexist. The learner thus faces the dual challenge of inhibiting the latter while strengthening the former (Kuhn & Pease, 2009).

Self-Regulation

A capacity to self-regulate as a condition for learning now appears all the more critical with the advent of the Common Core standards and their emphasis on deep rather than shallow learning (Porter, Hwang, & Yang, 2011). Self-regulation is a central and significant behavioral and cognitive-developmental achievement (Flavell, 1977), and allows for engagement in learning activities (Blair & Raver, 2015). As children enter early adolescence, they increasingly demonstrate signs of progress in self-regulation (Steinberg, 2014). Self-regulation is best conceptualized as a multidimensional process whereby individuals attempt to control aspects of their cognition and behavior (Zimmerman, 2000).

In the work undertaken here, we make a distinction between cognitive self-regulation and behavioral self-regulation as different in nature and possibly having different effects on learning and academic performance. The extent to which individuals regulate their cognition and behavior has been of heightened interest to researchers over the past several decades (Cleary, Callan, & Zimmerman, 2012), with a surge in the number of papers and symposia at national and international conferences focusing on in-depth understanding of the nature and origins of self-regulation (e.g., American Educational Research Association, Learning Sciences, Educational Psychologist, Metacognition and Learning) (Schraw, 2009). Compared to younger children, however, less emphasis has been placed on young adolescents (Blair & Razza, 2007; McClelland et al., 2007). Unfortunately, the research base needed to substantiate or further understand relations between self-regulation and learning is limited, since most research designed to examine factors affecting learning takes place at a group rather than individual level, i.e., does instituting a particular practice yield significant improvement in the average performance of a classroom as a whole? Much less is known about individual differences.

Self-regulation, however, does not explain learning; rather it is a necessary condition for it (Blair & Raver, 2015). Accordingly, many have begun to separate and focus on components of self-regulation – in particular cognitive regulation (Chevalier et al., 2013) and behavior regulation (Prencipe et al., 2011; Blair et al. 2015), the focus of the present work.

Behavior Regulation

Behavior regulation refers to behavioral aspects of self-regulation including controlling and inhibiting behavior – such as controlling an impulse to push a student who cuts to the front of the line – and following a teacher's instructions (Ponitz, McClelland, Jewkes, Connor, Farris, & Morrison, 2008). In a classroom setting, assessment of behavioral regulation includes measures of both on- and off-task behavior. On-task behavior is engagement with activities instructed by the teacher, such as actively listening to the teacher or working on a classroom assignment, whereas off-task behavior involves disengagement with the instructed activity and channeling attention elsewhere (such as playing with a cell phone (Ocumpaugh et al., 2012)).

Cognitive Regulation

Cognitive regulation, or executive function (EF), as it is often referred to, involve monitoring and management of cognitive functions. Key types of cognitive regulation include inhibition (i.e., dismissing a distracting thought) and switching (i.e., shifting attention from one task to another) when required. These are critical to learning and performance (Garcia & Pintrich, 1994; Pintrich, Smith, Garcia, & McKeachie, 1993). Cognitive regulation and executive functions (EF) are related, yet distinct (Miyake & Friedman, 2012), with executive functioning the broader construct. Cognitive regulation does not include working memory or planning: rather, it focuses more narrowly on the control of thought (Hasher, Zacks, & May, 1999). Individual differences in cognitive regulation and executive functioning show both “unity” and “diversity” (Teuber, 1972). That is, different executive functions correlate with one another, thus tapping some common dimension (unity), but also show some distinguishability from one another (diversity) (Miyake & Friedman, 2012). For example, studies have found inhibition to be positively associated with switching (Bull & Scerif, 2001); yet other studies have found them not completely independent (Miyake et al., 2000). It has been argued that unity of executive functions may be accounted for by inhibition, as all cognitive regulatory (and executive) functions involve some inhibitory processes to function properly (Miyake et al., 2000). Switching has also been referred to as central to both cognitive regulation and executive functioning (Heaton, Chelune, Talley, Kay, & Curtiss, 1993) and in a classroom setting it allows for switching attention among different academic tasks.

Furthermore, cognitive and behavior regulation interact (Morrison, Ponitz, & McClelland, 2010). Inhibition of inappropriate thoughts allows students to have control of their behavior (Blakemore & Choudhury, 2006) and engage cognitively with on-task behaviors.

The relations among these constructs may vary developmentally. Xu and colleagues (2013) examined the unity and diversity of cognitive regulatory/executive function processes in Chinese children and adolescents ages 7-9, 10-12, and 13-15. To assess whether cognitive regulatory processes show more unity or diversity across development, they used confirmatory factor analyses to examine how distinct cognitive regulatory processes – such as inhibition and switching – were related. A single-factor model, rather than a three-factor model, best explained cognitive performance in 7–9-year-old and 10–12-year-old groups, and explained different amounts of variance at these two ages, compared to the older 13-15-year-old age group. In contrast, a three-factor model that included inhibition, shifting and memory best accounted for the data of 13–15-year-olds. In contrast to older children, then, among children between the ages of 7 and 12, distinct facets of cognitive regulation, such as inhibition and shifting, were highly inter-correlated and loaded on one factor.

Previous studies have demonstrated a relation between cognitive regulatory processes and academic achievement (Blair & Razza, 2007), with numerous studies suggesting a distinct relation between cognitive regulatory processes and math (Bull & Scerif, 2001; Espy et al., 2004). For example, inhibition, at age six was related to performance on two standardized math assessments, both concurrently and for three subsequent years, suggesting moderate stability in the relation between cognitive regulatory processes and math performance (Mazzocco & Kover, 2007). Likewise, associations between cognitive regulation and classroom behavior have been found (McGlamery et al., 2007), though studies of younger school-aged children have only shown cognitive regulatory ability to predict learning skills (Rigas, Carling, & Brehmer, 2002).

Also well documented is the relation between behavior regulation and academic performance (Duckworth; Valiente, Lemery-Chalfant, Swanson, & Reiser, 2008; Welsh, Parke, Widaman & O'Neil, 2001). On-task behaviors exhibited in kindergarten predict children's achievement and performance through second grade (McClelland et al., 2000), while, growth in mathematics performance from kindergarten through third grade can be explained by children's on-task behaviors (Bodovski & Farkas, 2007). These studies, however, involve elementary-aged children.

The present work stands to contribute to existing literature by providing evidence pertaining to a relatively understudied older age group. We ask whether cognitive regulation and behavior regulation contribute similarly or differently to two related, yet distinct school outcomes – learning, and academic performance – in middle-school students.

Individual Differences in Learning and School Performance

Individual differences in cognitive processes are enormous and profoundly affect the benefits students acquire from schooling. Despite increased research on the learning process, understanding of individual differences in learning remains limited. A classical explanation of learning differences is that they reflect individual differences in intelligence. Indeed, a classical definition of intelligence is ability to learn. But IQ tests are, at best, indirect measures of learning. An IQ test does not ask the test-taker to learn anything. Instead IQ tests are tests of performance, the rationale being that how well individuals perform various tasks compared to age mates is a measure of how effectively they have been able to learn from their experience.

In classrooms, learning and performance similarly deserve to be distinguished. Most classroom assessments are performance assessments in which the student must demonstrate mastery of the knowledge being assessed. Almost always, this information will have already been presented to them and they must have absorbed and retained it in memory in order to successfully reproduce it on the assessment. A test may ask students to solve a math problem, for example, but the techniques for doing so have been taught prior to the test. Rarely do assessments ask students to produce information that they have acquired for themselves. In the present study, it is this type of self-directed learning of new material that is of interest and that we distinguish from measures of academic performance.

Students can be taught elements of self-regulated learning. Young learners may benefit from discussions and analysis of strategies for self- regulated learning. Such strategies include information regarding setting challenging goals, metacognitive knowledge, or self-regulation skills. Schunk and Ertmer (2000) add that interventions should also address self-efficacy for learning as to encourage students to continue to use the strategies after they have been taught. Educators may use open- ended instructional activities to scaffold self-regulated learning processes and to allow students to direct, monitor, and evaluate their own learning (Paris & Paris, 2001; Winne & Perry, 2000).

Behavioral, affective, and cognitive engagement are more likely to ensue when the appropriate interaction between the classroom context and the child occurs (Paris & Paris, 2001). Educators can create a classroom that provides students with an emphasis on effort over performance, opportunities for autonomy and for collaboration, and open-ended tasks involving student choice. When teachers include these experiences in the curriculum, students are more likely to find meaning into the learning experience (Thibeault, 2010). Students who are reinforced and encouraged for their effort to learn, as opposed to their achievement or intelligence, are likely to put forth greater effort, leading to higher levels of performance and higher self-efficacy (Schunk & Zimmerman, 2007; Blackwell, Trzesniewski, & Dweck, 2007). When children perceive their ability independent of external sources, and dependent on their effort, they exhibit greater task persistence and task enjoyment even in the face of challenges (Blackwell, Trzesniewski, & Dweck, 2007).

Present Research Questions

The goal of the present research is to examine the capacity of cognitive regulation (while distinguishing between its various facets such as inhibition and switching) and behavior regulation, as predictors of young adolescents' learning and academic performance. Do they contribute differently to the two outcomes? We also examine their contributions to change in outcomes over time.

The goal is to lead to deeper understanding of self-regulatory processes by examining two of its distinct facets separately but simultaneously, in relation to educational outcomes. Whether separate facets of self-regulation, specifically cognitive regulation and behavior regulation, differentially predict to learning versus academic performance, is a question yet to be addressed for the age group examined here. I hypothesize that the contributors to individual differences in learning effectiveness may differ from the factors that contribute to individual differences in academic performance. Furthermore, I examine aspects of self-regulation as potentially critical constructs in accounting for these differences. Although there exists a good deal of research on self-regulation (Cleary, Callan, & Zimmerman, 2012), most of it pertains to younger children, rather than the early adolescents examined in the present work (Blair & Razza, 2007; McClelland et al., 2007).

The present study therefore has a unique contribution to make in addressing this critical age period in children's academic lives.

Pilot Study

Method

Participants

Participants were twenty-one 6th and 7th grade students (aged 12-14; 12 female, 9 male) attending a charter public school in a low-income neighborhood in the Harlem neighborhood of New York City. Participants were approximately 75% African-American and 25% Latino, with 80% of students classified as economically disadvantaged and 65% qualified for free or reduced-price lunch. The majority of students perform below grade level, with less than 10% classified as proficient in English Language Arts and in mathematics on state tests.

Measures

Learning Task

The inquiry learning task was administered as a whole-class activity in students' classrooms. The task was the Cart problem developed and reported on by Kuhn and Pease (2008). Data students are given access to are presented in a laptop computer application (InspireData) designed for students of this age. The problem centers around a Renaissance figure, Rafael, who has available only a primitive machine (a cart) to transfer a pile of stones at a construction site. Four features of the cart (bucket size, bucket placement, handle length, and wheel size) can be varied and, in rough correspondence to the physical principles involved, do or do not affect the efficiency of the cart in moving the stones. Students worked in small groups of three or four to examine the effects of the different cart features and were provided notebooks to record their observations. Periodically, the groups were asked to indicate any conclusions they had come to. Absence also contributed to slow progress, with the majority of students completing only about six sessions of the nine twice-weekly sessions provided.

Cognitive Regulation

To assess cognitive regulation, Shape School (Espy, 1997) was used. For use with this aged students, the author collaborated with the original authors of Shape School (personal communication, October 23, 2013) to develop an age-appropriate version. (The task has most often been used with young children.) Shape School is designed to assess different aspects of cognitive regulation using colorful, affectively engaging stimuli presented in an age-appropriate and appealing format, a storybook. The "story" has 4 parts, referred to as Conditions A, B, C, and D. Each participant participated in all four conditions and in the same order.

In Condition A (Control Task), the participant named the color of each figure presented, arranged in 3 lines of 5 across the page. Figures consisted of different colored shapes (i.e., green square, red circle, blue triangle) as students. This condition was a baseline measure to establish relationships between stimulus property – color, and the participant's response – naming the stimulus color. Condition B (Inhibition Task), continued the storyline with the same figure presented, arranged in 3 lines of 5 across the page, and instructions remained the same. However 9 figures were happy-faced, and 6 sad-faced, a difference participants were to ignore requiring response inhibition. In Condition C (Switch Task), a second group of figures was introduced in the storyline, with the figures wearing hats. The participant was instructed that the figures wearing hats go by shape names, and not their color names. It was reinforced that figures without hats still go by their color names. In this condition, there were 8 figures without hats and 7 figures with hats presented arranged in 3 lines of 5 across the page, and the participant had to switch between naming hatted figures and hattless figures as cued, respectively. Finally, in Condition D (Both *Switch and Inhibit* Task), the "happy" and "sad" faces were both reintroduced, both on hatted and hatless figures. The participant had to inhibit naming the "sad" figures' names regardless of whether the figures were hatted or hatless, and name the "happy" figures regardless of whether they were hatted or hatless. There were 5 happy hatless figures, 3 hatted happy figures, 3 hatted unhappy figures, and 4 hatless unhappy figures. In all conditions, participants were not allowed to proceed to the task test page array unless they named the characters successfully on the practice page prior – a step taken to ensure adequate rule knowledge prior to application. The experimenter recorded number of stimuli correctly responded to.

Scoring Shape School. Each condition – A, B, C, and D – was given a separate score based on number of correct responses, and then a final composite score across conditions was computed as the overall Shape School performance score. Condition A had a total of 15 items, and so each participant received a score between 0 and 15. Condition B had 9 items, so each participant received a score between 0 and 9. Condition C had a total of 15 items, so each participant received a score between 0 and 15. Finally, Condition D had a total of 8 items, so each participant received a score between 0 and 8. Once scores for each condition were collected, a final composite score was comprised, and ultimately created 5 scores (Conditions A, B, C, D, and the Total Score).

Behavior Regulation

Behavior regulation was assessed using the Baker-Rodrigo Observation Method Protocol (BROMP; Ocumpaugh et. al., 2012), in which a trained coder (the first author in the present study) observes students in their natural classroom setting and codes time segments for each student as reflecting on-task or off-task behavior. Students were unaware of when they were targets of observation, and their observations were randomly but equally dispersed. The total observation period, per class, was approximately one hour (a full class period). During the allotted time, each student was observed approximately 9 times. The behavior coded was the first behavior displayed by the student within 20 seconds of the beginning of the observation.

Observation was conducted using a handheld Android app, HART, designed for this purpose (Baker et al., 2012). Observations were conducted in a pre-determined order to balance observations and avoid bias toward more noteworthy behaviors or affect. The author was BROMP- certified, meaning she had achieved inter-rater reliability of 0.6 or higher with another BROMP-certified coder on a minimum of 200 observations.

Each observed segment was coded as one of the following:

1. On-task behavior - work on the subject material instructed by the teacher.
2. On-task conversation - talk to teacher or another student about subject material.
3. Off-task behavior– any behavior that did not involve the subject material or another individual (e.g., playing with a personal possession such as cell phone).
4. Other – student was either out of his/her seat or temporarily out of class and unable to be coded. (These segments were excluded from analyses.)

A Total Behavior Regulation score was created for each student by adding the number of the student’s on-task segments and subtracting the number of off-task segments.

Pilot Study Results

Descriptive statistics for the two self-regulation measures appear in Tables 1 and 2. Scores on the learning task had a median score of 42, a mean score of 42.94, with a standard deviation of 3.95.

Table 1. Behavior Regulation (BROMP) Performance

Behavior Regulation	Possible Maximum	Mean	Range	Standard Deviation
BROMP On Task Behavior	9	3.52	0 - 9	3.12
BROMP On Task Conversation	3	1.52	0 - 3	2.79
BROMP Off Task Behavior	8	2.47	0 - 8	.99
BROMP Behavior Regulation Total (on-task indices, minus off-task)	12	2.58	-6 - 11	5.59

Note: n=21

Table 2. Cognitive Regulation (Shape School)

Shape School	Possible Maximum	Mean	Range	Standard Deviation
Control Task (Task A)	15	13.2	0 - 15	4.98
Inhibition Task (Task B)	9	7.53	0 – 9	2.93
Switch Task (Task C)	15	11.1	0 - 15	4.84
Both Task (Task D)	8	5.76	0 - 8	2.96
Shape School Total Score (Tasks A – D)	47	37.5	0 - 47	14.67

Note. n = 21

Interrelations Between Cognitive Regulation and Behavior Regulation

Inhibition was positively associated with on-task behavior (r=.485, p<0.05), and on-task conversation (r=.505, p<0.05). Both score (simultaneous inhibition and switching) similarly was positively correlated with on-task behavior (r=.600, p <0.05) and on-task conversation (r=.669, p<0.01). Overall cognitive regulation was also positively related to on-task behavior (r=.518, p<0.05) and on-task conversation (r=.594, p<0.05). See Table 3.

Table 3. Relations Between Cognitive Regulation and Behavior Regulation

	Behavior Regulation (BROMP)			
Cognitive Regulation (Shape School)	On Task Behavior	On Task Conversation	Off Task Behavior	Behavior Regulation Total
Control Task (Task A)	0.425	0.468	0.334	0.174
Inhibition Task (Task B)	**.485***	**.505***	0.158	0.303
Switch Task (Task C)	0.469	**.603***	0.294	0.248
Both Task (Task D)	**.600***	**.669****	0.279	0.344
Cognitive Regulation Total Score (Tasks A – D)	**.518***	**.594***	0.299	0.271

* Correlation is significant at the 0.05 level (2-tailed).
** Correlation is significant at the 0.01 level (2-tailed).
*** Correlation is significant at the 0.001 level (2-tailed).

Note: n=21

Relations between Behavior Regulation and Learning

None of the indices on BROMP (on-task behavior, on-task conversation, off-task behavior, or the behavior regulation total score) showed a significant correlation to the Learning task. Correlations were *r*=.272, (p = .246) for on-task behavior *r*=.007, (p = .978) for on-task conversation, and *r*=.085, (p = .721) for off-task behavior, and *r*=.039, (p = .872) for overall behavior regulation. See Table 4.

Table 4. Relations between Behavior Regulation and Learning

Behavior Regulation	Learning
BROMP On Task Behavior	.272
BROMP On Task Conversation	.007
BROMP Off Task Behavior	.085
BROMP Behavior Regulation Total (on-task indices, minus off-task)	.039
* Correlation is significant at the 0.05 level (2-tailed). ** Correlation is significant at the 0.01 level (2-tailed). *** Correlation is significant at the 0.001 level (2-tailed).	

Note: n=21

Relations between Cognitive Regulation and Learning

In contrast to behavior regulation, distinct facets of cognitive regulation showed significant correlations to the Learning task. Significant correlations were found between Both (simultaneous inhibiting and switching) and learning (*r*=.446, p <.05), as well as overall cognitive regulation and learning (*r*=.446, p <.05).

Table 5. Relations between Cognitive Regulation and Learning

Cognitive Regulation	**Learning**
Control Task (Task A)	.142
Inhibition Task (Task B)	.216
Switch Task (Task C)	.246
Both Task (Task D)	**.446***
Cognitive Regulation Total Score (Tasks A – D)	**.446***
* Correlation is significant at the 0.05 level (2-tailed). ** Correlation is significant at the 0.01 level (2-tailed). *** Correlation is significant at the 0.001 level (2-tailed).	

Note: n=21

Discussion

In this preliminary study, we found different results for measures of the two constructs as predictors of learning. Cognitive regulation, rather than behavioral regulation, was predictive of students' skill in learning how multiple variables were related to outcomes. Notably, it was not behavioral self-regulation, as one might assume, that came most into play in predicting students' learning. These findings suggest that if we are concerned to understand the individual as well as situational factors that are most powerful in promoting students' ability to engage successfully in independent learning, cognitive self-regulation may be a particularly productive area of investigation. At the least, the findings point to it as an individual predictor worthy of further exploration. I therefore undertook a larger study having this objective.

CHAPTER II: Method

Participants

Participants were 135 middle-class 5^{th} and 6^{th}-graders (55% female; age *M*=11.3, range= 10-12, *SD*=.67). These students attend a public middle school in a working-class neighborhood of a large city in the Northeast US. Their racial/ethnic backgrounds were 52% Caucasian, 12% Asian, 10% African-American, 5% Hispanic and 19% of mixed background. Over half (56%) were bilingual (most common languages spoken included Russian, Hebrew, Italian, Greek, and Mandarin). According to state DOE data, the school's performance ranking is in the 47^{th} percentile, in comparison to other schools in the city, based on the state standardized tests. 10% qualified for free or reduced-price lunch.

Measures

Learning Task

The learning task administered individually to all participants required them to freely examine a set of data consisting of instances that varied on multiple dimensions and to identify causal relations that characterized the data set. This form of task has been widely used in studies of causal learning and inductive inference (Fernbach & Sloman, 2009; Holyoak & Cheng, 2011; Sloman & Fernbach, 2008) and problem solving (Greiff et al., 2013) in adults as well as in children (Kuhn et al. 1995, 2015; Sobel & Munro, 2009; Schauble, 1990). This task took approximately one hour to administer per participant.

Introduction. In the version of such a task that was used here, the following scenario was introduced, illustrated by an accompanying PowerPoint graphic:

> A new Astro-World Foundation, funded by some wealthy businessmen, wants to provide money for a space station. Groups of young people would live there for several months. Many young people have applied. The Foundation president needs to choose the best ones. So she asked some applicants to spend a week in a space simulator [picture is shown and function explained]. She had background information about each applicant, and each one got a rating on how well they survived in the harsh conditions of the simulator. Some did fine; others okay, and some became sick and had to leave.
>
> Based on these records, she can decide which things are important to ask new applicants about and which ones aren't. Some of the factors, she noticed, made a big difference to how well an applicant did, some made a small difference, and some made no difference. She found out, for example, that body weight made no difference: Heavy people did as well in the simulator as light ones. But other things about people seemed to make a big difference in how well they did. So now, when she chooses final groups of astronauts to go on the real trips, she'll have a better idea what things to find out about applicants, so she can be pretty sure how an applicant will do and she'll be able to choose the ones who will do best.
>
> But, in order to be sure, she's asked for our help in analyzing their results. Which things are worth asking applicants about and which don't make any difference, like body weight? There are a lot of things that we can ask about but the foundation can't ask about everything. It would take too long. If we know what to ask applicants, we can choose the best team of astronauts.
>
> Here are four things the foundation thought might make a difference to how well people do in the simulator:
>
> 1) Fitness - does how well the person can run or do other exercises matter?
> 2) Family size - does the size of the family the person grew up in matter?
> 3) Education - does how much education a person has matter?
> 4) Parents' health - does the health of the person's parents matter? All the applicants seem healthy, but maybe their parents' health might say something about how healthy they will turn out to be.
>
> Will you help figure out which things are worth asking the applicants about and which ones don't matter? Then you'll be able to predict how well they'll do and choose the best ones for the team. Later, you can compare your results with those of your classmates and see who chose the best-performing astronaut team.

The participant was first asked for his or her own predictions about which factors will make a difference, following which the interviewer said, "Okay, now, let's find out what actually does make a difference and whether your predictions are right. We have some records of how people did in the simulator. Studying the records carefully, you can find out which factors make a difference to performance and which don't."

Learning phase. The interviewer then presented a set of 24 cards, each containing a different applicant's record, and explained how to read them. Each card contained the record for one applicant, with a blank space to fill in the applicant's performance rating in the simulator (initially left blank), along with information regarding the applicant's status on the four factors indicated above. Each factor could assume one of two levels except for education, which had three levels. Outcomes varied across five levels (1=very well, 2=well, 3=so-so, 4=poorly, 5=very poorly). (Three of the four variables affected outcome; the remaining variable had no effect.)

The interviewer suggested, " It would be best to investigate one factor at a time," and asked the participant to choose one factor to start with. The participant was then invited to look through the cards and choose one or two to study. The interviewer asked what the participant hoped to find out by examining the chosen cards, and then consulted her record book to reveal and record on the cards the performance outcomes for those applicants (possible performance outcomes were: *very well, well, so-so, poorly,* and *very poorly*). The interviewer invited, but did not require, the participant to draw a conclusion and then offered the participant the chance to choose another card that might be better for comparison and to find out the outcome for that case. The participant was again invited to draw a conclusion as to whether or not the factor "makes a difference," after which the interview proceeded to the next factor.

Application phase. After all four factors had been investigated, the interview proceeded to a second phase, assessing the participant's skill in application of what he or she had learned. A summary of the participant's conclusion (makes a difference or makes no difference) for each factor was displayed on a chart the participant could refer to as a reminder. The participant was allowed to keep a "Summary of Findings" sheet during this phase (which s/he had filled out on their own from their findings during the learning phase), as to exclude any use of memory throughout this final phase. The interviewer then said, "Now we have a set of new applicants. They've given us information about themselves but we don't know how they're going to perform in the simulator. Based on what you've learned, can you predict how each one will perform? The interviewer then presented one by one a sequence of 10 cards. Each displayed information about the applicant on the four factors but omitted any outcome information. The participant was asked to study each record and predict the outcome. Finally, the participant was asked to choose three applicants as the best ones to be selected for the space mission.

Scoring. The learning and application phases of the task were scored separately. For the learning phase, the participant received a score for each of the four variables he or she was asked to learn about. The correctness of a conclusion regarding a variable (makes a difference or doesn't make a difference) has a high chance of being correct by chance without being based on any learning. Hence, scoring for each variable was based on the evidence the participant referred to as the basis for the conclusion, as an indicator of learning strategy and effectiveness. A score between 0 and 4 was assigned for each variable. A score of 1 or more was assigned if the conclusion was based on a comparison of two cases (or more) on which the focal variable varied. (Otherwise the score was zero.) Scores of 2, 3, and 4 were assigned based on the soundness of the comparison, i.e., whether it allowed three, two, or one of the remaining variables to vary and hence serve as alternative explanations for an outcome difference. Total scores could thus range from 0 to 16.

For the application phase, scores were based on the correctness of each of the 10 predictions for new applicants. Scores for each ranged from 4 (correct prediction, based on the additive effects of the three contributing variables) to 0, based on how far removed (on the 5-point outcome scale) the prediction was from the correct one (from one to four levels). Total score for application could thus range from 0 to 40.

Academic Performance

As a measure of academic performance, state standardized test scores for both Math and English were available. All participants' parents signed consent forms to release this information.

Cognitive Regulation

The cognitive regulation measure, Shape School (Espy, 1997), is the same task used in the pilot study. It was also administered individually to each student outside of the classroom.

Behavior Regulation

The behavior regulation measure, BROMP (Ocumpaugh et al., 2012), is the same observational measure used in the pilot study, administered as described earlier.

CHAPTER III: Results

Learning

A summary of performance on the Learning task appears in Table 6. Learning scores were re-scaled to a maximum of 40 to facilitate comparison of the Learning and Application phases of the task. As apparent in Table 6, there exists considerable individual variation on both. The low end of the range is more restricted for Application as chance correctness is easier to achieve. The sample's frequency of beliefs in the hypothesis segment showed a normal distribution, thus no preliminary knowledge is expected to have any effect on performance on any segments of the learning task.

Table 6. Learning Task Results

	Possible Maximum	Mean	Range	Standard Deviation
Learning scores				
Learning	40	28	0 - 40	10.3
Application of learning	40	33	25 - 38	2.7
Total learning score (combined)	80	61	31 - 78	12.0

Note. n = 135

Learning and Standardized Test Performance

Academic performance as assessed by state standardized test scores showed a range of 280 to 393 for English, with a mean of 337 and a standard deviation of 28. Math scores showed a range of 258 to 404, with a mean of 343 and a standard deviation of 24. According to State DOE reports, approximately 70% of the students at this school meet state standards for English and approximately 80% meet state standards for Math.

As would be expected, learning scores and achievement test scores were correlated. The correlation between combined Learning scores and English test scores was .493 ($p < .01$). The correlation between combined Learning scores and Math test scores was .331 ($p< .01$). Correlations of Learning scores alone were nearly as high (.481 and .330, respectively, both $p < .01$), while correlations of the application of learning scores were lower, .344 ($p < .01$) for English scores, and .204 ($p < .05$) for Math scores. Nonetheless, these correlations indicate that the two constructs, while related, only partially overlap, with enough non-shared variance to warrant investigating them as distinct constructs.

Cognitive Regulation and Behavior Regulation as Predictors of Learning and Academic Performance

Descriptive statistics for cognitive regulation (Shape School) appear in Table 7. Descriptive statistics for behavior regulation (BROMP) appear in Table 8. As seen there, students displayed considerable individual variation. A majority of students scored quite well on the Shape School cognitive regulation measure (17% had perfect scores), but a significant number did not. In contrast, consistent on-task behavior or on-task conversation was rare and students scored much lower overall on the behavior regulation measure.

Table 7. Cognitive Regulation (Shape School)

Shape School	Possible Maximum	Mean	Range	Standard Deviation
Control Task (Task A)	15	14.90	12 - 15	.317
Inhibition Task (Task B)	9	8.73	4 - 9	0.69
Switch Task (Task C)	15	14.10	4 - 15	1.23
Both Task (Task D)	8	7.07	0 - 8	1.51
Shape School Total Score (Tasks A – D)	47	44.80	34 - 47	2.12

Note. n = 135

Table 8. Behavior Regulation (BROMP)

Behavior Regulation	Possible Maximum	Mean	Range	Standard Deviation
BROMP On Task Behavior	7	2.78	0 - 7	1.87
BROMP On Task Conversation	8	2.16	0 - 8	2.22
BROMP Off Task Behavior	8	2.46	0 - 8	2.02
BROMP Behavior Regulation Total (on-task indices, minus off-task)	9	2.19	-10 - 9	3.97

Note. n = 135

Relations Between Cognitive Regulation and Behavior Regulation

Regression analyses showed Both (simultaneous inhibiting and switching) to predict to overall behavior regulation B= .927, R^2=.12 ($p < .001$), and inversely predict to off-task behavior, B= -.393, R^2=.11 ($p < .01$).

We next ask to what extent cognitive regulation and behavior regulation predict scores on our learning task and on school achievement as measured by standardized test scores. We conducted regression analyses that included distinct facets of cognitive regulation – inhibition and switching – as well as distinct facets of behavior regulation – on-task behavior and on-task conversation. To address ceiling effects, skewed variables were transformed (if positively skewed a log transformation was performed; if negatively skewed, +1 was added to the variable followed by a square root transformation), and analyses (i.e., p-values) all remained identical to original data. Additionally, we employed the exclude-the-middle method by separating both the top quarter and bottom quarter of the distribution, in order to see if the two (high- and low- performing) groups would separately predict variation. Logistic regressions and t-tests were performed between the two (high v. low) groups, and the results remained significant and consistent with original findings. Analyses therefore remain in form of original data.

In addition we included as covariates in these analyses age, gender, and bilingualism, given the latter's prominence in this sample. Students' bilingualism was based on self-report; however, students reporting bilingualism were also asked to recite at least a couple of sentences in their second language, to confirm a basic level of proficiency. Bilingual students scored higher than monolingual students on Math scores (t =6.935, $p< .01$), English scores (t =7.396, $p< .01$), Application of learning (t =3.38, $p< .001$), Learning (t =2.186, $p< .05$), and the switching task of cognitive regulation (t =1.92, $p < .05$). Girls performed better than boys on English scores (t =2.847, $p< .05$). Age was included as a covariate based on findings suggesting components of cognitive regulation become more distinct during the transition into adolescence (Miyake & Friedman 2012).

Likewise, older students did better on learning tasks ($p<.01$) and English scores ($p<.05$).

Cognitive regulation was a significant predictor of learning, after controlling for age, gender, and bilingualism. The regression analysis appears in Table 9. Overall cognitive regulation predicted Total Learning, $F(4, 130) = 5.97$, $p < .001$, as well as its two components Application of Learning $F(4, 130) = 4.14$, $p < .01$, and Learning $F(4, 130) = 6.221$, $p < .001$. With respect to components of cognitive regulation, inhibition predicted learning $F(4, 130) = 5.86$, $p < .001$, switching predicted learning, $F(4, 130) = 5.39$, $p < .001$, and both (simultaneous inhibiting and switching) also predicted learning, $F(4, 130) = 7.66$, $p < .001$. While inhibition predicted application learning $F(4, 130) = 3.015$, $p < .05$, switching predicted application of learning, $F(4, 130) = 3.11$, $p < .01$, and both (simultaneous inhibiting and switching) also predicted application of learning, $F(4, 130) = 4.19$, $p < .01$. Inhibition also predicted total learning $F(4, 130) = 5.31$, $p < .001$, switching predicted total learning, $F(4, 130) = 4.92$, $p < .001$, and both (simultaneous inhibiting and switching) also predicted total learning, $F(4, 130) = 7.31$, $p < .001$.

Table 9. Cognitive Regulation as a Predictor of Learning

	Overall Learning		
	B	SE(B)	ß
Age	6.382***	1.54	0.353
Gender	0.988	1.986	0.041
Bilingualism	-1.625	2.056	-0.67
Total Cognitive Regulation	**0.985***	0.512	0.158

*** Significant at the 0.001 level (2-tailed),
** Significant at the 0.01 level (2-tailed),
* Significant at the 0.05 level (2-tailed). n=135

Cognitive regulation, in contrast, did not significantly predict academic performance as measured by standardized test scores, as seen in Table 10.

Table 10. Cognitive Regulation as a Predictor of Academic Performance

	Math Standardized Test Scores			English Standardized Test Scores		
	B	SE(B)	ß	B	SE(B)	ß
Age	4.92	3.73	.117	10.37***	3.07	.289
Gender	-1.3	4.87	-.02	11.24***	3.97	.234
Bilingualism	12.4**	4.99	.22	4.47	4.08	.093
Total Cognitive Regulation	1.27	1.14	.09	.266	.931	.024

*** Significant at the 0.001 level (2-tailed),
** Significant at the 0.01 level (2-tailed),
* Significant at the 0.05 level (2-tailed). n=135

Behavior regulation showed a distinctly different pattern of relations to learning and achievement than cognitive regulation. Behavior regulation did not predict learning. None of the BROMP indices (on-task behavior, on-task conversation, off-task behavior, or the total behavior regulation score) predicted learning scores, after controlling for age, gender, and bilingualism. See Table 11.

However, behavior regulation did show a significant relation to math standardized test scores, but not to English scores, as shown in Table 11. Overall behavior regulation predicted Math standardized test scores, $F(4, 130)=3.75$, $p < .01$. With respect to components of behavior regulation, on-task behavior predicted Math test scores $F(4, 130) = 3.12$, $p < .01$, and off-task behavior inversely predicted math scores, $F(4, 130) = 3.48$, $p < .01$. On-Task conversation showed no prediction to math scores, $F(4, 130) = 1.93$, $p = .110$.

Table 11. Behavior Regulation as a Predictor of Learning and Academic Performance

Behavior Regulation	Overall Learning		
	B	SE(B)	ß
Age	6.281***	1.559	.350
Gender	.910	2.018	.038
Bilingualism	-1.922	2.090	-.080
Total Behavior Regulation	.803	1.038	.065

	Math Standardized Test Scores			English Standardized Test Scores		
	B	SE(B)	ß	B	SE(B)	ß
Age	5.17	3.67	.124	10.08***	3.04	.284
Gender	-1.64	4.82	-.029	11.89***	3.98	.249
Bilingualism	11.01*	4.93	.196	3.951	4.08	.083
On-Task Behavior	**6.07****	2.45	.212	-2.36	2.04	-.097
Age	4.48	3.73	.108	10.09***	3.04	.284
Gender	-.489	4.89	-.009	11.62***	3.97	.244
Bilingualism	11.89**	5.01	.211	3.67	4.07	.077
On-Task Conversation	3.08	2.43	.110	2.36	1.98	.098
Age	4.81	3.64	.116	10.26***	3.05	.289
Gender	-2.105	4.807	-.037	11.45***	4.01	.240
Bilingualism	11.52*	4.90	.205	3.628	4.09	.076
Off-Task Behavior	**- 6.65*****	2.425	-.233	-.281	2.03	-.012
Age	4.55	3.63	.109	10.28***	3.05	.289
Gender	-1.63	4.77	-.021	11.62***	3.99	.244
Bilingualism	11.32*	4.88	.201	3.695	4.09	.077
Total Behavior Regulation	**7.05*****	2.40	.247	-.744	2.03	-.031

*** Significant at the 0.001 level (2-tailed),
** Significant at the 0.01 level (2-tailed),
* Significant at the 0.05 level (2-tailed). n=135

Longitudinal Predictions

I next asked to what extent learning and self-regulation predict longitudinally to subsequent school achievement (again measured by state standardized test scores). Regression analyses included distinct facets of learning, distinct facets of behavior regulation, and distinct facets of cognitive regulation.

As a measure of academic performance, state standardized test proficiency rating scores for both Math and English were obtained. The first wave of scores (reported on previously) were obtained 4 months after baseline self-regulation measures. The longitudinal wave of scores were obtained 16 months after baseline measures, (12 months after the first wave). All participants' parents again signed consent forms. State proficiency rating scores were utilized for longitudinal analyses. Due to attrition, 8 students were no longer a part of the sample. Thus, the original sample of 135 was reduced to a sample of 127.

A summary of performance on state standardized proficiency rating scores at Time 1 and Time 2 appears in Table 12.

Table 12. Descriptive Statistics of State Standardized Scores (Proficiency Rating scores)

Academic Performance	Mean		Range		Standard Deviation	
	Time 1	Time 2	Time 1	Time 2	Time 1	Time 2
Math Standardized Test Scores	3.71	3.70	1.79 – 4.50	2.12 – 4.44	.62	.97
English Standardized Test Scores	3.52	3.48	1.95 – 4.33	1.97 – 4.43	.64	.64

Note. *n = 127*

After controlling for age, gender and bilingualism, none of the behavior indices predicted to English standardized test scores at Time 2 (T2). However, for Math, on-task behavior did modestly predict scores at T2, B=.056, R^2=.1, ($p<.05$), while off-task behavior inversely predicted math scores, B=-.051, R^2=.1, ($p<.05$), and overall behavior regulation predicted math scores, as well, B=.027, R^2=.104, ($p<.05$).

Again, after controlling for age, gender and bilingualism, Learning score predicted math scores at T2, B=.025, R^2=.232, ($p<.001$), as did application of Learning, B=.079, R^2=.187, ($p<.001$), and total Learning, B=.023, R^2=.249, ($p<.001$). Learning predicted English scores at T2, B=.021, R^2=.161, ($p<.001$), as well as application of Learning B=.059, R^2=.114, ($p<.001$), and total Learning, B=.019, R^2=.166, ($p<.001$).

Again, after controlling for age, gender and bilingualism, Both (simultaneous inhibiting and switching) predicted math scores at T2, B=.069, R^2=.107, ($p<.05$), as did overall cognitive regulation, B=.026, R^2=.114, ($p<.05$). No prediction from cognitive regulation to English standardized test scores was found.

In addition, these analyses were repeated including as a covariate scores at Time 1 (T1). As seen in Table 13, behavior regulation showed very little prediction of English standardized test scores, and none of Math standardized test scores.

Table 13. Behavior Regulation as a Predictor of Academic Performance at Time 2

Behavior Regulation	Math Standardized Test Scores at Time 2				English Standardized Test Scores at Time 2			
	B	SE(B)	ß	R^2	B	SE(B)	ß	R^2
On-Task Behavior	.047	.020	.004	.603	**.098***	.041	.152	.514
Score at Time 1	.731***	.060	.745		.694***	.066	.698	
On-Task Conversation	-.093	.016	-.020	.619	-.055	.042	-.085	.498
Score at Time 1	.765***	.059	.747		.690***	.067	.694	
Off-Task Behavior	.018	.018	.032	.598	-.030	.041	-.047	.493
Score at Time 1	.756***	.061	.755		.682***	.067	.687	
Behavior Regulation Total	-.017	.009	-.023	.598	.041	.041	.063	.495
Score at Time 1	.755***	.061	.752		.684***	.067	.688	

*** Significant at the 0.001 level (2-tailed),
** Significant at the 0.01 level (2-tailed),
* Significant at the 0.05 level (2-tailed). n=127
Note: In addition to controlling for scores at Time 1, analyses included age, gender, and bilingualism as covariates.

In contrast, as seen in Table 14, after including test scores at Time 1 as a covariate, cognitive regulation predicted T2 Math standardized test scores, but not English standardized test scores.

Table 14. Cognitive Regulation as a Predictor of Academic Performance at Time 2

Cognitive Regulation	Math Standardized Test Scores at Time 2				English Standardized Test Scores at Time 2			
	B	SE(B)	ß	R^2	B	SE(B)	ß	R^2
Inhibition	.015	.049	.017	.614	-.039	.058	-.042	.500
Score at Time 1	.751***	.057	.755		.698***	.067	.696	
Switching	.026	.028	.052	.616	-.015	.033	-.030	.499
Score at Time 1	.750***	.057	.753		.703***	.067	.701	
Both	**.063*****	.022	.156	.638	.042	.027	.099	.507
Score at Time 1	.749***	.055	.753		.705***	.066	.703	
Cognitive Regulation Total	**.043*****	.016	.149	.635	.008	.019	.025	.498
Score at Time 1	.744***	.055	.748		.699***	.067	.697	

*** Significant at the 0.001 level (2-tailed),
** Significant at the 0.01 level (2-tailed),
* Significant at the 0.05 level (2-tailed). n =127
Note: In addition to controlling for scores at Time 1, analyses included age, gender, and bilingualism as covariates.

Finally, as seen in Table 15, including T1 test scores as a covariate, Learning continued to predict to T2 Math test scores and T2 English test scores, more so than did behavior regulation or cognitive regulation.

Table 15. Learning as a Predictor of Academic Performance at Time 2

Learning	Math Standardized Test Scores at Time 2				English Standardized Test Scores at Time 2			
	B	SE(B)	ß	R^2	B	SE(B)	ß	R^2
Learning	**.012*****	.004	.205	.629	**.011****	.004	.186	.514
Score at Time 1	.691***	.062	.679		.748***	.060	.745	
Application of Learning	**.049*****	.013	.216	.638	.024	.016	.101	.495
Score at Time 1	.713***	.059	.701		.684***	.072	.671	
Total Learning	**.012*****	.003	.230	.637	**.010****	.004	.184	.514
Score at Time 1	.682***	.061	.671		.659***	.071	.647	

*** Significant at the 0.001 level (2-tailed),
** Significant at the 0.01 level (2-tailed),
* Significant at the 0.05 level (2-tailed). n=127
Note: In addition to controlling for scores at Time 1, analyses included age, gender, and bilingualism as covariates.

Structural Equation Modeling

To better understand the direction of these relationships, we performed structural equation modeling (see theoretical model, Figure 1). The cognitive regulation Both measure (simultaneous inhibiting and switching) predicted Learning, which in turn predicted both Math scores (see Figure 2; Table 16) and English scores (see Figure 3; Tables 17) at Time 1, which then predicted respective scores at Time 2. No other cognitive regulation indices, such as overall cognitive regulation, were significant as SEM predictors (see Figures 4 and 5; Tables 18 and 19). No models were significant for any of the behavior regulation indices as predictors (i.e., see Figures 2-5).

Figure 1. Structural Equation Modeling: Theoretical Model

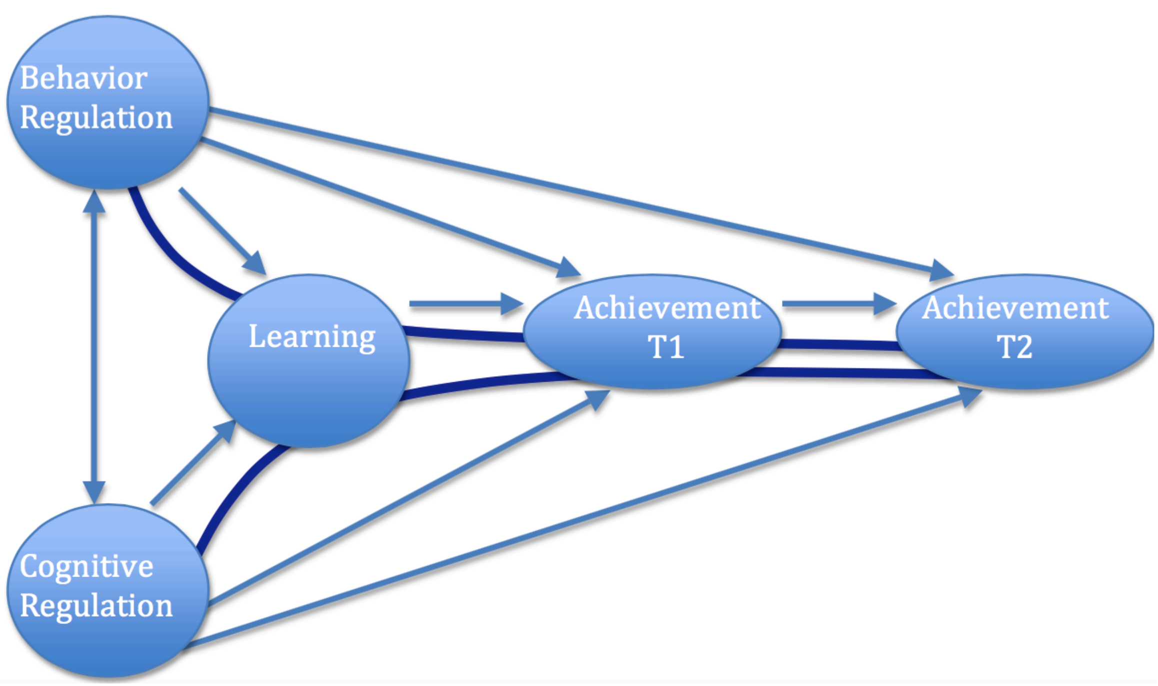
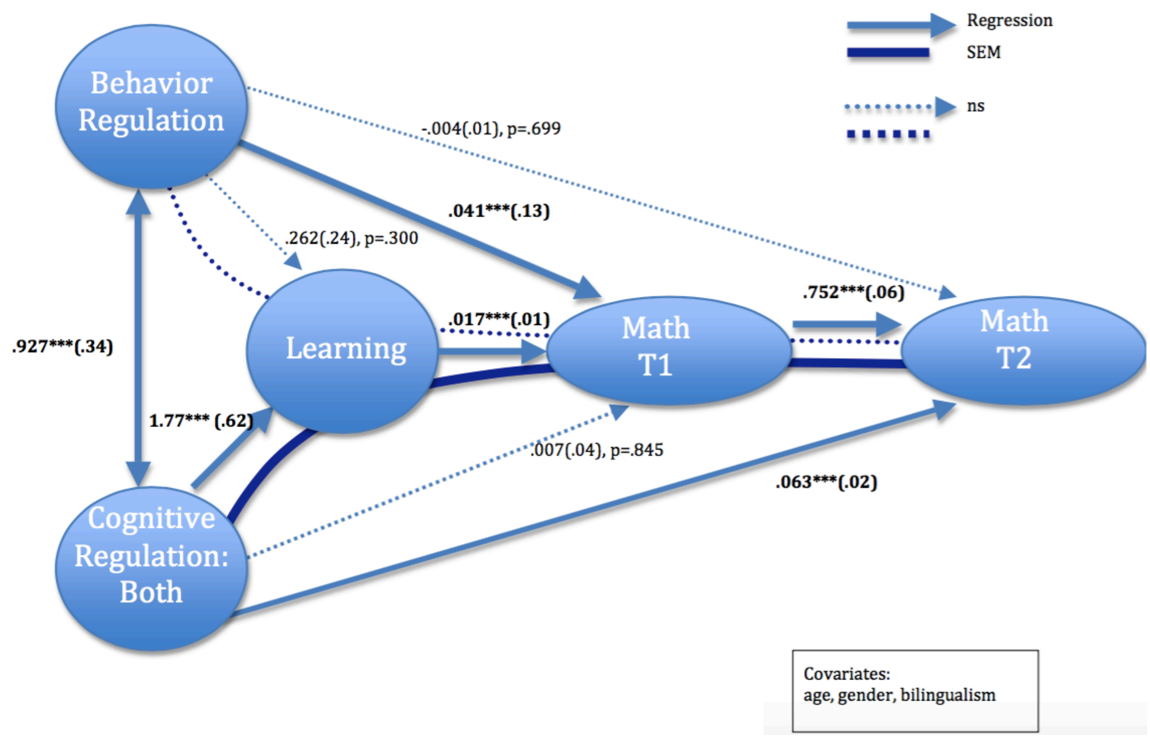


Figure 2. Structural Equation Model of Cognitive Regulation (Both; simultaneous inhibiting and switching), Learning, and Math Scores Over time
(Standardized Solution; n = 127)



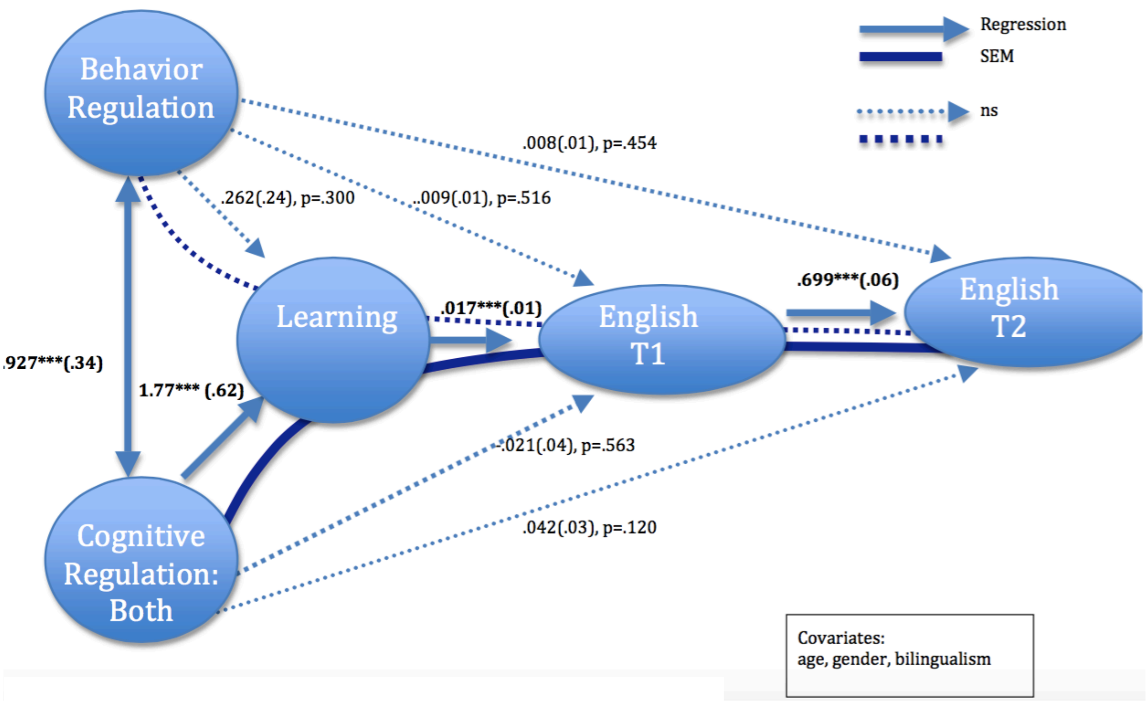
Note. Standard errors included in parentheses next to coefficients
Standardized solution, unable to conduct GF test with no parameters.
Acceptable fit is assumed.

Table 16. SEM: Cognitive Regulation (Both; simultaneous inhibiting and switching) predicting Learning, predicting Math Scores over time

	Coefficient	Standard Error	p>|z|	95% CI
Learning				
Cog Reg: Both	1.770	.622	.004	[.549, 2.99]
Age	6.561	1.472	.000	[3.675, 9.448]
Sex	1.463	1.910	.443	[-2.280, 5.208]
Bilingualism	-1.061	1.955	.587	[-4.893, 2.771]
constant	-21.148	17.035	.214	[-54.536, 12.239]
Math T1				
Learning	.017	.004	.000	[.008, .026]
Cog Reg: Both	-.023	.033	.474	[-.089, .041]
Age	-.039	.081	.627	[-.199, .120]
Sex	-.113	.098	.252	[-.306, .080]
Bilingualism	.312	.100	.002	[.116, .509]
constant	3.111	.873	.000	[1.399, 4.824]
Math T2				
Math T1	.691	.055	.000	[.583, .799]
Learning	.009	.003	.003	[.003, .015]
Cog Reg: Both	.047	.021	.026	[.005, .088]
Age	.062	.052	.235	[-.040, .165]
Sex	-.087	.063	.170	[-.211, .037]
Bilingualism	.077	.066	.244	[-.052, .207]
constant	-.424	.590	.472	[-1.582, .733]

n=127
Standardized solution, unable to conduct GF test with no parameters. Acceptable fit is assumed

Figure 3. Structural Equation Model of Cognitive Regulation (Both; simultaneous inhibiting and switching), Learning, and English Scores over time
(Standardized Solution; n = 127)



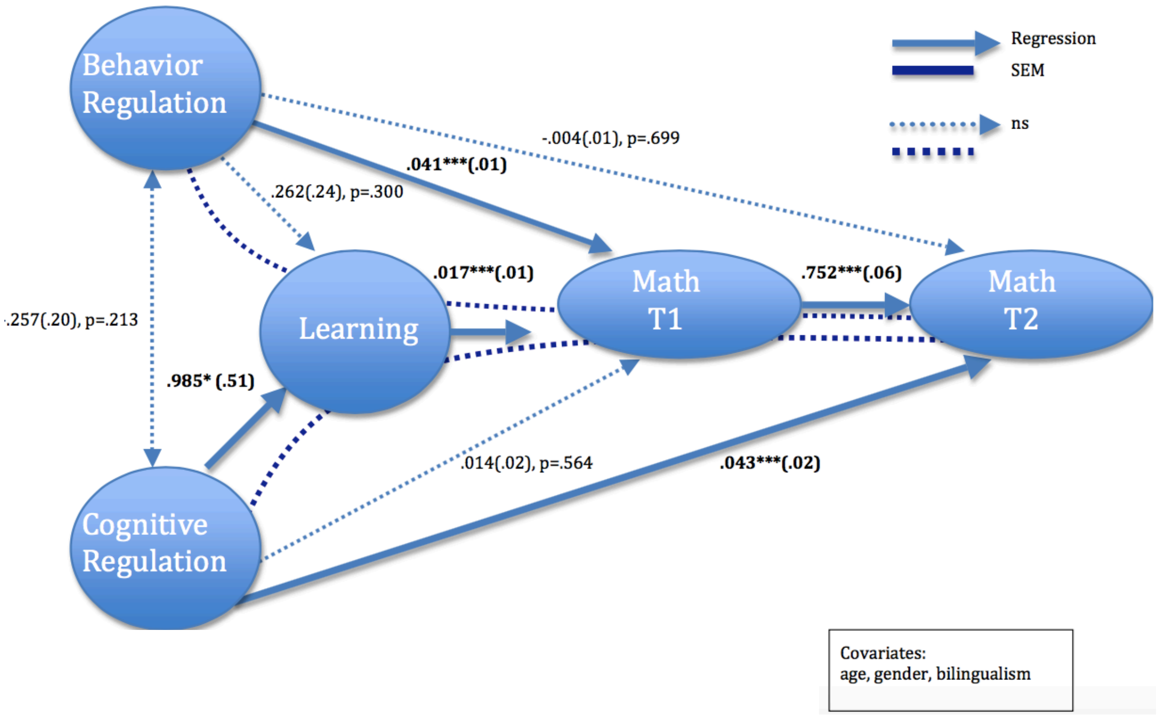
Note. Standard errors included in parentheses next to coefficients
Standardized solution, unable to conduct GF test with no parameters.
Acceptable fit is assumed.

Table 17. SEM: Cognitive Regulation (Both; simultaneous inhibiting and switching) predicting Learning, predicting English Scores over time

	Coefficient	Standard Error	p>|z|	95% CI
Learning				
Cog Reg: Both	1.808	.622	.004	[.588, 3.029]
Age	6.749	1.474	.000	[3.859, 9.639]
Sex	1.333	1.911	.485	[-2.412, 5.080]
Bilingualism	-.822	1.957	.675	[-4.659, 3.015]
constant	-23.447	17.05	.169	[-56.877, 9.982]
English T1				
Learning	.015	.004	.002	[.005, .024]
Cog Reg: Both	-.049	.034	.154	[-.116, .018]
Age	.094	.084	.266	[-.071, .260]
Sex	.309	.102	.002	[.109, .509]
Bilingualism	.099	.103	.336	[-.103, .303]
constant	1.689	.907	.063	[-.088, 3.467]
English T2				
English T1	.661	.065	.000	[.532, .789]
Learning	.008	.003	.018	[.001, .016]
Cog Reg: Both	.024	.026	.361	[-.027, .075]
Age	.020	.065	.757	[-.107, .147]
Sex	-.041	.080	.603	[-.198, .115]
Bilingualism	.059	.079	.453	[-.095, .214]
constant	.223	.706	.752	[-1.161, 1.607]

n=127
Standardized solution, unable to conduct GF test with no parameters. Acceptable fit is assumed

Figure 4. Structural Equation Model of Overall Cognitive Regulation, Learning, and Math Scores over time
(Standardized Solution; n = 127)



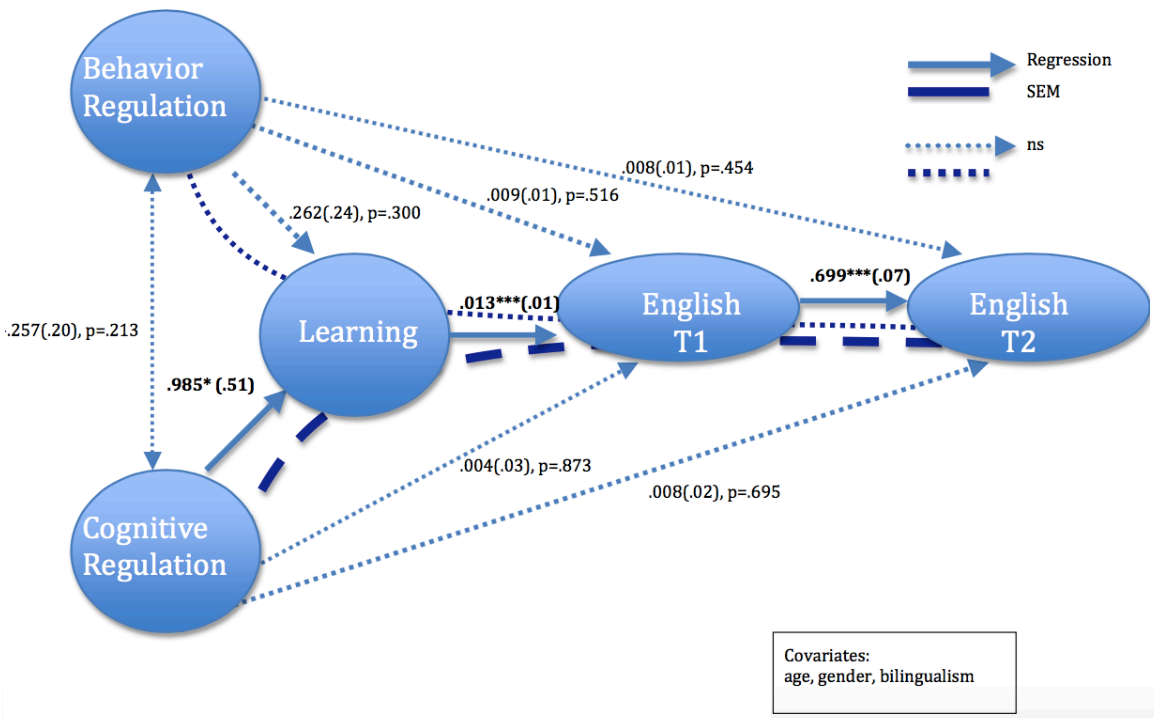
Note. Standard errors included in parentheses next to coefficients
Standardized solution, unable to conduct GF test with no parameters.
Acceptable fit is assumed.

Table 18. SEM: Overall Cognitive Regulation predicting Learning, predicting Math Scores over time

	Coefficient	Standard Error	p>|z|	95% CI
Learning				
Overall Cognitive Regulation	.859	.490	.08	[-.102, 1.822]
Age	6.334	1.494	.000	[3.40, 9.263]
Sex	.887	1.932	.646	[-2.89, 4.674]
Bilingualism	-1.424	1.996	.475	[-5.336, 2.487]
constant	-44.34	27.467	0.106	[-98.1, 9.493]
Math T1				
Learning	.0168	.004	.000	[.008, .026]
Overall Cog Reg	.000	.023	.996	[-.0460, .0462]
Age	-.0283	.080	.726	[-.187, .130]
Sex	-.106	.098	.280	[-.298, .086]
Bilingualism	.315	.100	.002	[.118, .513]
constant	2.857	1.379	.038	[.153, 5.56]
Math T2				
Math T1	.682	.055	.000	[.575, .790]
Learning	.009	.003	.001	[.003, .016]
Overall Cog Reg	.035	.015	.017	[.006, .064]
Age	.063	.052	.221	[-.038, .165]
Sex	-.107	.062	0.087	[-.231, .015]
Bilingualism	.073	.066	.268	[-.056, .203]
constant	-1.686	.901	.061	[-3.453, .080]

n=127
Standardized solution, unable to conduct GF test with no parameters. Acceptable fit is assumed

Figure 5. Structural Equation Model of Overall Cognitive Regulation, Learning, and English Scores over time
(Standardized Solution; n = 127)



Note. Standard errors included in parentheses next to coefficients
Standardized solution, unable to conduct GF test with no parameters.
Acceptable fit is assumed.

Table 19. SEM: Overall Cognitive Regulation predicting Learning, predicting English Scores over time

	Coefficient	Standard Error	p>|z|	95% CI
Learning				
Overall Cognitive Regulation	.935	.492	0.058	[-.030, 1.90]
Age	6.425	1.495	.000	[3.493, 9.356]
Sex	.786	1.932	.684	[-3.00, 4.574]
Bilingualism	-1.288	1.998	.519	[-5.204, 2.628]
constant	-48.722	27.507	0.077	[-102.63, 5.191]
English T1				
Learning	.0137	.004	.004	[.004, .0230]
Overall Cog Reg	-.009	.024	.692	[-.057, .038]
Age	.114	.084	.177	[-.051, .2803]
Sex	.325	.102	.001	[.125, .525]
Bilingualism	.106	.104	.308	[-.098, .311]
constant	1.648	1.439	.252	[-1.171, 4.469]
English T2				
English T1	.654	.065	.000	[.526, .782]
Learning	.010	.003	.008	[.002, .016]
Overall Cog Reg	-.002	.018	0.910	[-.038, .0342]
Age	.012	.0649	.841	[-.114, .140]
Sex	-.047	.080	0.553	[-.205, .109]
Bilingualism	.061	.079	.442	[-.094, .217]
constant	.531	1.108	.632	[-1.64, 2.704]

n=127
Standardized solution, unable to conduct GF test with no parameters. Acceptable fit is assumed

Before accepting these conclusions, we thought it wise to also consider behavior regulation as a covariate and thus include it in the same model as cognitive regulation predicting to learning then academic scores. Including behavior regulation as a covariate, we continued to find the cognitive regulation Both (simultaneous inhibiting and switching) to predict Learning, then scores at T1 and T2. Likewise, when including cognitive regulatory measures as covariates while assessing behavior as predictor, behavior still failed to predict scores at T1 then T2. Lastly, when we switched our main predictor variable to learning – that is, learning predicting cognitive regulation, then scores over time – none of the models persisted through to academic achievement at T2.

Notable, is that neither cognitive regulation or behavior regulation alone predict English scores at either T1 or T2; however, through learning, cognitive regulation persists in predicting English scores at T1 through to T2 (see Figure 3; Table 17).

CHAPTER IV: DISCUSSION

The purpose of this research was to examine the similarity, but distinction, between learning and academic achievement, and their differential prediction from separate self-regulatory processes. Specifically, whether cognitive regulation and behavior regulation would hold similar predictive power to deeper learning (as assessed by inductive inference) versus performance (as assessed by state standardized test scores). Beyond the "does self-regulation predict education outcomes?" question, I hoped to enhance understanding of distinct underlying mechanisms within both cognitive regulation and behavior regulation, and how learning and academic outcomes from these self-regulatory processes are differentially predicted at concurrent time points, and over time.

This research was conducted with the maximum possible degree of validated and reliable observational measures in the school setting. No rater bias is anticipated in any of the instruments utilized. A major strength of this research was that the academic scores were state standardized scores, thus not susceptible to teacher or rater-bias. Likewise, each student served as his/her own agent in the learning and cognitive regulation measures, where tasks were administered individually, maximizing internal validity. Furthermore, the advantage of this observational research design was that unlike usual studies on behavior regulation, teachers or parents did not rate students, nor did we utilize self-report measures, and students were observed in naturalistic classroom school settings.

Summary of Results

The results support the hypothesis that the factors that contribute to individual differences in academic achievement and those that contribute to individual differences in learning can be differentiated. Moreover, findings warrant learning and academic achievement as related, but, distinct constructs. Cognitive regulation appears a more important contributor to effective learning than does behavior regulation. Behavior regulation, which teachers and parents emphasize to young adolescent students as critical to success, shows little predictive power of any sort to learning. Behavioral standards have long been regarded as essential to all kinds of learning and hence to academic achievement. As we see here, behavior may have immediate prediction to academic achievement, but not necessarily to its improvement over time. Cognitive self-regulation does not have as long a history as a topic of investigation for junior high-aged students' learning, but studies of children early in their school careers report a prediction to academic success. What I hope my findings can contribute to existing literature, is the predictive power cognitive regulation has to not only learning in adolescence, but its conducive prediction to achievement over time.

In the present work on young adolescents, I found different results for the two constructs as predictors of self-directed learning skill. It was cognitive regulation, rather than behavioral regulation, that was predictive of students' skill in learning how multiple variables were related to outcomes. The pilot study was conducted under highly controlled conditions with students' performance assessed individually or guided in pairs or groups of three. The dissertation project was conducted under more naturalistic classroom conditions in a school setting. Under both of these conditions, the association between students' individually assessed cognitive self-regulation and their learning was evident. Moreover, it was not behavioral self-regulation, as one might assume, that came into play in predicting students' learning in the more naturalistic classroom setting. Behavioral self-regulation assumed no more predictive power in the naturalistic classroom setting of the pilot study than it had in the main project. Furthermore, behavior regulation did not predict change in academic achievement over time, whereas cognitive regulation did.

Limitations

The studies here focused solely on low-SES and middle-SES samples. While the middle-class sample was a diverse multi-ethnic sample, future work should look to investigate larger and more representative samples of both low-SES and affluent youth of this age group. Likewise, this study did not include self-regulation scores other than those at baseline, thus, the bidirectional relationship between these variables may still be unclear, even though structural equation modeling was employed. Lastly, the behavior regulation measure utilized is administered class-by-class, thus, the variation and scores between on-task behavior and on-task conversation is contingent upon each individual classroom's climate and teachers' instruction styles. Future research should consider taking classroom climate into account and possibly coding it as a separate variable to be used as a covariate in analyses.

Next Steps

Future work should focus on the bidirectional development of self-regulatory processes and deep learning. That is, does inquiry learning develop cognitive regulatory skills? Or is it indeed cognitive regulation that need be developed to develop learning skills? Furthermore, developmental psychologists and education professionals alike need to focus on such matters as it is imperative in developing one of the most multifaceted learning environments in our society -- classrooms.

Recent work comparing high-achieving affluent students, to average-performing middle class students, has produced preliminary results suggesting an inferior performance of affluent students on cognitive regulation and learning. One might expect the focus and expectations regarding academic achievement in privileged students' lives would lead to their becoming highly skilled both in cognitive regulation and in effective learning, relative to a less high-performing sample. High academic expectations on the part of parents, schools, and communities may incur a high potential cost (Pope et al., 2015) to many adolescent students. The costs of the high expectations associated with affluence are even greater to the extent that they extend to young people's cognitive skills and specifically to their ability to flexibly control and regulate their intellectual functions and to apply them in independent learning of new material.

Steinberg (*in press*) has suggested that charter schools do not provide students sufficient opportunity to develop self-control, impairing their transition to healthy young adulthood. It is possible that high-performing affluent students may perceive little control over what they do, since their performance and achievement efforts are externally expectation-driven. Rather, they feel that their behavior is being controlled (Pelletier et al., 2001), and that they are performing out of obligation and pressure. As a result they have insufficient experience of agency in their lives. Thus, students with high external self-control (behavior regulation) may in fact have lower internal self-control (i.e., cognitive regulation), as seen in the data presented here.

Self-control has many facets. If a young person's self-monitoring on a task like the one I used is impaired, it is likely the effects extend more broadly – in particular to the critical skill of learning, as my results suggest.

Implications

School achievement is a topic at the forefront of Americans' concern, as US students continue to perform poorly in international comparisons. Particularly in urban underachieving classrooms, classroom atmosphere has been a focus, the idea being that high behavioral standards and expectations must be imposed and maintained if the classroom environment is to be conducive to students' learning. Ideally, once high behavioral standards are in place, students gradually become able to regulate their own behavior and become more autonomous and effective learners. A capacity to self-regulate as a condition for learning now appears all the more critical with the advent of the Common Core standards and their emphasis on deep rather than shallow learning. The findings reported in this study suggest that emphasis on behavior regulation as a key to effective learning may be misplaced.

As Benjamin Franklin noted, the goal of an education is not just to learn a little about a lot, but also a lot about a little. Much of the essential knowledge about the world is causal in nature. Markman (2010), for example, stresses its importance when he notes its contemporary relevance:

> *In April, 2010, a BP oil rig in the Gulf of Mexico exploded… One question that has been on the minds of people everywhere is: Why? The question "Why?" seeks causal information… We care about causes in situations like this for many reasons. For one thing, we want to know who and what to blame for the mess in the Gulf…*
>
> *For another thing, causal knowledge will help us to prevent accidents like this in the future… One factor that makes causes so hard to think about is that there is never just one cause of any event in the world. There are many reasons why there are many causes… However, causal knowledge is also the engine of innovation and creativity. It is nearly impossible to create a new solution to a problem without understanding the causal forces at work that led to the problem in the first place. So, if you have any interest in solving new problems, it would help you to learn more about the way you think about causal information.*

If we are concerned to understand the individual as well as situational factors that are most powerful in promoting students' ability to engage successfully in self-directed learning, cognitive self-regulation may be a particularly productive area of investigation. At least part of the remaining variance in learning outcomes that our very basic measure of cognitive self-regulation did not capture may nonetheless be predictable by more comprehensive and exacting cognitive self-regulation assessments not yet developed. At minimum, our findings point to it as an individual predictor worthy of further exploration.

Increasingly, educators have begun to emphasize the need not only for deep learning but for individualized learning. What's more, is the freedom and empowerment that comes to any child, or young adolescent, when they are able to know what they want to know. If students are to be able to learn what they want to know and to learn well, they must have the necessary tools. To the extent some of these tools lie within the individual, they deserve our close investigation, along with the external factors under educators' more direct control. There now exists evidence that cognitive self-regulation can be fostered (Diamond, 2012; Diamond et al., 2007; Schunk, 2005). To this extent it becomes even more important to understand what its development stands to accomplish.

The fullest representations of humanity show people to be curious, self-motivated, and at their best, they are striving to learn, master new skills, and apply their knowledge responsibly. It has been established that human beings by nature, can be proactive and engaged or, alternatively, passive and alienated (Ryan and Deci, 2000), largely as a function of the social conditions in which they develop and function – such as classrooms.

The fact that human nature can be either active or passive, constructive or indolent, suggests more than mere dispositional differences and is a function of more than just instinctive endowments. We should, therefore, focus on malleability of young students and propose tailoring of classrooms and instruction, to better mold students to reach their full potential as learners. Research has identified basic needs for individuals -- the need for competence (Harter, 1978; White, 1963), and autonomy (deCharms, 1968; Deci, 1975)—of which appear to be essential for facilitating optimal functioning of the propensities for intellectual growth as well as for constructive cognitive development for learning. Developmentalists acknowledge that children, in their healthiest states, are active, inquisitive, curious, and playful, even in the absence of specific rewards (e.g., Harter, 1978). Yet, despite the fact that humans are liberally endowed with intrinsic motivational tendencies, the evidence is now clear that the maintenance and enhancement of this inherent propensity require supportive conditions, as it can be fairly readily disrupted by anything and everything that can ensue during early adolescence and beyond. Thus, the work here proposes factors that may elicit and sustain, versus subdue and diminish, this innate propensity – learning.

Learning can represent two facets – memorization of taught facts, or self-directed inductive learning. During inquiry, students come to understand that they are able to acquire knowledge they desire, by initiating, managing, and executing investigation on their own, and that the acquired knowledge is empowering. It is this empowerment, and sense of autonomy for acquiring knowledge, which educators must further foster. By satisfying, and providing, these opportunities to young learners in classrooms, we will move towards establishing equity in education, by re-empowering students to succeed as thinkers, knowers, and scientists. If every child were to reach their full potential of learning, to have higher competence in the world around them, then we will have moved one step closer towards honoring that all minds are created equal, regardless of social or economic barriers, and that they are endowed by right to life, liberty, and learning.

References

Black, A. E., & Deci, E. L. (2000). The effects of instructors' autonomy support and students' autonomous motivation on learning organic chemistry: A self‐determination theory perspective. Science education, 84(6), 740-756.

Blair, C., & Razza, R. P. (2007). Relating effortful control, executive function, and false belief understanding to emerging math and literacy ability in kindergarten. *Child development*, *78*(2), 647-663.

Blair, C., & Raver, C. C. (2015). Closing the achievement gap through modification of neurocognitive and neuroendocrine function: Results from a cluster randomized controlled trial of an innovative approach to the education of children in kindergarten. *PLoSONE*

Bodovski, K., & Farkas, G. (2007). Do instructional practices contribute to inequality in achievement? The case of mathematics instruction in kindergarten. *Journal of Early Childhood Research*, *5*(3), 301-322.

Bull, R., & Scerif, G. (2001). Executive functioning as a predictor of children's mathematics ability: Inhibition, switching, and working memory. *Developmental neuropsychology*, *19*(3), 273-293.

Carlson, S. M., & Meltzoff, A. N. (2008). Bilingual experience and executive functioning in young children. *Developmental science*, *11*(2), 282-298.

Chevalier, N., Huber, K. L., Wiebe, S. A., & Espy, K. A. (2013). Qualitative change in executive control during childhood and adulthood. *Cognition, 128(1),* 1-12.

Cleary, T. J., Callan, G. L., & Zimmerman, B. J. (2012). Assessing self-regulation as a cyclical, context-specific phenomenon: Overview and analysis of SRL microanalytic protocols. *Education Research International*, *2012*.

Corno, L., & Mandinach, E. B. (1983). The role of cognitive engagement in classroom learning and motivation. *Educational psychologist*, *18*(2), 88-108.

Corno, L., & Rohrkemper, M. (1985). The intrinsic motivation to learn in classrooms. *Research on motivation in education*, *2*, 53-90.

Cutright, P., & Fernquist, R. M. (2014). Cross-national differences in academic achievement: Why the United States lags behind other rich nations. *Sociological Focus, 47(2),* 71-83.

deCharms, R. (1968) Personal Causation. New York: Academic Press

Deci, E. L. (1975). Notes on the theory and metatheory of intrinsic motivation.Organizational behavior and human performance, 15(1), 130-145.

Deci, E. L., & Ryan, R. M. (1987). The support of autonomy and the control of behavior. Journal of personality and social psychology, 53(6), 1024.

Desoete, A., & Roeyers, H. (2002). Off-Line Metacognition—A Domain-Specific Retardation in Young Children with Learning Disabilities?. *Learning Disability Quarterly*, *25*(2), 123-139.

Diamond, A. (2012). Activities and programs that improve children’s executive functions. Current Directions in Psychological Science, 21(5), 335-341.

Diamond, A., Barnett, W. S., Thomas, J., & Munro, S. (2007). Preschool program improves cognitive control. Science (New York, NY), 318(5855), 1387.

Duckworth, A. L., & Seligman, M. E. (2005). Self-discipline outdoes IQ in predicting academic performance of adolescents. *Psychological science*, *16*(12), 939-944.

Duckworth, A. L., & Seligman, M. E. (2006). Self-discipline gives girls the edge: Gender in self-discipline, grades, and achievement test scores. *Journal of educational psychology*, *98*(1), 198.

Eccles, J., Wigfield, A., Harold, R. D., & Blumenfeld, P. (1993). Age and gender differences in children's self‐and task perceptions during elementary school. *Child development*, *64*(3), 830-847.

Efklides, A. (2008). Metacognition: Defining its facets and levels of functioning in relation to self-regulation and co-regulation. *European Psychologist*, *13*(4), 277-287.

Espy, K. A., McDiarmid, M. M., Cwik, M. F., Stalets, M. M., Hamby, A., & Senn, T. E. (2004). The contribution of executive functions to emergent mathematic skills in preschool children. *Developmental neuropsychology*, *26*(1), 465-486.

Feldlaufer, H., Midgley, C., & Eccles, J. S. (1988). Student, teacher, and observer perceptions of the classroom environment before and after the transition to junior high school. *The Journal of Early Adolescence*, 8(2), 133-156.\

Fischer, M. H., Kaufmann, L., & Domahs, F. (2012). Finger counting and numerical cognition. *Handy numbers: finger counting and numerical cognition*, 5.

Flavell, J. H. (1979). Metacognition and cognitive monitoring: A new area of cognitive–developmental inquiry. *American psychologist*, *34*(10), 906.

Garcia, T., & Pintrich, P. R. (1994). Regulating motivation and cognition in the classroom: The role of self-schemas and self-regulatory strategies.

Greiff, S., Wüstenberg, S., Molnár, G., Fischer, A., Funke, J., & Csapó, B. (2013). Complex problem solving in educational contexts—Something beyond g: Concept, assessment, measurement invariance, and construct validity. *Journal of Educational Psychology*, *105*(2), 364.

Greiff, S., Wüstenberg, S., Holt, D. V., Goldhammer, F., & Funke, J. (2013). Computer-based assessment of Complex Problem Solving: concept, implementation, and application. *Educational Technology Research and Development*, *61*(3), 407-421.

Harter, S. (1978). Effectance motivation reconsidered. Toward a developmental model. Human development, 21(1), 34-64.

Hasher, L., Zacks, R. T., & May, C. P. (1999). Inhibitory control, circadian arousal, and age.

Kelemen, W. L., Frost, P. J., & Weaver, C. A. (2000). Individual differences in metacognition: Evidence against a general metacognitive ability. *Memory & Cognition*, *28*(1), 92-107.

Kuhn, D., & Pease, M. (2008). What needs to develop in the development of inquiry skills?. *Cognition and Instruction*, *26*(4), 512-559.

Kuhn, D., Pease, M., & Wirkala, C. (2009). Coordinating the effects of multiple variables: A skill fundamental to scientific thinking. *Journal of experimental child psychology*, *103*(3), 268-284.

Kuhn, D., Iordanou, K., Pease, M., & Wirkala, C. (2008). Beyond control of variables: What needs to develop to achieve skilled scientific thinking?. *Cognitive Development*, *23*(4), 435-451.

Kuhn, D., Ramsey, S., & Arvidsson, T. S. (2015). Developing multivariable thinkers. *Cognitive Development*, *35*, 92-110.

Markman, A. (2010). Thinking about causes I: What is a cause? Retrieved November 14, 2015, *Psychology Today*

Mayer, R. E., & Wittrock, M. C. (2006). Problem solving. *Handbook of educational psychology*, *2*, 287-303.

McClelland, M. M., Morrison, F. J., & Holmes, D. L. (2000). Children at risk for early academic problems: The role of learning-related social skills. *Early childhood research quarterly*, *15*(3), 307-329.

McClelland, M. M., Cameron, C. E., Connor, C. M., Farris, C. L., Jewkes, A. M., & Morrison, F. J. (2007). Links between behavioral regulation and preschoolers' literacy, vocabulary, and math skills. *Developmental psychology*, *43*(4), 947.

McGlamery, M. E., Ball, S. E., Henley, T. B., & Besozzi, M. (2007). Theory of mind, attention, and executive function in kindergarten boys. *Emotional and Behavioural Difficulties*, *12*(1), 29-47.

Miyake, A., & Friedman, N. P. (2012). The nature and organization of individual differences in executive functions four general conclusions. *Current directions in psychological science*, *21*(1), 8-14.

Morrison, F. J., Ponitz, C. C., & McClelland, M. M. (2010). Self-regulation and academic achievement in the transition to school. *Child development at the intersection of emotion and cognition*, 203-224.

Mazzocco, M. M., & Kover, S. T. (2007). A longitudinal assessment of executive function skills and their association with math performance. *Child Neuropsychology*, *13*(1), 18-45.

Ocumpaugh, J. (2012). Baker-Rodrigo observation method protocol (BROMP) 1.0. Training manual version 1.0. *Baker-Rodrigo Observation Method Protocol (BROMP) 1.0. Training Manual version 1.0, Tech. Rep*.

Organisation for Economic Co-operation & Development (2013). *PISA 2012 Results in focus:* What 15 year-olds know and what they can do with what they know. *Paris, France:* Author.

Pelletier, L. G., Fortier, M. S., Vallerand, R. J., & Briere, N. M. (2001). Associations among perceived autonomy support, forms of self-regulation, and persistence: A prospective study. *Motivation and Emotion*, 25(4), 279-306.

Pintrich, P. R., Smith, D. A., García, T., & McKeachie, W. J. (1993). Reliability and predictive validity of the Motivated Strategies for Learning Questionnaire (MSLQ). *Educational and psychological measurement*, *53*(3), 801-813.

Ponitz, C. E. C., McClelland, M. M., Jewkes, A. M., Connor, C. M., Farris, C. L., & Morrison, F. J. (2008). Touch your toes! Developing a direct measure of behavioral regulation in early childhood. *Early Childhood Research Quarterly*, *23*(2), 141-158.

Porter, A., McMaken, J., Hwang, J., & Yang, R. (2011). Common core standards the new US intended curriculum. *Educational Researcher, 40(3),* 103-116.

Prencipe, A., Kesek, A., Cohen, J., Lamm, C., Lewis, M. D., & Zelazo, P. D. (2011). Development of hot and cool executive function during the transition to adolescence. *Journal of experimental child psychology*, *108*(3), 621-637.

Rigas, G., Carling, E., & Brehmer, B. (2002). Reliability and validity of performance measures in microworlds. *Intelligence*, *30*(5), 463-480.

Salmela-Aro, K. (2015). Towards a new science of academic engagement. *Research in Human Development*, *12*(3-4), 304-311.

Salmela-Aro, K., Kiuru, N., Pietikäinen, M., & Jokela, J. (2008). Does school matter? *European Psychologist*, *13*(1), 12-23.

Schraw, G., & Nietfeld, J. (1998). A further test of the general monitoring skill hypothesis. *Journal of Educational Psychology*, *90*(2), 236.

Schunk, D. H. (2005). Self-regulated learning: The educational legacy of Paul R. Pintrich. Educational Psychologist, 40(2), 85-94.

Skinner, E. A., Wellborn, J. G., & Connell, J. P. (1990). What it takes to do well in school and whether I've got it: A process model of perceived control and children's engagement and achievement in school. Journal of educational psychology, 82(1), 22.

Steinberg, L. (Ed.). (*in press*). *Our last best chance: Why adolescence matters more than ever*: New York: Houghton Mifflin Harcourt.

Steinberg, L. (2014). *Age of opportunity: Lessons from the new science of adolescence.* Houghton Mifflin Harcourt: Chicago.

Teuber, H. L. (1972). Unity and Diversity of Frontal Lobe Functions. *Acta neurobiol. exp*, *32*, 615-656.

Valiente, C., Lemery-Chalfant, K., Swanson, J., & Reiser, M. (2008). Prediction of children's academic competence from their effortful control, relationships, and classroom participation. *Journal of educational psychology*, *100*(1), 67.

Van der Stel, M., & Veenman, M. (2008). Relation between Intellectual Ability and Metacognitive Skillfulness as Predictors of Learning Performance of Young Students Performing Tasks in Different Domains. *Learning and Individual Differences, 18,* 128-134.

Van der Stel, M., & Veenman, M. (2010). Development of Metacognitive Skillfulness: A Longitudinal Study. *Learning and Individual Differences, 20,* 220-224.

Welch, W. W., Klopfer, L. E., Aikenhead, G. S., & Robinson, J. T. (1981). The role of inquiry in science education: Analysis and recommendations. *Science education*, 65(1), 33-50.

Welsh, M., Parke, R. D., Widaman, K., & O'Neil, R. (2001). Linkages between children's social and academic competence: A longitudinal analysis. *Journal of School Psychology*, *39*(6), 463-482.

White, R. W. (1963). Sense of interpersonal competence: Two case studies and some reflections on origins.

Wüstenberg, S., Greiff, S., & Funke, J. (2012). Complex problem solving—More than reasoning?. *Intelligence*, *40*(1), 1-14.

Xu, F., Han, Y., Sabbagh, M. A., Wang, T., Ren, X., & Li, C. (2013). Developmental differences in the structure of executive function in middle childhood and adolescence. *PLoS ONE, 8*(10), 1-8.

Zimmerman, B. J. (2000). Self-efficacy: An essential motive to learn. *Contemporary educational psychology*, *25*(1), 82-91