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"Same But Different": Associations Between Multiple Aspects of Self-Regulation, Cognition, and Academic Abilities

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Self-regulation describes the ability to control both behaviors and internal states against a backdrop of conflicting or distracting situations, drives, or impulses. In the cognitive psychology tradition, individual differences in self-regulation are commonly measured with performance-based tests of executive functioning, whereas in the personality psychology tradition, individual differences in self-regulation are typically assessed with report-based measures of impulse control, sustained motivation, and perseverance. The goal of this project was (a) to comprehensively examine the structure of associations between multiple self-regulatory constructs stemming from the cognitive and personality psychology traditions; (b) to estimate how these constructs, individually and collectively, related to mathematics and reading ability beyond psychometric measures of processing speed and fluid intelligence; and (c) to estimate the extent to which genetic and environmental factors mediated the observed associations. Data were available for 1,019 child participants from the Texas Twin Project (M age = 10.79, range = 7.8–15.5). Results highlighted the differentiation among cognitive and personality aspects of self-regulation, both at observed and genetic levels. After accounting for processing speed and fluid intelligence, EF remained a significant predictor of reading and mathematics ability. Educationally relevant measures of personality—particularly an openness factor representing curiosity and intellectual self-concept—incrementally contributed to individual differences in reading ability. Collectively, measures of cognition, self-regulation, and other educationally relevant aspects of personality accounted for the entirety of genetic variance in mathematics and reading ability. The current findings point to the important independent role that each construct plays in academic settings.

Keywords: self-regulation, executive function, personality, cognitive skills, academic abilities

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> It takes something more than intelligence to act intelligently.
> —Fyodor Dostoyevsky (1866)

For more than a century, scholars and educators have embraced the idea that attributes other than intelligence are important in predicting educational attainment and lifelong accomplishment. Binet and Simon (1916), the creators of the first Intellectual Quotient (IQ) test, argued that, beyond intelligence, qualities such as "attention, will and character" (p. 254) are important for educational success. Similarly, David Wechsler (1943), the creator of the most widely adopted intelligence tests for children and adults, argued that "nonintellective factors of general intelligence" contributed to the development of intelligent behavior. The current study examined how a broad class of self-regulatory factors—not directly tapped by psychometric measures of intelligence—relate to one another and contribute, individually and collectively, to predicting academic abilities. As academic skills are important predictors of professional success, health, wellbeing and longevity (Cutler & Lleras-Muney, 2012; Marioni et al., 2016), understanding how different factors contribute to their variation is a research priority (OECD, 2013).

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Self-Regulation: What Is Being Measured and How Is It Being Measured

Self-regulation encompasses a constellation of effortful psychological processes that regulate behavior and internal states toward desired goals. These processes often operate against a backdrop of conflicting or distracting situations, drives, and impulses (Diamond, 2013). The umbrella of self-regulation includes constructs such as executive functioning, emotion-regulation, effortful control, temperament, impulse control, delay of gratification, and willpower (Blair, Ursache, Greenberg, Vernon-Feagans & the Family Life Project Investigators, 2015; Nigg, 2017). All of these constructs are typically conceptualized as dynamic adaptive processes that support goal-directed behavior (Blair et al., 2015).

Several taxonomies of self-regulation have been proposed; while some were developed with the aim of identifying different facets within the broad domain of self-regulated behavior (Forgas, Baumeister, & Tice, 2009), others have argued for the need of approaching self-regulation from a domain general standpoint (e.g., Nigg, 2017). In a recent review, Nigg (2017) argued for the domain generality of self-regulatory processes, which operate across three broad areas: actions, emotions and cognition. Within this framework, *regulation of action* is defined as the goal-directed optimization of overt physical actions, such as ocular, motor and vocal responses. *Regulation of emotion* describes the processes that regulate the onset and characteristics of an emotional response, such as its magnitude, duration, and intensity. *Regulation of cognition* is defined as the goal-oriented modification of cognitive processes, such as attention and memory, in the absence of regulation of action or emotion. The current work primarily focuses on constructs that most closely align with these latter areas of self-regulation, investigating how executive functions (EF), impulse control and other educationally relevant aspects of personality relate to one other, and how each contributes to accounting for individual differences in academic abilities, beyond psychometric measures of intelligence.

Self-regulation constructs have been measured using a variety of techniques, ranging from performance-based assessments (*tests* or *tasks*) to self- and informant-report inventories (Harden et al., 2017; Saunders, Milyavskaya, Etz, Randles, & Inzlicht, 2017). Some aspects of self-regulation are conventionally measured using test batteries (Diamond, 2013), whereas other aspects tend to be assessed using rating scales (Duckworth & Yeager, 2015). Differences in assessment modality are likely to stem from the different literatures that produced different conceptualizations of self-regulation. Specifically, the conceptualization and measurement of EF largely stems from the cognitive psychology tradition (Lezak, Howieson, & Loring, 2004; Miyake et al., 2000; Salthouse, 2005; Welsh & Pennington, 1988), whereas impulse control is closely linked to the personality psychology literature (Aluja, Garća, & Garća, 2003; Duckworth & Steinberg, 2015; Rothbart & Posner, 1985; Whiteside & Lynam, 2001; Zuckerman, Kuhlman, Joireman, Teta, & Kraft, 1993).

Both social and cognitive theories of self-regulation have nevertheless drawn on findings using both tests and rating scales (Crandall, Deater-Deckard, & Riley, 2015). An unfortunate side effect that results from cognitive and personality literatures informing one another is that labels previously used to describe, and empirical findings obtained, using performance-based tests are increasingly applied to constructs measured with rating scales, and vice versa, even when the available evidence points to their distinction. In fact, the literature on the convergent validity of performance-based and report-based measures of self-regulation, suggests that the dimensions tapped by the two formats are only weakly related (Cyders & Coskunpinar, 2011; McAuley, Chen, Goos, Schachar, & Crosbie, 2010; Nęcka, Gruszka, Orzechowski, Nowak, & Wǒjcik, 2018; Toplak, West, & Stanovich, 2013).

It has been suggested that performance-based measures of self-regulation capture cognitive processes that are distinct from affective-motivational processes that are assessed by questionnaire-based measures (Stanovich, 2012). Toplak et al. (2013) proposed that performance-based measures describe an "algorithmic" level of analysis, which is concerned with processing efficiency and performance in highly structured environments. Because of the structured way in which tests of self-regulation are administered, they are likely to reflect optimal, rather than typical, performance (Cronbach, 1949, 1960). Individuals who are exposed to cognitive testing perform tasks in highly controlled environments and are appropriately cued by the experimenter to perform optimally on the task at hand. In contrast, questionnaire-based ratings are proposed to describe a "reflective" level of analysis, such that they tap the goals of the person and behavior in the real-world environment. Questionnaire responses are not cued or constrained by a specific test environment or by instructions aimed at maximizing performance. Some have, therefore, proposed that report-based measures of self-regulation may provide a closer assessment of typical performance (McAuley et al., 2010; Toplak et al., 2013).

As researchers have continued to develop, validate, and use relatively decontextualized measures of general self-regulation constructs, a parallel literature has emerged on contextualized, report-based measures of tendencies of thinking, feeling, and behaving specifically in educational and vocational settings. These educationally relevant measures of personality, alternatively described in the literature as "noncognitive factors" (Heckman & Rubinstein, 2001), "motivational factors" (Duckworth & Yeager, 2015), or "character" (Tucker-Drob, Briley, Engelhardt, Mann, & Harden, 2016), include constructs such as self-control and effortful control that have been considered part of the self-reported self-regulation umbrella (Bridgett, Burt, Edwards, & Deater-Deckard, 2015; Duckworth & Gross, 2014). In a review focusing on the development of self-regulation, Bridgett et al. (2015) describe self-regulation as comprising not only aspects of EF and emotion and cognitive regulation, but also aspects that have traditionally appeared in the personality literature, such as sustained effortful control (also described as grit; Duckworth, Peterson, Matthews, & Kelly, 2007) and temperament (also described as personality; Bridgett et al., 2015). Other educationally relevant aspects of personality, including intellectual interest, self-perceived ability, the value attributed to learning, and belief in the malleability of intelligence, have remained conceptually more distant from the characterization of self-regulation (Tucker-Drob et al., 2016).

The current work aimed to, first, examine the multivariate structure of associations between measures of self-regulation traditionally stemming from the cognitive literature (performance-based measures of EF) and from the personality literature (report-based measures of impulse control—defined as the capacity to regulate behavior to achieve long term goals (Lydon-Staley & Geier, 2018)—and other educationally relevant aspects of personality). Applying a genetically informative design the present study also investigated the extent to which overlapping genetic and environmental factors characterized the associations between these multiple aspects of self-regulation. Second, the present study investigated, within a genetically informative framework, how self-regulatory constructs accounted for variation in reading and mathematics abilities, beyond measures of processing speed and fluid intelligence. In the sections that follow, we detail the state of knowledge on the interface between aspects of self-regulation stemming from the cognitive and personality traditions, and on their association with cognitive and academic abilities.

EFs: Assessing Self-Regulation Within the Cognitive Tradition

Originating from the cognitive and neuropsychology literatures, *executive functioning* describes cognitive processes that supervise, monitor, and control more basic cognitive processes to give rise to higher-order thinking, reasoning, and decision making. EF that are commonly studied in contemporary research include *Inhibition* (the ability to control prepotent responses), *Working Memory* (the ability to maintain information in immediate memory simultaneous with cognitive processing), *Switching* (the ability to efficiently shift attention to a different stimulus or task rule), and *Updating* (the ability to monitor incoming stimuli and replace old information with new (Diamond, 2013; Engle, 2002).

A prolific body of research has investigated the dimensionality of EF and how the different skills forming this multifaceted construct relate to one another. Because individual differences in any given measure of EF have the potential to reflect a mixture of executive and nonexecutive factors, confirmatory factor analytic methods that examine shared variance across sets of EF measures are important for distilling executive sources of variance from both nonexecutive factors and measurement error. An influential empirical taxonomy proposed by Miyake et al., 2000 and Miyake & Friedman, 2012, emphasizes "unity and diversity" between components of EF. This model can be represented hierarchically, with individual EF tasks loading on EF domains, which in turn load on a higher-order common factor (Engelhardt, Briley, Mann, Harden, & Tucker-Drob, 2015; Engelhardt et al., 2016). The common EF factor has been suggested to reflect an ability to formulate and maintain goals (Friedman & Miyake, 2017) or a general capacity for controlled attention (Engle, 2002).

We have previously reported that the common EF factor shares a strong genetic association with intelligence as early as middle childhood, even after controlling for more basic processing speed ability (Engelhardt et al., 2016). Despite their strong association, common EF and intelligence are dissociable in a number of ways. For instance, quantitative genetic decompositions of variation in both EF domains and common EF in childhood indicate very high heritability (the extent to which individual differences in a trait are explained by differences in DNA between people), small nonshared environmentality, and no evidence for shared environmentality (Engelhardt et al., 2015; Engelhardt et al., 2016; Friedman et al., 2008). That is, children raised in the same home are not similar for their EF abilities above what can be explained by their genetic similarity. In contrast, intellectual abilities, while also highly heritable, consistently evince nontrivial proportions of shared environmentality in childhood (Petrill, 1997; Tucker-Drob & Briley, 2014).

Previous studies that have investigated broad EF indices in relation to academic abilities and achievement have reported moderate to strong associations (Best, Miller, & Naglieri, 2011; Miller & Hinshaw, 2010; St Clair-Thompson & Gathercole, 2006; Titz & Karbach, 2014). Studies that have used individual EF measures, rather than composite scores or latent factors, show substantially lower associations with academic achievement (Gijselaers, Meijs, Neroni, Kirschner, & De Groot, 2017). This may be attributable to low reliability and high contamination by non-EF variance that is characteristic of individual EF tasks. Longitudinal research in a sample of 4- to 6-year-old children showed that EFs, measured as a factor score comprising six different tests, may be foundational to the development of academic achievement, as indicated by stronger links from EF to later achievement than vice versa (Fuhs, Nesbitt, Farran, & Dong, 2014). The link between EF and mathematics ability has been found to be particularly strong, potentially reflecting a fundamental EF demand involved in mathematics (Bull & Lee, 2014; Fuhs et al., 2014).

Associations Between EFs and Self-Regulatory Constructs Stemming From the Personality Literature

Research investigating the association between measures of self-regulation stemming from the cognitive traditions (such as tests of EF) and self-regulatory constructs closely linked to the personality psychology literature (such as self-reports of self-control) has found only mild correspondence between these two formats. Saunders et al. (2017) explored the relation between self-reported self-control—defined as the specific ability to resist temptation and override impulses (Diamond, 2013)—and performance-based measures of Inhibition, concluding that they were only weakly related (Saunders et al., 2017). These findings are consistent with those of a meta-analysis and a review exploring the convergent validity of measures of self-regulation (Duckworth & Kern, 2011; Toplak et al., 2013), which reported only weak associations between self-reported measures of self-control and performance-based tests of EF. Similarly, weak associations (r = .09–0.13) were reported by another meta-analysis on the correspondence between multiple aspects of self-reported and test-based assessments of impulsivity—defined as acting without considering consequences (Cyders & Coskunpinar, 2011). A further study found that a measure of self-reported executive problems was not correlated with tests of Switching (trail making), Working Memory (digit span) and phonemic and semantic fluency (Buchanan, 2016).

Weak to moderate relations have also been observed between test-based measures of EF and the dimensions of the Five Factor Model of personality (Big Five; Costa & McCrae, 1992): Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism. Variation in Neuroticism has been associated with lower performance in tests of Common EF (Williams, Suchy, & Kraybill, 2010) and specific facets of EF, such as Inhibition (Jónsson et al., 2017; Linnenbrink, Ryan, & Pintrich, 1999; Muris et al., 2009), Working Memory, Attention Control (Robison, Gath, & Unsworth, 2017), and Updating (Murdock, Oddi, & Bridgett, 2013). Murdock et al. (2013), also found weak positive associations between tests of Updating and Cognitive Flexibility and the personality dimension of Openness

(Murdock et al., 2013). The association between tests of EF and the Big Five dimension of Extraversion is characterized by inconsistencies, as studies have found that Extraversion relates positively to some EF tasks (i.e., Updating; Campbell, Davalos, McCabe, & Troup, 2011) and negatively to others (i.e., Inhibition, Muris et al., 2009; and Set Shifting, Campbell, et al., 2011). The association between Conscientiousness and test-based EF tasks is reported to be relatively small, with some associations reported as weak, but positive (i.e., Set Shifting Ability, Fleming, Heintzelman, & Bartholow, 2015; Updating, Jensen-Campbell et al., 2002), and others found to be null (i.e., Inhibition and Updating). However, using self-report measure of executive problems across three distinct studies, negative associations have been found between Conscientiousness and self-reported executive problems (Buchanan, 2016). These inconsistences and weak associations for relationships between Conscientiousness or Extraversion and EF suggests that the overall effect in the population is either quite small, or highly contingent on the form of EF task used (e.g., Inhibition vs. Updating).

While a number of investigations have explored the associations between performance in tests of EF and the Big Five, the relations between more targeted educationally relevant aspects of personality and tests of EF remain mostly unexplored. One study investigated the association between test-based EF and intellectual self-concept, finding a weak positive association (Roebers, Cimeli, Röthlisberger, & Neuenschwander, 2012); furthermore EF, but not intellectual self-concept, predicted mathematics and language ability in a sample of 8 year-olds. These educationally relevant traits, which include, beyond intellectual self-concept, constructs such as intellectual interest, self-perceived ability, the value attributed to learning, and belief in the malleability of intelligence, have also seldom been investigated in relation to other aspects of personality, traditionally considered under the self-regulation umbrella, such as self-control and impulse control. One notable exception is grit (defined as perseverance and passion to achieve long-term goals; Duckworth et al., 2007), a construct closely related to Conscientiousness (Rimfeld, Kovas, Dale, & Plomin, 2016) and self-control (Duckworth & Gross, 2014). Grit has been found to share strong associations with questionnaire-based measures of self-regulation (Duckworth et al., 2007)—so much so that both grit and Conscientiousness have themselves been conceptualized as aspects of self-regulation (Bridgett et al., 2015; Bridgett, Oddi, Laake, Murdock, & Bachmann, 2013).

Overall, several gaps characterize the state of knowledge on the association between measures of self-regulation stemming from the cognitive tradition and aspects of self-regulation originating from the personality literature. First, studies examining the association between tests of EF and the Big Five dimensions report mixed results. Inconsistencies may be due, at least in part, to the low reliability of individual EF tasks, or an inability to distil executive from nonexecutive sources of variance that would be afforded by a latent variable framework. Moreover, research investigating the association between EF and the Big Five has often been conducted on convenience samples of adults or college students. Results may not generalize to the broader population or to earlier developmental periods, particularly since the association between personality dimensions and performance has been found to vary over development (Poropat, 2009; Vedel & Poropat, 2017). Second, the association between performance in tests of EF and other educationally relevant self-regulatory aspects of personality remains underexplored. Research has suggested that some of these more targeted, educationally relevant, constructs share closer associations with academic performance than the Big Five (Briley, Domiteaux, & Tucker-Drob, 2014). It remains unclear whether this closer associations could be, at least in part, attributable to variance shared with executive control beyond other self-regulatory aspects of personality. Third, the association between the majority of these more targeted, educationally relevant, aspects of personality, and traditional measures of self-regulation steaming form the personality psychology tradition, such as impulse control, remains unmapped. Lastly, the extent to which the overlap between cognitive and personality aspects of self-regulation can be attributed to shared genetic and environmental variance has not been investigated. The present study aimed to fill these gaps by examining the associations between comprehensively measured aspects of self-regulation stemming from the cognitive and personality literatures within a genetically informative framework. Figure 1 provides a visual summary of the multiple aspects of self-regulation considered in the current work.

Associations Between Personality-Based Self-Regulatory Constructs and Academic Abilities

Individual differences in self-regulatory constructs originating from the personality research tradition have consistently been found to relate to academic skills. Higher levels of impulse control have been associated with positive scholastic outcomes in childhood and adolescence, including school achievement (Tangney, Baumeister, & Boone, 2004). In line with such evidence, high levels of impulsivity have been linked with lower levels of academic achievement and abilities in both clinical (Merrell, Sayal, Tymms, & Kasim, 2017), and nonclinical (Lozano, Gordillo, & Perez, 2014; Vigil-Colet & Morales-Vives, 2005) samples. Additionally, several investigations have linked higher levels of self-control to higher grades in high-school and university samples (Muenks, Wigfield, Yang, & O'Neal, 2017; Tangney et al., 2004).

Several studies have linked the Big Five factors of personality, and particularly the dimensions of Conscientiousness (Briley et al., 2014; Poropat, 2009; Rimfeld et al., 2016; Vedel & Poropat, 2017) and Openness (Neuenschwander, Cimeli, Röthlisberger, & Roebers, 2013; Poropat, 2009) to variation in academic abilities and achievement, reporting modest to moderate positive effects. Narrower educationally relevant aspects of personality, including self-perceived ability and intellectual interest, have also been consistently found to covary with academic skills. For instance, academic self-perceived ability and interest were found to be related to performance in multiple academic domains (Garon-Carrier et al., 2016; Guay, Ratelle, Roy, & Litalien, 2010; Tucker-Drob & Harden, 2012, 2014), even after accounting for intelligence (Chamorro-Premuzic, Harlaar, Greven, & Plomin, 2010; Tucker-Drob & Briley, 2012). In a subset of data from the Texas Twin Project, used in the current investigation, Tucker-Drob et al. (2016) found that second-order conscientiousness and openness super factors capturing covariation among multiple educationally relevant mea-

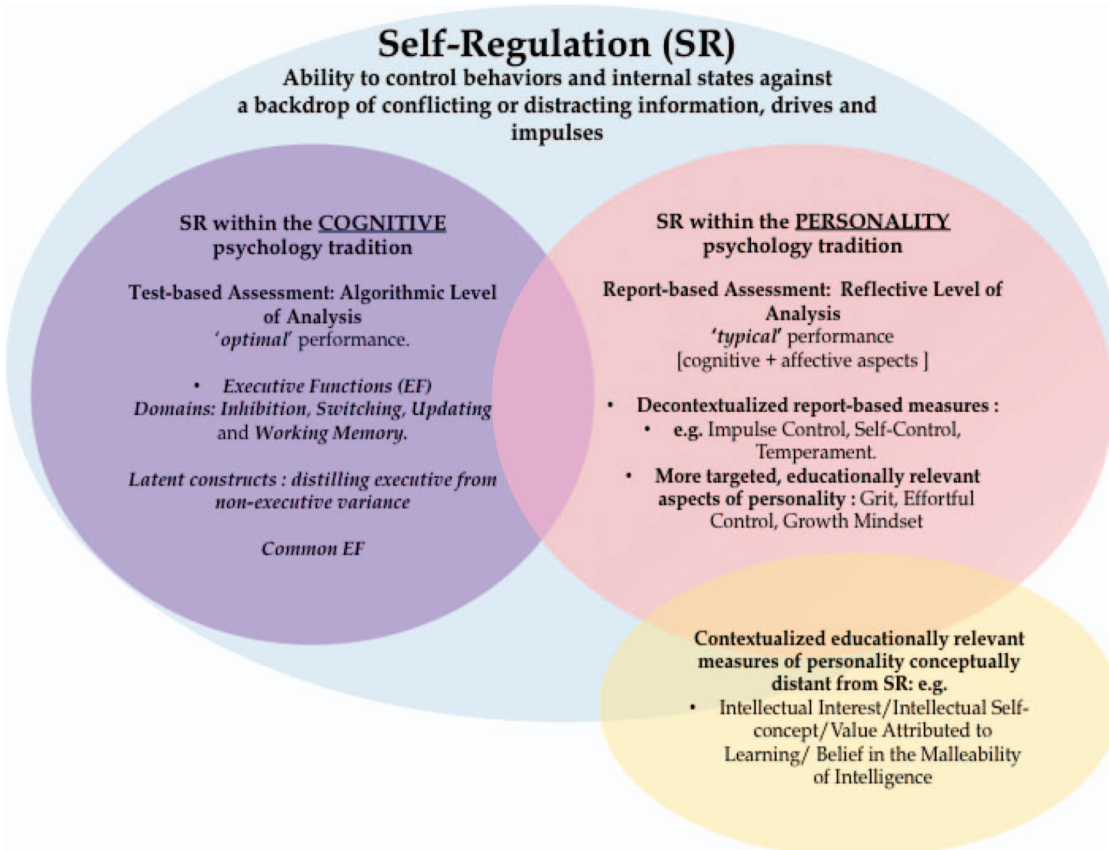

Figure 1. Visual representation of the taxonomy of self-regulation considered in the current work. See the online article for the color version of this figure.

sures of personality were moderately heritable and shared genetic links with academic achievement, even after controlling for fluid intelligence, that is, the ability to solve novel reasoning problems.

A further study found that the genetic and environmental factors explaining variation in self-perceived ability and intellectual interest for reading were highly stable over time, and that reciprocal longitudinal links existed between these educationally relevant measures of personality and reading comprehension (Malanchini et al., 2017). These cross-lagged links differed in their proportion of genetic and environmental variance: Whereas the path from early reading to later variation in self-perceived ability and interest was almost entirely genetically mediated, the path from early self-perceived ability and interest to subsequent reading comprehension was explained by both genetic and environmental factors. All associations remained after controlling for intelligence (Malanchini et al., 2017). Similar longitudinal associations between educationally relevant aspects of personality, such as self-evaluation, and academic abilities have been observed in the domain of mathematics (Luo, Kovas, Haworth, & Plomin, 2011) and when using a composite score of achievement across several domains (Luo, Haworth, & Plomin, 2010). Altogether, modest to moderate associations between measures of personality, each varying in its degree of being conceptualized as forming the broad construct of self-regulation, and academic skills are consistently observed.

Combining Multiple Self-Regulatory Constructs to Explain Academic Skills

More important, very little research has been devoted to understanding how multiple aspects of self-regulation, ranging from executive to personality and motivational processes, intersect in shaping academic abilities (Pessoa, 2009). Recently, one study found that, in a sample of prekindergarten children, tests of EF and teacher-reported behavioral regulation were moderately associated with academic achievement (Duncan, McClelland, & Acock, 2017). Relatedly, a number of studies indicated that both Working Memory and reported self-regulation predicted academic abilities longitudinally during prekindergarten (Becker, Miao, Duncan, & McClelland, 2014; McClelland et al., 2007). However, these effects were not examined within the same statistical model. Neuenschwander et al. (2013) investigated the relative contribution of aspects of the Big Five and EF, measured as a latent factor constructed from three tests, in predicting individual differences in achievement and found that Openness, and to a lower extent Extraversion, predicted academic performance beyond EF, in a sample of 7- to 8-year-old children.

The Present Study

The current study aimed to provide a significantly novel contribution by addressing three major research goals. First, we examined the multivariate association between test-based aspects of self-regulation that emerged from the cognitive tradition (measured via a comprehensive battery of EF tasks), and multiple report-based measures of self-regulation stemming from the personality literature (including a decontextualized measure of impulse control, the Big Five dimensions of personality, and several more targeted and educationally relevant aspects of personality). Second, we investigated the relative contribution of these multiple self-regulatory constructs to variation in academic abilities (reading and mathematics), taking into consideration the role of processing speed and fluid intelligence. Third, both research goals were addressed using a multivariate genetically informative framework, which allowed for the examination of the extent to which these associations were mediated by genetic and environmental factors.

Method

The University of Texas Institutional Review Board granted ethical approval for the current study (Protocol number: 2014–11-0021; Study title: Cortisol, Socioeconomic Status and Genetic Influences on Cognitive Development).

Participants

The current investigation included an ethnically and socioeconomically diverse sample of 1,019 third through eighth grade twins and higher order multiples from the Texas Twin project (Harden, Tucker-Drob, & Tackett, 2013). The sample comprised 538 unique sibling pairs, 481 of which were twin pairs and 57 of which were pairs created from 19 triplet sets. Of the total number of children who contributed data, 358 were identical (monozygotic) and 661 were fraternal (dizygotic) twins. Participants' age ranged from 7.8 to 15.5 years ($M = 10.79$, $SD = 1.75$). Of the total sample, 50.4% were female ($N = 514$). The sample was ethnically diverse and representative of the population of the Austin metropolitan area for IQ ($M = 104$, $SD = 14.09$, measured using the Wechsler Abbreviated Scale of Intelligence-II, WASI-II; Wechsler, 2011) and socioeconomic composition; 28.3% of families received a form of means tested public assistance, such as food stamps, at some point since the twins were born. Families with twin pairs were identified from the public school rosters obtained from school districts in the Austin metropolitan area and surrounding locales. Research assistants contacted families via telephone, and invited the twins to come to the research laboratory at the University of Texas at Austin to take part in a study of genetics, experience, and development. Data collection lasted approximately 4.5 h. Self-report measures were collected form the children via questionnaires administered on a computer. Children completed test-based measures of EF and cognitive and academic abilities administered either by computer, or orally and on paper by a research assistant. The treatment of the relatively wide age range and sex in the analyses is discussed in the Analytic Strategies section.

Measures

Measures of self-regulation within the cognitive tradition: EFs. During the in-lab visit, participants completed a comprehensive battery of 12 tests assessing four domains of EF: Inhibition, Switching, Working Memory, and Updating. Tasks were administered orally, on the computer, and on paper (Engelhardt et al., 2015). After the third year of data collection, three tasks (one Switching, one Inhibition, and one Updating task) were replaced with three tasks from the same domains. This change was motivated by the need to include tasks amenable for administration in the magnetic resonance imaging (MRI) scanner, since the Texas Twin project research program expanded to include a neuroimaging component. We use data obtained using these tasks outside of the MRI scanner. The choice of which tasks to replace was based on conceptual similarity between old and new tests. For example, within the domain of Inhibition, the original auditory stop signal task, unsuitable for administration in the MRI scanner, was replaced by a visual stop signal task. Figure 2 depicts all the measures of EF included in the present investigation.

Four tasks assessed the domain of *Inhibition.* (a) *Animal Stroop* (Wright, Waterman, Prescott, & Murdoch-Eaton, 2003) asked children to identify animals from drawings under three conditions: congruent (when the face of the animal matched the body), incongruent (when the face did not match the body and identification was based on the body), and neutral (presenting the body of animals with a blank space instead of the face). (b) *Mickey* (Lee, Bull, & Ho, 2013), asked children to identify the side of the screen on which a square containing Mickey Mouse's face appeared while ignoring other, previously presented, squares flashing on the screen. Mickey presented three conditions: congruent, incongruent, and neutral. (c) The *Auditory Stop Signal* task (Verbruggen, Logan, & Stevens, 2008) required participants to indicate where an arrow was pointing, but to withhold their response if they heard a tone after the arrow was presented. After the third year of data collection, the auditory stop signal task was replaced with a visual stop task. (d) The *Visual Stop Signal* task (Chevrier, Noseworthy, & Schachar, 2007) asked participants to indicate in which direction an arrow on the screen had pointed, but to withhold their response when a red '*x*' appeared on top of the arrow.

Four tasks assessed *Switching*. (1) *Trail Making* (Salthouse, 2011) asked participants to connect circles including numbers and letters based on changing rules. (2) *Local-Global* (Miyake et al., 2000) required participants to verbally identify letters and shapes composed of smaller letters and shapes. The task presented three conditions: (a) local, asking participants to name the small letters or shapes; (b) global, naming the larger letter or shapes; and (c) alternating, asking participants to alternate between global and local responses. (3) *Plus-Minus* (Miyake et al., 2000) required participants to complete add to or subtract 1 from a number under three conditions: addition, subtraction, or alternating. After the third year of data collection, the *Plus-Minus* task was replaced by Cognitive Flexibility. (4) *Cognitive Flexibility* (Baym, Corbett, Wright, & Bunge, 2008) is a cued-switching task that required participants to determine which of two stimuli matched a target stimulus on either color or shape; the cued rule (match on color or match on shape) could remain the same or switch from trial to trial.

Three tasks assessed *Working Memory* using three tasks. (a) *Digit Span Backward* (Wechsler, 2003) asked participants to memorize and repeat strings of numbers of increasing length. (b) *Symmetry Span* (Kane et al., 2004) required participants to encode a sequence of flashing squares presented on a grid. After every sequence was presented, participants were shown a pattern of black and white squares and were asked to judge whether the

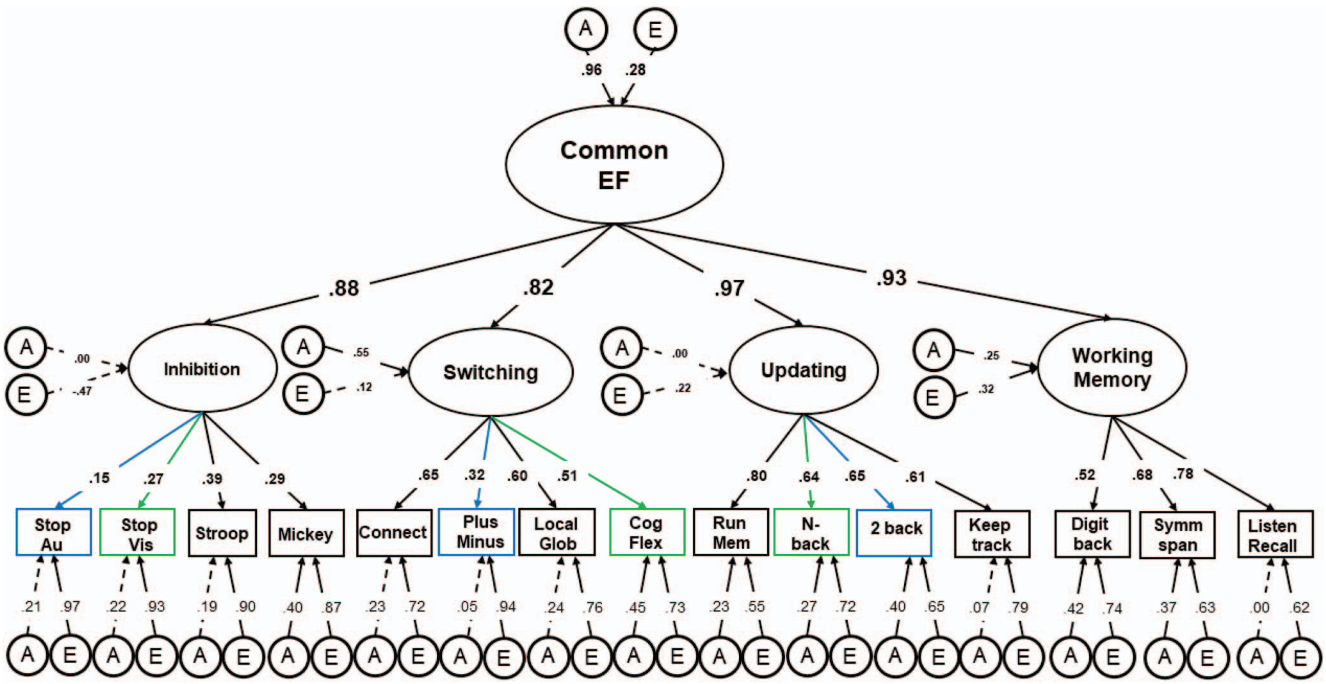

Figure 2. Factor structure, factors loadings and ACE estimates of executive functions (EF); the blue rectangles indicate those tasks that were included in the first 3 years of data collection (2013–2015), the green rectangles those included in the data collected from the end of 2015 onward. A = additive genetic variance; C = shared environmental variance; E = nonshared environmental variance; all paths are standardized. Age was controlled for at the level of the first-order EF domains. The loadings of those domains on the second-order factor are standardized with respect to age-independent variance. See the online article for the color version of this figure.

pattern was symmetrical. After 3–6 flashing squares and symmetry judgments, participants were asked to recall the location and order of the flashing squares. Sequences became increasingly long as the task progressed. (c) *Listening Recall* (Daneman & Carpenter, 1980) asked participants to listen to a series of letters presented orally, one at a time and recall the series after having judged whether a sentence made sense in the English language. Sequences of letters became increasingly long as the task progressed.

Four tasks assessed individual differences in *Updating*. (a) *Keeping Track* (A Miyake et al., 2000) required participants to listen to words belonging to four different categories and to recall the last word listed from a given category. (b) *Running Memory for Letters* (Broadway & Engle, 2010) required participants to view a sequence of letters and identify the last *n* digits. (c) The *2-Back* task (Jaeggi et al., 2010) asked children to view a series of individual shapes and indicate when the shape matched the shape that was presented two trials prior. The 2-Back task was replaced after the third year of data collection with the N-Back task. (d) *N-Back* (Jaeggi et al., 2010) required participants to visualize a series of individual shapes and indicate whether the presented shape matched the one presented in 1 trial prior or, in a separate block, 2 trials prior.

Therefore, the present investigation included a battery of 15 EF tasks, 6 of which presented missing data because of the change in study design. To accommodate missingness by design, we used full information maximum likelihood estimation to fit structural equation models to all available data (Salthouse, 2004). The Ns for every EF task, together with information on the reliability of each test, are reported in supplementary material Table 1a. Previous work from our research group on the factor structure of EF using the same measures (Engelhardt et al., 2015; Engelhardt, Mann, Briley, Church, Harden, & Tucker-Drob, 2016) found that the four first-order factors of Inhibition, Switching, Working Memory, and Updating loaded very strongly on a single second-order factor, a Common EF factor. Building on these previous findings, the majority of the analyses presented in the Results emphasize findings based on this Common EF factor (see Figure 2). Model fit for this hierarchical model of EF was good (root mean square error of approximation [RMSEA] = 0.045, comparative fit index [CFI] = 0.900, Tucker-Lewis Index [TLI] = 0.904, standardized root mean square residual [SRMR] = 0.092). It is worth noting that we use the term Working Memory here to refer to tasks that require the simultaneous processing and storage of information and we use Updating here to refer to tasks that involve monitoring incoming stimuli and replacing old information with new, more relevant information.

Measures of self-regulation stemming from the personality psychology tradition. Measures were obtained through self-report questionnaires completed on a computer and ratings of test motivation provided by research assistants after the in-lab session. The present study includes nine self-reported measures of self-regulation linked to the personality psychology tradition, tapping different aspects of self-personality, motivations, and beliefs. As shown in the supplementary material Table 1b, the sample size for individual constructs ranged between $N = 825$ (for Grit), and $N = 1013$ (for the BFI personality scale). This fluctuation in sample size resulted largely from the inability to complete the entire battery of measures during the time allocated to the in-lab visit. However, more than 80% of the sample completed all self-report measures. We used Full Information Maximum Likelihood (FIML) to handle missing data. FIML provides the advantage of producing unbiased estimates under the assumption that the pattern of missingness that relates to missing scores can be accounted for by the data that are available. Following is a description of each measure. Additional details are included in Tucker-Drob et al., 2016.

Self-reported impulse control. Self-reported impulse control was assessed using an adapted version of the self-reported impulsivity scale from the Zuckerman–Kuhlman–Aluja Personality Questionnaire (ZKA-PQ; Aluja et al., 2003; Zuckerman & Aluja, 2014). The ZKA-PQ measures five constructs of personality: Sensation Seeking, Neuroticism, Aggressiveness, Activity, and Extraversion. One of the subcomponents of the broader Sensation Seeking domain is Impulsivity. We reverse-coded the impulsivity items from the ZKA-PQ, to obtain a measure of self-reported Impulse Control. Participants were asked to rate six statements as either true = 1 or false = 0. Examples of items are: "*I am an impulsive person*" (Reverse) and "*I usually think about what I am going to do before doing it*." A latent measure of impulse control was created from the six items (see Figure 3) and adopted in all subsequent analyses including impulse control.

The Big Five dimensions of personality. The *Big Five Inventory* (*BFI*) assesses five major dimensions of personality (Openness, Conscientiousness, Extraversion Agreeableness, and Neuroticism), which are known to be relatively are stable across time and context (Anusic & Schimmack, 2016; Briley & Tucker-Drob, 2015). Our battery includes a modified version of the BFI for children (John, Naumann, & Soto, 2008) that was adapted from Oliver John's Web site (https://www.ocf.berkeley.edu/~johnlab/measures.htm). Our version included 46 items, examples of which are: "*I am someone who has an active imagination*" (Openness), and "*I am someone who keeps working until things are done*" (Conscientiousness).

Scores were ipsatized (standardized within person) to adjust for acquiescence, the within person tendency to respond in the upper or lower range of a Likert scale. Acquiescence was computed by calculating person-specific means and standard deviations for responses to pairs of items with opposite implications for personality, for example, "Is sometimes shy, inhibited" and "Is outgoing, sociable," 30 items (15 pairs) in total were included in these scores. Ipsatization was accomplished by subtracting from every item in the BFI inventory (46 in total) the mean of acquiescence and dividing each difference score by the previously computed *SD* for acquiescence. Composite scores for the five domains were created using this ipsatized items.

Intellectual interest (*need for cognition*) describes the aptitude toward engaging in intellectually challenging activities and experiences. Need for cognition (Cacioppo, Petty, Feinstein, & Jarvis, 1996) was assessed using a version of the scale adapted for children (Kokis, Macpherson, Toplak, West, & Stanovich, 2002), from the original need for cognition scale (Cacioppo, Petty, & Kao, 1984). This measure included nine items rated on a 5-point

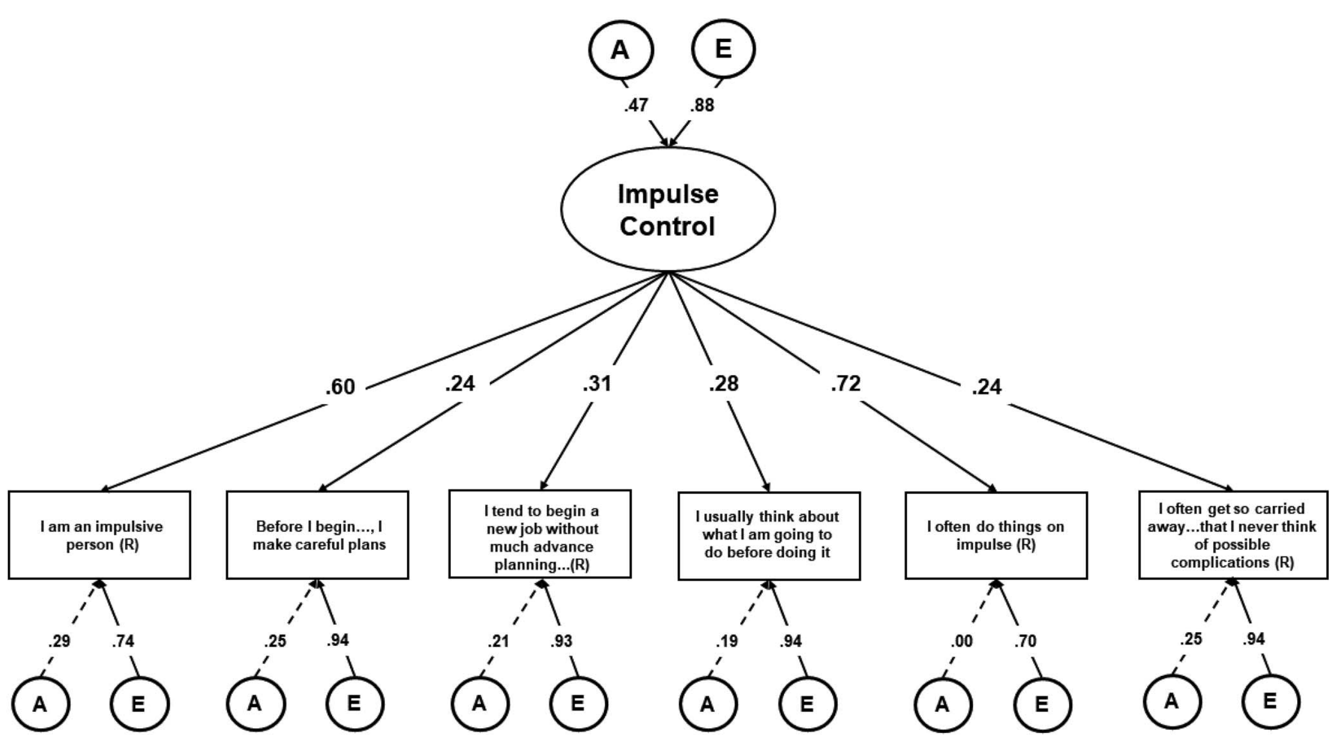

Figure 3. Factor structure, factor loadings and ACE estimates of impulse control. A = additive genetic variance; C = shared environmental variance; E = nonshared environmental variance; all paths are standardized.

Likert scale (1 = *strongly disagree*, 5 = *strongly agree*). Examples of statements are: "*I like to do jobs that make me think hard*" and "*I'm not interested in learning new ways to think*" (Reverse).

Intellectual self-concept describes individuals' perception of their own intellectual ability (Marsh & O'Mara, 2008). Intellectual self-concept has also been termed self-perceived ability (Chamorro-Premuzic et al., 2010). Within an educationally relevant context, intellectual self-concept thought to index an expectancy about someone's ability to learn (Wigfield & Eccles, 2000). Intellectual self-concept was assessed with a measure combining one item "I am smart" and six items from the Multidimensional Achievement-relevant Personality Scale (MAPS; Briley et al., 2014), including: "*I quickly get the idea of things*" and "*I am full of ideas*." Items were rated on a 5-point scale ranging from 1 = *strongly disagree* to 5 = *strongly agree*.

Intelligence Mindset is the view of the extent to which intelligence is malleable during the life span. Incremental mindset is the belief that intelligence is malleable and lies at one pole of a dimension, the other pole of which lies entity mindset, the belief that intelligence is fixed and unlikely to change (Dweck, 2006). It has been proposed that individuals holding an incremental intelligence mindset would invest a greater deal of energy into studying and learning, and consequently show higher levels of academic abilities and achievement if compared with those holding an entity mindset (Dweck, 2006). Incremental intelligence mindset was assessed using the same 6-item scale developed by Dweck (2006). Examples of items, rated on a 5-point scale from 1 = *strongly disagree* to 5 = *strongly agree*, are: "*You can always greatly change how intelligent you are*" and "*You have a certain amount of intelligence, and you really cannot do much to change it*" (Reverse).

Effortful persistence (*grit*) describes perseverance and passion for long-term goals (Duckworth et al., 2007), and has been found to predict academic abilities beyond cognitive skills and other personality domains (Duckworth & Gross, 2014). Grit shares strong associations with the BFI factor of conscientiousness (e.g., Rimfeld et al., 2016). We used a measure of grit including eight items (adapted from Duckworth & Quinn, 2009) that participants rated on a 5-point scale, from 1 = *strongly disagree* to 5 = *strongly agree*. Examples of items are: "*I am a hard worker*" and "*Setbacks (delays and obstacles) do not discourage me*."

Mastery goal orientation describes a specific type of attitude toward learning, namely the motivation to learn for the sake for understanding and improving one's knowledge, rather than to achieve a high grade or be praised by others. In self-determination theory (Ryan & Deci, 2000), mastery orientation is labeled intrinsic motivation, while performance orientation termed extrinsic motivation. Mastery orientation is more strongly linked to academic skills than performance orientation (Deci & Ryan, 2008). We assessed the construct with the five-item Mastery goal orientation scale (Revised) obtained from the Patterns and Adaptive Leaning Scale (PALS; Midgley et al., 2005). Examples of items, rated on a 5-point scale (1 = *not true at all*, 5 = *very true*), are: "*It's important to me that I improve my skills this year*" and "*One of my goals in class is to learn as much as I can*."

Attitude toward education (*educational value*) involves beliefs that children hold about the importance of education for their future career and success in life. Expectancy Value Theory proposes that educational value, together with expectations, are at the core of students' academic interests, their persistence in engaging in studying and, ultimately, their academic performance (Wigfield & Eccles, 2000). We used the six-item Scepticism about the Relevance of School for Future Success Scale (PALS; Midgley et al., 2005), which we reverse-coded, to assess educational value. Examples of items, rated on a 5-point scale are: "*My chances of succeeding later in life do not depend on doing well in school*" and "*Even if I am successful in school, it will not help me fulfil my dreams*" (both reverse coded).

Test motivation encompasses one item that research assistants (RAs) completed for every child after their in-lab visit. Examiners were asked: "*On the whole, how motivated did the participant appear to do well in the tasks?*," and they rated each participant on a scale from 1 (*indexing very low motivation*) to 7 (*indexing a great deal of motivation*). Each member of the twin pair was examined, and consequently rated on motivation, by a different research assistant.

Previous work on the factor structure of these measures of educationally relevant aspects of personality (described as measures of "character" by Tucker-Drob et al., 2016) found that a model including two latent factors, rather than one common factor, provided a better fit for the data. Consequently, this two-factor model (see Figure 4) was interpreted as a more accurate way of summarizing the covariance structure between these educationally relevant aspects of personality. Each of the two superfactors includes seven educationally relevant measures of personality (grit, need for cognition, intellectual self-concept, mastery, educational value, incremental intelligence mindset, and RA-rated motivation) and one subcomponent each of the BFI. The Conscientiousness superfactor includes the BFI-conscientiousness composite score as its eight contributing construct; the Openness superfactor includes BFI-openness. The majority of the analyses presented in the results section of the current article, with the exception of those presented in Table 2 and Figure 6, were conducted on these two superfactors. Fit indices (RMSEA = 0.034, CFI = 0.934, TLI = 0.937, SRMR = 0.067) indicated that this model was a good fit for the data.

Measures of academic and cognitive abilities. *Reading ability* was modeled as a latent factor using three tasks from the Woodcock Johnson Tests of Achievement-III (Woodcock, McGrew, & Mather, 2001) as indicators: Word Attack, Word Identification, and Passage Comprehension. Factor loadings for the latent reading construct are presented in Figure 5a. The latent construct of *Mathematics ability* included two tasks: Calculation and Applied Problems, also from the Woodcock Johnson Test of Achievement-III. The factor structure of the mathematics construct is reported in Figure 5b.

Fluid intelligence (*gf*), which indexes the ability to reason abstractly, was assessed using three tests: *Matrix Reasoning* and *Block Design*, which were part of the Wechsler Abbreviated Scale of Intelligence-II (WASI-II; Wechsler, 2011), and *Spatial Relations* (Bennett, Seashore, & Wesman, 1947). A latent *gf* factor created from the three tests (see Figure 5c) was adopted in all analyses.

In order measure individual differences in lower level cognitive processes, we created a latent factor of *Processing Speed* (Figure 5d). This latent factor comprised a test of *Letter Comparison* and a test of *Pattern Comparison* (Salthouse & Babcock, 1991), which asked participants to compare similarities between letters or patterns as quickly as possible. Lastly, *Symbol Search* (from the

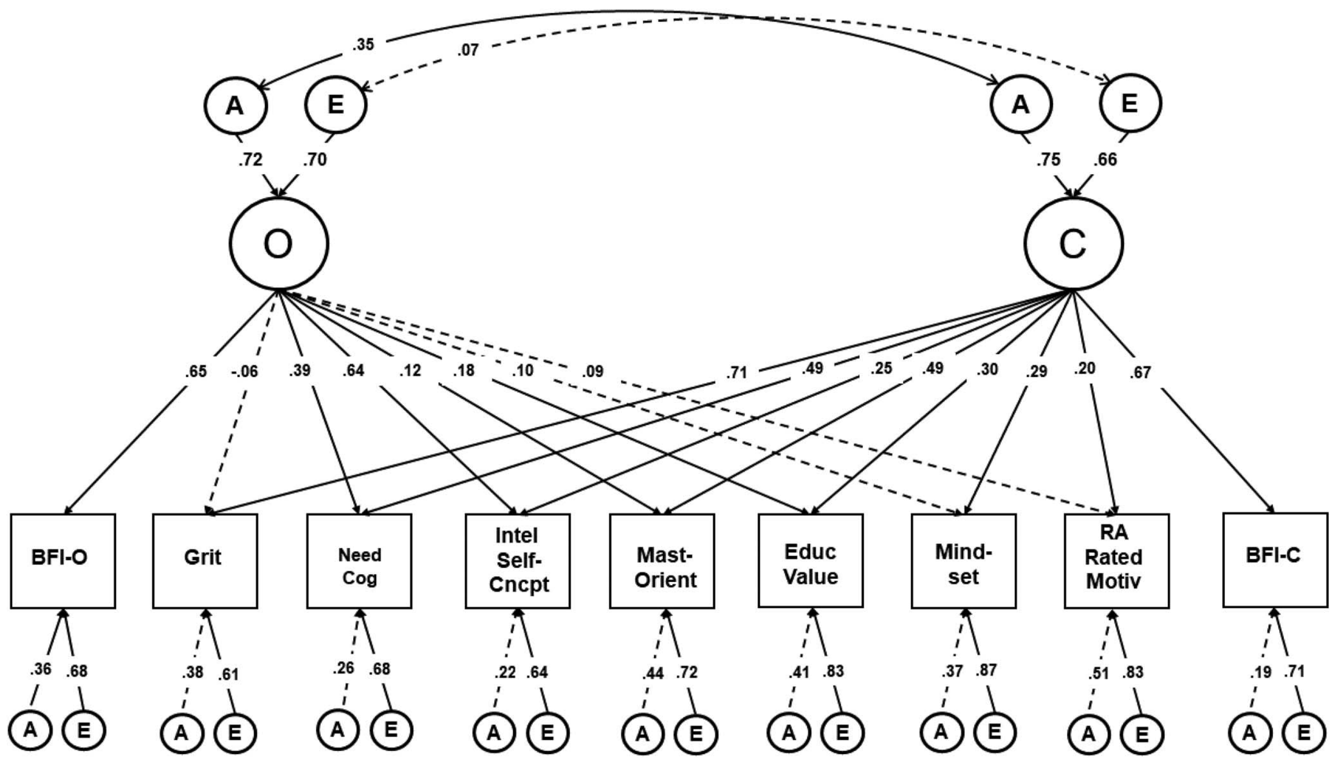

Figure 4. Factor structure, loadings and ACE estimates for the two-factor model of educationally relevant aspects of personality. A = additive genetic variance; C = shared environmental variance; E = nonshared environmental variance; all paths are standardized.

Wechsler Intelligence Scale for Children-Fourth Edition; Wechsler, 2003) asked participants to specify, as quickly as possible, whether one of two symbols presented on the right hand side of a page matched one of five symbols presented on the right-hand side of the page.

Analytic strategies. Descriptive statistics and correlations were calculated using the "psych" packages in R, Version 1.8.4 (Ravelle, 2018). Structural equation modeling (SEM) was conducted using MPlus7 (Muthén & Muthén, 2012). The 'TYPE = COMPLEX' command was used for all phenotypic analyses to account for nonindependence of observations of children or twin pairs from the same family. Full information maximum likelihood was used to account for missing data in all models (including the genetic models).

Genetic analyses: The twin method. We used a twin design to estimate the relative contribution of genetic and environmental factors to all outcomes and their interrelations. The twin method relies on two core identifying assumptions. The first assumption is that monozygotic twins (MZ) who share 100% of their genes and dizygotic twins (DZ) share 50% of their segregating genes on average. The second assumption is that the effects of being reared in the same family does not systematically vary with zygosity. When these assumptions are met, the differences in twin pair similarity in the outcome under study can be used to estimate the relative contribution of genetic and environmental factors to variation in that outcome.

The univariate twin model, or univariate ACE model, decomposes the variance in an outcome into additive genetic (A), shared environmental (C), and nonshared environmental (E) components. 'A' represents the total additive effect of genetic variation on the outcome; 'C' represents the total effects of factors that serve to make siblings reared together more similar on the outcome than can be accounted for by their genetic similarity; and 'E' represents variation that exists within pairs of individuals who share the same family rearing environment and the same genes (i.e., monozygotic twins reared together). Variance in A can be estimated by comparing intraclass correlations for MZ and DZ twins on the outcome of interest. Larger intraclass correlations for MZ twins than for DZ twins indicates genetic contributions to variance in that outcome. Heritability, the proportion of variance in a trait that can be attributed to genetic variance, can be intuitively calculated as double the difference between the MZ and DZ twin correlations. Here, we use a more formal structural equation modeling approach that decomposes covariance, rather than correlation, structure (Neale & Cardon, 2004).

The univariate ACE model can be extended to multivariate models to genetic and environmental mediation of the association between traits. In multivariate ACE models, the covariance between outcomes is decomposed into A, C, and E by comparing MZ and DZ pairs' cross-twin cross-trait correlations. Higher cross-twin cross-trait correlations for MZ than for DZ twins implicate genetic factors in the association relationship between the two outcomes.

ACE model fitting applies full structural equation modeling to the estimation of A, C, and E, which is advantageous for several reasons. First, SEM capitalizes on information about sample means and variances, in addition to correlations, to more com-

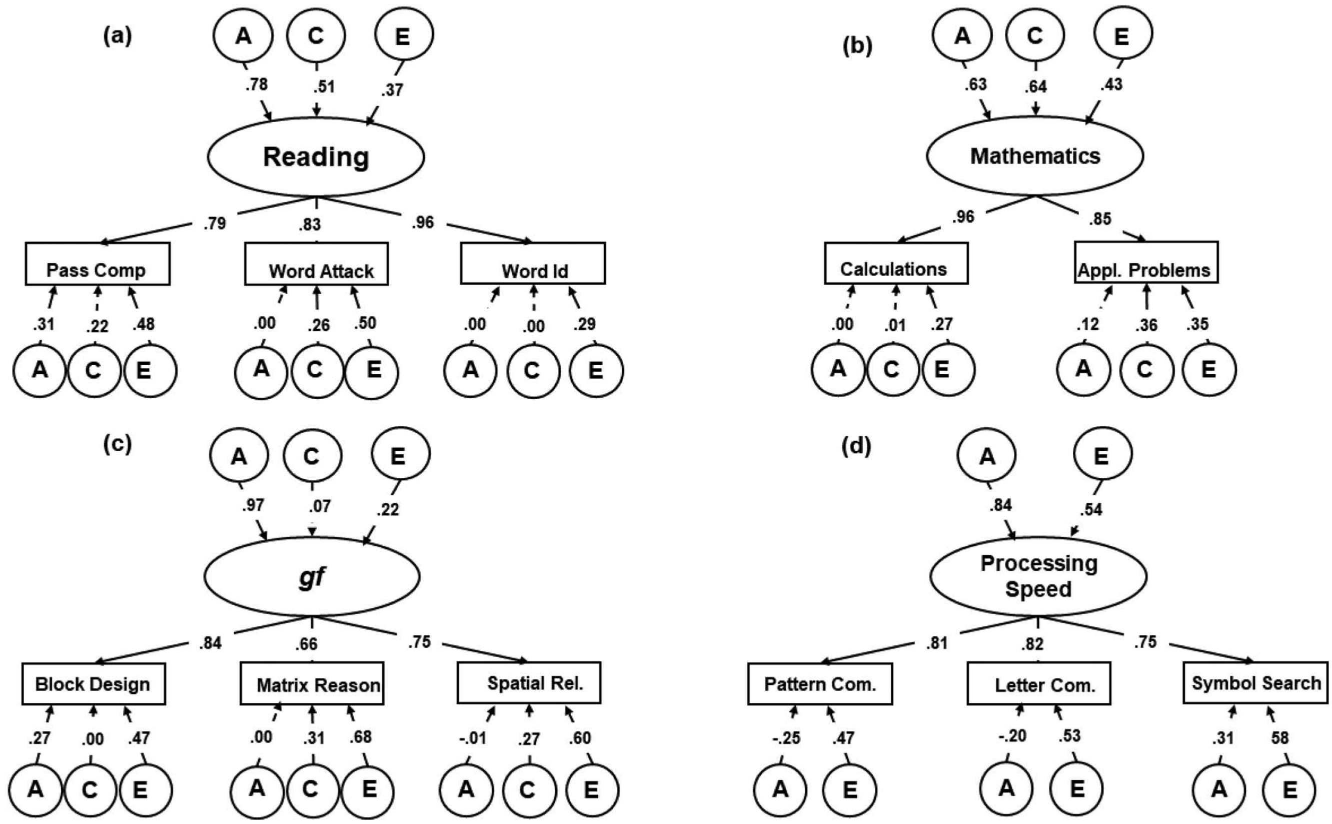

Figure 5. Factor structure, loadings and ACE estimates of (a) reading ability, (b) mathematics, (c) *gf*, and (d) processing speed. A = additive genetic variance; C = shared environmental variance; E = nonshared environmental variance; all paths are standardized.

pletely describe the observed data pattern. Second, SEM allows for the assessment of the goodness-of-fit of the model by comparing it with a saturated model (a model based on the observed data) and to more parsimonious models. Third, SEM straightforwardly produces confidence intervals (CIs) for all parameters. For ACE models conducted using observed variables, nonshared environmental variance encompasses measurement error. This is not the case for ACE models conducted on latent constructs, as measurement error is confined to the variance of observed constructs and not subsumed under the latent construct (Muthén, Asparouhov, & Rebollo, 2006).

The Cholesky decomposition. The Cholesky decomposition (see supplementary material Figure 1) allows for examination of common and independent genetic (A), shared environmental (C), and nonshared environmental (E) effects on the covariance of two or more traits (Neale, Boker, Bergeman, & Maes, 2005). The model assesses the independent contribution of a predictor variable to the variance in the outcome variable, after accounting for the variance accounted for by other predictors. As illustrated by the path diagram in supplementary material Figure 1, the genetic and environmental variance that the outcome (mathematics in the example shown in supplementary material Figure 1) shares with the last predictor entered in model (Openness) is calculated after accounting for the variance that is accounted for by the two predictors entered in the model at previous stages (Conscientiousness and EFs). Following the same logic, it is possible to derive the genetic and environmental components of variance that the second construct entered in the model (Conscientiousness) shares with the following two constructs (Openness and mathematics), after accounting for the variance they all share with the first construct entered in the model (EFs) and so on. The analysis can be extended to include more variables. Therefore, as for hierarchical regression analysis, the order in which variables are entered in a Cholesky decomposition is of importance. The order in which the constructs of interest were entered in the following multivariate Cholesky analyses was determined by hypotheses testing. For instance, one of our aims was to test the extent to which educationally relevant measures of personality accounted for variance in reading and mathematics ability beyond test-based assessments of cognitive abilities and EFs. To this end, we entered cognitive measures first in the Cholesky decomposition, followed by EFs, followed by educationally relevant measures of personality, and lastly reading and mathematics ability.

Results

Descriptive Statistics and Correlations Between Observed Measures

Descriptive statistics for the observed measures of personality, EF, cognitive, and academic abilities are reported in supplementary material Table 1. The large majority of variables met the criteria for normal distribution. Positive skewness was corrected using logarithmic or square root transformations (supplementary material Table 1a). All variables were residualized for sex prior analyses. Variation in age was accounted for by including age as a covariate in each model (see supplementary material Table 1a including the size of the associations between age and the four EF first-order domains).

Observed associations between educationally relevant measures of personality are reported in supplementary material Table 2. Correlations were positive and ranged from $r = .05$ (between BFI extraversion and researcher-rated motivation) to $r = .47$ (between intellectual self-concept and need for cognition). The only exception was BFI neuroticism, which correlated negatively with all other measures. Supplementary material Table 3 reports the phenotypic associations among the 15 measures of EF, which ranged from weak (average $r = .10$) effects for the associations between measures for Inhibition to moderate-strong effects observed between measures of updating (average $r = .47$). Supplementary material Table 4 presents the phenotypic correlations among measures of cognitive and academic abilities. Correlations among cognitive measures ranged from $r = .27$ to $r = .64$. Similarly, correlations among measures of academic abilities ranged between $r = .38$ and $r = .76$.

Factor Structure and Behavioral Genetic Decomposition of Self-Regulatory Constructs and Cognitive and Academic Abilities

As described in the Method section, the present investigation builds on the foundations of previous work that explored the factor structure and behavioral genetic decomposition of EFs (Engelhardt et al., 2015) and educationally relevant aspect of personality (Tucker-Drob et al., 2016), as well as their association with intelligence and academic abilities (Engelhardt et al., 2016; Tucker-Drob et al., 2016). Based on this previous work, the present article considers the structure of EF as described by one second-order latent factor (the Common EF factor; RMSEA = 0.045, CFI = 0.900, TLI = 0.904, SRMR = 0.092) created from four first-order latent variables (Inhibition, Switching, Updating, and Working Memory), each including three to four individual tests (see Figure 2). Of note is that—as has been reported across several different data sets (Miyake et al., 2000)—the first-order factor of Inhibition was characterized by tasks showing lower reliability compared with the other three domains. Particularly low reliability ($\alpha = .40$) and factor loading ($\lambda = .15$) were observed for the auditory Stop signal test. However, dropping this particular test from the latent factor of inhibition was neither found to increase the factor loadings of the other tests on the Inhibition factor nor the loading of Inhibition on the second order Common EF factor (see Engelhardt et al., 2016 for a more detailed discussion of the issue of reliability within our EF battery). The average variance in the individual EF measures accounted for by the corresponding EF domain factors was 31.1%. Of the age independent variance in the EF domain factors, the common EF factor accounted for an average of 81.0%. Because age effects are controlled at the level of the first-order EF domains, we calculate variance accounted for as shared variance/ (shared + unique variance), and do not include age-related variance in this calculation.

Based on a subset of the current data Tucker-Drob et al.'s (2016) reported that that the nine educationally relevant personality scales are best summarized by the superfactors of Openness and Conscientiousness. This factor structure, presented in Figure 4, showed very good model fit indices in the current sample (RMSEA = 0.034, CFI = 0.934, TLI = 0.937, SRMR = 0.067). Therefore, we explored phenotypic and behavioral genetic associations between EF, impulse control and these two superfactors.

The five items included in the self-reported impulse control measure loaded onto a single latent factor (see Figure 3). A model including one latent factor was found to be a good fit for each of processing speed, *gf*, reading and mathematics (see Figure 5). Figures 2–5 also present univariate ACE estimates for every latent construct, as well as the residual ACE estimates for all observed variables. Table 1 summarizes this first set of univariate genetic analyses by presenting the heritability (h^2), shared environmental (c^2), and nonshared environmental (e^2) estimates, including 95% CIs, for every latent construct.

In line with previous findings, individual differences in EF were explained in very large part by genetic differences between participants (92%). Genetic variation was found to be the main source of individual differences also in *gf* (94%) and processing speed (71%), with small nonshared environmental variance. Variation in Openness and Conscientiousness superfactors was accounted for, in almost equal parts, by genetic (51 and 56%, respectively) and nonshared environmental factors (49 and 44%, respectively). In line with extant findings obtained cross-culturally (e.g., Luo et al., 2011; Malanchini et al., 2017; Tucker-Drob et al., 2016), shared

Table 1
Heritability, Shared Enviromentality, and Nonshared Enviromentality Estimates for Latent Constructs

Latent construct	Heritability	Shared enviromentality	Nonshared enviromentality
Common executive functioning	.92 [.83, 1.00]	—	.08 [.02, .19]
Openness superfactor	.51 [.31, .77]	—	.49 [.28, .74]
Conscientiousness superfactor	.56 [.40, .76]	—	.44 [.27, .64]
Processing speed	.71 [.56, .86]	—	.29 [.16, .46]
Impulse control	.23 [.03, .61]	—	.77 [.52, 1.00]
Fluid intelligence (*gf*)	.94 [.69, 1.00]	.01 [−1.00, 1.00]	.05 [.00, .16]
Reading	.61 [.36, .90]	.26 [.07, .56]	.13 [.07, .22]
Mathematics	.40 [.17, .72]	.41 [.20, .71]	.19 [.10, 30]

Note. Numbers in brackets are 95% confidence intervals around the estimates.

environmental factors were not implicated in individual differences in educationally relevant aspects of personality. On the contrary, shared environmental factors played a role in variation in reading and mathematics ability, explaining between 26 and 41% of the variance, respectively. The remaining variance in latent reading and mathematics factors was accounted for by genetic factors, and in smaller part, by nonshared environmental influences.

Observed and Behavioral Genetic Associations Between Measures of Self-Regulation (EF and Self-Reported Impulse Control) and Each Educationally Relevant Measure of Personality

Table 2 reports observed correlations between the latent constructs of EF and Impulse Control and each observed educationally relevant measure of personality. Correlations between the common EF factor and measures of personality ranged from $r = -.14$ (CIs [−.20, −.07]) between EF and BFI neuroticism to $r = .44$ (CIs [.37, .50]) between EF and RA-rated motivation. The phenotypic associations between the latent factor of impulse control and measures of personality ranged from −.25 (CIs [−.34, −.16]) with BFI extraversion, to $r = .56$ (CIs [.45, .67]) with BFI conscientiousness.

Bivariate Cholesky decompositions were conducted in order examine the extent to which variation in each educationally relevant measure of personality overlapped with test-based EF (Figure 6a) and self-reported Impulse Control (Figure 6b). Each measure of personality was entered as the second variable in every Cholesky decomposition, together with either EF (Figure 6a) or impulse control (Figure 6b), which were entered first in the analysis. All estimates presented in Figure 6 represent the proportion of variance in each educationally relevant personality measure that is accounted for by the genetic and environmental variance in EF (Figure 6a) and Impulse Control (Figure 6b), as well as construct-unique genetic and environmental variance. Supplementary material Tables 5a and 5b report the standardized estimates with 95% CIs.

As shown in Figure 6a, genetic and environmental overlap between EF and each educationally relevant measure of personality was modest. Only for one measure (researcher-rated motivation) was the genetic variance shared with EF greater than its unique genetic variance. In most cases, the genetic variance shared with EF was less than one third of the heritability of each measure. The nonshared environmental overlap between EF and most constructs was negligible, with the only exception being BFI conscientiousness, for which that estimate reached significance. Thirteen percent of the nonshared environmental variance in BFI conscientiousness was accounted for by nonshared environmental factors also explaining variance in EF.

Figure 6b presents genetic and environmental overlap between latent impulse control and each educationally relevant measure of personality. Overlap varied greatly between measures. The greatest genetic overlap was observed between impulse control and grit. Interestingly, the covariance between the latent impulse control factor and BFI-conscientiousness was explained by both genetic and nonshared environmental influences. The smallest genetic overlap was observed between impulse control and need for cognition.

Table 2
Phenotypic Correlations (and 95% Confidence Intervals) Between Educationally Relevant Measures of Personality and the Latent EF and Impulse Control Factors

Measures	Common executive functioning factor	Latent impulse control
BFI-Conscientious	.21 [.14, .27]	.56 [.45, .67]
BFI-Openness	.29 [.21, .36]	.04 [−.06, .14]
BFI-Extraversion	.09 [.02, .17]	−.25 [−.34, −.16]
BFI-Neuroticism	−.14 [−.20, −.07]	−.11 [−.22, −.01]
BFI-Agreeableness	.16 [.10, .25]	.29 [.14, .45]
Grit	.17 [.09, .25]	.38 [.19, .57]
Need for cognition	.30 [.23, .37]	.14 [.01, 27]
Intellectual self-concept	.18 [.10, .26]	.05 [−.08, .17]
Mastery	.09 [.02, .17]	.15 [−.04, .33]
Educational value	.32 [.25, .39]	.17 [.03, .29]
Incremental mindset	.19 [.13, .26]	.09 [−.00, .18]
RA motivation	.44 [.37, .50]	.13 [.03, .23]

Note. BFI = Big Five Inventory; EF = executive function; RA = research assistant. All pairwise estimates were calculated after accounting for the variance explained by age (included in the model as a covariate) and sex (controlled for by means of linear regression).

Observed and Behavioral Genetic Association Between EF, Impulse Control, and the Two Superfactors of Openness and Conscientiousness

In line with Tucker-Drob et al.'s (2016) finding that the nine educationally related scales presented in Figure 4 are best summarized by the superfactors of Openness and Conscientiousness, supported by very good model fit indices in partly overlapping larger sample, we explored phenotypic and behavioral genetic associations between EF, impulse control, and these two superfactors. Phenotypic correlations between measures of self-regulation and the two superfactors are presented in Table 3. These correlations were estimated after entering all latent constructs in the same model simultaneously. The correlation between the Openness and Conscientiousness superfactors was $r = .263$, 95% CIs [.109, .418]. The correlation between EF and the Conscientiousness superfactor was $r = .271$, 95% CI [.136, .406], and the correlation between EF and the Openness superfactor was $r = .432$, 95% CIs [.256, .607]. A pronounced differentiation was observed in the phenotypic associations between impulse control and the two superfactors of educationally relevant aspects personality: while the correlation between impulse control and the Conscientiousness superfactor was strong ($r = .668$, 95% CI [.534, .802]), its association with the Openness superfactor was weak and did not reach significance ($r = .108$, 95% CIs [−.059, .274]). All latent constructs correlated positively with processing speed with modest to moderate effects.

To examine genetic and environmental overlap across measures of self-regulation stemming from the cognitive (test-based EF) and personality (impulse control and the superfactors Openness and Conscientiousness) traditions, we conducted a multivariate Cholesky decomposition. To account for the variance that all constructs shared with lower-level cognitive processes, we entered processing speed as the first variable in the Cholesky decomposition. Results of this multivariate model are reported Figure 7, and 95% CIs are included in

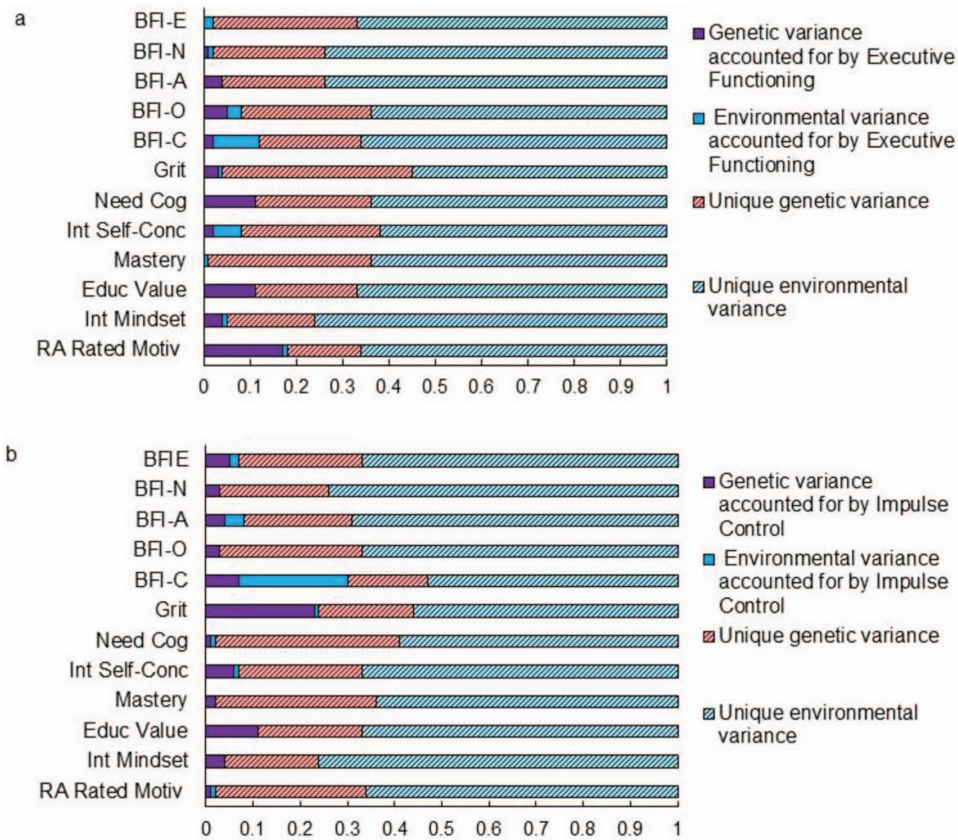

Figure 6. Genetic and nonshared environmental variance in each educationally relevant measure of personality accounted for by the genetic and environmental variance in executive functioning (Figure 2a) and impulse control (Figure 2b). BFI = Big Five Inventory; E = Extraversion; N = Neuroticism; A = Agreeableness; O = Openness; C = Conscientiousness; Need Cog = Need for Cognition; Int Self-Conc = Intellectual Self-Concept; Mastery = Mastery Orientation; Educ Value = Educational Value; Int Mindset = Intelligence Mindset; RA Rated Motiv = Research Assistant-rated Motivation. See the online article for the color version of this figure.

supplementary material Table 6. The shared environmental component (C) was dropped a priori from this analysis, as none of the latent constructs included in the model showed evidence of shared environmental influences (see Table 1) and, consequently, shared environment was not expected to appreciably account for the covariation between the measures.

Because our model of common EF was constructed form four first-order indicators, two of which tapped into different aspects of working memory (one reflecting variation in the ability to update information—i.e., Updating, and the other indexing variation in the ability to maintain information in working memory—i.e., Working Memory), we conducted an additional Cholesky decom-

Table 3
Phenotypic Associations Between Common EF, Reported Impulse Control, the Two Superfactors of Openness and Conscientiousness, and Processing Speed

Measures	Speed	EF	IC	O	C
Speed	1.00	.604 [.530, .677]	.145 [.028, .261]	.343 [.223, .463]	.190 [.081, .299]
EF		1.00	.250 [.146, .353]	.432 [.256, .607]	.271 [.136, .406]
IC			1.00	.108 [−.059, .274]	.668 [.534, .802]
O				1.00	.263 [.109, .418]
C					1.00

Note. Speed = processing speed; EF = Executive Functioning; IC = Impulse Control; O = superfactor of Openness, C = super-factor of Conscientiousness. Associations were calculated by entering all latent constructs into the model simultaneously. All significant estimates met the $p < .001$ threshold. The effect of age was controlled for by including age as a covariate in the model; all observed variables were residualized for sex prior model fitting.

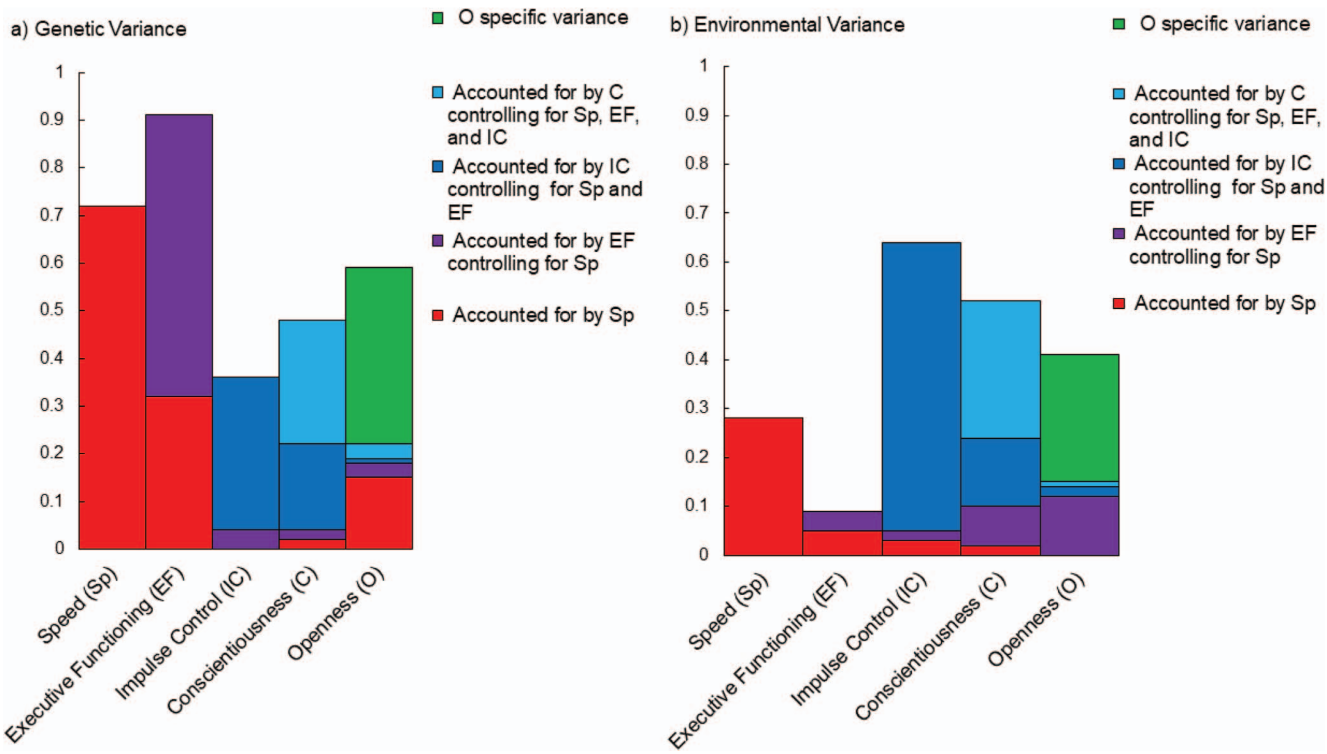

Figure 7. Proportion of genetic (panel a) and environmental (panel b) overlap between the latent factors of: processing speed (Sp), executive functioning (EF), Impulse Control (IC), and Conscientiousness (C) and Openness (O) superfactors. See the online article for the color version of this figure.

position to examine whether dropping one of these two memory factors would produce different results (supplementary material Table 7). The outcomes of this sensitivity analyses showed that results were highly consistent across the two Cholesky decompositions (supplementary material Table 6 and Table 7), with highly similar point estimates and completely overlapping 95% CIs. This was consistent with a previously reported sensitivity analysis (Engelhardt et al., 2016) conducted in this same sample, which found that removing the first-order Working Memory factor, consequently characterizing a model of EF in line with that proposed by Friedman et al. (2008), did not alter the phenotypic and genetic correlation between common EF and intelligence (Engelhardt et al., 2016).

Moreover, to examine whether the above multivariate associations were consistent across the four EF domains, we conducted four additional Cholesky decomposition, each replacing the common EF factor with including one of the first-order EF domains. Overall, results of these analyses (presented in supplementary material Table 8a–d) were highly consistent with those obtained with a common EF factor.

As shown in Figure 7, genetic factors accounted for the majority of the variance in processing speed (72%). This genetic variance in processing speed accounted for part of the genetic variance in EF and the Openness superfactor, 35 and 28%, respectively; but did not account for a significant proportion of genetic variation in either impulse control or the Conscientiousness superfactor. After accounting for processing speed, the genetic variance in EF did not substantially contribute to variation in all other self-regulatory constructs of personality. The vast majority of genetic variance in impulse control was independent of the genetic variance in processing speed and EF. While this genetic variance specific to impulse control accounted for 45% of the genetic variance in the superfactor of Conscientiousness, it did not account for any significant proportion of variance in the superfactor of Openness. The remaining 50% of the genetic variance in the superfactor of Conscientiousness that was not shared with the other self-regulatory constructs accounted for only a very small portion of the genetic variance in the superfactor of Openness; in fact, ~70% of the genetic variance in the superfactor of Openness was found to be independent of all other measures. Nonshared environmental overlap between all latent measures was generally small, with two main exceptions: the nonshared environmental overlap between (a) Impulse Control and the Conscientiousness superfactor and (b) EF and the Openness superfactor. As for the phenotypic results, greater overlaps were observed between impulse control and the superfactor of Conscientiousness and between EF and the superfactor of Openness. Interestingly, while at the genetic level the overlap between EF and Openness was accounted for by the genetic variance they both shared with processing speed, their environmental overlap was not accounted for by processing speed, and was found to be unique to their association. Overall, a substantial proportion of genetic and environmental variance in each self-regulation measures was found to be independent of all other constructs, pointing to their differentiation. The results presented up to this point addressed the primary aim of the current investigation: providing a comprehensive look into the relation between multiple aspects of self-regulation, and their genetic and environmental overlap.

Associations Between Processing Speed, Fluid Intelligence (*gf*), Measures of Self-Regulation Stemming From the Cognitive and Personality Traditions, and Academic Abilities

The second aim of the current study was to explore the multivariate associations between measures of self-regulation academic abilities (mathematics and reading), also taking into account the role of psychometric measures of processing speed and fluid intelligence (*gf*). To test whether individual measures of self-regulation and educationally relevant aspects of personality were independently associated with mathematics and reading ability, we conducted two multiple regression models (see Figure 8). After accounting for its association with all other predictors, *gf* significantly predicted mathematics ability (β = .217, 95% CIs [.065, .370]) above and beyond EF, although EF remained the strongest predictor of variation in mathematics ability (β = .389, 95% CIs [.261, .517]). The superfactor of Conscientiousness significantly predicted variation in mathematics ability with a weaker effect (β = .154, 95% CIs [.040, .267]). Conversely, *gf* did not significantly predict reading ability beyond EF and the Openness superfactor. Consistent with what is presented in Figure 8, EF (β = .505, 95% CIs [.335, .675]) and the Openness superfactor (β = .238, 95% CIs [.09, .367]) were the only two substantial predictors of individual differences in reading ability, beyond their associations with one another and all other latent constructs.

A set of two multivariate Cholesky decompositions was conducted to examine the genetic and environmental overlap between measures of self-regulation and academic abilities after accounting for cognitive skills (that, to this end, were entered first in the Cholesky decomposition). Figure 9 presents the results of these two sets of analyses. The first Cholesky decomposition (Figure 9a–b and supplementary material Table 9a) examined the genetic and environmental overlap between measures of self-regulation stemming from the cognitive and personality traditions and individual differences in mathematics ability, after controlling for processing speed and *gf*. As shown in Figure 9a, processing speed and *gf* accounted for more than half of the genetic variance in mathematics ability, with most of the variance accounted for by lower-level processing speed. After accounting for processing speed and *gf*, an additional 33% of the genetic variance in mathematics ability was uniquely shard with EF. Self-report measures of impulse control and the Conscientiousness and Openness superfactors did not incrementally account for the genetic variance in mathematics ability. Interestingly, the shared and nonshared environmental variance in *gf* accounted for nearly the entire shared and nonshared environmental variance in mathematics. Collectively, cognitive and self-regulatory measures accounted for the entire genetic and environmental variance in mathematics ability.

The second Cholesky decomposition (Figure 9c–d and supplementary material Table 9b) explored the genetic and environmental overlap between EF, impulse control, the Conscientiousness and Openness superfactors and reading ability, after controlling for processing speed and *gf*. As for mathematics ability, we found a significant overlap between EF and reading ability above and beyond processing speed and *gf*. EF accounted for an additional 30% of the genetic variance in reading ability. However, different from what observed for mathematics ability, the two superfactors of educationally relevant aspects of personality, Conscientiousness and Openness, accounted for a significant portion of the genetic variance in reading ability. Beyond processing speed, gf and EF, the superfactor of Conscientiousness accounted for an additional 7% of the genetic variance in reading ability. The superfactor of Openness, after accounting for all other cognitive and self-regulatory constructs accounted for an additional 17% of the genetic variance in reading ability. Both proportions of shared and nonshared environmental variances in reading were small, each

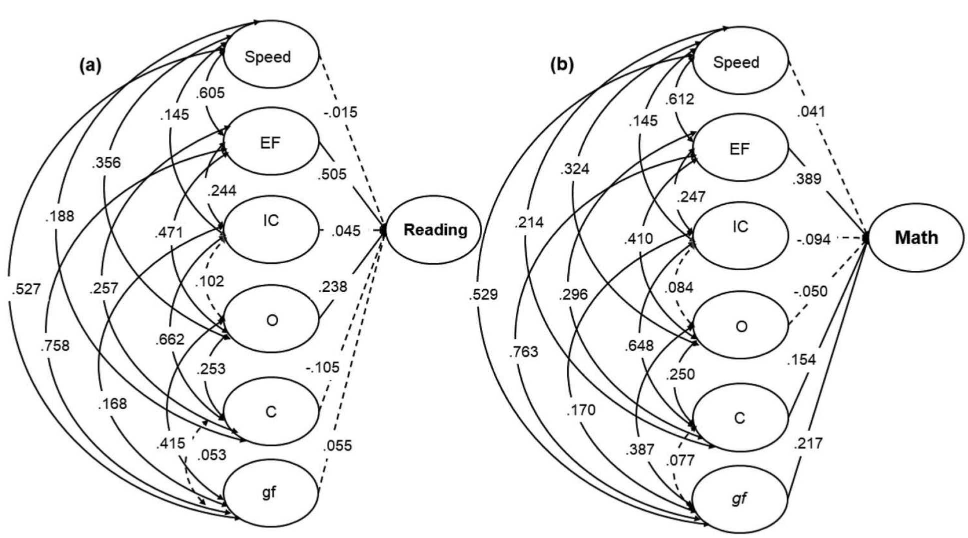

Figure 8. Multiple regression models exploring the prediction from the latent factors of processing speed, fluid intelligence (*gf*); executive functioning (EF), Impulse Control and the two superfactors of Openness (O) and Conscientiousness (C) to (a) Reading and (b) Mathematics. Age was included as a covariate in the model; all manifest variables were residualized for sex prior model fitting.

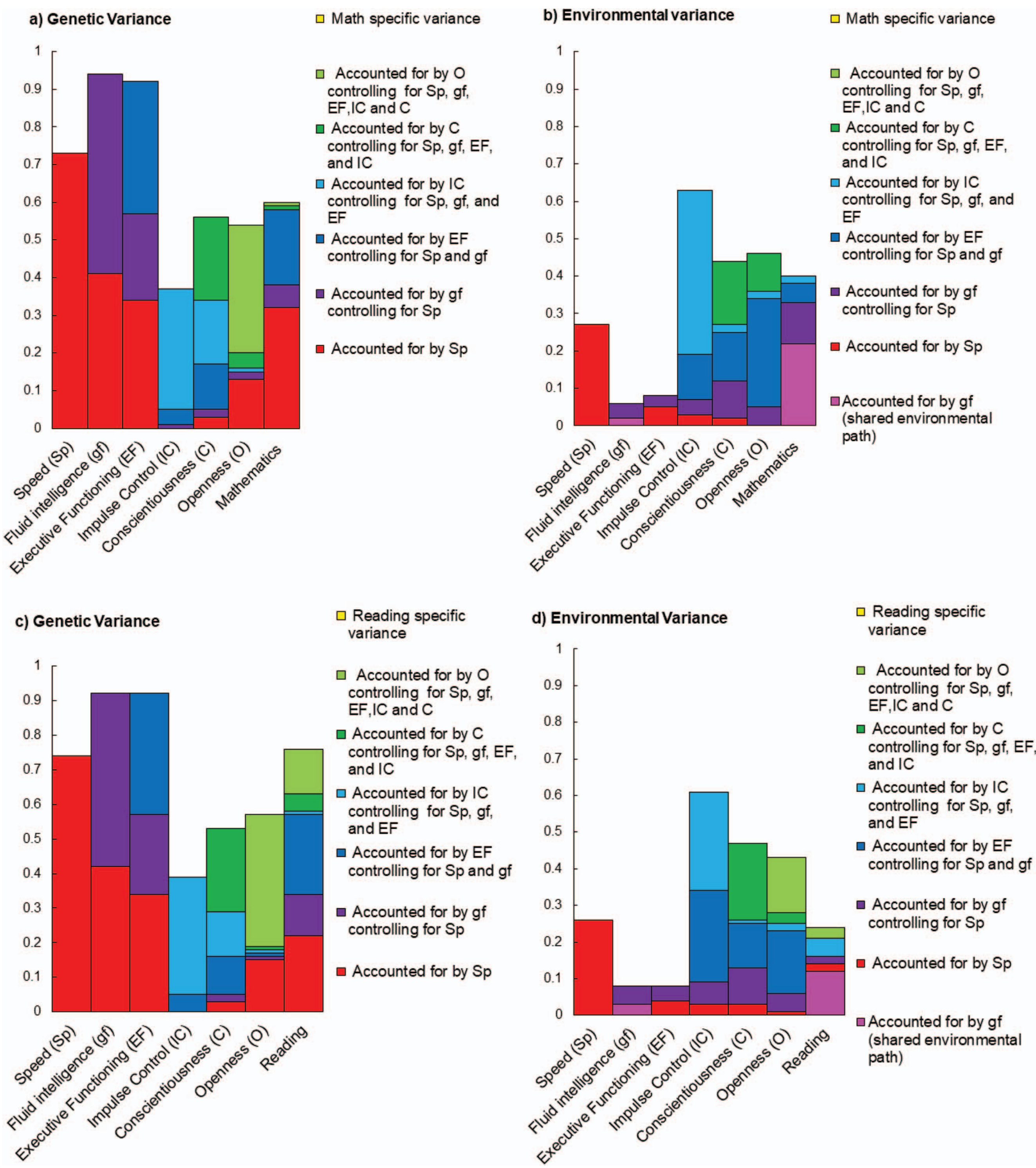

Figure 9. (a–b). Proportion of genetic (panel a) and environmental (panel b) overlap between the latent factors of: processing speed (Sp), fluid intelligence (*gf*), executive functioning (EF), Impulse Control (IC), Conscientiousness (C) superfactor, Openness (O) superfactor, and mathematics ability. (c–d) Proportion of genetic (panel c) and environmental (panel d) overlap between the latent factors of: processing speed (Sp), fluid intelligence (*gf*), executive functioning (EF), Impulse Control (IC), Conscientiousness superfactor (C), Openness superfactor (O), and reading ability. See the online article for the color version of this figure.

accounting for 12% of its total variance. Shared environmental variance in reading entirely overlapped with shared environmental variance in *gf*. The only small, yet significant, overlap in the nonshared environmental variance of reading ability was with processing speed (2%).

Discussion

This study provided a comprehensive investigation of associations among multiple components of self-regulation, psychometric measures of fluid intelligence and processing speed, and reading and mathematics abilities. We included a broad array of self-regulatory measures stemming from both cognitive and personality psychology traditions (see Figure 1 for a visual summary). These included a comprehensive battery of Executive Functioning measures and relatively decontextualized personality measures (e.g., impulse control and the Big Five dimensions of personality). We also included more educationally contextualized personality measures (e.g., grit and mind-set). We investigated the associations between these many measures of self-regulation and other educationally relevant aspects of personality. Overall, we found a substantial differentiation among measures of self-regulation stemming from the cognitive and personality research traditions. An interesting find, the overlap between test-based Executive Functioning and a superfactor of Openness, indexing curiosity, enjoyment of learning and self-belief, which are aspects of personality that have traditionally remained distant from self-regulation, was numerically larger ($r = .432$) than the overlap between Executive Functioning and either impulse control ($r = .250$) or a superfactor of Conscientiousness ($r = .271$), indexing traits traditionally included in taxonomies of self-regulation, such as grit. We additionally examined the associations between self-regulatory constructs and reading and mathematics abilities, beyond psychometric measures of processing speed and fluid intelligence. Results differed between the two academic domains: Whereas individual differences in mathematics ability were almost exclusively accounted for by cognitive constructs, individual differences in reading abilities were accounted for by variation in both cognitive measures and personality constructs. The superfactor of Openness played a particularly prominent role in the prediction of reading ability, both at the observed and genetic levels. The sections that follow provide a detailed discussion of these results, their interpretations and potential implications.

Associations Between Measures of Self-Regulation Stemming From the Cognitive and Personality Traditions

Our findings on the association between Executive Functioning and the Big Five dimensions of personality in childhood were consistent with those previously obtained in adult samples and selected samples of university students. In line with previous studies examining the associations between the Big Five dimensions of personality and test-based measures of Executive Functioning (Jensen-Campbell et al., 2002; Murdock et al., 2013), we found positive associations between a common latent measure of EF and the dimensions of BFI-openness ($r = .29$) and BFI-conscientiousness ($r = .29$). Similarly consistent with a wealth of research in adult populations (Williams et al., 2010), we found that our common EF factor shared a positive association with BFI-agreeableness ($r = .16$) and a negative association with BFI-neuroticism ($r = -.14$). The association between BFI-extraversion and EF, in line with the mixed findings reported in the literature, was weak ($r = .09$).

With the exception of its strong relation with BFI-conscientiousness, self-reported impulse control evinced weak relations with the Big Five dimensions of personality. This is consistent with previous findings (Roberts et al., 2014). More targeted, educationally relevant, aspects of personality also tended to evince weak associations with self-reported impulse control, with the only exception of a substantial association observed between impulse control and grit. It is not surprising that grit and BFI-conscientiousness shared similarly strong associations with impulse control (Briley & Tucker-Drob, 2017; Rimfeld et al., 2016).

These findings corroborate the state of knowledge on the association between test-based measures of self-regulation and the Big Five dimensions of personality and, importantly, extend them to include several other report-based measures of self-regulation and to a developmental sample. Although differences in the association between aspects of personality and abilities have been suggested to characterize different developmental periods (Poropat, 2009; Vedel & Poropat, 2017), our findings correspond remarkably well with known associations in the adult literature and in older samples of university students.

Our examination of the associations between targeted educationally relevant measures of personality and test-based EF was highly novel. Whereas some measures, for example, need for cognition, value attributed to education and RA-rated motivation displayed moderate associations with EF, other measures, including mind-set, mastery orientation and grit displayed weak to modest associations with test-based EF. We are aware of one previous study that tested the association between EF and academic intellectual self-concept (Roebers et al., 2012), and found it to be weak. In line with these observed associations, the genetic and environmental overlap between EF and impulse control and these multiple educationally relevant aspects of personality was generally weak. A more substantial overlap was only observed between self-reported impulse control and both grit and BFI-conscientiousness.

To supplement our examination of associations between EF and individual self-regulatory personality measures, we estimated associations between EF and two broad superfactors of educationally relevant personality that we previously identified in a subset of these data (Tucker-Drob et al., 2016). One superfactor, labeled Conscientiousness had strong links to BFI-conscientiousness, grit, and mastery orientation. Consequently, this broader conceptualization of conscientiousness reflects qualities such as diligence, focus, and perseverance. A second superfactor, labeled Openness, had strong links to BFI-openness, need for cognition and intellectual self-concept. Consequently, this broader conceptualization of openness indexes characteristics such as curiosity, intellectual interest, and enjoyment of intellectual activities. These two superfactors of educationally relevant aspects of personality were only moderately correlated.

More importantly, the association between Executive Functioning and the superfactor of Openness, which includes aspects of personality that had, for the most part, not featured in taxonomies of self-regulation, was numerically larger than that with the superfactor of Conscientiousness. This finding was interesting since aspects such as perseverance, conscientiousness and diligence, that featured prominently within the superfactor of Conscientiousness, are nearly ubiquitously considered prominent features of the broad umbrella of self-regulation (Nigg, 2017; Toplak et al., 2013). The substantial association between the superfactor of Openness and Executive Functioning was found to be mediated by both genetic and environmental factors. The observed genetic link between Executive Functioning and the superfactor of Openness was largely accounted for by processing speed. In contrast, the non-shared environmental overlap between Executive Functioning and the superfactor of Openness was found to be specific to their association, and not accounted for by either processing speed or fluid intelligence. Overall, the Openness-EF link may be viewed as consistent with previous studies reporting a particularly strong link between personality characteristics such as openness to experience, curiosity and creativity and intelligence (Silvia, Nusbaum, Berg, Martin, & O'Connor, 2009) and cognitive control (Benedek, Jauk, Sommer, Arendasy, & Neubauer, 2014).

The superfactor of Conscientiousness correlated strongly with reported impulse control, but less so with EF. Thus, reported measures of self-regulation may encompass a broader and largely distinct range of processes beyond those encapsulated by measured rooted in the cognitive tradition (Saunders et al., 2017). Such personality measures of self-regulation may reflect the more globally relevant abilities of self-discipline and goal-directed behavior. While it is possible that similarities in their assessment modality may contribute to the observed strong associations, the weaker association between self-reported impulse control and the superfactor of Openness is at odds with such an account.

Overall, the modest association between the superfactor of Openness and Conscientiousness, as well as their differential association with measures of self-regulation stemming from the cognitive and personality traditions, highlights the multifaceted nature of educationally relevant aspects of personality, which encompass qualities such as perseverance and diligence (that are more closely linked to reported self-regulation), as well as qualities such as curiosity, enjoyment of learning and self-belief, which are conceptually and genetically more distant from reported self-regulation, but more closely empirically associated with test-based cognitive skills (Connelly, Ones, & Chernyshenko, 2014).

Multivariate Associations Between Self-Regulation and Academic Abilities

The second aim of the current investigation was to examine how measures of self-regulation stemming from different research traditions, individually and collectively, accounted for variation in academic abilities. Moreover, because of the strong associations that both test-based measures of EF and educationally relevant aspects of personality share with psychometric measures of intelligence (Duncan, Emslie, Williams, Johnson, & Freer, 1996; Chamorro-Premuzic et al., 2010; Engelhardt et al., 2016), we examined these associations after accounting for measures of lower-level (processing speed) and higher-level (fluid intelligence) cognitive abilities.

The current findings point to the importance of test-based EF in explaining variance in academic abilities beyond psychometric measures of processing speed and fluid intelligence. This contrasts with existing evidence obtained in young samples (Blair et al., 2015; Fuhs et al., 2014). Particularly, a number of previous studies examining the association between processing speed, Executive Functioning and mathematics achievement had suggested that the association between EF and mathematics was mostly accounted for by processing speed (Rose et al., 2011; van der Sluis, de Jong, & van der Leij, 2007). An important advantage of our study that may potentially account for this difference is that we obtained a highly reliable index of executive functioning by applying a latent factor approach to data from an extensive EF measurement battery.

It has been proposed that EFs provide a narrow assessment of self-regulation, reflecting optimal performance measured in standardized laboratory settings rather than real life self-regulatory abilities (Stanovich, 2012; Toplak et al., 2013). On the contrary, self-reported impulse control has been proposed to be a closer representation of real-life self-regulatory skills, concerned with a reflective level of analysis which encompasses both the cognitive and affective components of self-regulation (Stanovich, 2012). As such, it would be reasonable to assume an association between self-reported impulse control and academic abilities (that are acquired in real-world scholastic settings, even if measured in the laboratory) beyond cognitive competence, a proposition supported by several studies finding associations between multiple measures of motivation and academic abilities beyond general intelligence (Luo et al., 2010, 2011; Malanchini et al., 2017). Our results contrast this view, as we found that self-reported impulse control did not predict academic abilities beyond cognitive skills, while a common EF factor, assessed via a collection of multiple tests tapping several subdomains, was the best predictor of academic abilities, even after accounting for other cognitive and personality measures. That said, it will be highly informative to examine these patterns of associations with academic performance obtained from school transcript data, which much more directly reflects performance in real-world settings.

More important, the very strong genetic overlap between a common EF factor and general intelligence documented in previous work (e.g., Engelhardt et al., 2016), should be taken into consideration when interpreting the genetic associations between EF and academic abilities. In fact, the observed associations between EF and reading and mathematics abilities may reflect highly general processes.

The common factor of Executive Functioning considered in the present study was found to have very similar associations with both reading and mathematics ability. Previous studies have reported a particularly strong link between mathematics and EF (Bull & Lee, 2014). Our results indicate a substantial link between EF and both domains of academic abilities, with a particularly strong association with reading ability observed even when accounting for processing speed and *gf*. It may be that difficulties with Executive Functioning may impact the acquisition of skills relevant to mathematics and reading abilities both in the course of naturally occurring development as well as in more specific academic settings, including learning in the classroom (Lee et al., 2013). Evidence from our developmental sample suggests that this link is partly explained by a shared genetic factors.

Whereas Executive Functioning played a nearly equally important role in accounting for variation in both reading and mathematics abilities, we found that educationally relevant aspects of personality, and particularly the superfactor of Openness were differentially associated with reading and mathematics abilities.

The Openness superfactor was substantially related to reading, but not mathematics ability, beyond the variance accounted for by the other cognitive and self-regulatory constructs. In contrast, the Conscientiousness superfactor was negligibly related academic abilities beyond the other cognitive and self-regulatory constructs. This conflicts with evidence that self-control and grit differentially predict educational achievement (Duckworth et al., 2007). Duckworth et al. (2007) found that grit predicted achievement beyond self-control but not vice versa and proposed that, although both constructs involve aligning actions with intentions, grit may be more closely linked to academic skills than self-control because grit emphasizes maintaining fewer high-stake goals over a more extended period of time despite setbacks (Duckworth & Gross, 2014). Evidence emerging from the current investigation points to the role of qualities other than grit and self-control in explaining variation between students in academic abilities. Attributes such as interest, curiosity and enjoyment of learning were found to be of particular importance in statistically accounting for variation in reading skills in childhood.

Collectively, the findings of the current investigation suggest that the genetic architecture of academic abilities is complex and different for reading and mathematics. Whereas the genetic variance in mathematics uniquely overlaps with cognitive abilities (i.e., processing speed, *gf* and EF), but not personality, the genetic variance in reading uniquely overlaps with both cognitive abilities and personality (superfactor of Openness).

Strengths, Limitations, and Future Directions

The current study has several strengths, first of which is the comprehensive battery of measures of EF and educationally relevant aspects of personality. The findings and implications of research in these domains and their association with academic abilities are too often limited by a poor characterization of the EF and educationally relevant measures of personality. The second main strength of the present investigation is that of applying SEM, which allowed us to model the complexity of the constructs under investigation and their associations. Relatedly, a further strength of the current investigation is that each construct was included in every model in its latent form. This is particularly relevant for behavioral genetic modeling, as measurement error was not subsumed under the latent nonshared environmental components. To our knowledge, this is the first investigation that has explored the relative contribution of differentially measured aspects of self-regulation, stemming from two different epistemological traditions, and other educationally relevant aspects of personality to variation in academic abilities in childhood applying both latent variable and genetically informative research frameworks.

The current study also presents some limitations, including relying on the assumptions of the twin method. The equal environments assumption, for example, is the assumption that shared environmental similarity is the same for pairs of twins reared together, regardless of zygosity (Knopik, Neiderhiser, Defries, & Plomin, 2016). More important, it is important to keep in mind that we would expect that if interests, proclivities, abilities, and aptitudes are partly genetically influenced, then more genetically similar individuals (e.g., MZ twins compared with DZ twins) will select, pursue, and evoke more similar experiences than will less genetically similar individuals. We do not view such phenomena as violations of the equal environment assumption. Rather, these processes may actually be a key mechanism of the emergence and amplification of genetic influences on psychological and educational phenotypes over development (Scarr & Mccartney, 1983; Tucker-Drob, 2017).

A further assumption of the twin method is random mating, the principle that people are assumed to mate at random and not with other people that resemble them. In reality this assumption is often violated, as people tend to mate with people who resemble them phenotypically and genetically, a concept known as assortative mating (Ask, Idstad, Engdahl, & Tambs, 2013). Greater genetic similarity between parents of DZ twins that results from assortative mating increases the estimates of shared environmental influences, and reduces the estimates of genetic influence, produced by a model that incorrectly assumes no assortment. However, this limitation is likely to not have had an impact on the current results, as most of the shared environmental estimates did not reach significance.

Another limitation is that we did not test for gene-environment correlations or gene × environment interactions. Indeed, the modeling framework that we applied treats the genetic and environmental variance components as independent of one another. Estimates of genetic variance in outcomes may partly reflect processes whereby children are differentially select, evoke, modify, and attend to their educational environments on the basis of their genetically influenced interests, motivations, abilities, and proclivities (Knopik et al., 2016; Tucker-Drob & Harden, 2017).

In addition to the limitations that pertain to the methodology adopted, it should be noted that the current study considered test-based measures of academic abilities rather than broader measures of academic achievement indexed by grades or teacher-rated assessment. Examining the multivariate structure of the association between self-regulation and other educationally relevant aspects of personality and classroom performance, rather than in-lab tests of abilities, may produce a different pattern of associations. In particular, educationally relevant aspects of personality may play a greater role in in school achievement measured in more naturalistic settings, such as through exam scores or teacher evaluations. Exploring these associations is an ongoing direction of research program. A further avenue of our future research is to move toward testing the observed associations between self-regulation and academic abilities and achievement beyond linearity. In fact, the association between educationally relevant measures of personality and academic abilities may be characterized by a greater complexity that is not necessarily captured by linear associations. In line with this hypothesis, Fite et al. have observed an interaction between conscientiousness and intellectual self-concept in predicting the interest (passion) component of grit (Fite, Lindeman, Rogers, Voyles, & Durik, 2017), and Tucker-Drob et al. (2014) reported evidence for an interaction between interest and intellectual self-concept in accounting for variation in science achievement test scores (Tucker-Drob, Cheung, & Briley, 2014). Exploring this further level of complexity is part of our future research goals.

Conclusions

Results of the current study highlighted the multidimensionality of self-regulatory measures. Fuhs et al. (2014) argued that an in-depth understanding of children's developing cognitive skills is necessary to create successful programs to enhance school readiness and early reading and mathematics abilities. Based on the results of the current study it may also be fruitful to additionally focus on aspects of self-regulation and other educationally relevant personality factors. Although it is often assumed that characteristics such as hard-work, perseverance and diligence are key to academic success, the current findings point to the importance of other aspects of personality, such as curiosity, enjoyment of learning and self-belief, captured by the superfactor of Openness, in fostering academic abilities, and particularly reading skills.

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