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The Hungry Mind: Intellectual Curiosity Is the Third Pillar of Academic Performance

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Abstract

Over the past century, academic performance has become the gatekeeper to institutions of higher education, shaping career paths and individual life trajectories. Accordingly, much psychological research has focused on identifying predictors of academic performance, with intelligence and effort emerging as core determinants. In this article, we propose expanding on the traditional set of predictors by adding a third agency: intellectual curiosity. A series of path models based on a meta-analytically derived correlation matrix showed that (a) intelligence is the single most powerful predictor of academic performance; (b) the effects of intelligence on academic performance are not mediated by personality traits; (c) intelligence, Conscientiousness (as marker of effort), and Typical Intellectual Engagement (as marker of intellectual curiosity) are direct, correlated predictors of academic performance; and (d) the additive predictive effect of the personality traits of intellectual curiosity and effort rival that the influence of intelligence. Our results highlight that a "hungry mind" is a core determinant of individual differences in academic achievement.

Keywords

intelligence, academic performance, conscientiousness, intellectual curiosity, meta-analysis

> Curiosity is, in great and generous minds, the first passion and the last.
>
> Samuel Johnson (1750)

The selection of candidates for higher education and professional recruitment is traditionally based upon previous academic performance. Interpersonal variations in academic performance, for example in school and university, have been explained in terms of individual differences in intelligence and personality traits (e.g., Alexander, 1935; Poropat, 2009; Webb, 1915). In particular, students with higher cognitive ability (quicker learners), and those who are more hard-working and well-organized (higher Conscientiousness) tend to perform better in educational settings. That is, ability and effort are important determinants of academic achievement; however, their application is driven by a third, to date often overlooked factor: intellectual curiosity.

In this article, we first briefly review the societal function of academic performance in the context of educational and occupational status attainment. Then, we discuss the research literature that focuses on ability and nonability factors as psychological predictors of academic performance. Finally, based on meta-analytic evidence and theoretical considerations, we demonstrate the importance of a curious mind for scholarly success in addition and in relation to ability and effort.

Academic Performance: Why It Matters

In the second half of the 19th century, the industrial revolution led to an increasing specialization and complexity of jobs. As a result, compulsory schooling was introduced in the United States and Europe to enable the general population to meet the latest job demands (G. A. Martin, 2008). Because of the new emphasis on educational qualifications, individual careers became less predefined by social class background or parental occupation, but depended more on demonstrated ability and skill.

Prior to World War I, only a small fraction of the population extended their education beyond elementary schooling, and

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even Ivy League universities, including Harvard and Yale, could admit all applicants without reaching the limits of their capacity (Hubin, 1988; Lehmann, 1999). However, as more and more people sought higher education to enhance their employability, universities had to introduce selective student admissions.[1] Thus, previous academic performance became the gatekeeper to higher education and a master key to the labor market. Today, academic performance continues to be understood as an accurate proxy for aptitude and is a core determinant of career paths and status attainment, even though some question its value (Chamorro-Premuzic & Furnham, 2010). Academic performance is also a key to understanding the development of one of psychology's most well-known "tools": the intelligence test.

Academic Performance and Intelligence: Criterion Par Excellence?

Sir Francis Galton (1822–1911), the father of intelligence research (Fancher, 1985),[2] was the first to suggest that individual differences in intelligence were reflected in academic performance outcomes:

> There can hardly be a surer evidence of the enormous difference between the intellectual capacity of men, than the prodigious differences in the numbers of marks obtained by those who gain mathematical honours at Cambridge. (Galton, 1869, p. 16)

Because academic performance was thought to mirror individual differences in ability, it became the "the criterion par excellence" for intelligence tests (Chamorro-Premuzic & Furnham, 2006, p. 253). Indeed, Théodore Simon (1872–1961) and Alfred Binet (1857–1911) developed the first intelligence test to identify children who struggled with the school curriculum and their academic performance. Likewise, subsequently developed ability tests were (and continue to be) validated by educational achievement as accurate measures of intelligence (e.g., Spearman, 1904; Terman, 1916). Indeed, if an intelligence test failed to account for interindividual differences in academic performance, it was not regarded as a meaningful measure of intellectual capacity (e.g., Bolton, 1892; Sharp, 1899).

At present, an abundance of empirical research shows that mental ability test scores are substantially correlated with academic performance, reaching values of up to $r = .81$ (Deary, Strand, Smith, & Fernandes, 2007), although cross-sectional correlations tend to be lower than $r = .50$ (e.g., Johnson, McGue, & Iacono, 2006; see also Hell, Trapmann, & Schuler, 2007; Kuncel, Hezlett, & Ones, 2004; Poropat, 2009; Sackett, Kuncel, Arneson, Cooper, & Waters, 2009). The association between cognitive ability and academic performance persists across educational levels, although it tends to decrease in more advanced academic settings due to differential range restrictions. For instance, candidates in graduate school have been selected already on the basis of their intellectual capacity, which increases the relative variability and importance of nonability factors (cf. Jensen, 1980). In line with this, recent research has assessed the degree to which individual differences in academic performance can be explained by personality factors.

Academic Performance Beyond Intelligence: Does Personality Matter?

Although intelligence is an important predictor of academic success, recent research has shown that personality dispositions, notably traits assessing individuals' typical levels of persistence and hard work, account for substantial amounts of variance in academic performance (e.g., O'Connor & Paunonen, 2007; Poropat, 2009; Trapmann, Hell, Weigand, & Schuler, 2007). For example, Chamorro-Premuzic and Furnham (2003b) found that personality traits accounted for four times as much variance in exam results of elite university students than did intelligence. This result echoes the effect of range restriction in intelligence on the predictive validity for nonability factors (as detailed earlier).

Maximum versus typical performance

Nonability traits have traditionally been operationalized by typical performance measures to reflect the strength of a behavioral tendency for accomplishment, whereas *ability* is ordinarily construed as measures of maximal performance (Cronbach, 1949; Fiske & Butler, 1963). Ability test scores indicate what an individual can do, whereas personality scales provide a measure of what a person is most likely to do (Fiske & Butler, 1963, pp. 258–259). Klehe and Anderson (2007) demonstrated in a recent laboratory study that behavior dispositions, including the direction and level of effort, as well as participants' perceived self-efficacy, were more predictive of typical than of maximum performance outcomes. Conversely, ability, which was conceptualized in terms of declarative knowledge and procedural skills, was found to be of greater significance for maximum than typical performance outcomes (Klehe & Anderson, 2007). The authors concluded that psychological predictors of accomplishment vary in their predictive validity across maximum or typical performance settings depending on the nature of the measurement instrument in question.

In education, assessments of academic achievement span both conditions of maximum and typical performance. For example, students usually demonstrate their learning success by addressing specific questions or topics in timed examinations. Although such examinations constitute a maximum performance setting, the assessment outcome also reflects the students' typical performance in terms of their breadth and depth of preparation. Therefore, nonability factors are plausibly more meaningful variables when determining academic performance outcomes than cognitive ability measures, which invariably capture maximum rather than typical potential.

The role of Conscientiousness

Since the early 1990s, there has been a growing consensus on the Five Factor Model as the preferred taxonomy for classifying individual differences in normal personality (e.g., Goldberg, 1990). This model comprises five major dimensions of personality: Neuroticism, Extraversion, Openness to Experience, Agreeableness and Conscientiousness (Costa & McCrae, 1992).

Of these, Conscientiousness has been repeatedly shown to be positively related to the academic performance of university students (e.g., Chamorro-Premuzic & Furnham, 2003a, 2003b, 2006; Poropat, 2009) as well as to several job performance criteria across a broad range of occupations (Barrick & Mount, 1991; Chamorro-Premuzic & Furnham, 2010; Salgado, 1997; Tett, Jackson, & Rothstein, 1991). Conscientiousness is comprised of six facets—Competence (efficacy), Order (planning ahead), Dutifulness (following rules), Achievement striving (effort), Self-Discipline, and Deliberation (Costa & McCrae, 1992)—that indicate individual differences in persistence, responsibility, and effort, all of which are associated with better academic and occupational performance. Several recent meta-analyses estimated associations between indicators of academic performance and Conscientiousness from $r = .23$ to $r = .27$ (O'Connor & Paunonen, 2007; Poropat, 2009; Trapmann, Hell, Hirn, & Schuler, 2007). Even though the magnitude of these associations confirms the importance of Conscientiousness in academic settings, the construct was not initially conceptualized for the purpose of predicting school or university performance.

Intelligence and Conscientiousness have been found to be largely independent, although some studies reported modest negative correlations between Conscientiousness and ability measures (e.g., Ackerman & Heggestad, 1997; Moutafi, Furnham, & Crump, 2006). To explain this negative association, it has been argued that "less" able individuals may become increasingly more conscientious to compensate for their lower levels of cognitive ability, whereas more intelligent people rely to a greater extent on their intelligence and can "afford" to be less dutiful and organized and nevertheless excel (Chamorro-Premuzic & Furnham, 2005). According to this theory, the effects of intelligence on academic performance would be mediated by Conscientiousness in an inconsistent mediation model (MacKinnon & Fairchild, 2009). That is, intelligence would have a direct positive effect on academic performance, as well as an indirect negative effect, mediated by Conscientiousness. Therefore, direct and indirect effects would be of opposite signs or inconsistent. It is not clear yet if intelligence and Conscientiousness are independent predictors of academic performance or if one mediates the effects of the other.

Effort, Intelligence, . . . and What Else?

It has been argued that crystallized intelligence, which "consists of discriminatory habits long established in a particular field" (Cattell, 1943, p. 178), results from the application of fluid intelligence, which is the "ability to discriminate and perceive relations between any fundaments, new or old" (Cattell, 1943, p. 178). In simple words, knowledge and expertise result from applying one's reasoning ability. The direction and strength of such application, in turn, is directed by so-called *investment traits* (Cattell, 1943, 1971)—that is, personality characteristics that determine where, when and how people apply their mental capacity. Accordingly, investment traits explain interindividual differences in the pursuit of learning opportunities such as visiting museums and galleries, solving riddles and puzzles, and reading the newspapers. Hayes (1962) suggested that all variation in intelligence resulted from individual differences in the drive or motivation to pursue learning opportunities. He claimed that "differences commonly referred to as intellectual [are] nothing more than differences in acquired abilities" (p. 303), and rejected the existence of a general intelligence factor. Even though Hayes' (1962) motivational-experiential theory takes an extreme stand (cf. McDougall, 1933), it is plausible that the motivation to learn is reflected in differences in acquired skills.

In the psychological literature, numerous theoretical and psychometric concepts have been proposed to capture individual differences in the desire to comprehend and engage in cognitively demanding tasks and, hence, to invest in one's intellectual competence (von Stumm, 2010). However, these so-called investment traits have to date not been explicitly associated with research on curiosity and exploration (Ackerman & Heggestad, 1997; Berlyne, 1954, 1960; Litman & Spielberger, 2003), despite their striking resemblance.

Investment and curiosity

Historically, different types of curiosity have been identified: Hume (1777/1888) theoretically differentiated the curiosity of "love of knowledge" from the "passion derived from a quite different principle [that is] an insatisfiable desire for knowing the actions and circumstances of neighbours" (p. 453). Berlyne (1954) proceeded to introduce the conceptual distinction between epistemic and perceptual curiosity. Epistemic curiosity refers to individual differences in seeking out opportunities for intellectual engagement, acquiring facts and knowledge, or simply the "drive to know" (Berlyne, 1954, p. 187), whereas perceptual curiosity is evoked by visual, auditory, and tactile stimulation and refers to a "drive to experience and feel" (Berlyne, 1954). Later, Litman and colleagues developed corresponding psychometric scales to assess epistemic and perceptual curiosity (cf. Collins, Litman, & Spielberger, 2004; Litman & Spielberger, 2003). Epistemic curiosity is conceptually very similar to other intellectual investment traits, all of which refer to a desire or hunger for knowledge. For example, Cacioppo and Petty (1982) sought "to identify differences among individuals in their tendency to engage in and enjoy thinking" (p. 116), and thus developed the Need for Cognition scale, which stretches from "cognitive misers to cognizers"

(Cacioppo, Petty, Feinstein, & Jarvis, 1996, p. 197). Later, Goff and Ackerman (1992) proposed the Typical Intellectual Engagement (TIE) scale as "a dispositional construct that . . . is associated with intelligence as typical performance" (p. 539). The TIE scale captures people's typical expression of engaging with and understanding their environment and their desire to solve and be absorbed by complex, intellectual problems (Goff & Ackerman, 1992). To that effect, TIE specifically refers to settings of advanced stages of education in which the predictive validity of maximal intelligence is diminished (Goff & Ackerman, 1992).

Need for cognition, epistemic curiosity, and TIE are exemplary representatives of a group of investment trait constructs that describe tendencies to seek out, engage in, enjoy, and pursue opportunities for effortful cognitive activity—in short, intellectual curiosity. In addition to their conceptual similarities, trait scales of intellectual curiosity also share a number of semantically identical items (von Stumm, 2010). Not surprisingly, epistemic curiosity, need for cognition, and other investment traits have been found to lack discriminant validity[3] (e.g., Mussel, 2010; Rocklin, 1994; Woo, Harms, & Kuncel, 2007). Furthermore, investment traits are uniformly positively associated with academic performance with medium effect sizes (Cacioppo et al., 1996; von Stumm, 2010), and also with intelligence but to a notably lesser extent (e.g., Cacioppo, Petty, & Morris, 1983; Furnham, Swami, Arteche, & Chamorro-Premuzic, 2008; Goff & Ackerman, 1992). That is, measures of intellectual investment and curiosity have matching conceptual roots, include semantically identical items, and share criteria validity for academic performance and intelligence; therefore, they appear to assess the same trait dimension, and corresponding scales might be interchangeably used.

Investment and Openness to Experience

In the Five Factor Model, Openness to Experience is comprised of six facets: Fantasy (vivid imagination), Aesthetic Sensitivity, Attentiveness to Inner Feelings, Actions (engagement in unfamiliar and novel activities), Ideas (intellectual curiosity), and Values (readiness to reexamine traditional social, religious, and political concepts; Costa & McCrae, 1992; McCrae, 1994). Openness to Experience is conceptually very similar to intellectual investment traits (Ackerman, 1996; Chamorro-Premuzic & Furnham, 2006). Furthermore, Openness is associated with general intelligence and domain-specific knowledge (e.g., Ackerman & Heggestad, 1997; Ackerman & Rolfhus, 1999). It has been argued that more intelligent individuals are better capable of understanding difficult information and processing new experiences, which in turn facilitates open-minded attitudes and expands knowledge (e.g., Moutafi et al., 2006). Conversely, individuals with low levels of intelligence are more challenged by intellectually demanding tasks, and prefer routine and, to some degree, closed-mindedness (that is not to say, smart individuals could not also be closed-minded and dogmatic). However, three recent meta-analyses on Openness and academic performance estimated correlations between .06 and .13 (O'Connor & Paunonen, 2007; Poropat, 2009; Trapmann et al., 2007), suggesting that Openness may have negligible effects on academic performance outcomes.

In a recent series of studies, DeYoung, Peterson, and Higgins (2005); DeYoung, Quilty, and Peterson (2007); and DeYoung, Shamosh, Green, Braver, and Gray (2009) empirically substantiated previous notions of Openness incorporating two related but distinct factors (e.g., Saucier, 1992): Intellect, reflecting intellectual engagement with the Ideas facet as the main marker, and Openness, comprised of artistic and contemplative qualities related to engagement in sensation and perception including facets of Fantasy, Aesthetics, Feelings, and Actions. Note that the Values facet scale was a distinct marker of neither Openness nor Intellect (DeYoung et al., 2005). Using fMRI in a sample of 104 community members from the Washington area, DeYoung et al. (2009) showed that Intellect was associated with brain activity in neural systems of working memory but that Openness was not. The authors concluded that Openness to Experience is comprised of two separable, neurally distinctive aspects of one larger personality domain (Fig. 1).

Further evidence for the two-dimensionality of Openness comes from behavior genetics. Wainwright, Wright, Luciano, Geffen, and Martin (2008) analyzed data from 754 families on intelligence, academic achievement, and the six facets of Openness. The results showed a general genetic factor that explained variance in intelligence, academic performance and several Openness facets. Most notably, the general factor was associated with Ideas and Values. Conversely, a specific genetic factor was related to Fantasy, Aesthetics, Feelings, and Action (Wainwright et al., 2008). Overall, these results suggest that Intellect, marked by Ideas and Values, shares more genetic variance with intelligence and academic performance than does Openness, marked by Fantasy, Aesthetics, Feelings, and Actions. Studies reporting low phenotypic associations of Openness and intellectual accomplishments typically measure Openness as a higher order factor and do not sample its facets. Therefore, the apparent lack of empirical evidence for associations of Openness and academic performance may be due to a methodological problem. That is, the investment theory is not invalidated because of negligible associations between Openness and academic performance, but an alternative, more precise conceptualization of intellectual curiosity should be put to test.

The Current Study

To date, the role of intellectual curiosity has not been studied within the complex nexus of academic achievement predictors. In this study, we empirically evaluate our proposal of intellectual curiosity as a core determinant of academic performance, compare associations of Openness to Experience and intellectual curiosity with academic performance, and disentangle

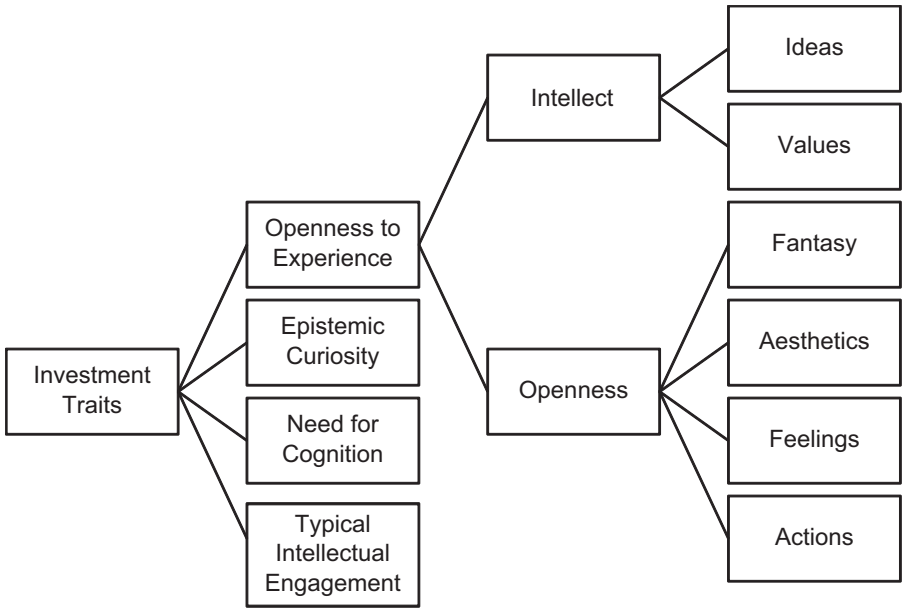

Fig. 1. Typology of psychometric investment trait scales. Note: Only a small selection of investment trait scales is shown. For a full review of existing investment trait scales and constructs see von Stumm (2010).

curiosity's associations with intelligence and Conscientiousness. Following Viswesvaran and Ones' (1995) approach, we composed a correlation matrix of meta-analytic coefficients to fit a series of path models. In part, correlation coefficients were extracted from previously published meta-analyses on associations between academic performance, intelligence, Openness, and Conscientiousness. Because no meta-analysis to date reported corresponding associations with intellectual curiosity, four new meta-analyses were conducted focusing on TIE as representative construct for intellectual curiosity. We chose TIE as the representative scale because it has been more frequently employed in research on intelligence, personality and academic performance than other investment trait scales, such as Need for Cognition and epistemic curiosity. Below, we briefly outline the employed methods; a detailed account can be found in the Appendix.

Methods

Database searches

We searched the psychological database PsychINFO for large-scale meta-analytic reviews that investigated associations among two or more variables, including academic performance, Conscientiousness and Openness (measured within the Five Factor Model), and intelligence. We identified three excellent studies: Kuncel et al. (2004); Judge, Jackson, Shaw, Scott and Rich (2007); and Poropat (2009). From each of those, we borrowed one or more meta-analytic coefficients to create a correlation matrix for our analysis; details on these studies, their methods, and the choice of coefficients are outlined in the Appendix.

For TIE, no suitable meta-analytic study has been previously published,[4] and subsequently, four new, independent meta-analyses were conducted. To this end, we completed a literature search on PsychINFO and ERIC using the key term "typical intellectual engagement." Identified studies were excluded from the analysis if they did not include empirical data, did not include zero-order correlations, and reported previously published data (e.g., Rocklin, 1994). References of all studies were screened for additional manuscripts. Overall, 11 studies were identified (Table 1), all of which employed the same measure of TIE (Goff & Ackerman, 1992) and were comprised of predominantly student samples. Without exception, the identified studies operationalized Conscientiousness and Openness to Experience with measures from the Five Factor Model. Similarly, academic performance was consistently assessed as grade point average (GPA) or as an academic performance composite. For intelligence, only tests measuring general intelligence and omnibus IQ tests were included. The obtained coefficients were corrected for sampling and measurement error and were meta-analyzed following the validation generalization approach in random effect models (see Appendix).

Results

Results of the TIE meta-analyses

As shown in Table 2, TIE was most strongly associated with Openness to Experience at $\hat{\mu}_p = .64$ ($N = 1{,}998$), followed by academic performance with $\hat{\mu}_p = .33$ ($N = 608$). The association between TIE and Conscientiousness was at $\hat{\mu}_p = .28$ ($N = 1{,}662$) and between TIE and intelligence at $\hat{\mu}_p = .22$ ($N = 1{,}230$).

Table 1. Overview of Studies Included in the Meta-Analysis of TIE's Associations With Openness, Intelligence, Conscientiousness, and Academic Performance

Study	Criterion	Measure	*N*	*r*
Ackerman, Kanfer, and Goff, 1995	C	NEO-PIR	93	.08
	O	NEO-PIR	93	.70
Beier and Ackerman, 2001	O	NEO-FFI	153	.55
Chamorro-Premuzic, Furnham, and Ackerman, 2006a	g	Wonderlic	201	.36
	C	NEO-PIR	201	.25
	O	NEO-PIR	201	.26
Chamorro-Premuzic, Furnham, and Ackerman, 2006b	AP	Composite	104	.36
	g	Composite	104	.27
	C	NEO-FFI	104	.36
	O	NEO-FFI	104	.24
Dellenbach and Zimprich, 2008	g	Raven's Matrices	364	.18
Ferguson, 1999	C	BAM	281	.20
	O	BAM	281	.46
Furnham et al. 2008	g	Wonderlic	101	−.06
	C	NEO-FFI	101	.28
	O	NEO-FFI	101	.66
Goff and Ackerman, 1992	C	NEO-PI	138	.27
	O	NEO-PI	138	.65
	AP	GPA	138	.04
Gow, Whiteman, Pattie, and Deary, 2005	C	IPIP	460	.20
	I	IPIP	460	.53
	g	Moray House Test	460	.13
Rolfhus and Ackerman, 1996	C	NEO-FFI	203	.24
	O	NEO-FFI	203	.67
Wilhelm, Schulze, Schmiedek, and Süß, 2003	O	NEO-PIR	183	.50
	AP	Humanities GPA	183	−.26a
	AP	Science GPA	183	−.37a
Woo, Harms, and Kuncel, 2007	C	BFI	81	.29
	O	BFI	81	.65

[a]Wilhelm et al. (2003) tested German students; in the German marking system, lower numbers indicate better grades. The coefficients were reversed for the analysis.

Note: The reported coefficient (*r*) values are not corrected for scale reliability. Criterion refers to the variable that was investigated in a respective study in relation to TIE, while measurement refers to the psychometric instrument that was used to assess the study's variable of interest. *r* = Uncorrected study correlation; C = Conscientiousness; O = Openness; g = general intelligence; AP = Academic performance; GPA = Grade Point Average; NEO-PIR = NEO-Personality-Inventory-Revised; NEO-PI = NEO-Personality Inventory; NEO-FFI= NEO Five Factor Inventory; BFI = Big Five Inventory; BAM = Bipolar Adjective Markers; IPIP = International Personality Item Pool.

Table 3 shows the correlation matrix that was used for the subsequent path models.

Models of academic performance

In a stepwise process, five path models were fitted; Table 4 shows the model fit index results across tested models. Model fit was assessed using the model χ^2 (Jöreskog, 1969), the incremental goodness-of-fit indices including Comparative Fit Index (CFI), the Tucker-Lewis Index (TLI), as well as the root-mean-square error of approximation (RMSEA). CFI and TLI indicate an adequate model fit at values of .90 and .95 or above (Hu & Bentler, 1999), whereas RMSEA values of .08 and below are considered acceptable (Browne & Cudeck, 1993).

Model 0 was a full intercorrelation model whereby all predictor variables were allowed to freely correlate and to directly

Table 2. Meta-Analytic Coefficients of TIE With Conscientiousness, Openness to Experience, Academic Performance and Intelligence

Study	*N*	*k*	*M*	*Mean est. reliability*	ρ	$\hat{\sigma}_\rho^2$	SE_{RE}	95% CI_{RE}
TIE-C	1,662	9	.229	TIE: .870, C: .784	.277	.0	.022	[.233, .321]
TIE-O	1,998	11	.519	TIE: .870, O: .758	.639	.024	.050	[.542, .737]
TIE-AP	608	4	.260	TIE: .868, AP: .720	.328	.017	.080	[.171, .486]
TIE-g	1,230	5	.179	TIE: .864, g: .768	.224	.013	.061	[.104, .343]

Note: *k* = number of independent samples; *M* = mean correlation; ρ = sample size weighted and corrected validity; $\hat{\sigma}_\rho^2$ = estimated variance of ρ; SE_{RE} = standard error of ρ, random effects model; 95% CI_{RE} = confidence interval with *p* = .95, random effects model; TIE = Typical Intellectual Engagement; C = Conscientiousness; O = Openness; AP = academic performance; g = general intelligence.

affect academic performance. It was a just identified, saturated model with 0 degrees of freedom and a χ^2 of 0, which makes the computation of informative fit indices impossible (Table 4). The model showed a negative association between Openness and academic performance of −.26 after controlling for the predictor's high intercorrelations with the other variables; subsequently, Openness was excluded from all models (Fig. 3a). Model 1 constituted a full mediation model, whereby TIE and Conscientiousness independently mediated the effects of intelligence on academic performance (Fig. 2). The model fit indices suggested a poor fit. Model 2 replicated the previous model but allowed additionally for the two mediators—TIE and Conscientiousness—to freely correlate. Model fit indices suggested a slight improvement over the previous model but by no means an adequate fit. Model 3 tested if intelligence had a direct effect on academic performance and also indirectly influenced the outcome through TIE and Conscientiousness. That is, TIE and Conscientiousness were specified to mediate the impact of intelligence on academic performance (Fig. 2). Model 3 showed a poor fit to the data. Overall, the series of models suggested that personality traits were inadequate mediators of intelligence effects on academic performance, and thus, a final Model 4 conceptualized Conscientiousness, intelligence, and TIE as direct predictors of academic performance while controlling for the predictor's intercorrelations (Fig. 2). Note that there was no correlation between Conscientiousness and intelligence. This model accounted overall for 25.7% of the variance in academic performance and proved a superior and acceptable fit (Fig. 3b). All paths were significant at $p < .01$. TIE correlated with intelligence at .23 and with Conscientiousness at .29. After controlling for these positive associations among the predictor variables, intelligence sustained the strongest effect on academic performance with a path weight of .35. TIE and Conscientiousness had slightly lower, identical path parameters of .20.

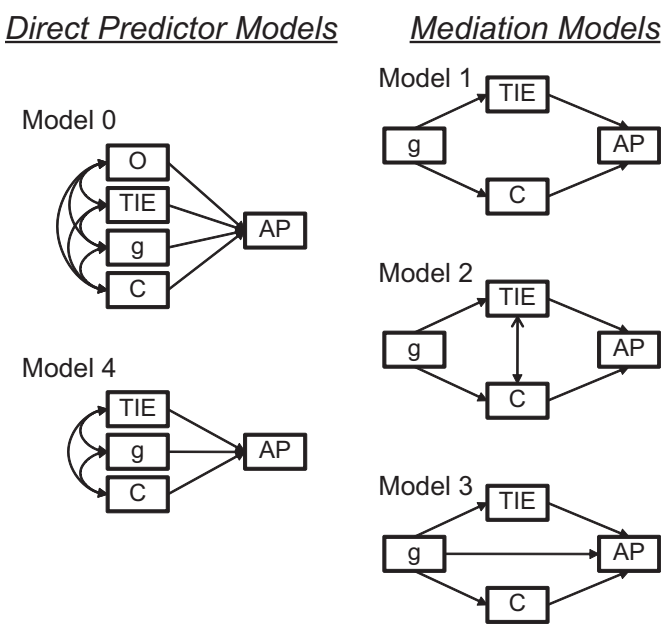

Fig. 2. Five different path models predicting academic performance. Note: Double-headed arrows represent correlations; single headed arrows imply direct causal effects. O = Openness; TIE = Typical Intellectual Engagement; g = general intelligence; C = Conscientiousness; AP = academic performance.

Models of Academic Performance: The Interplay of Intelligence, Effort, and Investment

Previous research has identified intelligence and effort as "core pillars" of academic performance, but other variables have traditionally received less attention in the prediction of scholarly success. The current study evaluated intellectual curiosity as potentially meaningful third pillar of academic achievement. To this end, four independent meta-analyses of TIE estimated its associations with general intelligence, Conscientiousness, Openness to Experience, and academic performance. Furthermore, psychological predictors of academic performance were investigated within meta-analytic path models.

Consistent with previous research (e.g., Goff & Ackerman, 1992; Mussel, 2010; Rocklin, 1994), Openness and TIE overlapped considerably, sharing 41% of variance. Also consistent with previous research (e.g., Ackerman, 1996; Ackerman, Kanfer, & Goff, 1995; Goff & Ackerman, 1992), both constructs differed in their associations with general intelligence

Table 3. Correlation Matrix of Meta-Analytic Coefficients From Currently and Previously Conducted Studies

		1	2	3	4
1	g	—			
2	AP	.39	—		
3	C	−.04	.24	—	
4	O	.22	.07	.09	—
5	TIE	.22	.33	.28	.64

Note: Sample sizes range from *N* = 608 to *N* = 28,471.
Key: g = general intelligence; AP = academic performance; C = Conscientiousness; O = Openness; TIE = Typical Intellectual Engagement.

and academic performance. TIE was more strongly related to academic performance than to intelligence, even though the difference was small. In contrast, Openness shared a substantial amount of variance with intelligence, and almost none with academic performance (cf. Judge et al., 2007; Poropat, 2009). TIE and Openness also differed in their associations with Conscientiousness, with TIE being more strongly linked to this omnibus measure of persistence and diligence than Openness.

The second set of analyses evaluated a series of path models (Fig. 2 and 3). Here, TIE and Openness differed substantially in the direction of association with academic performance after controlling for their associations with the remaining predictor variables. To that effect, Openness was shown to negatively affect academic performance, whereas TIE was a strong positive predictor despite its considerable inter-correlations with the remaining predictors.

In our opinion, the observed differences in associations of Openness and TIE with academic performance, intelligence and Conscientiousness are best explained in terms of the theoretical and psychometric designs of these two investment traits. Openness was originally conceptualized as a multifarious trait construct, which entails not only intellectual curiosity but also aesthetic awareness, heightened imagination or fantasy life, and receptivity to one's own inner feelings (McCrae, 1994). Griffin and Hesketh (2004) reported differential validities of the facets of Openness for the prediction of job performance and suggested distinguishing two factors of Openness: *internal experience*, including aesthetics, fantasy, and feelings, and *external experience*, spanning actions, ideas, and values. It seems plausible that internal experience is unrelated to effort and knowledge acquisition, whereas external experience may capture conscientious behaviors that are elementary to transform actions and ideas into reality. To that effect, the inclusion of an undifferentiated Openness construct (i.e. at factor rather than facet level) in the current study may have blurred the association between external experience and Conscientiousness, as indicated by negligible correlation coefficient. This perspective is also consistent with findings from behavior genetics and brain imaging studies (DeYoung et al., 2005, 2009; Wainwright et al., 2008) suggesting two distinct factors of Openness (cf. Fig. 1).

Conversely, TIE was designed to assess intelligence as typical behavior and constitutes a precise measure of intellectual engagement in the pursuit of knowledge (e.g., Ackerman & Rolfhus, 1999). In this study, TIE was used as a representative for intellectual investment traits that (a) are scattered across the literature, (b) share conceptual roots and even scale items, (c) are alike in criterion validity, (d) lack discriminant validity, and (e) therefore might be used interchangeably (Mussel, 2010; von Stumm, 2010; Woo et al., 2007). TIE was initially defined as "desire to engage and understand [the] world" and as "need to know" (Goff & Ackerman, 1992, p. 539). As such, it refers to a consistent and purposeful process of learning, which is without doubt also effortful. Accordingly, individuals

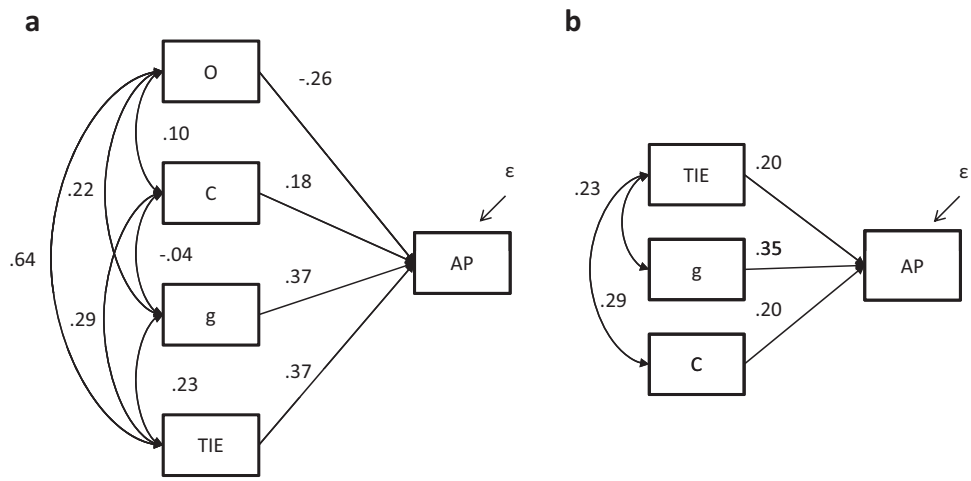

Fig. 3. Results model of predictors of academic performance and their inter-relations. Panel a displays the overall model including all variables as intercorrelated, direct predictors, whereas Panel b shows the final, best-fitting model. O = Openness; TIE = Typical Intellectual Engagement; g = general intelligence; C = Conscientiousness; AP = academic performance.

Table 4. Model Fit Indices

Model	χ^2	*df*	TLI	CFI	RMSEA	90% CI_{RMSEA}
0. Full inter-correlation	0	0	—	1.00	—	—
1. Full mediation model	561.96	2	−.661	.446	.345	.321, .369
2. Model 1 with correlation	345.58	1	−1.044	.659	.383	.349, .417
3. Partial mediation	216.38	1	−.278	.787	.302	.269, .337
4. Final model	3.77	1	.984	.997	.034	000, .074

Note: TLI = Tucker-Lewis Index; CFI = Comparative Fit Index; RMSEA = root-mean-square error of approximation; 90% CI_{RMSEA} = 90% confidence intervals, RMSEA.

who seek intellectual stimulation present an increased level of persistence and zeal, which is reflected in TIE's positive association with Conscientiousness (cf. Arteche, Chamorro-Premuzic, Furnham, & Ackerman, 2009).

Our results ran counter to the idea that effects of intelligence on academic performance are in any way mediated by personality traits (Chamorro-Premuzic & Furnham, 2005, 2006; Moutafi et al., 2006), as all mediation models failed to achieve adequate model fit. Instead, the data was best represented by a path model, in which intelligence, TIE, and Conscientiousness were direct, intercorrelated predictors of academic performance (Fig. 3b). In this model, intelligence accounted for the greatest amount of variance; however, the combined effects of curiosity and effort equaled the impact of intelligence on academic performance. This model confirmed intelligence and effort as antecedents of academic performance but added incremental validity by including intellectual curiosity. Therefore, the current results supported that intellectual investment is a key determinant of academic performance (Ackerman, 1996; Chamorro-Premuzic, Furnham, & Ackerman, 2006a, 2006b; Goff & Ackerman, 1992).

The Hungry Mind: Vindicating Intellectual Curiosity

Pre-modern writers, including Aristotle (384 BC–322 BC) and Cicero (106 BC–43 BC), understood curiosity as "an intense, intrinsically motivated appetite for information" (Loewenstein, 1994, p. 77). In a similar vein, the American psychologist and philosopher John Dewey (1859–1952) stated:

> The curious mind [is] constantly alert and exploring [and] seeking material for thought, as a vigorous and healthy body is on the qui vive for nutriment. . . . Such curiosity is the only sure guarantee of acquisition of primary facts . . . . (Dewey, 1910, p. 31)

Dewey (1910) proposed a developmental perspective of curiosity, beginning with "an abundant organic energy" (p. 31) that is associated with children's hunger to explore and probe their surroundings. This basic experimentation is hardly intellectual but essential to later develop reflective reasoning (Dewey, 1910). In the second developmental stage, social stimuli affect curiosity resulting in children's endless series of "why?" questions. Dewey (1910) noted that this "why" is not aimed at a precise, scientific explanation but illustrates the mastery of gathering and processing information, both of which constitute "the germ of intellectual curiosity" (Dewey, 1910, p. 32). Finally, "curiosity raises above organic and social planes [and] is transformed into interest in problems provoked by the observation of things and the accumulation of material" and hence, becomes a "positive intellectual force" (Dewey, 1910, p. 32). Therefore, curiosity may start as a hungry and exploratory mind but ultimately transforms into intellectual maturity.

Practical implications

The association of intellectual curiosity with academic performance, has two important practical implications for higher education. For one, academic performance may be further enhanced if students' intellectual curiosity is continuously stimulated and nurtured. Dewey (1910) observed:

> In a few people, intellectual curiosity is so insatiable that nothing will discourage it, but in most its edge is easily dulled and blunted. . . . Some lose it in indifference or carelessness; others in a frivolous flippancy; many escape these evils only to become incased in a hard dogmatism which is equally fatal to the spirit of wonder. (p. 33)

Schools and universities must early on encourage intellectual hunger and not exclusively reward the acquiescent application of intelligence and effort (Charlton, 2009). It is not only the diligent class winner who writes an excellent term paper but also the one who asks annoyingly challenging questions during the seminar (a habit that is, unfortunately, not appreciated by all teachers). Also, intellectually stimulated students are likely to be more satisfied with their university experience and to enjoy their studies to a greater extent than students who fell victim to Dewey's hard dogmatism. It is worth noting here that curiosity may be as much a trait as a state (Berlyne, 1960; Loewenstein, 1994), suggesting that educational settings should fully exploit their plentiful opportunities to induce and inspire curiosity.

For the other, selection methods for university admissions and professional recruitment should pay greater attention to

intellectual curiosity as important indicator of potential and ability. In fact, intellectual curiosity incorporates intelligence, zeal, and the hunger for information and novelty in one. To this effect, it seems imperative to expand current research efforts in this field and to investigate effects of intellectual curiosity on job performance and cognitive development throughout the lifespan. That said, this study, like most personality research, relied on self-report measures, which only capture the explicit (accessible by introspection) personality and not the implicit (inaccessible by introspection) personality (James, 1998). Furthermore, self-report measures of personality are susceptible to fakability (e.g., Furnham, 1986; Viswesvaran & Ones, 1999); however, such distortions do not affect criterion related validity (e.g., Hough, Eaton, Dunnette, Kamp, & McCloy, 1990; Martin, Bowen, & Hunt, 2002). It seems unlikely that the current findings are merely a consequence of faking or social desirability. However, future research on intellectual investment must employ psychometric tests that are less susceptible to reporting bias, such as observer ratings or conditional reasoning tests (cf. James, 1998).

Strengths and Limitations

The greatest strength of the current study is perhaps also its greatest weakness—namely the fact that results are based on meta-analytic correlation coefficients. An extensive body of research was synthesized across a large number of studies and participants; however, the current study design was equally constrained by the quality of the reanalyzed studies and datasets. Furthermore, the current methodological approach limited the number of variables that could be included; that is, other trait determinants of academic performance, such as self-estimates of ability, fluid and crystallized intelligence, and sex were presently not included because we failed to identify suitable meta-analyses that would have summarized the effects of these factors across studies. Also, only Conscientiousness was included as a measure of effort but not others, such as academic motivation, self-efficacy, achievement striving or ambition. In a similar vein, the personality factor *V* from the Five Factor Model was predominantly conceptualized in terms of Openness to Experience despite the fact that other, related trait designs—for example Goldberg's (1990) Intellect—may constitute more reliable constructs (e.g., De Raad, 1994).

Applying path modeling to meta-analytic data is commonly associated with three statistical challenges: determining the appropriate sample size to fit the model, recognizing the sampling variation across studies, and analyzing a correlation rather than a covariance matrix (Cheung & Chan, 2005). These factors all potentially bias model fit indices and standard errors of parameters; thus, the current results are to be cautiously interpreted. Finally, most studies included in the previous and present meta-analyses were single-wave and not longitudinal, which makes causal inferences somewhat speculative. Specifically, academic performance and personality will likely not only be associated in a one-way direction but will have reciprocal effects on one another; that is, achieving a high grade may increase the probability of future conscientious and curious behaviors and vice versa.

Despite these limitations, this study crucially advances the understanding of academic performance. First, it shows that variances in academic performance are best accounted for by a combination of predictor variables (Chamorro-Premuzic & Furnham, 2006). Second, intellectual curiosity was demonstrated to constitute a meaningful addition to the traditional set of predictors of academic performance. In fact, both Conscientiousness and intellectual curiosity influenced academic performance to the same extent as intelligence. However, our final model accounted only for a quarter of the variance in academic performance; therefore, other variables, for example choice of subject, socio-economic status, learning style, and self-confidence, are likely to be influential, too.

Conclusions

The current study suggests that traditional sets of predictors of academic performance, notably general intelligence and Conscientiousness, should be accompanied by a third factor: intellectual curiosity. Jensen (1998) stated that "[general intelligence] *g* acts only as a threshold variable that specifies the essential minimum ability required for different kinds of achievement. Other, non-*g* special abilities and talents, along with certain personality factors . . ., are also critical determinants of educational and vocational success" (p. 544–545). A remarkable number of studies on determinants of academic achievement have focused exclusively on ability and effort; the present findings, however, recommend further expanding the "*g*-nexus" for a better understanding of individual differences in academic performance. The latter requires—beyond intelligence and effort—a hungry mind.

Appendix

Herein, we will report the database procedures for identifying previous meta-analytic reviews, our statistical approach to the TIE meta-analyses, and the prediction model of academic performance.

1. Identifying meta-analytic coefficients from the previous literature

For associations of academic performance with Conscientiousness and Openness, three meta-analyses were identified (i.e., O'Connor & Paunonen, 2007; Poropat, 2009; Trapmann et al., 2007), all of which conceptualized Conscientiousness and Openness within the framework of the Five Factor Model. Moreover, each used exam grades, essay marks, and GPA as indicators of academic performance but excluded academic aptitude tests as outcome variable, such as the SAT (formerly Scholastic Aptitude Test) or the American College entrance Test (ACT). However, the three meta-analyses were not

Table A1. Coefficients Borrowed From Previous Meta-Analyses

Correlation	Source	*N*	*k*	Rho
C–AP	Poropat, 2009	32, 887	92	.23 [a]
O–AP	Poropat, 2009	28, 471	77	.07 [a]
O–C	Mount, Barrick, Scullen, and Rounds, 2005	4, 000	4	.09 [a]
g–AP	Kuncel, Hezlett, and Ones, 2004	11, 368	70	.39 [a,b]
g–C	Judge, Jackson, Shaw, Scott, and Rich, 2007	15, 429	56	−.04 [a]
g–O	Judge et al. 2007	13, 182	46	.22 [a]

[a]Corrected for scale reliability. [b]Corrected for range restriction.
Note: C = Conscientiousness; AP = academic performance; g = general intelligence; O = Openness; TIE = typical intellectual engagement; N = overall sample size; *k* = number of independent samples; Rho = sample size weighted and corrected validity.

independent and differed considerably in their methodological approach. For the current study, correlation coefficients between academic performance and Conscientiousness and Openness were borrowed from Poropat (2009), who conducted the most comprehensive, accurate meta-analysis on associations of personality and academic performance to date.

For the coefficient between intelligence and academic performance, Kuncel et al. (2004) summarized research of the Millers Analogies Test (MAT) and academic performance and reported an estimated "true" score correlation of the MAT with reasoning measures of .75 in a sample of $N = 1{,}753$ from 15 studies. In addition, Kuncel et al. (2004) found the MAT to be closely related to verbal ability (.88; $N = 3{,}614$) and to math ability (.68; $N = 2{,}874$). The MAT is composed of 100 analogies, which are considered to be excellent markers of general intelligence (Carroll, 1993, p. 212; Spearman, 1927).

Judge et al. (2007)[5] recently evaluated studies on personality associations with general mental ability; their meta-analytic study included "valid indicators of ability" (p.111), as well as measures of Conscientiousness and Openness within the Five Factor taxonomy. From their study, we borrowed the intelligence-personality coefficients of −.04 ($N = 15{,}429$) for Conscientiousness and .22 ($N = 13{,}182$) for Openness with general intelligence, respectively (see also Table A1). Finally, Mount, Barrick, Scullen, and Rounds (2005) computed a full inter-correlation matrix of the Five Factors by reevaluating scores from four standardization samples with overall $N = 4{,}000$ and estimating the inter-correlation of Conscientiousness and Openness at .09.

2. Methodological approach to TIE meta-analyses

Data were analyzed in line with the validation generalization approach (Raju, Burke, Normand, & Langlois, 1991), which roots in the meta-analytic method of Hunter, Schmidt, and Jackson (1982). Raju and Fleer (2003) developed a software program for this purpose, which was used in the present study to calculate meta-analytic coefficients under random-effects conditions, which is suitable for the current research purpose (Erez, Bloom & Wells, 1996; Hunter & Schmidt, 2000; Schmidt, Oh, & Hayes, 2009). Coefficients were corrected for sampling error and attenuation by error of measurement in both predictors and criteria. We used reliability coefficients from the primary studies, mostly the alpha coefficient of internal consistency. In cases of missing reliability data, a weighted reliability estimate was calculated based on the reliability-information given in the other studies.

3. Predictor models of academic performance

Following previous models of meta-analytically derived correlation matrix, estimates of the true-score correlations were used for all matrix entries (e. g. Fried, Shirom, Gilboa, & Cooper, 2008; Heller, Watson, & Ilies, 2004; Verhaeghen & Salthouse, 1997; Viswesvaran, Ones, & Schmidt, 1996). Recently, Beretvas and Furlow (2006) inspected 26 studies that applied structural-equation-modeling analyses to pooled correlation matrices not to covariance matrices. They made the following conclusion:

> When the model of interest assesses relations between psychological constructs (e. g., mathematical self-concept, motivation) that are measured using different scales across studies, then correlations should be used instead of covariances because the variances of different measures (of a single construct) will vary and thus so will the associated covariances. The differences in the resulting covariances might not originate only from the relation (i.e., correlation) between constructs but also from the scale of the measures used to assess the construct. (Beretvas & Furlow, 2006, p. 158)

As cells or coefficients of the matrix differ in sample sizes, researchers have used a variety of ad-hoc solutions to achieve an appropriate sample size, including the harmonic or arithmetic mean, the median or the total of sample sizes (Cheung & Chan, 2005). Here, we have opted for the harmonic mean ($N_{hamonic} = 2{,}356$) instead of the arithmetic mean ($N_{arithmetic} = 8{,}383$), which is recommended in the literature on unweigthed analysis of variance (Viswesvaran & Ones, 1995).

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The authors declared that they had no conflicts of interest with respect to their authorship or the publication of this article.

Notes

1. This is admittedly a simplified account of American education history; please see Lehmann (1999) for a more detailed review.
2. In 1575, the Spanish physician Juan Huarte de San Juan published *Examen de Ingenios para las Ciencias*, which may be considered the earliest scientific writing on intelligence (Fernández-Ballesteros & Colom, 2004).
3. Discriminant validity describes the degree to which one measurement instrument diverges from others that are theoretically different (Campbell & Fiske, 1959).
4. Ackerman and Heggestad (1997) computed meta-analytic associations of TIE and factors of intelligence; however, these coefficients were mostly based on an insufficient number of studies.
5. Judge, Jackson, Shaw, Scott, and Rich's (2007) meta-analysis partially replicates Ackerman and Heggestad's (1997) earlier meta-analytic results on intelligence-personality associations and is more comprehensive.

*marks studies included in the TIE meta-analysis

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