Learning and Individual Differences 32 (2014) 26–39

Contents lists available at ScienceDirect

Learning and Individual Differences

journal homepage: www.elsevier.com/locate/lindif

Achievement-relevant personality: Relations with the Big Five and validation of an efficient instrument

Daniel A. Briley [a,*], Matthew Domiteaux [b], Elliot M. Tucker-Drob [a]

[a] Department of Psychology and Population Research Center, University of Texas at Austin, United States
[b] Department of Psychology, University of Virginia, United States

ARTICLE INFO

Article history:
Received 10 August 2013
Received in revised form 10 February 2014
Accepted 17 March 2014
Available online xxxx

Keywords:
Achievement-relevant personality
Academic achievement
Effort
Approaches to learning
Big Five
Intellectual investment

ABSTRACT

Many achievement-relevant personality measures (APMs) have been developed, but the interrelations among APMs or associations with the broader personality landscape are not well-known. In Study 1, 214 participants were measured on 36 APMs and a measure of the Big Five. Factor analytic results supported the convergent and discriminant validity of five latent dimensions: performance, mastery, self-doubt, effort, and intellectual investment. Conscientiousness, neuroticism, and openness to experience had the most consistent associations with APMs. We constructed a more efficient scale– the Multidimensional Achievement-Relevant Personality Scale (MAPS). In Study 2, we replicated the factor structure and external correlates of the MAPS in a sample of 359 individuals. Finally, we validated the MAPS with four indicators of academic performance and demonstrated incremental validity.

1. Introduction

Beyond the well-established connection between academic achievement and general cognitive ability, a number of individual differences in terms of general patterns of academically-relevant behavior impact trajectories of learning. For example, Ackerman and Rolfhus (1999) point out that "abilities are only one part of the complex causal framework that determines whether a student pursues the acquisition of knowledge and skills within a particular domain" (p. 176). In addition to ability, determinants of typical performance such as personality, motivation, or interest may influence academic achievement. To tap these determinants of typical performance, a diverse array of achievement-relevant personality measures (APMs) have been developed by differential and educational psychologists. Developing APMs has been somewhat successful with meta-analytic evidence that APMs, such as effort, intellectual investment, approaches towards learning, and self and school values, predict variance in academic achievement (Huang, 2012; Hulleman, Schrager, Bodmann, & Harackiewicz, 2010; Poropat, 2009; Richardson, Abraham, & Bond, 2012; von Stumm & Ackerman, 2013). However, these APMs remain studied relatively independently of one another with little empirical or theoretical examination of factor overlap. This critical gap in the literature has hindered the construction of useful theories of academic achievement because of the inability to aggregate knowledge across study domains.

1.1. A need for integration

Many APMs are in use, but little has been done to integrate findings driven by different theoretical backgrounds. Several recent reviews have commented on the need for a multivariate examination of the interrelations among the many APMs in order to establish the convergent and discriminant validity of different operationalizations. In Ackerman and Heggestad's (1997) influential meta-analysis of investment traits, they concluded that the various investment constructs are "isolated personality measures … with no linkage to any personality theory" (p. 222). Citing this rather clear call for future research, von Stumm, Chamorro-Premuzic, and Ackerman (2011) quizzically determined that "a unifying research endeavor is yet to be undertaken" despite the clear interest in the topic and the length of time between the initial and the recent review (p. 225). Recently, von Stumm and Ackerman (2013) assessed the state of the intellectual investment literature and found a "scarcity of data" despite "the large number of identified investment constructs" (p. 852). Wigfield and Cambria (2010) comprehensively described the many APM constructs commonly used by educational psychologist and noted that there is little information about how different operationalizations relate. In their review, a table spanning three pages was required to display all of the commonly used APMs. Despite these calls for unification, a multivariate, cross-domain synthesis has yet to be undertaken.

* Corresponding author at: Department of Psychology, University of Texas at Austin, 108 E. Dean Keeton Stop A8000, Austin, TX 78712-0187, United States.
E-mail address: daniel.briley@utexas.edu (D.A. Briley).

http://dx.doi.org/10.1016/j.lindif.2014.03.010
1041-6080/

Four meta-analytic studies are noteworthy for moving the field in this direction. Richardson et al. (2012) conducted the most comprehensive, in terms of content breadth, meta-analysis of individual difference correlates of academic performance and found that many APMs significantly predict achievement. Richardson et al. (2012), however, did not examine the factor structure underlying the multivariate relations among APMs. In fact, the authors concluded that the "development of an improved multimeasure assessment instrument would provide more parsimonious and reliable assessments" (p. 374). This task may be more difficult than simply aggregating previous studies. For example, Hulleman et al. (2010) and Huang (2012) performed meta-analyses on the approaches towards learning domains. Huang (2012) found that very small proportions of variance in achievement were accounted for by approaches towards learning, but Hulleman et al. (2010) found evidence of heterogeneity in patterns of association between approaches to learning and achievement. Hulleman et al. (2010) rationally coded item content of different scales and found evidence that different research groups had given similar labels to different constructs. The same label (e.g., performance-approach orientation) had both positive and negative associations with achievement, and this heterogeneity was partly associated with the item content. Thus, the largely null findings of Huang (2012) may have resulted from aggregating such psychometrically confused measures. Finally, von Stumm and Ackerman (2013) found similar meta-analytic evidence for the intellectual investment domain. In light of heterogeneous effect sizes being assigned to supposedly the same construct, the authors concluded that "some investment traits have been assessed by different scales with different foci despite supposedly assessing the same trait dimension" (p. 856). Although the methods applied by Hulleman et al. (2010) and von Stumm and Ackerman (2013) convincingly demonstrate measurement confusion, the interpretation relies on face validity. We will complement these findings by assessing the empirical associations between instruments.

We emphasize that these meta-analytic studies were specifically designed to test the predictive or criterion validity of APMs. However, as these authors and critics have pointed out, building a consistent framework of APMs depends on settling psychometric issues of content, convergent, and discriminant validity before any evidence of criterion validity can reasonably be integrated. Furnham (2011) argued that APM research could flourish by placing these constructs within the well-established Big Five framework. This consistent taxonomy of individual differences provides a construct map that can ground APM research. To address these limitations in the previous literature, we test the convergent and discriminant validity of many APMs drawn from the differential and educational psychology traditions and place them within the context of the Big Five.

1.2. The differential psychology tradition

The Big Five personality traits – extraversion, agreeableness, conscientiousness, neuroticism, and openness to experience – are thought to provide a fairly comprehensive description of variation in human behavioral tendencies (John, Naumann, & Soto, 2008). The codification of five simple, replicable, and highly predictive personality traits unified what was previously a "chaotic plethora" of different measures (Funder, 2001, p. 200). The Big Five traits have proven to be extremely productive constructs for personality researchers interested in academic achievement and provide a model for the benefit of unified and relatively universal construct measurement. Poropat (2009) performed a meta-analysis that assessed the predictive validity of the Big Five for academic achievement. This study found substantial associations between academic performance (typically course grades or GPA) and conscientiousness (r corrected for unreliability = .22) and openness (r corrected for unreliability = 12). For comparison, the corrected r for intelligence was estimated at .25. Students that are more diligent in their coursework (i.e., high in conscientiousness) and those that are more curious or intellectually engaged (i.e., high in openness) tend to perform better at school.

Several explanations for the association between conscientiousness and achievement have been advanced: conscientiousness may reflect strength of character, a general sense of willpower, or a compensation strategy for lower levels of cognitive ability (von Stumm, Hell, & Chamorro-Premuzic, 2011; von Stumm et al., 2011). Little progress has been made in determining what aspect of conscientiousness is most influential, but academic effort has received considerable attention (Chamorro-Premuzic & Furnham, 2005). Effort refers to an individual's care and persistence in a given activity. Different measurement perspectives have been used to assess effort including constructs ranging from procrastination to perfectionism (Frost, Marten, Lahart, & Rosenblate, 1990; Lay, 1986).

Intellectual investment, conceptually related to openness, is also linked to achievement (von Stumm & Ackerman, 2013). Following from Cattell's (1971, 1987) investment hypothesis, individuals that possess a hungry mind tend to invest their intelligence in learning activities and thus facilitate achievement. However, disagreement exists in the choice of preferred instrument. Initial organizing work has been conducted to show that different measures of intellectual investment lack discriminant validity, and a content analysis of different scales reveals many semantically identical items (Mussel, 2010, 2013; von Stumm et al., 2011).

We include narrow measures of effort and intellectual investment in the current study to further clarify the convergent and discriminant validity of these outcomes. Although the Big Five and associated traits provide a consistent framework from which to judge the relations between individual differences and academic achievement, there is considerable evidence for traits that are *outside* Big Five factor space (Paunonen & Jackson, 2000). This is particularly the case for traits that are thought to be highly influenced by situations or that only apply in certain contexts. Behavioral tendencies that primarily occur in the schooling context are crucial for understanding achievement. Such tendencies have traditionally been neglected in personality research but strongly focused on in educational research.

1.3. The educational psychology tradition

Educational researchers place importance on motivational or emotional qualities of students that relate to perceptions, attitudes, and goals within the school context (for a recent review, see Mega, Ronconi, & De Beni, 2013). Theories of academic goal orientation describe various approaches to learning that emerge from challenging educational experiences that instill differing levels of motivation to demonstrate or obtain competence (Ames, 1984; Dweck, 1999; Elliot, 1999). Approaches to learning are thought to influence academic achievement by way of guiding interactions with the educational environment (Elliot & Murayama, 2008). Although different labels have been used in this literature, the most common distinction is between performance and mastery orientations. Performance goal oriented individuals have a desire to demonstrate their competencies. Mastery goal oriented individuals, in contrast, have a desire to complete challenging tasks that may increase their competence. Goal orientations are further subdivided into approach tendencies, where the student is driven to display indicators of competence, or avoidant tendencies, where the student is driven to hide indicators of a lack of competence (Elliot & Harackiewicz, 1996). Thus, a student who possesses a performance-approach orientation would desire to outperform other students, and a student with a performance-avoid orientation would desire to avoid giving an incorrect answer. Goal orientations focus on why students study, but there are also individual differences in how students study. For example, deep and surface study processes describe students who seek to learn course material completely and those who seek to only learn the minimum requirement, respectively (Biggs, Kember, & Leung, 2001).

The motivational attributes that follow from evaluations of the self or school environment are the final domain that this article will attempt to integrate. The Expectancy–Value model (Eccles & Wigfield, 2002; Jacobs & Eccles, 2000), recently reframed as the Expectancy × Value model (Nagengast et al., 2011), is one of the most influential theories of academic motivation. This model predicts that academic motivation results from a combination of student beliefs about the ability to successfully complete a task and the value of the task outcome. According to the Expectancy × Value version of this model, for a student to be academically motivated, both expectancy and value must be high. If a student does not believe the task can be completed, there will be little motivation to complete the task no matter how valuable completion may seem. Similarly, if the task holds no value, the student is unlikely to complete even the easiest of tasks. A core component of the Expectancy × Value model is that assessments of the self and the environment can have a large influence on the pursuit of academic achievement. These types of "core self-evaluations" are thought to influence motivation to engage in academic or any type of work (Judge & Hurst, 2007; Judge, Locke, & Durham, 1997). Other researchers have constructed similar measures that are contextualized within the academic classroom to assess student evaluations of academic self-worth or efficacy and aspects of the educational environment (Midgley et al., 2000).

2. Methodology

We provide evidence from two studies. In the first study, we included a total of 36 APMs from the areas of approaches to learning, effort, intellectual investment, and self and school evaluations. Measures were selected based on their widespread use, availability, brevity, and their emphasis in recent reviews. We chose measures that were sufficiently narrow to assess one specific construct. For example, we included focused indicators of intellectual investment, such as curiosity and love of learning (Goldberg et al., 2006), instead of other widely used measures, such as need for cognition (Cacioppo, Petty, & Kao, 1984) and typical intellectual engagement (Goff & Ackerman, 1992). As has been discussed above and by others (e.g., Mussel, 2010), general measures in this domain are very highly intercorrelated, and narrow measurement may better delineate construct overlap and differences. The Big Five were included to provide a reference point to broad personality. We attempted to fully explore the within-APM nomological network with factor analysis and by situating the APMs in the context of the Big Five (Cronbach & Meehl, 1955). Additionally, we conducted item-level analyses to remove redundant item content and create a reduced self-report instrument. In the second study, we replicated the factor structure of the reduced scales and provide preliminary evidence of predictive validity with academic achievement. Importantly, the primary goal of both studies was to aid in clarifying the psychometric relations of various APMs. By piecing together these separate frames of reference, our goal is to offer an interpretive guide that allows the disparate measures and theoretical orientations to be compared.

2.1. Study 1

This study used the undergraduate research participant pool at a large, public research institution in Texas. Participants were recruited through an online database of available studies as part of the research requirement of a foundational psychology course. The original sample consisted of 249 individuals. Thirty-five participants were removed from the sample because they incorrectly responded to one or more of seven validation items (e.g., "Please select option three for this question"). The final sample of 214 individuals included 153 females and 61 males. Participants ranged in age from 17 to 23 with the majority reporting being 18 or 19 years old (83.6%). The racial/ethnic composition of the sample was relatively diverse, containing non-Hispanic White (59.8%), Asian (23.4%), Hispanic (22.4%), Black (7.5%), American Indian (2.3%), and Other race/ethnicity (10.3%) participants.

2.1.1. Materials

A diverse collection of measures from five measurement domains was included in the current study: approaches to learning, effort, intellectual investment, self and school evaluations, and the Big Five. All items were rated on a scale ranging from 1 to 7, with 1 representing strong disagreement and 7 representing strong agreement. Means, standard deviations, reliability estimates, and the number of items per scale are presented in Table 1. The majority of APMs displayed adequate levels of reliability. The average reliability estimate was .84 with a range of .57 to .95.

Three widely used operationalizations of approaches to learning were included: the Achievement Goal Questionnaire (AGQ; Elliot & McGregor, 2001), the Study Process Questionnaire (SPQ; Biggs et al., 2001), and the Patterns of Adaptive Learning Scales (PALS; Midgley et al., 2000). The AGQ has four subscales representing the performance-approach,

Table 1
Descriptive statistics of each APM divided into content areas.

Variables	# Items	Mean	SD	Alpha
Approaches to learning				
1. AGQ performance approach	3	4.75	1.58	.93
2. AGQ performance avoid	3	5.48	1.33	.71
3. AGQ mastery approach	3	5.62	1.08	.84
4. AGQ mastery avoid	3	4.83	1.41	.81
5. SPQ — deep	10	4.36	0.93	.80
6. SPQ — surface	10	3.59	0.93	.79
7. PALS performance approach — original	5	4.92	1.35	.88
8. PALS performance approach — revised	5	3.91	1.52	.92
9. PALS performance avoid — original	6	3.78	1.43	.88
10. PALS performance avoid — revised	4	3.77	1.58	.90
11. PALS mastery — original	6	5.22	1.11	.85
12. PALS mastery — revised	5	5.73	1.00	.91
Effort				
13. Procrastination	20	3.97	0.81	.76
14. FMPS — mistakes	9	3.46	1.35	.91
15. FMPS — standards	7	3.98	1.07	.70
16. FMPS —parent expectations	5	3.33	1.39	.82
17. FMPS — parent criticism	4	4.20	1.21	.66
18. FMPS — doubts	4	4.98	1.19	.81
19. FMPS — organization	6	4.91	1.47	.95
20. Achievement striving	10	5.50	0.95	.90
21. Motivation to pursue interests	18	5.30	0.74	.89
Intellectual investment				
22. Tolerance for ambiguity	18	4.05	0.75	.83
23. Avoidance of novelty	5	3.70	1.20	.87
24. Ingenuity	9	4.96	1.14	.90
25. Intellect	11	4.82	0.94	.81
26. Quickness	10	5.00	0.95	.87
27. Creativity	10	5.17	0.97	.70
28. Depth	9	5.29	0.99	.87
29. Love of learning	10	4.82	0.94	.81
Self and school evaluations				
30. Self-esteem	10	5.35	1.16	.92
31. Self-efficacy	8	5.70	1.06	.85
32. Locus of control	8	4.79	0.64	.57
33. Academic efficacy	5	5.46	1.13	.92
34. Avoidance of achievement	7	2.49	1.11	.85
35. Skepticism about school	6	2.61	1.33	.89
36. Competence	10	5.09	0.94	.86
Big Five domains				
37. Extraversion	8	0.74	9.21	.90
38. Agreeableness	9	8.73	8.47	.82
39. Conscientiousness	9	4.77	8.22	.82
40. Neuroticism	8	-4.93	8.37	.83
41. Openness to experience	10	1.47	8.56	.80

Note. APM = achievement-relevant personality measure. AGQ = Achievement Goal Questionnaire. SPQ = Study Processes Questionnaire. PALS = Patterns of Adaptive Learning Scales. FMPS = Frost Multidimensional Perfectionism Scale. All scales were responded to on a 7-point Likert scale ranging from strongly disagree to strongly agree. A within-person centering approach was used to score the Big Five Inventory, making the means for these scales less easily interpretable (see John et al., 2008).

performance-avoid, mastery-approach, and mastery-avoid goal orientations. The SPQ assesses deep or surface approaches for to-be-learned material. The student personal achievement goal orientation scales from the PALS materials were included. Similar to the AGQ, the PALS scales conceptualize student goals in terms of performance and mastery, with performance further subdivided into approach and avoid. Additionally, revised versions of each scale were included as well as originals. The revised scales attempted to remove references to specific behaviors or the intrinsic value of certain outcomes. We included each student scale in order to further evaluate how the original and revised scales relate both to each other and to the other measures.

We included measures that tapped into a broad range of positive and negative aspects of effort. First, a measure of procrastination was included as a negative marker of effort (Lay, 1986). The Frost Multidimensional Perfectionism Scale (FMPS) was included (Frost et al., 1990). This measure assesses different manifestations of perfectionistic thinking. A measure of achievement striving was obtained from the International Personality Item Pool (IPIP; Goldberg et al., 2006). An additional scale that measured a largely positive view of general effort or initiative that could include work, school, or social life was sought, but we found most to be either domain specific or relating to perseverance in the face of adversity (e.g., the Short Grit Scale; Duckworth & Quinn, 2009). Rather than self-regulatory or goal maintenance processes, an investment trait related to exposing oneself to new experiences may provide a more direct explanation for the link between conscientiousness and academic achievement. Individuals that are simply predisposed to pursue opportunities to learn rather than remaining content with their current environment may be more likely to achieve academically. Sample items of the newly created scale include highly face valid statements such as “I pursue my interests by seeking out new activities,” “I like to keep up to date on events related to my interests,” and “I like to have a full schedule.”

Intellectual investment was assessed by several scales relating to a desire for new ideas or complex situations such as tolerance for ambiguity, avoidance of novelty, ingenuity, intellect, quickness, creativity, depth, and love of learning. Tolerance for ambiguity indicates a lack of discomfort in complex situations or with problems that lack a clear solution (Judge, Thoresen, Pucik, & Welbourne, 1999). Conversely, avoidance of novelty refers to preferences for avoiding unfamiliar work in a classroom setting. The remaining scales are taken from the international personality item pool (Goldberg et al., 2006).

Several of the measures of self and school evaluations are core self-evaluations. These include measures of self-esteem (Rosenberg, 1965), self-efficacy (Judge, Locke, Durham, & Kluger, 1998), and locus of control (Levenson, 1981). Additionally, evaluations of the school or academic environment were assessed using measures from PALS (Midgley et al., 2000). These include academic efficacy, avoidance of achievement, and skepticism about the worth of school for one's life. Finally, a scale assessing self-perceived competence was taken from the IPIP (Goldberg et al., 2006).

The Big Five Inventory was used as a measure of personality (John et al., 2008). This widely used instrument produces scores for the domains of extraversion, agreeableness, conscientiousness, neuroticism, and openness to experience. We used the scoring approach described by John et al. (2008) which corrects for acquiescent response sets.

2.1.2. Procedure

All procedures were approved by the appropriate Institutional Review Board. The self-report materials were completed in a laboratory setting with a research assistant overseeing the data collection. The measures were administered using the REDCap data management system (Harris et al., 2009). The laboratory was equipped with three computers in separate, small rooms. This procedure ensured that the participants experienced a private and distraction-free environment to complete the instrument in the presence of a research assistant to answer any questions about the study.

All models were fit using full-information maximum-likelihood estimation in M*plus* statistical software (Muthén & Muthén, 1998-2010).

2.1.3. Results

2.1.3.1. APM — Big Five associations. As a first step, we examined the associations between the APMs and the Big Five. Standardized regression coefficients from regressing each APM on the Big Five are presented in Table 2. Instruments designed to assess approaches to learning had associations primarily with conscientiousness, neuroticism, and openness. Higher levels of conscientiousness were positively associated with AGQ and PALS mastery-approach orientations and deep study processes. Conscientiousness was negatively related to AGQ mastery-avoid orientation and surface study processes. With the exception of AGQ performance-approach, which was positively associated with conscientiousness, performance orientations were uncorrelated with conscientiousness. Higher neuroticism was most strongly associated with avoidant or performance orientations. Similar to the pattern seen for conscientiousness, openness was unrelated to performance orientations, positively associated with mastery orientations and deep study processes, and negatively associated with surface study processes. The Big Five accounted for a modest amount of variance in each measure ranging from 6% to 27% (mean = 16.8%).

Conscientiousness was the primary Big Five domain associated with measures of effort. Associations in the expected direction were found between conscientiousness and procrastination, perfectionistic standards, doubts, organization, achievement striving, and motivation to pursue interests. Perfectionistic tendencies reflective of self-image or the perceptions of others were unrelated to conscientiousness, but tended to be associated with neuroticism. Openness was positively associated with parent criticism, doubts, achievement striving, and motivation to pursue interests. The amount of variance explained by the Big Five varied considerably across effort measures. Achievement striving displayed the largest amount of variance explained (48%), but a much smaller amount of the variance in parental expectations (8%) was explained.

The intellectual investment domain was highly related to openness. Furthermore, four of the eight intellectual investment measures were negatively associated with neuroticism. Other minor associations were found with the remaining three Big Five factors. Four of the eight intellectual investment measures were associated with lower levels of agreeableness, and three measures were associated with higher levels of conscientiousness. Substantial amounts of variance were explained for each measure ranging from 23% to 59%.

The final domain of self and school evaluations was largely associated with conscientiousness and neuroticism. For six out of the seven indicators, more positive evaluations were associated with higher levels of conscientiousness. Four measures of positive evaluations were associated with lower levels of neuroticism. The strongest associations with neuroticism were found for the self rather than school evaluations. Avoidance of achievement was unrelated to any of the Big Five. Apart from this scale, a moderate amount of variance was associated with the Big Five for the remaining measures (ranging from 11% to 52%).

2.1.3.2. Within-APM structure at the scale-level and latent associations with the Big Five. Next, we examined the psychometric structure of the APMs at the scale-level. An oblique, geomin rotated exploratory factor analysis (EFA) of each APM was conducted. To determine the number of factors to extract, we examined scree plots and conducted a parallel analysis. Originally described by Horn (1965), parallel analysis involves comparing eigenvalues derived from actual data to eigenvalues derived from randomly generated data with the decision rule to extract the number of factors that have eigenvalues greater than the associated eigenvalue for random data. This procedure helps avoid under and over extraction of factors (see O'Connor, 2000 for more technical details).

Table 2
Standardized regression coefficients for each APM on the Big Five.

Variables	E	A	C	N	O	R^2
Approaches to learning						
1. AGQ performance approach	.03	.02	**.24***	**.29****	−.02	.11
2. AGQ performance avoid	.00	**.16**	−.05	**.27***	.06	.07
3. AGQ mastery approach	−.07	.05	**.25****	**.17**	**.29****	.16
4. AGQ mastery avoid	.12	−.03	**−.19***	**.40****	**.19***	.20
5. SPQ — deep	.05	−.06	**.31****	.10	**.38****	.27
6. SPQ — surface	.05	.00	**−.35****	**.17**	**−.15**	.22
7. PALS performance approach — original	−.06	.01	.00	**.24***	.03	.06
8. PALS performance approach — revised	−.04	−.09	−.05	**.21***	.02	.08
9. PALS performance avoid — original	−.06	.08	−.10	**.29****	−.07	.13
10. PALS performance avoid — revised	−.04	.14	−.05	**.34****	−.01	.12
11. PALS mastery — original	.01	.11	**.14**	−.01	**.39****	.23
12. PALS mastery — revised	−.03	.11	**.26****	.07	**.25****	.16
Effort						
13. Procrastination	−.01	.01	**−.65****	.01	.08	.45
14. FMPS — mistakes	−.04	−.06	−.01	**.42****	.00	.22
15. FMPS — standards	−.10	.02	**−.27****	**.28****	.14	.19
16. FMPS — parent expectations	−.04	**−.21***	−.10	.06	.14	.08
17. FMPS — parent criticism	−.07	−.04	.10	**.23***	**.21***	.09
18. FMPS — doubts	−.07	−.01	**.37****	.11	**.25****	.21
19. FMPS — organization	−.07	.01	**.64****	.09	.08	.41
20. Achievement striving	**.11**	.02	**.61****	.09	**.19***	.48
21. Motivation to pursue interests	**.15***	−.09	**.24****	−.04	**.38****	.32
Intellectual investment						
22. Tolerance for ambiguity	.06	−.07	−.09	**−.51****	**.24****	.38
23. Avoidance of novelty	.01	**.15**	**−.18***	**.15**	**−.35****	.23
24. Ingenuity	**.18***	**−.13**	.09	−.07	**.65****	.59
25. Intellect	.02	**−.15**	.05	.01	**.62****	.40
26. Quickness	.02	**−.16***	**.23****	**−.19***	**.51****	.45
27. Creativity	−.04	.03	.08	**−.16***	**.65****	.53
28. Depth	−.10	.00	.02	.12	**.61****	.32
29. Love of learning	−.04	−.07	**.26****	.09	**.46****	.29
Self and school evaluations						
30. Self-esteem	**.15**	.09	**.26****	**−.35****	.10	.40
31. Self-efficacy	**.15**	.11	**.26****	**−.29****	.10	.36
32. Locus of control	.03	−.05	**.37****	−.09	**.19***	.23
33. Academic efficacy	.02	.05	**.29****	**−.19**	**.20***	.25
34. Avoidance of achievement	−.10	.03	−.06	−.02	−.07	.02
35. Skepticism about school	−.13	−.14	**−.26****	−.05	.07	.11
36. Competence	**.14**	.03	**.57****	**−.12**	**.13**	.52

Note: APM = achievement-relevant personality measure. E = extraversion. A = agreeableness. C = conscientiousness. N = neuroticism. O = openness. AGQ = Achievement Goal Questionnaire. SPQ = Study Processes Questionnaire. PALS = Patterns of Adaptive Learning Scales. FMPS = Frost Multidimensional Perfectionism Scale. Values printed in bold are significant at $p < .05$.
* Indicates values significant at $p < .01$.
** Indicates values significant at $p < .001$.

The first five eigenvalues of the EFA (with the 95th percentile eigenvalues from a parallel analysis given in parentheses) were 8.95 (1.91), 5.69 (1.77), 2.67 (1.69), 1.99 (1.61), 1.62 (1.54) followed by 1.46 (1.48) and 1.30 (1.44). Because only the first five eigenvalues from the dataset exceeded those from the parallel analysis, a five factor solution was indicated (choosing 90th percentile did not change the five factor determination). We fit an exploratory five factor model with structural components to regress the latent factors on the Big Five using the confirmatory factor analysis (CFA) in EFA feature of M*plus*. This allows for a seamless flow of analysis from exploratory to confirmatory interpretation and avoids model specification issues that may be pragmatically unimportant. The factor structure of the APMs is presented in Table 3, and the relations among the latent factors and the Big Five are presented in Table 4.

The factors were readily identifiable. Factor 1 was labeled performance orientation because only scales assessing performance orientation substantially loaded on this factor. Factor 2 was labeled mastery orientation because the primary loadings were of mastery approaches towards learning, deep study processes, and a few indicators of intellectual investment. Factor 3 was labeled self-doubt because the primary positive loadings were for perfectionistic tendencies in regard to mistakes, standards, criticism, and doubts with substantial negative loadings for self-esteem and self-efficacy. Factor 4 was labeled effort because the primary loadings were for achievement striving, competence, and several efficacy oriented measures. Finally, factor 5 was labeled intellectual investment because the primary loadings were largely from this domain.

Associations between the latent factors and the Big Five were largely similar to those found at the scale-level. Factor 1, performance orientation, was primarily associated with neuroticism. Factor 2, mastery orientation, was associated with higher levels of conscientiousness and openness. Factor 3, self-doubt, was associated with neuroticism. Factor 4, effort, was strongly associated with conscientiousness and weakly with openness. Factor 5, intellectual investment, was strongly associated with openness. The Big Five accounted for large portions of variance in the effort and intellectual investment factors and considerably less variance for the remaining factors.

2.1.3.3. Dimensionality reduction of APMs at the item-level. Due to the substantial overlapping content of the scales used in Study 1, we attempted to construct a reduced scale to efficiently assess the five factors. Single factor confirmatory models were analyzed that included the items of each scale that loaded greater than an absolute value of .30 in the exploratory results (see Table 3). Although an absolute loading of .3 is

Table 3
Factor structure of APM and variance explained.

Variables	F1 (perf.)	F2 (mast.)	F3 (doubt)	F4 (effort)	F5 (intellect.)	R^2
Approaches to learning						
1. AGQ performance approach	**.34**	−.19	**.38**	**.44**	.01	.44
2. AGQ performance avoid	.21	.23	.02	−.09	−.17	.10
3. AGQ mastery approach	.23	**.36**	.18	−.27	−.01	.25
4. AGQ mastery avoid	.05	**.56**	.22	.17	−.04	.47
5. SPQ — deep	−.02	**.64**	.12	.19	.08	.63
6. SPQ — surface	.22	**−.38**	.09	−.21	.09	.31
7. PALS performance approach — original	**.50**	−.11	**.39**	.28	.07	.57
8. PALS performance approach — revised	**.69**	−.08	.14	.10	.09	.56
9. PALS performance avoid — original	**.89**	.14	−.01	−.10	−.03	.81
10. PALS performance avoid — revised	**.96**	.16	−.05	.01	−.01	.88
11. PALS mastery — original	−.02	**.78**	−.15	−.05	.13	.67
12. PALS mastery — revised	.07	**.76**	−.07	.15	−.09	.63
Effort						
13. Procrastination	.12	−.19	−.01	**−.55**	.19	.40
14. FMPS — mistakes	.24	−.07	**.71**	−.01	.02	.70
15. FMPS — standards	.14	.01	**.47**	−.21	.17	.35
16. FMPS — parent expectations	−.02	−.13	**.47**	−.08	**.30**	.28
17. FMPS — parent criticism	.06	−.01	**.78**	.23	.24	.71
18. FMPS — doubts	.03	.08	**.51**	**.53**	.17	.63
19. FMPS — organization	−.02	.15	.13	**.56**	−.18	.37
20. Achievement striving	−.02	.18	.06	**.77**	−.01	.74
21. Motivation to pursue interests	.04	.20	.13	.29	**.43**	.52
Intellectual investment						
22. Tolerance for ambiguity	−.25	−.06	−.26	−.07	**.45**	.40
23. Avoidance of novelty	.27	**−.42**	.05	.01	−.20	.41
24. Ingenuity	.00	.01	.03	.19	**.77**	.74
25. Intellect	−.01	.12	.03	.02	**.64**	.49
26. Quickness	−.06	.10	−.01	.24	**.59**	.60
27. Creativity	.02	.00	−.13	.22	**.62**	.55
28. Depth	.12	**.34**	.04	−.09	**.50**	.45
29. Love of learning	−.15	**.59**	.08	.01	.20	.55
Self and school evaluations						
30. Self-esteem	.02	−.05	**−.63**	**.50**	.14	.76
31. Self-efficacy	.03	−.06	**−.60**	**.54**	.16	.75
32. Locus of control	−.05	.02	.09	**.56**	.15	.41
33. Academic efficacy	.08	.12	−.07	**.44**	.23	.40
34. Avoidance of achievement	−.02	−.06	.27	−.11	.05	.09
35. Skepticism about school	−.21	.00	.13	**−.49**	.19	.25
36. Competence	.00	.04	−.22	**.83**	.00	.80

Note: APM = achievement-relevant personality measure. AGQ = Achievement Goal Questionnaire. SPQ = Study Processes Questionnaire. PALS = Patterns of Adaptive Learning Scales. FMPS = Frost Multidimensional Perfectionism Scale. These values come from a model that included the Big Five. Values printed in bold indicate that the scale was included in the item-level analysis of that factor. Descriptive factor labels indicate performance, mastery, self-doubt, effort, and intellectual investment latent factors.

Table 4
Factor intercorrelations and standardized regression coefficients for Big Five.

	F1 (perf.)	F2 (mast.)	F3 (doubt)	F4 (effort)	F5 (intellect.)
Factor correlations					
F1 (perf.)	1.00				
F2 (mast.)	−.04	1.00			
F3 (doubt)	**.30****	.10	1.00		
F4 (effort)	.15	**.30****	.09	1.00	
F5 (intellect.)	.10	.16	.16	**.32****	1.00
Regression coefficients for Big Five					
Extraversion	−.03	−.06	−.13	.11	.06
Agreeableness	.12	.05	.12	.04	**−.16***
Conscientiousness	−.12	**.28***	.04	**.71****	−.08
Neuroticism	**.34****	.15	**.43****	−.06	**−.20***
Openness to experience	−.10	**.46****	.06	**.13**	**.77****
Variance accounted for (R^2) by Big Five	.17	.30	.27	.65	.71

Note: Descriptive factor labels indicate performance, mastery, self-doubt, effort, and intellectual investment latent factors. Values printed in bold are significant at $p < .05$.
* Indicates values significant at $p < .01$.
** Indicates values significant at $p < .001$.

relatively weak, we wanted to retain scales that may have some items that are highly related to the latent factor, even if the overall scale is not. From these models, the ten highest loading items were selected as representative of that factor with three decision rules. In order to sample the entire range of content, a maximum of three items from a scale were selected. If an item loaded on two factors, it was retained for the factor on which it loaded most strongly. We required at least two reverse coded items for each factor. When this did not occur naturally, we reversed an item, typically by adding or removing the word "not." In practice, this procedure often included items from different scales that had semantically identical meaning. When this occurred, we reversed the meaning of one of the items, but kept the content the same. This allowed us to create an acquiescence index based on items that have opposite implications for personality. An acquiescent response set is defined by consistently agreeing (yea-saying) or disagreeing (nay-saying) with all test items. Using within-person centering based on this procedure has been found to produce more reliable and valid scale scores when there is an imbalance of forward and reverse coded items, as was the case in the current analysis (McCrae, Herbst, & Costa, 2001).

From this analysis, exemplar items were identified. All loadings in the CFA were significant with a minimum absolute value of the standard loading of .56 and a mean of .71. The reliability of each scale was uniformly high and greater than .90. The resulting items were highly face valid indicators of the extracted factors and were a dramatic reduction in the number of items (50 compared to 282). This reduced instrument was labeled the Multidimensional Achievement-Relevant Personality Scale (MAPS).

The psychometric properties of the MAPS were evaluated using oblique EFA with target rotation aimed for simple structure. The results of this analysis are presented in Table 5. Item content and a description of the scoring procedure including creating of the acquiescence index and reverse coding of the final scale can be found in the online supplement (Table S1). Next, we predicted each original scale by the latent factors to determine how much of the variance in the original scales was retained. On average, the reduced scales were able to account for the majority of variance in the original scales (mean $R^2 = .55$, SD = .30). The zero-order correlations between the MAPS factors and the Big Five can be found in the online supplement (Table S2). The results largely resemble those found with the latent scale-indicated factors.

Table 5
Results of target rotated exploratory factor analysis of reduced scale items.

Item number	Performance	Mastery	Self-doubt	Effort	Intellectual investment
Performance (α = .934)					
1.	**.94**	.19	−.12	.00	.00
2.	**.78**	−.10	.09	.06	.15
3.	**.91**	.17	−.08	−.12	.18
4.	**.87**	.17	−.06	.09	−.10
5.	**.74**	−.04	.10	.07	.11
6.	**.77**	.01	−.04	.19	.03
7.	**.82**	.05	−.04	.04	−.01
8.	**.82**	.12	−.03	−.01	.02
9.	**.79**	.11	.01	−.07	.11
10.	**.64**	−.04	.13	.17	.15
Mastery (α = .904)					
11.	.00	**.79**	−.09	−.17	.11
12.	.02	**.72**	.07	−.05	.19
13.	.03	**.94**	−.06	.07	−.27
14.	.09	**.94**	−.09	−.05	−.14
15.	−.02	**.55**	.08	.08	.22
16.	−.01	**.46**	.15	.17	.18
17.	.00	**.54**	.13	.08	.19
18.	.07	**.68**	.14	.07	−.07
19.	.01	**.49**	.17	.05	.19
20.	.21	**−.60**	−.01	.17	−.06
Self-doubt (α = .920)					
21.	−.07	.12	**.94**	−.10	.03
22.	−.12	.11	**.85**	−.15	.00
23.	−.10	.05	**.88**	−.06	.01
24.	.11	−.01	**−.68**	.18	.12
25.	−.08	.00	**.87**	.05	.04
26.	−.06	.04	**.78**	−.16	.05
27.	.19	−.05	**.75**	.19	.10
28.	.15	−.07	**.70**	.28	.01
29.	.27	.05	**.62**	.17	.09
30.	.23	.19	**.41**	−.11	.01
Effort (α = .904)					
31.	−.01	−.12	.13	**.93**	.06
32.	.01	.03	.04	**.86**	−.02
33.	.06	.18	.11	**.99**	−.33
34.	.01	−.03	.08	**.91**	−.07
35.	−.05	−.22	.08	**.95**	−.11
36.	.00	.09	.17	**.67**	.08
37.	.08	−.13	−.01	**.59**	.29
38.	.04	.08	.07	**.58**	.11
39.	.15	.15	−.10	**.38**	.15
40.	.00	.05	.14	**.79**	−.32
Intellectual investment (α = .902)					
41.	.05	.03	.06	−.14	**.90**
42.	.08	.14	.07	−.14	**.80**
43.	.11	.28	.08	.15	**.43**
44.	.07	−.12	.03	.09	**.80**
45.	.09	.09	.09	.15	**.53**
46.	.05	−.08	.10	−.20	**.95**
47.	.09	−.20	.02	−.17	**.99**
48.	−.10	−.03	.13	−.08	**.76**
49.	.01	.15	.18	.25	**.41**
50.	.04	−.07	.05	−.07	**.82**

Note. Values printed in bold are the highest value for the item.

2.2. Study 2

Participants were students who voluntarily completed the study materials from a foundational psychology course. We collected self-report data on 359 students and course performance information from the complete population of the course ($n = 490$). Examining the course performance data, 13 students were missing data for each exam grade and were dropped from all further analyses. Thus, we were able to sample 75.26% of the eligible course population. The majority of the students were female (59%). The age range of the sample was wide with a minimum age of 17 and a maximum age of 43. The mean age was 19.5 years old with 92% of the sample under 21 years of age. The sample was similarly diverse in terms of the racial and ethnic composition, in that the sample contained non-Hispanic White (66.3%), Hispanic (23.1%), Asian (13.1%), Black (8.1%), American Indian or Pacific Islander (0.2%), and Other race/ethnicity (12%) participants.

2.2.1. Materials

The primary measure under investigation was the MAPS established in Study 1. See the online supplement (Table S1) for complete item content and scoring procedure.[1] We sought to replicate or test the associations between the MAPS and three classes of constructs: demographics, personality, and objective indices of academic performance. First, we included the demographic characteristics of age, gender, and socioeconomic status. Age was recorded in years. Gender was recorded as 0 for male participants and 1 for female participants. Socioeconomic status was computed with three indicators: paternal educational attainment, maternal educational attainment, and the log of family income. These were standardized and averaged to produce a socioeconomic status composite. Due to a desire to restrict the materials to a relatively short length, we used the Ten Item Personality Inventory (TIPI) to assess the Big Five (Gosling, Rentfrow, & Swann, 2003). This scale is widely used in the personality literature and provides good general indicators of personality that correlate substantially with more extensive measures (average convergent validity = .77) and have substantial test–retest reliability (average correlation across two weeks = .72). All items were rated on a scale ranging from 1 to 7, with 1 representing strong disagreement and 7 strong agreement.

As our academic outcomes, we obtained percent participation grade, percent correct quiz grade, and percent correct on three exams associated with the course in which all participants were enrolled. Each of these indicators of achievement requires different cognitive or motivational factors. Class participation required attending the course and using a remote electronic device to respond to multiple choice questions during the lecture. Participation grade represents the percent of questions responded to regardless of the correctness of the answer. Exam grades, on the other hand, are limited by time constraints, have important outcomes, and require accurate knowledge of material. Quiz grades lay intermediately between these two extremes. Quizzes were frequently administered, and students were allowed to use their notes.

[1] We made use of the acquiescence index for all analyses. However, omitting this procedure did not alter the pattern of the reported results in terms of significance or direction. The only exception to this was the small in magnitude but significant performance-agreeableness and conscientiousness associations were nonsignificant when omitting the acquiescence index ($p = .14$ and .06, respectively).

The course measures have strengths and weaknesses. A primary strength is that we were able to obtain data on every individual in the sampled population. Complete data allows for the comparison of responders and non-responders. This analysis is not typically performed in many studies because measured psychological outcomes are difficult to obtain without participation. Additionally, the subject content and test material were the same for every individual, and therefore, we do not conflate course performance with course difficulty (Berry & Sackett, 2009). However, course-specific indices of performance may be less generalizable due to idiosyncratic interactions between the person and the course-specific content. Typical measures of academic performance (e.g., GPA) cover a wider range of learning situations. Because we were also interested in more generalized academic performance, we obtained self-reported college GPA. This was reported as a continuous measure on a four-point scale.

2.2.2. Procedure

All procedures were approved by the appropriate Institutional Review Board. Participants were informed during lecture and via email that the materials were available to be completed with the REDCap system (Harris et al., 2009). The participants completed the materials during their free time in a place of their choosing and did not receive class credit for completing the instrument. The participation experience was used to complement lecture material. At the conclusion of the semester, the indicators of academic performance were obtained from the instructor.

All models were fit using full-information maximum-likelihood estimation in M*plus* statistical software (Muthén & Muthén, 1998-2010).

2.2.3. Results

2.2.3.1. Non-response characteristics. First, we compared survey responders to non-responders. We fit a multiple group model in which the mean and variance of the academic outcomes were constrained to be equal for responders and non-responders. Model misfit incurred by this constraint can be tested by the χ^2 distribution with 2 degrees of freedom. The critical value for this test is 5.99 for $p < .05$. For each outcome, a significant amount of misfit occurred (χ^2 ranged from 35.84 to 159.50). For responders, the average grades (and standard deviations) were 86.81 (22.49), 92.26 (10.55), and 77.92 (10.58) for participation, quiz, and exam grades respectively. The associated values for the non-responders were 63.04 (34.39), 84.52 (22.90), and 71.64 (13.11) for participation, quiz, and exam grades respectively. Responders tended to have better overall grades with less variation. Although we were able to sample a large majority of the total population, it is important to note that the relations between the MAPS and our indices of academic performance may be attenuated due to a restriction of the range of the academic indicators.

2.2.3.2. MAPS Structure replication at the item-level. Next, we evaluated the psychometric structure of the MAPS in comparison to that found in Study 1. The first five eigenvalues (with the 95th percentile eigenvalues from a parallel analysis given in parentheses) were 12.37 (1.67), 5.75 (1.60), 3.65 (1.55), 2.45 (1.51) and 1.71 (1.47) followed by 1.40 (1.43) and 1.28 (1.41). Choosing 90th percentile eigenvalues did not alter interpretation. The factor loadings and factor correlations from the five factor solution are presented in Table 6. The structure of the scale was largely replicated. Across two samples, the congruence of the factor structure was high with coefficients ranging from .84 to .94 (Tucker, 1951). One item each from the effort and intellectual investment domains did not load most strongly on the expected factor and were dropped. We computed scale scores as the mean of the items within a domain. Descriptive statistics for the scale scores and other measures are presented in Table 7. Reliability estimates were all high for the final scales assessing performance ($\alpha = .86$), mastery ($\alpha = .88$), and self-doubt ($\alpha = .90$). Reliability did not differ

Table 6
Factor loadings, congruence coefficients and factor correlations from five factor EFA of the MAPS.

Item number	Performance	Mastery	Self-doubt	Effort	Intellectual investment
Performance					
1.	**.55**	.09	−.07	.03	.00
2.	**.67**	.00	−.04	−.09	−.02
3.	**.64**	−.07	.05	.04	.04
4.	**.55**	−.05	.09	−.10	.07
5.	**.84**	−.01	−.09	−.07	.02
6.	**.67**	.15	−.06	.09	−.05
7.	**.43**	.05	.04	.05	.10
8.	**.52**	−.05	.25	−.01	−.10
9.	**.62**	−.05	.11	.00	−.02
10.	**.64**	.10	.04	.07	.16
Mastery					
11.	.02	**.69**	−.08	−.15	−.03
12.	−.10	**.58**	.07	.14	.12
13.	.01	**.82**	.03	.02	.01
14.	.10	**.74**	−.09	−.01	−.01
15.	.06	**.40**	.00	.17	.34
16.	.10	**.66**	−.01	.11	−.02
17.	−.03	**.61**	.05	.04	.19
18.	−.03	**.73**	.03	.15	−.06
19.	.03	**.60**	.00	−.08	.03
20.	−.10	**.58**	−.10	−.21	.09
Self-doubt					
21.	−.02	−.03	**.78**	.00	−.01
22.	−.02	.04	**.68**	−.20	−.04
23.	−.02	.07	**.78**	−.22	.04
24.	.00	−.10	**.65**	−.14	−.09
25.	.05	.11	**.74**	−.03	−.02
26.	−.02	−.02	**.76**	.02	−.06
27.	.41	−.02	**.51**	−.01	−.02
28.	.33	−.09	**.53**	.09	.08
29.	.39	.09	**.38**	−.04	−.02
30.	.09	−.03	**.48**	−.02	−.12
Effort					
31.	.09	.13	−.20	**.51**	−.04
32.	.08	.16	−.02	**.37**	.31
33.	.02	.12	−.03	**.65**	.05
34.	−.03	−.05	−.09	**.65**	.23
35.	−.01	−.14	−.14	**.52**	.20
36.	.00	.03	−.03	**.61**	.12
37.	−.02	.15	−.28	**.44**	−.02
38.	−.02	.13	.10	**.55**	−.01
39.	.00	**.37**	−.20	−.02	.22
40.	.05	.14	−.01	**.46**	−.06
Intellectual investment					
41.	.04	−.01	.01	−.11	**.86**
42.	−.05	.16	.13	.03	**.66**
43.	−.07	**.42**	.02	.22	.20
44.	.06	−.03	−.06	.12	**.78**
45.	−.10	.20	−.02	.17	**.38**
46.	.07	.11	−.09	.05	**.28**
47.	.01	−.02	−.14	−.19	**.81**
48.	−.04	.13	−.07	.12	**.17**
49.	.05	.22	−.07	.10	**.27**
50.	−.04	.07	.02	−.02	**.74**
CCC	.94	.92	.91	.90	.84
Factor correlations					
Performance	1.00				
Mastery	.00	1.00			
Self-doubt	.12	−.18	1.00		
Effort	.11	.48	−.40	1.00	
Intellectual Investment	.04	.38	−.39	.37	1.00

Note. EFA = exploratory factor analysis. APM = achievement-relevant personality measure. Factor loadings printed in bold indicate the item's highest loading. Item numbers printed in bold indicate that the item did not load highest on the expected factor, and were therefore excluded from the final scale. CCC stands for the column congruence coefficient (Tucker, 1951) which calculates the agreement between the columns in Tables 5 and 6. The inverse factor loadings for items 20 and 24 from Table 5 were used because they are reverse coded items, and all items were forward coded for the current analysis.

Table 7
Descriptive statistics of measures used in Study 2.

Variable	n	Mean	SD	Range
Age	371	19.51	2.27	17–43
Gender	362	.59	.49	0–1
Socioeconomic status	402	.00	.92	−3.48–7.29
Performance	360	−.20	1.13	−3.19–3.15
Mastery	359	1.42	.95	−2.31–3.20
Self-doubt	359	−1.15	1.22	−3.50–2.54
Effort	359	1.24	.97	−1.69–2.95
Intellectual investment	357	1.44	.90	−1.57–3.50
Extraversion	352	4.48	1.61	1.00–7.00
Agreeableness	352	4.93	1.19	1.50–7.00
Conscientiousness	352	5.56	1.21	1.50–7.00
Neuroticism	351	3.10	1.38	1.00–7.00
Openness	351	5.52	1.19	2.00–7.00
Quiz grade	490	90.21	12.58	0–100
Participation grade	490	80.50	28.23	0–100
Exam grade	477	76.36	11.60	35.74–101.43
College GPA	343	3.12	.65	0–4.0

Note. All self-report measures were responded to on a 7-point Likert scale ranging from strongly disagree to strongly agree. A within-person centering approach was used to score the performance, mastery, self-doubt, effort, and intellectual investment scales.

Table 9
Zero-order correlations and standardized regression coefficients for the prediction of quiz grades.

Predictors	Quiz grade				
	(0)	(1)	(2)	(3)	(4)
Age	**−.13**	**−.17**			**−.13**
Gender	.07	.09			.05
SES	.05	.04			.06
Performance	**.13**		**.14**		.04
Mastery	.04		−.09		−.08
Self-doubt	−.06		−.01		.12
Effort	**.25****		**.50****		**.33***
Intellectual investment	−.03		**−.26***		−.06
Extraversion	**−.11**			−.09	**−.13**
Agreeableness	.08			−.01	−.01
Conscientiousness	**.30****			**.38****	**.20**
Neuroticism	**−.17****			**−.19***	**−.24****
Openness	**−.12**			**−.18***	**−.16***
R^2		.04	.21	.25	.33

Note. SES = socioeconomic status. The column labeled 0 presents zero-order correlations. The columns labeled 1-3 present within domain regressions for demographics, achievement-relevant personality, and the Big Five separately. Column 4 presents a combined model that includes all predictors. Values printed in bold are significant at $p < .05$.
* Indicates values significant at $p < .01$.
** Indicates values significant at $p < .001$.

substantially for effort before ($\alpha = .85$) or after ($\alpha = .84$) dropping an item. Similarly, reliability did not differ substantially for intellectual investment before ($\alpha = .85$) or after ($\alpha = .82$) dropping an item.

2.2.3.3. MAPS external associations with the big five. Zero-order correlations between the MAPS and the Big Five can be found in the online supplement (Table S3). The MAPS were then predicted by the Big Five. The standardized regression coefficients from this analysis are presented in Table 8. The majority of the results were similar to those found in the previous analysis. Mastery was significantly predicted by higher levels of conscientiousness and openness. A large, positive effect was found for neuroticism predicting self-doubt. A strong association was found between effort and conscientiousness and a weaker relation was found with openness. Intellectual investment was predominantly associated with openness, but it retained less substantial relations in the expected direction with agreeableness. Each of these results replicates earlier findings. Additionally, the general trend of performance and mastery having less variance in common with the Big Five and effort and intellectual investment constructs having more common variance was replicated. However, there were some divergent findings. Performance, originally significantly predicted by higher levels of neuroticism, was found to be unrelated to neuroticism and significantly associated with higher levels of conscientiousness and lower levels of agreeableness. In Study 1, self-doubt was largely unrelated to broad personality domains, but in Study 2 the variance accounted for increased by 12% to share similar amounts of variance as effort and intellectual investment. The remaining changes were primarily in regard to smaller magnitude coefficients.

Two sources are likely to explain the majority of the differences between Study 1 and Study 2. First, Study 2 included nearly twice as many participants as Study 1 meaning that trends that were marginal in Study 1 appear significant in Study 2. Second, we used a very brief measure of the Big Five that may sample a slightly different item content. However, despite these minor discrepancies, there were strong similarities between the results of Study 1 and Study 2. For coefficients that are significant in both samples, all except the relatively small coefficient for neuroticism predicting intellectual investment are in the same direction, and nearly 80% of the associations found in Study 1 were replicated.

2.2.3.4. MAPS predictive validity. Tables 9–12 report the zero-order correlations of each predictor variable with the academic outcomes and the results of four regression models that were used to predict each academic indicator separately. Focusing on the zero-order correlations, effort consistently had a moderate, positive association with all academic outcomes. Performance, while slightly weaker, was also positively associated with each outcome. Participation and exam grades were more strongly associated with mastery than performance, but mastery was unrelated to quiz grades. Intellectual investment was only positively associated with exam grades and college GPA. Self-doubt was negatively correlated with college GPA.

Turning to the domains of demographics and the Big Five, some consistent results are found. Older participants and men tended to perform somewhat worse, and students from higher socioeconomic status backgrounds tended to perform better on exams and college GPA. Higher levels of extraversion, neuroticism and openness were associated with lower quiz achievement. More agreeable students tended to participate in class more. Similar to effort, conscientiousness was significantly correlated with each achievement outcome positively.

Table 8
Standardized regression coefficients for the MAPS constructs on the Big Five.

Predictors	Performance	Mastery	Self-doubt	Effort	Intellectual investment
Extraversion	.05	.02	**−.23****	**.15****	**.12**
Agreeableness	**−.13**	.02	−.01	.01	**−.13***
Conscientiousness	**.12**	**.29****	**−.16****	**.62****	**.12***
Neuroticism	.09	−.01	**.46****	−.07	**−.13***
Openness	−.07	**.25****	−.07	**.16****	**.50****
R^2	.04	.18	.39	.51	.38

Note. MAPS = Multidimensional Achievement-Relevant Personality Scale. Values printed in bold are significant at $p < .05$.
* Indicates values significant at $p < .01$.
** Indicates values significant at $p < .001$.

Table 10
Zero-order correlations and standardized regression coefficients for the prediction of participation grades.

Predictors	Participation grade				
	(0)	(1)	(2)	(3)	(4)
Age	−.07	−.06			−.08
Gender	**.13**	**.15**			.08
SES	.09	.09			**.14**
Performance	**.11**		.07		−.03
Mastery	**.22****		**.14**		**.14**
Self-doubt	−.06		.06		.12
Effort	**.30****		**.39****		**.21***
Intellectual investment	.09		**−.15**		.05
Extraversion	−.04			−.01	−.06
Agreeableness	**.11**			.05	.04
Conscientiousness	**.32****			**.38****	**.22***
Neuroticism	−.07			−.01	−.06
Openness	−.05			−.11	**−.19***
R^2		.04	.17	.16	.25

Note. SES = socioeconomic status. The column labeled 0 presents zero-order correlations. The columns labeled 1-3 present within domain regressions for demographics, achievement-relevant personality, and the Big Five separately. Column 4 presents a combined model that includes all predictors. Values printed in bold are significant at $p < .05$.
* Indicates values significant at $p < .01$.
** Indicates values significant at $p < .001$.

Table 12
Zero-order correlations and standardized regression coefficients for the prediction of grade point average.

Predictors	Grade point average				
	(0)	(1)	(2)	(3)	(4)
Age	.02	.06			.05
Gender	.09	.10			.03
SES	**.20****	**.24****			**.22****
Performance	**.13**		**.13**		.06
Mastery	**.22****		.10		.11
Self-doubt	**−.16***		−.09		−.05
Effort	**.33****		**.28****		**.28***
Intellectual investment	**.13**		−.12		−.09
Extraversion	.10			.12	.04
Agreeableness	.03			−.03	−.04
Conscientiousness	**.21****			**.22****	.01
Neuroticism	−.06			−.02	.01
Openness	.03			−.05	−.08
R^2		.06	.13	.06	.18

Note. SES = socioeconomic status. The column labeled 0 presents zero-order correlations. The columns labeled 1-3 present within domain regressions for demographics, achievement-relevant personality, and the Big Five separately. Column 4 presents a combined model that includes all predictors. Values printed in bold are significant at $p < .05$.
* Indicates values significant at $p < .01$.
** Indicates values significant at $p < .001$.

We ran three models to determine the within-domain overlap among variables in the prediction of achievement. In models that included all demographic variables, the results from the zero-order correlations were largely unchanged, indicating that much of the variance that was associated with achievement among these variables was unique of other demographic factors. A similar pattern was largely observed with a model that includes all of the Big Five personality factors. Conscientiousness remained the primary variable of importance with smaller, negative associations found for neuroticism and openness in the prediction of quiz grades.

The results for the MAPS constructs differed slightly depending on the outcome. When all factors are included for quiz grades, the effect size of effort increased substantially, and the effect size for intellectual investment increased to statistical significance and was negative. This is indicative of a contrast or suppression effect. The most likely interpretation of this result is that, holding the level of effort given to studying constant, a student with a higher level of intellectual investment will tend to perform worse on quizzes. This was not borne out at the zero-order level for intellectual investment because those who possess a high level of intellectual investment also tend to possess a high level of effort ($r = .39$). Additionally, performance orientation retained a relatively small, positive association with quiz grades. Moving to participation grade, a similar suppression effect was found between effort and intellectual investment. Interestingly, mastery, rather than performance, retained a small, positive association with participation grades. Exam grades were significantly predicted by performance and effort. Controlling for the other MAPS, only higher levels of performance orientation and effort significantly predicted college GPA.

Each domain accounted for a modest proportion of variance in the achievement outcomes. For demographics this ranged from .04 to .08. Variance accounted for by the MAPS ranged from .09 to .21, and it ranged from .06 to .25 for the Big Five.

Finally, each variable was included as a predictor of achievement. Effort and conscientiousness remained significant predictors of quiz and participation grades. The coefficients were somewhat attenuated compared to previous models as would be expected due to the shared variance between effort and conscientiousness. Other results include significant negative coefficients of neuroticism and openness predicting quiz grades. Openness was associated with a lower participation grade, and mastery orientation was associated with higher participation grades. For exam grades, extraversion was the only uniquely significant predictor when all variables were including. The final model for college GPA indicated a special position for the academically contextualized effort domain in that it was the only personality trait that remained significantly predictive. Overall, demographics, MAPS, and broad personality traits accounted for roughly a quarter of the variance in the achievement measures.

To provide evidence of incremental predictive power by the MAPS, we compared two models. The first model is model 4 presented in Tables 9–12 which freely estimated the coefficients for the MAPS. We compared this model to a model in which each achievement outcome was predicted by demographics, the Big Five, and MAPS, but the coefficient for each MAPS factor was constrained to be zero.[2] Importantly, the exact same variables were included in both models which is a necessary condition for the use of nested χ^2 differences tests. As the freely estimated model has perfect fit to the data, a significant χ^2 value for the constrained model would indicate that variance in the outcome

Table 11
Zero-order correlations and standardized regression coefficients for the prediction of exam grades.

Predictors	Exam grade				
	(0)	(1)	(2)	(3)	(4)
Age	−.08	−.03			−.05
Gender	**.12**	**.13**			.10
SES	**.23****	**.24****			**.26****
Performance	**.17***		**.18***		.06
Mastery	**.18****		.11		.12
Self-doubt	−.10		−.07		−.02
Effort	**.23****		**.15**		.10
Intellectual investment	**.13**		−.04		.04
Extraversion	−.06			−.11	**−.19***
Agreeableness	.01			−.04	−.04
Conscientiousness	**.18***			**.18***	.08
Neuroticism	−.09			−.08	−.09
Openness	.05			.07	.02
R^2		.08	.09	.06	.19

Note. SES = socioeconomic status. The column labeled 0 presents zero-order correlations. The columns labeled 1-3 present within domain regressions for demographics, achievement-relevant personality, and the Big Five separately. Column 4 presents a combined model that includes all predictors. Values printed in bold are significant at $p < .05$.
* Indicates values significant at $p < .01$.
** Indicates values significant at $p < .001$.

[2] This method is equivalent to computing F statistics of the difference and produces identical results.

was associated with the MAPS factors above and beyond the variance accounted for by the Big Five and demographics. This was indeed found for participation grades ($\chi^2 = 18.80$, $df = 5$, $p < .01$), quiz grades ($\chi^2 = 13.62$, $df = 5$, $p < .05$), exam grades ($\chi^2 = 12.46$, $df = 5$, $p < .05$), and college GPA ($\chi^2 = 24.22$, $df = 5$, $p < .001$). Omitting the MAPS factors, the explained variance for quiz grades ($R^2 = .29$), participation grades ($R^2 = .20$), exam grades ($R^2 = .15$), and college GPA ($R^2 = .12$) were all significantly lower than those reported for the full model (see Tables 9–12).

3. Discussion

In two studies, we have attempted to shed light on the relations among APMs, the items that compose these scales, and their associations with the Big Five personality traits and academic achievement. Because items from different inventories shared large amounts of variance, we refined this item content to produce the MAPS which is both efficient and predictive of achievement. Our results indicated that academically contextualized orientations, traits, and habits share substantial amounts of variance with personality. Thus, in seeking to measure individual differences in trait-like constructs that relate to individual differences in academic achievement, the educational and differential literatures have converged on overlapping dimensions of individual differences. Importantly, however, there were also substantial amounts of variance in academically relevant personality measures and personality traits that were not shared. Indeed MAPS factors incrementally predicted academic outcomes over and above demographics and the Big Five. Thus, researchers interested in the relation between individual differences and achievement should not focus exclusively on the Big Five. Similarly, work using specialized measures may not be sufficiently generalizable without linking those measures to related construct through a generalizable nomological network. The results of the current study provide a framework for this process, and can be used as a legend from which to understand how APMs relate to the Big Five and to one another.

To reiterate the present findings, we performed factor analytic and regression analyses to explore the covariance structure of 36 scales with 282 items thought to be related to academic success. The item content of the scales was refined to produce the MAPS, a brief measure (ultimately only 48 items) of five achievement-relevant factors: performance, mastery, self-doubt, effort and intellectual investment. The psychometric properties of the MAPS were replicated across two samples. We placed the original scales, latent factors derived from them, and the novel measure in the context of the Big Five. Most results replicated across studies. Performance orientation was largely unrelated to the Big Five. Mastery orientation displayed significant, positive associations with conscientiousness and openness, but the Big Five did not explain a large portion of variance. Self-doubt was strongly associated with higher levels of neuroticism. Effort was highly related to conscientiousness. Intellectual investment displayed many small associations with the Big Five, but it retained a primary relation with openness. We also found evidence of the practical utility of the MAPS in terms of predicting academic achievement. Each domain of the reduced scale was found to be correlated with college GPA, and evidence of incremental prediction above the Big Five and demographics was found, primarily driven by the effort domain. On the whole, this is initial evidence for the utility of the brief scale for research purposes. Although effort was the primary domain that remained a statistically significant predictor of achievement in the final model, individual differences in motivation, beliefs, traits, and habits measured by the MAPS all were associated with achievement at the zero-order level indicating the possibility of moderating or mediating effects. By reducing the dimensionality of the APM domain in this manner and situating the constructs within the domain of the most widely used taxonomy of individual differences, researchers may be better able to incorporate such predictors in theories and studies of achievement.

3.1. Comparison of novel and original scales

We have presented evidence of the consistency and validity of a novel measure that is both brief and broad. This scale does deviate from the original scales in some important ways. Beginning with the domain of approaches to learning, past research has indicated that approach-avoid versions of the performance and mastery domains have discriminant validity (Elliot & McGregor, 2001; Huang, 2012), but the current results are somewhat mixed. Discriminant mastery and performance factors did emerge, but the approach-avoid distinction did not. This is somewhat consistent with previous research. Many operationalizations of mastery goal orientation do not include an avoidance construct (such as the PALS). Additionally, the performance approach-performance avoid correlation was the strongest among approaches to learning constructs in Hulleman et al.'s (2010) meta-analysis indicating a lack of discriminant validity. It is noteworthy that the AGQ performance-avoid scale did not load substantially on any factor in our analyses. The variance associated with the scale is not shared with any of the other measures, indicating its discriminant validity. Further, the SPQ deep and surface scales both converged with the other mastery scales, but their loadings were in opposite directions. Mastery and performance manifested as distinct dimensions, but deep and surface study processes appear to be two ends of the mastery continuum. Theoretically, deep and surface study processes tap into how people study, and goal orientations tap into why people study. Differences in how people study may relate strongly to whether they are high or low in terms of their mastery orientation. Our goal was to reduce complexity and provide a streamlined measurement approach rather than incorporate every distinction that is potentially important. When such distinctions are required for theoretical or applied reasons, the use of specific instruments may be preferable to the MAPS.

Overlapping content was found for the domains of effort, intellectual investment, and self and school evaluations. The extracted effort factor included variables related to behavioral tendencies to complete tasks and more cognitively oriented assessments of effort related to the intellectual investment domain. The self-doubt factor included perfectionistic scales as well as other academic evaluations. Finally, the intellectual investment factor was primarily composed of within-domain scales. This is in line with assertions by Mussel (2010, 2013) that the individual indicators of this construct lack discriminant validity.

3.2. Scale replication and validation

We will first address differential MAPS-Big Five associations found between the two studies. The most obvious source of divergence is that a different measure of the Big Five was used in each study. This decision was made to accommodate the time constraints of the participants and may have introduced noise due to the TIPI, as a very brief measure of the Big Five, not fully encompassing the range of content that is assessed by the Big Five Inventory. However, this is only a minor concern. In fact, replication across *both* measures and samples is more convincing than replication across samples (Lykken, 1968). The majority of results were replicated, with deviations primarily among relatively small coefficients that may have crossed the arbitrary significance threshold between studies due to increased sample size. Overall, we interpret the results as largely in favor of replication.

Interpretation of the results of Study 2 must incorporate the potential selection effects that occurred when recruiting this sample. The first sample was recruited as part of a general research requirement for introductory psychology courses. This means that a roughly random sample of everyone in this population would participate in the study or other studies that provided research hours. The second study relied on students within a single introductory psychology course to use their free time to complete the materials with no concrete academic requirement or reward. Although we were able to test for group differences between responders and non-responders in terms of achievement, we were unable to test this for self-report variables. The responders tended to obtain better objective grades within the course and display significantly less variance. Because the full range of achievement scores and trait variation was likely not sampled, true associations may have been attenuated. If we did not sample the lower end of the distribution, it reduces the power to find significant effects. It is unclear if the largely nonsignificant results for performance, self-doubt, and intellectual investment might be due to the selection effect. It is conceivable that these traits may have a nonlinear association with achievement such that the majority of the influence is found at lower levels of achievement. In spite of these selection issues, it is important to highlight that we were successful in obtaining self-report data from 75% of the course population, and the sample included a moderate amount of individuals who earned marks below a C- level (11.98%).

3.3. Theoretical issues and implications

Before making strong conclusions about theoretical issues, we would highlight again the measurement uncertainty that remains in this area of research. We second the sentiment expressed by Hulleman et al. (2010) that theoretical progress can be best advanced by first settling measurement issues. Building on previous efforts to conceptually organize a multitude of APMs (Richardson et al., 2012; von Stumm & Ackerman, 2013), we have attempted to use multivariate, empirical methods to continue the process of creating a consistent measurement paradigm for achievement-relevant personality.

Our finding that performance orientation is positively associated with achievement at the zero-order level in several domains is somewhat controversial. Many researchers (e.g. Midgley, Kaplan, & Middleton, 2001) claim that mastery approaches to learning are the only adaptive construct on which interventions should be based. Instructing students to base their motivation on extrinsic rewards such as grades and social comparisons is argued to have the harmful side-effect of instilling a fragile sense of self-esteem. Other researchers (e.g., Harackiewicz, Barron, & Elliot, 1998) argue that performance goals can be adaptive in certain context such as highly competitive or rewarding situations. This may prepare students for an understanding of how labor markets work and teaches that academic *achievement* is intrinsically important. It is clear that education and succeeding in the academic system are highly important for life outcomes (Montez, Hummer, Hayward, Woo, & Rogers, 2011). Recent meta-analytic evidence (Cerasoli, Nicklin, & Ford, 2014) suggests that intrinsic and extrinsic sources of motivation are not entirely antagonistic and may both function to raise achievement in meaningful ways. Regardless of the source of motivation, however, a central finding of the current study is that the domain of effort is centrally important academic success, a finding that is consistent with much previous research (e.g., Moffitt et al., 2011).

It is important to note that the course-specific measures of academic achievement that we obtained were from an introductory level psychology course that primarily enrolls freshmen. The requirements of other courses may reflect the skills or techniques associated with mastery to a greater degree. For instance, two of our measures, participation and quiz grades, primarily rely on skills that may be more closely aligned with being motivated by grades. Mastery was more strongly associated with overall college GPA which may indicate that this construct can be applied to a wider range of course content. A closer analysis of the exact behavioral requirements of various measures of academic achievement would likely clarify some of the differential patterns of association.

Based on the theoretical model of Brunswik symmetry, some have argued (e.g., Wittmann & Süβ, 1999) that different classifications (in terms of construct generality) of academic achievement will be most highly predicted by factors that have a matching level of generality. For example, GPA, as a very broad and wide reaching academic outcome, would be best predicted by an equally broad independent variable, whereas participation grade, as a relatively narrow outcome, would be best predicted by a narrow independent variable. This theory has not received much empirical support in the literature on academic achievement. Personality-achievement correlations that focus on broad traits do not place strong limits on the extent to which more specific or contextualized measures correlate with achievement. In fact, narrow measures have been found to better predict academic performance (Luciano, Wainwright, Wright, & Martin, 2006; Noftle & Robins, 2007; Paunonen & Ashton, 2001; Paunonen, Haddock, Forsterling, & Keinonen, 2003), with a recent meta-analysis concluding that such narrow measures “are generally stronger predictors of academic performance than are the Big Five personality factors” (O'Connor & Paunonen, 2007, p. 971). Similarly, von Stumm (2013) found that personality factors equally predicted academic outcomes that were narrow (i.e., domain-specific knowledge) and broad (i.e., general crystallized intelligence).

We argue that Cronbach and Gleser's (1957) bandwidth-fidelity dilemma provides a more accurate characterization of broad and narrow measurement. Broad bandwidth measures may have some advantages by capturing more content, but specific measures that are better representations of circumscribed behaviors may also possess a predictive advantage when the content domain of the outcome is well known. This seems to be the case for the domain of education research in light of the conclusion of O'Connor and Paunonen (2007). These types of findings have led some researchers (e.g., Briley & Tucker-Drob, 2012; DeYoung, Quilty, & Peterson, 2007) to argue for the increased use of narrow measurement of personality. The current results also support this position. Broad conscientiousness was predictive of achievement, but the more circumscribed effort domain added incremental predictive power. Supplementing broad, domain-level personality measurement with more specific, narrow, and mechanistically motivated personality facet measurement can facilitate educational research.

3.4. Strengths and limitations

The current study evaluated the psychometric structure of measures that were only tangentially connected in previous research, but a few limitations are noteworthy. First, the current studies were specifically concerned with the factor structure and correlates of achievement-relevant personality in university students. The extent to which the current findings would generalize to students in grades K-12 is unclear. Additionally, the sample was drawn from a specific region limiting generalizability, but the sample had substantial racial/ethnic diversity which increases generalizability. Another limitation is the choice of variables administered. There are a large number of scales that have been put forward as related to achievement, and it was impossible to include all of them in a single study. Our strategy was to gather as many of the most prevalent and specific instruments in use that are representative of important research areas. To stay within the reasonable limits of what we could expect the participants to accurately complete, some measures were omitted. The current study consolidated many scales but, there are certainly more that are in need of integration. Related to this point, some may criticize reducing 36 scales with substantial nuance and complexity to only five factors. We desired to reduce and simplify the content as much as possible to fulfill the aim of creating efficient and precise measures. Sample size for Study 1 was comparatively small for the number of variables used. Additional large sample size studies (such as Study 2) may be needed to more fully map the associations among APMs and the Big Five.

A final limitation concerns the use of a very brief measure of the Big Five in Study 2. Brief measures of personality have the benefit of requiring very little time to administer, but suffer from reduced reliability and less content coverage. Credé, Harms, Niehorster, and Gaye-Valentine (2012) have demonstrated that brief measures are likely to be susceptible to not only Type 2 errors (i.e., failing to find an association with the Big Five most likely due to the preponderance of measurement error), but also to Type 1 errors. Type 1 errors can be inflated when a researcher claims to demonstrate incremental validity over the Big Five in the prediction of some outcome using a brief measure. That said, Credé et al. (2012) report the most dramatic decreases in reliability and validity for single item measures of the Big Five and a substantial increase for measures with two items per construct (such as the TIPI). Nevertheless, it will be important for the results of Study 2 to be replicated using a longer measure of the Big Five.

3.5. Future directions

We have introduced an efficient inventory of items. However, as with all new scales, a more complete understanding of its psychometric properties, patterns of associations, and generalizability across samples and age ranges will necessitate future empirical use in independent samples. MAPS greatly reduces the complexity of extant APMs, while at the same time removing some of the nuance that was found with measures within a domain. Testing whether more differentiated scales can predict additional variance above the broad domain scales will be an important task. For example, does knowing a participant's level of depth and ingenuity, components of intellectual investment, provide more predictive power than simply knowing the score on the intellectual investment scale? Pragmatically, does the increment in prediction outweigh the cost of adding items to a study design?

Additional omitted measures can be incorporated into the current framework. For example, we did not include need for cognition (Cacioppo et al., 1984) or grit (Duckworth & Quinn, 2009). Some researchers may, nevertheless, be interested in how these scales fit into the nomological network of the MAPS. At the most basic level, application of correlation and regression techniques to data collected on the MAPS and supplementary measures can evaluate shared and unique variance when predicting achievement. We propose extension analysis (Dwyer, 1937) and contextual analysis (Salthouse, Pink, & Tucker-Drob, 2008) as more psychometrically rigorous methods of answering these same questions. These types of analysis take a known factor structure and then include one or more extension variables to determine its relation with the known factor (see O'Connor, 2001 for helpful syntax files). Although not widely used, these methods can be used to determine if an excluded variable is largely accounted for by the MAPS (high factor loading), possesses discriminant validity from the MAPS (high residual variance), or predicts unique variance in achievement. Importantly, the new variable(s) can be examined without influencing the known factor structure. These methods may prove particularly useful for examining the item content of other scales in relation to the MAPS. Multiple items, rather than a scale, can be included in the analysis to determine if content from a MAPS domain is not fully represented or if an additional factor is required. Gorsuch (1997) demonstrated that traditional methods to answer these types of questions (e.g., correlation with factor or scale scores) provide biased estimates compared to extension analysis.

4. Conclusion

This study offers an initial framework to synthesize the personality traits associated with the intellectual skills formed during the educational process. By establishing dimensions of personality that are associated with achievement, researchers will be better able to evaluate the contextual influences on learning from the perspective of individual students with unique characteristics. One goal of this project was to reduce the noisy number of different APMs so that a single study can efficiently cover many relevant factors. Only by undertaking multivariate studies that obtain information about the student, the learning and home environment, and the atmosphere of the school can researchers fully explore the dynamic nature of the educational process. We have assisted in this endeavor by refining the scale content of many personality measures associated with achievement. This synthesis will aid future research into interventions intended to boost student motivation and academic success by establishing a framework from which to view individual differences and their impact on achievement.

Appendix A. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.lindif.2014.03.010.

References

Ackerman, P. L., & Heggestad, E. D. (1997). Intelligence, personality, and interests: Evidence for overlapping traits. *Psychological Bulletin*, *121*, 219–245. http://dx.doi.org/10.1037/0033-2909.121.2.219.

Ackerman, P. L., & Rolfhus, E. L. (1999). The locus of adult intelligence: Knowledge, abilities, and non-ability traits. *Psychology and Aging*, *14*, 314–330. http://dx.doi.org/10.1037/0882-7974.14.2.314.

Ames, C. (1984). Achievement attributions and self-instruction under competitive and individualistic goal structures. *Journal of Educational Psychology*, *76*, 478–487. http://dx.doi.org/10.1037/0022-0663.76.3.478.

Berry, C. M., & Sackett, P. R. (2009). Individual differences in course choice results in underestimation of the validity of college admissions systems. *Psychological Science*, *20*, 822–830. http://dx.doi.org/10.1111/j.1467-9280.2009.02368.x.

Biggs, J., Kember, D., & Leung, D. Y. P. (2001). The revised two-factor Study Process Questionnaire: R-SPQ-2F. *British Journal of Educational Psychology*, *77*, 133–149. http://dx.doi.org/10.1348/000709901158433.

Briley, D. A., & Tucker-Drob, E. M. (2012). Broad bandwidth or high fidelity? Evidence from the structure of genetic and environmental effects on the facets of the Five Factor Model. *Behavior Genetics*, *42*, 743–763. http://dx.doi.org/10.1007/s10519-012-9548-8.

Cacioppo, J. T., Petty, R. E., & Kao, C. F. (1984). The efficient assessment of need for cognition. *Journal of Personality Assessment*, *43*, 306–307. http://dx.doi.org/10.1207/s15327752jpa4803_13.

Cattell, R. B. (1971). *Abilities: Their structure, growth, and action.* Boston, MA: Houghton Mifflin.

Cattell, R. B. (1987). *Intelligence: Its structure, growth, and action.* Amsterdam: North-Holland.

Cerasoli, C. P., Nicklin, J. M., & Ford, M. T. (2014, February). Intrinsic motivation and extrinsic incentives jointly predict performance: A 40-year meta-analysis. *Psychological Bulletin*. http://dx.doi.org/10.1037/a0035661 (Online first publication).

Chamorro-Premuzic, T., & Furnham, A. (2005). *Personality and intellectual competence.* Mahwah, NJ: Lawrence Erlbaum Associates.

Credé, M., Harms, P., Niehorster, S., & Gaye-Valentine, A. (2012). An evaluation of the consequences of using short measures of the Big Five personality traits. *Journal of Personality and Social Psychology*, *102*, 874–888. http://dx.doi.org/10.1037/a0027403.

Cronbach, L. J., & Gleser, G. C. (1957). *Psychological tests and personnel decisions.* Urbana, IL: University of Illinois Press.

Cronbach, L. J., & Meehl, P. E. (1955). Construct validity in psychological tests. *Psychological Bulletin*, *52*, 281–302.

DeYoung, C. G., Quilty, L. C., & Peterson, J. B. (2007). Between facets and domains: 10 aspects of the Big Five. *Journal of Personality and Social Psychology*, *93*, 880–896. http://dx.doi.org/10.1037/0022-3514.93.5.880.

Duckworth, A. L., & Quinn, P. D. (2009). Development and validation of the Short Grit Scale (Grit-S). *Journal of Personality Assessment*, *91*, 166–174. http://dx.doi.org/10.1080/00223890802634290.

Dweck, C. S. (1999). *Self-theories: Their role in motivation, personality, and development.* Philadelphia, PA: Psychology Press.

Dwyer, P. S. (1937). The determination of the factor loadings of a given test from the known factor loadings of other tests. *Psychometrika*, *2*, 173–178.

Eccles, J. S., & Wigfield, A. (2002). Motivational beliefs, values, and goals. *Annual Review of Psychology*, *53*, 109–132. http://dx.doi.org/10.1146/annurev.psych.53.100901.135153.

Elliot, A. J. (1999). Approach and avoidance motivation and achievement goals. *Educational Psychologist*, *34*, 149–169. http://dx.doi.org/10.1207/s15326985ep3403_3.

Elliot, A. J., & Harackiewicz, J. M. (1996). Approach and avoidance achievement goals and intrinsic motivation: A meditational analysis. *Journal of Personality and Social Psychology*, *70*, 461–475. http://dx.doi.org/10.1037/0022-3514.70.3.461.

Elliot, A. J., & McGregor, H. A. (2001). A 2 × 2 achievement goal framework. *Journal of Personality and Social Psychology*, *80*, 501–519. http://dx.doi.org/10.1037/0022-3514.80.3.501.

Elliot, A. J., & Murayama, K. (2008). On the measurement of achievement goals: Critique, illustration, and application. *Journal of Educational Psychology*, *100*, 613–628. http://dx.doi.org/10.1037/0022-0663.100.3.613.

Frost, R. O., Marten, P., Lahart, C., & Rosenblate, R. (1990). The dimensions of perfectionism. *Cognitive Therapy and Research*, *14*, 449–468. http://dx.doi.org/10.1007/BF01172967.

Funder, D. C. (2001). Personality. *Annual Review of Psychology*, *52*, 197–221. http://dx.doi.org/10.1146/annurev.psych.52.1.197.

Furnham, A. (2011). Personality and approaches to learning. In T. Chamorro-Premuzic, S. von Stumm, & A. Furnham (Eds.), *Handbook of individual differences.* Oxford: Wiley-Blackwell.

Goff, M., & Ackerman, P. L. (1992). Personality-intelligence relations: Assessment of typical intellectual engagement. *Journal of Educational Psychology*, *84*, 537–552. http://dx.doi.org/10.1037/0022-0663.84.4.537.

Goldberg, L. R., Johnson, J. A., Eber, H. W., Hogan, R., Ashton, M. C., Cloninger, C. R., et al. (2006). The International Personality Item Pool and the future of public-domain personality measures. *Journal of Research in Personality*, *40*, 84–96. http://dx.doi.org/10.1016/j.jrp.2005.08.007.

Gorsuch, R. L. (1997). New procedure for extension analysis in exploratory factor analysis. *Educational and Psychological Measurement*, *57*, 725–740. http://dx.doi.org/10.1177/0013164497057005001.

Gosling, S. D., Rentfrow, P. J., & Swann, W. B., Jr. (2003). A very brief measure of the Big-Five personality domains. *Journal of Research in Personality*, *37*, 504–528. http://dx.doi.org/10.1016/S0092-6566(03)00046-1.

Harackiewicz, J. M., Barron, K. E., & Elliot, A. J. (1998). Rethinking achievement goals: When are they adaptive for college students and why? *Educational Psychologist*, *33*, 1–21. http://dx.doi.org/10.1207/s15326985ep3301_1.

Harris, P. A., Taylor, R., Thielke, R., Payne, J., Gonzalez, N., & Conde, J. G. (2009). Research electronic capture (REDCap) — A metadata-driven methodology and workflow process for providing translational research informatics support. *Journal of Biomedical Informatics*, *42*, 377–381. http://dx.doi.org/10.1016/j.jbi.2008.08.010.

Horn, J. L. (1965). A rationale and test for the number of factors in factor analysis. *Psychometrika*, *30*, 179–185.

Huang, C. (2012). Discriminant and criterion-related validity of achievement goals in predicting academic achievement: A meta-analysis. *Journal of Educational Psychology*, *104*, 48–73. http://dx.doi.org/10.1037/a0026223.

Hulleman, C. S., Schrager, S. M., Bodmann, S. M., & Harackiewicz, J. M. (2010). A meta-analytic review of achievement goal measures: Different labels for the same constructs or different constructs with similar labels? *Psychological Bulletin*, *136*, 422–449. http://dx.doi.org/10.1037/a0018947.

Jacobs, J. E., & Eccles, J. S. (2000). Parents, task values, and real-life achievement-related choices. In C. Sansone, & J. M. Harackiewicz (Eds.), *Intrinsic motivation* (pp. 405–439). San Diego, CA: Academic Press.

John, O. P., Naumann, L. P., & Soto, C. J. (2008). Paradigm shift to the integrative Big Five trait taxonomy: History, measurement, and conceptual issues. In O. P. John, R. W. Robins, & L. A. Pervin (Eds.), *Handbook of personality* (pp. 114–158). New York: Guilford Press.

Judge, T. A., & Hurst, C. (2007). Capitalizing on one's advantages: Role of core self-evaluations. *Journal of Applied Psychology*, *92*, 1212–1227. http://dx.doi.org/10.1037/0021-9010.92.5.1212.

Judge, T. A., Locke, E. A., & Durham, C. C. (1997). The dispositional causes of job satisfaction: A core evaluations approach. *Research in Organizational Behavior*, *19*, 151–188.

Judge, T. A., Locke, E. A., Durham, C. C., & Kluger, A. N. (1998). Dispositional effects on job and life satisfaction: The role of core evaluations. *Journal of Applied Psychology*, *93*, 17–34. http://dx.doi.org/10.1037/0021-9010.83.1.17.

Judge, T. A., Thoresen, C. J., Pucik, V., & Welbourne, T. M. (1999). Managerial coping with organizational change: A dispositional perspective. *Journal of Applied Psychology*, *84*, 107–122. http://dx.doi.org/10.1037/0021-9010.84.1.107.

Lay, C. H. (1986). At last, my research article on procrastination. *Journal of Research in Personality*, *20*, 474–495. http://dx.doi.org/10.1016/0092-6566(86)90127-3.

Levenson, H. (1981). Differentiating between internality, powerful others, and chance. In H. M. Lefcourt (Ed.), *Research with the locus of control construct*, *Vol. 1*. (pp. 15–36). New York: Academic Press.

Luciano, M., Wainwright, M. A., Wright, M. J., & Martin, N. G. (2006). The heritability of conscientiousness facets and their relationship to IQ and academic achievement. *Personality and Individual Differences*, *40*, 1189–1199. http://dx.doi.org/10.1016/j.paid.2005.10.013.

Lykken, D. T. (1968). Statistical significance in psychology research. *Psychological Bulletin*, *70*, 151–159.

McCrae, R. R., Herbst, J. H., & Costa, P. T., Jr. (2001). Effects of acquiescence on personality factor structures. In R. Riemann, F. M. Spinath, & F. Ostendorf (Eds.), *Personality and temperament: Genetics, evolution, and structure* (pp. 217–231). Berlin, Germany: Pabst Science Publishers.

Mega, C., Ronconi, L., & De Beni, R. (2013, July 1). What makes a good student? How emotions, self-regulated learning, and motivation contribute to academic achievement. *Journal of Educational Psychology*. http://dx.doi.org/10.1037/a0033546 (Advance online publication).

Midgley, C., Kaplan, A., & Middleton, M. J. (2001). Performance-approach goals: Good for what, for whom, under what circumstances, and at what costs? *Journal of Educational Psychology*, *93*, 77–86. http://dx.doi.org/10.1037/0022-0663.93.1.77.

Midgley, C., Maehr, M. L., Hruda, L. Z., Freeman, K. E., Gheen, M., Kaplan, A., et al. (2000). *Manual for the Patterns of Adaptive Learning Scales (PALS)*. Ann Arbor: University of Michigan.

Moffitt, T. E., Arseneault, L., Belskey, D., Dickson, N., Hancox, R. J., & Caspi, A. (2011). A gradient of childhood self-control predicts health, wealth, and public safety. *Proceedings of the National Academy of Sciences*, *108*, 2693–2698. http://dx.doi.org/10.1073/pnas.1010076108.

Montez, J. K., Hummer, R. A., Hayward, M. D., Woo, H., & Rogers, R. G. (2011). Trends in the educational gradient of U.S. adult mortality from 1986 through 2006 by race, gender, and age group. *Research on Aging*, *33*, 145–171. http://dx.doi.org/10.1177/0164027510392388.

Mussel, P. (2010). Epistemic curiosity and related constructs: Lacking evidence of discriminant validity. *Personality and Individual Differences*, *49*, 506–510. http://dx.doi.org/10.1016/j.paid.2010.05.014.

Mussel, P. (2013). Intellect: A theoretical framework for personality traits related to intellectual achievements. *Journal of Personality and Social Psychology*, *104*, 885–906. http://dx.doi.org/10.1037/a0031918.

Muthén, L. K., & Muthén, B. O. (1998–2010). *Mplus user's guide* (6th ed.). Los Angeles, CA: Muthén and Muthén.

Nagengast, B., Marsh, H. W., Scalas, F., Xu, M. K., Hau, K., & Trautwein, U. (2011). Who took the × out of Expectancy–Value Theory? A psychological mystery, a substantive-methodological synergy, and a cross-national generalization. *Psychological Science*, *22*, 1058–1066. http://dx.doi.org/10.1177/0956797611415540.

Noftle, E. E., & Robins, R. W. (2007). Personality predictors of academic outcomes: Big Five correlates of GPA and SAT scores. *Journal of Personality and Social Psychology*, *93*, 116–130. http://dx.doi.org/10.1037/0022-3514.93.1.116.

O'Connor, B. P. (2000). SPSS and SAS programs for determining the number of components using parallel analysis and Velicher's MAP test. *Behavior Research Methods, Instruments, & Computers*, *32*, 396–402.

O'Connor, B. P. (2001). EXTENSION: SAS, SPSS, and MATLAB programs for extension analysis. *Applied Psychological Measurement*, *25*, 88. http://dx.doi.org/10.1177/01466216010251011.

O'Connor, M. C., & Paunonen, S. V. (2007). Big Five personality predictors of post-secondary academic performance. *Personality and Individual Differences*, *43*, 971–990. http://dx.doi.org/10.1016/j.paid.2007.03.017.

Paunonen, S. V., & Ashton, M. C. (2001). Big five predictors of academic achievement. *Journal of Research in Personality*, *35*, 78–90. http://dx.doi.org/10.1006/jrpe.2000.2309.

Paunonen, S. V., Haddock, G., Forsterling, F., & Keinonen, M. (2003). Broad versus narrow personality measures and the prediction of behaviour across cultures. *European Journal of Personality*, *17*, 413–433. http://dx.doi.org/10.1002/per.496.

Paunonen, S. V., & Jackson, D. N. (2000). What is beyond the Big Five? Plenty! *Journal of Personality*, *68*, 821–835. http://dx.doi.org/10.1111/1467-6494.00117.

Poropat, A. E. (2009). A meta-analysis of the Five-Factor Model of personality and academic performance. *Psychological Bulletin*, *135*, 322–338. http://dx.doi.org/10.1037/a0014996.

Richardson, M., Abraham, C., & Bond, R. (2012). Psychological correlates of university student's academic performance: A systematic review and meta-analysis. *Psychological Bulletin*, *138*, 353–387. http://dx.doi.org/10.1037/a0026838.

Rosenberg, M. (1965). *Society and the adolescent self-image*. Princeton, NJ: Princeton University Press.

Salthouse, T. A., Pink, J. E., & Tucker-Drob, E. M. (2008). Contextual analysis of fluid intelligence. *Intelligence*, *36*, 464–486.

Tucker, L. R. (1951). *A method for synthesis of factor analysis studies (Personnel Research Section Report No. 984)*. Washington, D.C.: Department of the Army.

von Stumm, S. (2013). Investment traits and intelligence in adulthood: Assessment and associations. *Journal of Individual Differences*, *34*, 82–89. http://dx.doi.org/10.1027/1614-0001/a000101.

von Stumm, S., & Ackerman, P. L. (2013). Investment and intellect: A review and meta-analysis. *Psychological Bulletin*, *139*, 841–869. http://dx.doi.org/10.1037/a0030746.

von Stumm, S., Chamorro-Premuzic, T., & Ackerman, P. L. (2011a). Re-visiting intelligence — personality associations: Vindicating intellectual investment. In T. Chamorro-Premuzic, S. von Stumm, & A. Furnham (Eds.), *Handbook of individual differences*. Oxford: Wiley-Blackwell.

von Stumm, S., Hell, B., & Chamorro-Premuzic, T. (2011b). The hungry mind: Intellectual curiosity is the third pillar of academic performance. *Perspectives on Psychological Science*, *6*, 574–588. http://dx.doi.org/10.1177/1745691611421204.

Wigfield, A., & Cambria, J. (2010). Students' achievement values, goal orientations, and interest: Definitions, development, and relations to achievement outcomes. *Developmental Review*, *30*, 1–35. http://dx.doi.org/10.1016/j.dr.2009.12.001.

Wittmann, W. W., & Süβ, H. M. (1999). Investigating the paths between working memory, intelligence, knowledge, and complex problem-solving performances via Brunswik symmetry. In P. L. Ackerman, P. C. Kyllonen, & R. D. Roberts (Eds.), *Learning and individual differences: Process, trait, and content determinants* (pp. 77–108). Washington, DC: American Psychological Association.