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Understanding the Link Between Noncognitive Attributes and College Retention

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Abstract The attention to students' noncognitive attributes has recently flourished within academic research and public discourse. This paper adds to the literature by examining the interrelationships among several key noncognitive attributes as well as exploring direct and indirect relationships between noncognitive attributes and second-year retention. Within a multi-institutional sample of 10,622 students, academic self-efficacy, academic grit, self-discipline, and time management all load onto a single noncognitive factor with strong inter-item correlations and internal reliability. Moreover, structural equation modeling analyses indicate a sizable and positive indirect effect of noncognitive attributes on college retention, which is mediated by social adjustment, institutional commitment, and college grade point average.

Keywords Noncognitive attributes · Self-efficacy · Grit · Self-discipline · Time management · College students · College retention

Introduction

College student departure is quite costly for students, institutions, and society alike (e.g., Schuh and Gansemer-Topf 2012). Although research on this issue has occurred for almost a full century (Berger et al. 2012), a great deal of student attrition from college goes unexplained. Higher education studies often focus on many of the same types of predictors,

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which include student demographics, precollege academic achievement, institutional characteristics, and college experiences. The reliance on these constructs is, at least to some extent, likely explained by the availability of these measures on large-scale national and institutional college student surveys.

In contrast, a large body of evidence in psychology and other fields has examined personal qualities other than cognitive skills and demographics that may influence student success. These characteristics are described using several umbrella terms, including "noncognitive" attributes, "character skills," "social and emotional learning," and "21st century competencies," among others (Duckworth and Yeager 2015, p. 238). The use of divergent language can obscure the fact that different researchers may be examining very similar—if not identical—constructs without knowledge of these parallel lines of research (Bryk et al. 2015; Rowan-Kenyon et al. 2017). Some specific constructs under this broad umbrella may be familiar to many higher education practitioners, administrators, and researchers; these include self-efficacy, resilience, time management, study skills, and others. Some higher education interventions attempt to directly target these attributes; for instance, many first-year seminars seek to promote particular skills, knowledge, and habits to help incoming students adjust successfully to academic and social life (see Hunter and Linder 2005).

However, many of these noncognitive studies contain some key limitations. First, they frequently examine single-institution samples, so it is unclear whether and when the findings generalize to other colleges and universities. Second, they often use a cross-sectional design, so the temporal sequence of the constructs is not well-established. Third, the processes through which these noncognitive attributes operate is rarely studied directly. Fourth, many studies are conducted outside of the field of higher education, and they do not include key constructs that are well-established predictors of college student success (e.g., institutional commitment). Finally, noncognitive constructs are often conceptualized individually and studied accordingly, but they may contain considerable empirical and conceptual overlap with one another.

The present study attempts to address these gaps and limitations. Specifically, it uses a large, multi-institutional dataset to explore the interrelationships among several commonly used noncognitive attributes that are among the strongest predictors of college student success: academic self-efficacy, self-discipline, time management, and academic grit (perseverance of effort). It also investigates not only the direct relationship between entering noncognitive attributes and retention to the second year of college, but also whether and how this association is explained by students' social adjustment, institutional commitment, and college grade point average (GPA).

Noncognitive Attributes and Student Success

A Theoretical and Empirical Synthesis

Farrington et al. (2012) have provided an influential systematic review and theoretical framework for understanding noncognitive attributes and student GPA among college and K-12 students. They distinguish among five types of noncognitive factors: (1) *academic behaviors* that are associated with coursework engagement (e.g., regularly attending class, participating in class, doing homework, studying), (2) *academic perseverance* that exemplifies working diligently even in the face of obstacles or challenges (e.g., grit, delayed gratification, self-discipline, self-control), (3) *academic mindsets* regarding beliefs about oneself in relation to academics (e.g., self-efficacy, relevance of schoolwork to one's life, ability to improve with hard work, sense of belonging), (4) *learning strategies* used to engage effectively in academic tasks (e.g., study skills, metacognitive strategies, time management, goal setting), and (5) *social skills* that may help students when engaging with instructors or peers (e.g., interpersonal skills, empathy, cooperation, responsibility).

In their theoretical framework, Farrington et al. (2012) propose that academic mindsets have a direct effect on each of the other four noncognitive factors. That is, if students believe that they belong within the academic community, can improve their performance through hard work, and are capable of succeeding academically, then they are more likely to exhibit effective behaviors, skills, and tendencies and therefore receive strong grades. Moreover, academic behaviors mediate or explain the link between the other four noncognitive factors and academic performance; this indirect relationship means that noncognitive factors are influential only insofar as they contribute to positive academic behaviors within and outside of the classroom. Effective learning strategies are also believed to contribute to academic perseverance. Finally, these dynamics are further shaped by the classroom, school, and socio-cultural contexts in which they occur, along with student background characteristics.

Across the five types of noncognitive attributes that Farrington et al. (2012) reviewed, they found strong evidence that academic behaviors, academic mindsets, and learning strategies affect students' grades in college and K-12 settings. The findings for academic perseverance are less clear, since existing studies often conflate tendencies for being perseverant with academic behaviors, and longitudinal research is less common and typically yields more modest results than cross-sectional research. Social skills have the weakest relationships with grades; any effect appears to be indirect, and most studies have focused on young children rather than high school or college students. Thus, the research clearly indicates the importance of noncognitive attributes, but some types of factors appear to be more important than others.

Higher Education Theory and Noncognitive Attributes

Theoretical perspectives in higher education that attempt to explain college student attrition and persistence have been highly contested (see Braxton 2000; Museus 2014). However, many of these frameworks include noncognitive attributes as entering student characteristics, such as "self-efficacy" and "personality" (Bean and Eaton 2000), "academic dispositions" (Museus 2014), and "skills and abilities" (Bean and Eaton 2000; Tinto 1993). Thus, a cognizance of the potential role of noncognitive attributes in shaping student attrition and persistence is not new to the field.

As discussed elsewhere in this paper, considerable research has explored the direct relationship between specific noncognitive attributes and student success. However, the particular paths posited by higher education theories have received little empirical attention. That is, do entering noncognitive attributes predict students' engagement with the academic and social domains of college life? Farrington et al.'s (2012) theoretical perspective suggests that this is the case, since they argue that academic behaviors fully explain the link between several types of noncognitive attributes and academic performance. Furthermore, higher education theories also posit that incoming student attributes may affect both academic and non-academic behaviors.

Noncognitive attributes may constitute an important set of inputs within Astin's input–environment–outcome model (see Astin 1970; Astin and antonio 2012). In terms of this framework, most higher education research focuses on the link between environments and outcomes (while controlling for relevant inputs that may include a pretest), and some inquiry has also examined the direct relationships between inputs and subsequent outcomes. This model further posits that inputs play a notable role in shaping college students' environments or experiences, which then affect a variety of outcomes. Such indirect relationships are quite important for noncognitive variables, since these are believed to influence both the environments that students encounter and how students engage with these environments (Farrington et al. 2012; Tough 2012).

Research on Specific Constructs

A discussion of broad categories of noncognitive attributes can overshadow the fact that each category consists of several constructs, some of which have been examined extensively. This literature has largely focused on predicting grades, so the discussion below reflects this existing evidence while also describing research on college retention when available. Perhaps the most well-known construct is self-efficacy, which is the belief that one is able to complete a task successfully (e.g., Bandura 1977, 1986). A quantitative meta-analysis from over 25 years ago found that academic self-efficacy had a sizable relationship with college academic achievement ($r = .35$; Multon et al. 1991). Subsequent meta-analyses that examined various psychological, behavioral, and demographic constructs indicate that self-efficacy is one of the strongest—if not the single strongest—predictor of college grades ($r = .38$ in Robbins et al. 2004; $r = .31$ for "academic self-efficacy" and $r = .59$ for "performance self-efficacy" in Richardson et al. 2012). In these meta-analyses, the relationships for self-efficacy were on par with those for high school grades and standardized test scores, both of which are likely affected by students' earlier levels of self-efficacy. Robbins et al. also found that self-efficacy was the second-strongest predictor of retention ($r = .26$); this relationship was comparable to that for high school GPA and retention ($r = .24$) and notably stronger than that for standardized test scores ($r = .12$). In Richardson et al.'s review of postsecondary academic achievement, two other noncognitive attributes also emerged as sizable predictors of college grades: effort regulation (i.e., self-discipline; $r = .32$) and time management ($r = .22$).

More recently, grit has been nominated as an attribute that may contribute to academic and vocational success. According to Duckworth et al. (2007), grit consists of a combination of perseverance and passion for long-term goals. Grit is sometimes framed as a component of conscientiousness (Credé et al. 2017; Roberts et al. 2014), which is a personality domain that consistently predicts greater academic achievement (Connelly and Ones 2010; Poropat 2009; Richardson et al. 2012). A meta-analysis has shown that grit is positively correlated with college GPA, intent to persist, and college retention (Credé et al. 2017), Moreover, individual studies have also demonstrated that grit significantly predicts college grades and intent to persist even when controlling for potential confounding variables (Akos and Kretchmar 2017; Bowman et al. 2015; Duckworth et al. 2007; Duckworth and Quinn 2009; Strayhorn 2014).

The focus on the link between noncognitive attributes and GPA in previous research implies that academic achievement may constitute the primary (or perhaps the only) mechanism through which these characteristics might bolster retention, persistence, and graduation. Although college grades constitute the strongest within-college contributor to undergraduate persistence and bachelor's degree attainment (Mayhew et al. 2016; Pascarella and Terenzini 2005), noncognitive factors may also affect retention and graduation above and beyond their relationship with college GPA. As higher education theories have asserted, students' entering noncognitive attributes may affect success indirectly by shaping their college experiences, which then promote college GPA, retention, and persistence. Providing some initial evidence for this possibility, Bowman et al. (2015) observed that perseverance of effort (which is one component of grit) was positively associated with co-curricular engagement, college sense of belonging, and overall college satisfaction. Thus, grit may operate to improve student success by easing the adjustment process to college, since gritty students should be more likely, by definition, to persevere when confronted with a variety of academic and social challenges.

Present Study

This paper examines four noncognitive attributes that have been well-established as correlates of student success. As discussed earlier, academic self-efficacy is probably the strongest noncognitive predictor of college grades and retention (Richardson et al. 2012; Robbins et al. 2004), and time management and self-discipline are also notable positive predictors of college grades (Richardson et al. 2012). Grit has also gained attention as a predictor of persistence in college and the workplace (Duckworth et al. 2007; Eskreis-Winkler et al. 2014; Robertson-Kraft and Duckworth 2014). Within Farrington et al.'s (2012) theoretical framework, grit and self-discipline reflect dimensions of academic perseverance, self-efficacy is a form of academic mindset, and time management is related to learning strategies. We intentionally chose not to include direct indicators of academic behavior, since these are believed to mediate the link between other noncognitive attributes and academic performance.

We explored several hypotheses regarding noncognitive attributes and student success. First, several key noncognitive attributes (academic self-efficacy, time management, self-discipline, and academic grit) will be so strongly related to one another that they can be combined into a single latent noncognitive construct. Conceptually, these attributes seem interdependent to some extent: self-discipline is arguably necessary to persevere in one's effort and to maintain consistent goals over time (i.e., the two components of grit), and successful time management is clearly easier when one is self-disciplined. Second, noncognitive attributes will be positively associated not only with college grades, but also with social adjustment and institutional commitment. Institutional commitment is an important construct to consider when exploring student success, since it predicts greater retention even when controlling for precollege achievement, socioeconomic status, and noncognitive attributes (for meta-analytic reviews, see Credé and Niehorster 2012; Robbins et al. 2004). Third, academic achievement (i.e., college GPA), social adjustment, and institutional commitment will fully explain the relationship between noncognitive attributes and retention.

Unlike many previous studies of noncognitive indicators, this paper utilized a multi-institutional sample (to enhance the generalizability of the findings), collected data longitudinally (so that the noncognitive measures occurred before college grades and retention), and conducted structural equation modeling (SEM) analyses (to provide a nuanced understanding of underlying processes). This paper examined retention from the first to second year, since student attrition from 4-year institutions is greatest at this point (e.g., Chen 2012; Ishitani 2006). Although some students ultimately graduate after leaving college, stopout dramatically reduces the probability of degree completion (e.g., Ishitani 2006; Li 2010; Roksa 2010), so it is important to understand whether and how noncognitive attributes predict success at this early and influential point in time.

Method

Data Source and Participants

This study examined first-year students enrolled at 1 of 16 four-year institutions that participated in the 2013–2014 administration of Skyfactor Mapworks, which is a student success and retention system. Although more than 125 institutions participate annually in Mapworks, the 16 schools described in this study volunteered to pilot new questions related to academic grit and uploaded three key student variables into the Mapworks database: high school GPA, Fall 2013 college GPA, and retention from Fall 2013 to Fall 2014. Each institution administered the Mapworks Fall Transition survey to all first-year students early in the Fall 2013 semester (typically 3–5 weeks after the beginning of the academic year). Students received electronic invitations to complete the online survey either via email or through an institutional portal. The sample included 10,622 participants, with an overall response rate of 74%. Comparisons with Integrated Postsecondary Education Data System (IPEDS) data showed that these participants were demographically representative of the colleges and universities that they attended.

Of the 16 institutions, 13 were public and 3 were private. The institutional sample was heterogeneous in terms of region (5 in Great Lakes, 4 in Southeast, 3 in New England, 3 in Plains, and 1 in Southwest), enrollment size (3 within 1000–4999 range, 5 in 5000–9999 range, 4 in 10,000–19,999 range, and 4 within 20,000+ range), selectivity (3 were inclusive, nine were selective, and 4 were more selective, per the undergraduate profile labels from the IPEDS 2016), and residentiality (2 primarily non-residential, 8 primarily residential, and 6 highly residential). The IPEDS first-to-second-year full-time retention rates at these institutions ranged from 62 to 91%, with an average of 76%.

Measures

The primary dependent variable was retention at the same institution to the fall of the second year (1 = yes, 0 = no). College GPA from fall semester of the first year was measured on a 4.0 scale. Commitment to the institution was assessed with a three-item index (e.g., “to what degree do you intend to come back to this institution for the next academic year”, Cronbach’s $\alpha = .77$).

Social adjustment was indicated with a latent variable that consisted of two other indices: social integration (e.g., “overall, to what degree do you belong here”, three items, $\alpha = .87$) and peer connections (e.g., “on this campus, to what degree are you connecting with people who you like”, three items, $\alpha = .93$). Multiple definitions exist about the nature of “social integration”; consistent with the preceding sample item, the current operationalization focuses on a student feeling a sense of belonging rather than “fitting in” with prevailing campus norms. Four noncognitive attributes were used to create an overall latent factor: academic self-efficacy (e.g., “to what degree are you certain that you can do well on all problems and tasks assigned in your courses”, three items, $\alpha = .88$), time management (e.g., “to what degree are you the kind of person who plans out your time”, four items, $\alpha = .77$), self-discipline (e.g., “to what degree are you the kind of person who is dependable”, three items, $\alpha = .80$), and academic grit (e.g., “When I get a poor grade, I work harder in that course”, four items, $\alpha = .82$). Duckworth et al.’s (2007) conceptualization of grit has two components; the present measure of academic grit focused on perseverance of effort, which is more strongly related to academic and non-academic outcomes than is consistency of interest (Bowman et al. 2015; Credé et al. 2017). The grit items in this study were informed by—but were not the same as—prior measures in Duckworth et al. (2007) and Duckworth and Quinn (2009).

Financial means was assessed with a three-item scale (e.g., "to what degree are you confident that you can pay for next term's tuition and fees", three items, $\alpha = .87$). The use of this subjective construal is consistent with theories that argue the impact of finances on students' decisions is explained by students' perceptions of their financial circumstances (e.g., Cabrera et al. 1992). Finally, high school GPA was measured on a 4.0 scale (with a bonus point awarded for taking honors, Advanced Placement, and International Baccalaureate coursework). An overview of these constructs and measures, including descriptive statistics, is provided in Table 1.

Analyses

A principal components factor analysis was conducted to examine the structure of the four noncognitive attributes (academic self-efficacy, time management, self-efficacy, and academic grit). Eigenvalues, scree plots, factor loadings, and Cronbach's αs were used to determine the number of factors and the internal reliability of the factor(s) (see Furr and Bacharach 2008). Correlations among the noncognitive attributes were also computed; these values included raw correlations as well as correlations that are adjusted for attenuation, which indicates what the bivariate relationship would be if the constructs were measured with perfect reliability (see Cohen et al. 2003). Fisher r-to-Z transformations examined whether differences across correlations are significant; these tests were used to further understand the nature of interrelationships among noncognitive constructs, which provided insights into whether the strength of these relationships aligns with prevailing theoretical frameworks, such as that of Farrington et al. (2012).

To explore the direct and indirect relationships between noncognitive attributes and retention, SEM analyses were conducted using the lavaan package in R. To account for the binary nature of the retention outcome, a weighted least squares means and variance-adjusted (WLSMV) estimator was used (for more information about this statistical approach and software package, see Finney and DiStefano 2006; Lavaan n.d.; Rosseel 2012). This approach avoids the problems with using maximum likelihood (ML) estimation (for SEM) and ordinary least squares regression for predicting non-continuous variables, since these incorrect approaches yield less accurate estimates and increase the chance of committing a Type I error (Finney and DiStefano 2006; Long 1997).

Measurement models yielded excellent fit indices, so structural models were examined. For each of the two latent constructs (noncognitive attributes and social adjustment), a path from the latent measure to one of the observed indicator variables was fixed to one to properly identify the model (Kline 2016). The direct paths among key constructs were based on findings from existing literature (e.g., Credé and Niehorster 2012; Mayhew et al. 2016; Pan 2010; Pascarella and Terenzini 2005; Robbins et al. 2004). Financial means was the only exogenous variable in the model (i.e., variable that was not predicted by any other variable); it had direct paths to high school GPA, noncognitive attributes, social adjustment, and retention. The latent variable for noncognitive attributes had direct paths to high school GPA, social adjustment, institutional commitment, college GPA, and retention. Given that noncognitive attributes are relatively stable over time (Farrington et al. 2012; Roberts and DelVecchio 2000), we felt it was appropriate to use this construct to predict high school GPA, even though these grades occurred before the survey was administered. High school

Table 1 Overview of constructs included in the study

Constructs	Definitions	Number of items	Cronbach's α	Mean	SD
Financial means	Students' concerns about being able to pay for education and other expenses	3	.87	5.03	1.52
High school GPA	Cumulative high school grade point average (measured on a 4.0 scale)	1	–	3.48	.58
Noncognitive attributes	Latent construct that consists of four different noncognitive attributes (described below)	–	–	–	–
Academic self-efficacy	Students' beliefs that they can succeed academically, even in their most difficult coursework	3	.88	5.35	1.01
Time management	Students plans their time effectively and adhere to balanced time commitments	4	.77	5.53	1.06
Self-discipline	Students follow through with commitments and completes their intended tasks	3	.80	5.94	.86
Academic grit	Students persevere within their academics, even when they encounter challenges	4	.82	5.67	.96
Social adjustment	Latent construct that consists of two domains of social adjustment (described below)	–	–	–	–
Social integration	Students feel a sense of belonging and satisfaction with their social life	3	.87	5.58	1.35
Peer connections	Students feel connected with people on campus who share their interests and engage in activities	3	.93	5.60	1.37
Commitment to the institution	Students are committed to returning to the institution and to receiving a degree from that institution	3	.77	6.45	.93
College GPA	Students' grades from the first semester of college (measured on a 4.0 scale)	1	–	2.93	.83
Retention	Students were enrolled at the same institution at the beginning of the second year	1	–	.80	.40

The definitions provided above are specific to the measures used in this study; other research may not necessarily define or operationalize these constructs in the same manner. The use of italic for the names of some constructs indicate that these directly predict—and/or are predicted by—other constructs (as opposed to serving as part of a broader latent construct)

GPA predicted social adjustment, institutional commitment, and college grades. Social adjustment had direct paths to institutional commitment, college grades, and retention. Finally, both institutional commitment and college grades predicted retention. According to several frequently used fit indices, the data fit the model well: Tucker–Lewis Index (TLI) = .97, Comparative Fit Index (CFI) = .98, Root Mean-Square Error of Approximation (RMSEA) = .05, and Standardized Root Mean Square Residual (SRMR) = .03. These values meet or exceed Hu and Bentler's (1999) recommendations of TLI and CFI of at least .95, RMSEA of no more than .06, and SRMR of no more than .08 (note that Hu and Bentler's guidelines were for ML estimation; preliminary analyses showed that the current model still meets or exceeds these recommendations when using an ML estimator). A visual representation of this model is provided in Fig. 1.

These analyses generally met the assumptions of structural models for SEM, as discussed by Kline (2012). The first assumption deals with proper temporal sequence. Indeed, the final outcome (retention) was collected after all other measures, and the penultimate outcome (college GPA) was collected after the end of the first semester, which occurred well before the survey items were administered. Given the relative stability of family income over time, the only exogenous outcome (financial means) likely occurred before all other measures. Potential exceptions to this temporal sequence are discussed in the "Limitations" section. Second, to establish evidence for a potential causal association, covariation between the variables of interest must be present. As shown below, significant relationships are observed for virtually all direct paths, and we do not suggest the presence of any meaningful relationship within the single non-significant path. Third, the expected relationship among two variables must not be explained by confounding variables. Consistent with this assumption, the present results persist when controlling for other variables in the model that were chosen based on existing theory and research. SEM inherently involves tradeoffs pertaining to model parsimony, so it is possible that other unobserved variables may exist that could confound these relationships. Fourth, the method used to estimate the model must align with the distribution of the data. A key issue pertaining to this assumption is discussed above; specifically, the analysis used the WLSMV estimator to account for the binary nature of the retention outcome. Finally, the direction of the causal relationship

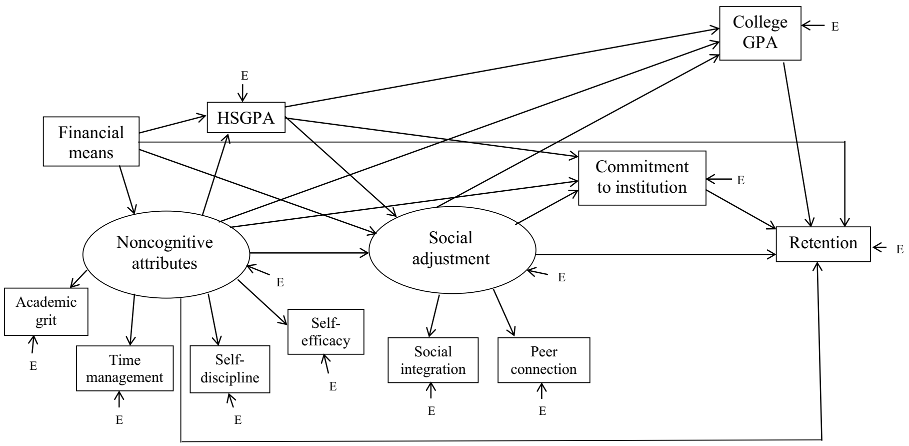

Fig. 1 Diagram of structural equation model predicting second-year college retention. E represents an error term

must be correctly specified. As discussed earlier, the directional paths were selected based on extensive theory and previous research, along with the temporal occurrence of these constructs.

Preliminary analyses examined the intraclass correlations (ICCs) for the each of the college outcomes (social adjustment, institutional commitment, college GPA, and retention) to explore whether multilevel SEM analyses were necessary. The ICCs for these variables were all below 5%, which is often used as a criteria for determining whether multivariate analyses are necessary (Heck and Thomas 2009; Porter 2006). As a result, single-level analyses were used. Finally, because the sample size for this study was large, a fairly conservative threshold for statistical significance was employed to reduce the chance of making Type I errors ($p < .01$).

Limitations

Some limitations should be noted. First, although the multi-institutional design strengthens the generalizability of the findings, the institutional sample consisted of schools that participated in this pilot data collection and provided Skyfactor Mapworks with key academic success indicators. The 16 institutions in this sample are certainly heterogeneous, but they are not necessarily representative of all US 4-year, not-for-profit colleges and universities. In particular, this sample has a greater proportion of public institutions and lower proportion of primarily non-residential campuses than national norms (IPEDS 2016). However, this sample is similar to all US 4-year, not-for-profit institutions in other ways, most notably in terms of the average first-to-second-year retention rate. Second, given the importance of parsimony in SEM, only a modest number of precollege and college variables could be included within the model.

Third, while grades and retention were measured after the primary data collection, financial means, noncognitive variables, social integration, and commitment to the institution were all reported at the same time within the same survey. Moreover, given that many noncognitive attributes are fairly stable through the teenage years and beyond (Farrington et al. 2012; Roberts and DelVecchio 2000), the measure of noncognitive attributes had a direct path to high school GPA even though it was assessed after high school. The direct paths among these constructs are consistent with existing theory (e.g., Bean and Eaton 2000; Cabrera et al. 1992; Tinto 1993; Tough 2012), but the analyses cannot directly test whether they occurred in this particular temporal sequence. Although we obviously could not change this sequence of data collection, we explored the potential impact of this analytic decision by removing the path between noncognitive attributes and high school GPA from the model. These supplemental analyses showed that removing this path had no substantive effect on the findings. Fourth, the dependent variable measured retention at the same college or university, not persistence within higher education more generally. Therefore, the analyses cannot distinguish among students who dropped out versus transferred, so conclusions from this study should be drawn accordingly.

Results and Discussion

Relationships Among Noncognitive Attributes

The exploratory factor analysis indicates that the four noncognitive attributes can be reduced to a single noncognitive factor. Specifically, the first component had an Eigenvalue of 2.41, and it explained more than 60% of the variance in the four attributes. The scree plot decreased sharply from the first to the second component, and it was essentially flat from the second to the fourth. All noncognitive attributes had factor loadings of more than .71, which are considered "excellent" in terms of strength (Tabachnick and Fidell 2007); the overall noncognitive construct had a Cronbach's α of .77. Correlations among the four noncognitive attributes are provided in Table 2. The raw correlations are generally large according to Cohen's (1988) guidelines; by definition, these are even stronger when adjusting for attenuation. Therefore, it appears that these noncognitive constructs are sufficiently related to be treated as a single noncognitive factor, but they are not completely synonymous with one another.

The correlation table also reveals some interesting patterns in the bivariate relationships among these constructs. The raw correlation between self-discipline and time management ($r=.61$) is significantly stronger than all other correlations ($Z\text{s} > 14$, $p\text{s} < .001$). However, according to Farrington et al.'s (2012) framework, these two constructs actually belong to different categories of noncognitive factors (academic perseverance for self-discipline and learning strategies for time management). In fact, academic grit and self-discipline were the only two constructs from the same category, and the correlation between these measures was very similar to those for grit and the two noncognitive measures from other categories (time management and academic self-efficacy).

Therefore, although the noncognitive factors proposed by Farrington et al. provide a useful theory-based classification system, they do not necessarily reflect the empirical strength of relationships among constructs within or across categories. Instead, from a definitional perspective, self-discipline and time management both pertain to accomplishing tasks expeditiously, which is probably why they are highly correlated. Grit also deals with accomplishing tasks and goals, especially since the measure used in the present study focused on perseverance of effort rather than consistency of interest. As a result, academic self-efficacy was somewhat of an outlier in that it was less directly related to completing academic tasks than the other noncognitive constructs. Perhaps not surprisingly, then, the correlations between academic self-efficacy and two other measures—self-discipline

Table 2 Correlations among noncognitive attributes

	Self-discipline	Time management	Academic self-efficacy	Academic grit
Self-discipline	–	.78**	.51**	.59**
Time management	.61**	–	.44**	.59**
Academic self-efficacy	.43**	.37**	–	.54**
Academic grit	.48**	.47**	.46**	–

Correlations below the diagonal are raw correlations; those above the diagonal are adjusted for attenuation (i.e., unreliability) in the noncognitive measures

** $p < .001$

($r = .43$) and time management ($r = .37$)—were significantly weaker than for any correlation that did not involve self-efficacy ($Zs > 4$, $ps < .001$).

Structural Equation Modeling Analyses

Results for Predicting Intermediate Outcomes

The full results for the SEM analysis are displayed in Table 3. Financial means is positively related to noncognitive attributes. This finding is consistent with previous research (Robbins et al. 2004) and with assertions that environmental stressors and low-quality K-12 schools may inhibit the development of such attributes among children from lower-SES backgrounds (Tough 2012). That said, because this financial construct is subjective, it is also possible that students with greater noncognitive attributes would have a more positive construal of the same "objective" financial situation. Thus, although noncognitive

Table 3 Standardized coefficients from the structural equation modeling analysis

Outcome variables and predictors	Direct	Indirect	Total	R^2
Noncognitive attributes				.063**
Financial means	.250**		.250**	
High school GPA				.040**
Financial means	.123**	.033**	.156**	
Noncognitive attributes	.131**		.131**	
Social adjustment				.204**
Financial means	.128**	.101**	.229**	
Noncognitive attributes	.406**	− .003	.403**	
High school GPA	− .026		− .026	
Commitment to the institution				.214**
Financial means		.131**	.131**	
Noncognitive attributes	.113**	.167**	.280**	
High school GPA	.093**	− .010	.083**	
Social adjustment	.383**		.383**	
College GPA				.310**
Financial means		.108**	.108**	
Noncognitive attributes	.275**	.003	.278**	
High school GPA	.464**	.004	.468**	
Social adjustment	− .144**		− .144**	
Retention to second year				.328**
Financial means	.090**	.080**	.170**	
Noncognitive attributes	− .150**	.290**	.140**	
High school GPA		.247**	.247**	
Social adjustment	.157**	.010	.167**	
Commitment to the institution	.213**		.213**	
College GPA	.499**		.499**	

Tucker–Lewis Index = .97, Comparative Fit Index = .98, Root Mean Square Error of Approximation = .05, Standardized Root Mean Square Residual = .03

**$p < .001$

attributes are very likely a product of perceived financial means, this relationship may also be reciprocal to some extent.

Noncognitive attributes have a sizable positive relationship with social adjustment; the magnitude of this direct effect is notably stronger than that for financial means, which is frequently discussed as a factor in shaping student adjustment to college. Thus, noncognitive attributes may play a notable role in helping college students adapt socially, as these skills and tendencies potentially shape students' behaviors and perceptions. The role of both behaviors and perceptions may be important: students with more favorable noncognitive attributes likely engage in beneficial interpersonal behaviors (e.g., following through on their social commitments) as well as having positive perceptions of the experiences in which they engage (e.g., not being dismayed by challenges to social adjustment).

Noncognitive attributes also have a significant direct effect on institutional commitment as well as a substantial indirect effect via social adjustment and high school GPA. It makes sense that grit (which entails working diligently toward long-term goals) and self-efficacy (which entails the belief in one's ability to succeed), in particular, might lead students to feel more strongly committed to pursuing a degree at their current college or university. It is important to note that institutional commitment and social adjustment were measured early in the first semester, so students had likely received little meaningful feedback from instructors on their academic performance when the survey was completed. As a result, the findings for the adjustment and commitment outcomes are unlikely to be largely explained by students' academic performance in college.

Consistent with previous research (Richardson et al. 2012; Robbins et al. 2004), noncognitive attributes are positively and directly related to college GPA even when controlling for prior achievement and other variables. Noncognitive attributes are also positively associated with high school grades. In both instances, these relationships likely reflect the greater quantity and quality of academic work among students who exhibit self-discipline, time management, academic self-efficacy, and academic grit. The link between noncognitive variables and college GPA is entirely direct, since there is not a significant indirect relationship.

Results for Predicting Retention

Importantly, noncognitive attributes have a positive overall association with retention to the second year, which is driven by a sizable indirect effect. This indirect effect is partially attributable to college GPA, since noncognitive attributes are strongly and positively related to college academic achievement, which is then strongly associated with retention. This academic pathway is the one that is generally assumed by Farrington et al. (2012), Richardson et al. (2012), and others who focus on academic achievement as the primary outcome of noncognitive attributes.

In addition to this academic route, social adjustment and institutional commitment also play considerable roles in contributing to the positive indirect effect on retention, which suggest the presence of a notable social pathway that is rarely discussed at the postsecondary level. Interestingly, high school GPA actually has a fairly weak relationship with institutional commitment and no significant relationship with social adjustment, so these particular indirect paths appear to be largely or entirely independent of academic influences. As discussed earlier, noncognitive attributes can affect how students engage with their college environment as well as how students perceive those interactions. Specifically, time management can help students arrange their schedules and tasks to accommodate both academic and social pursuits, self-discipline can minimize procrastination and thereby facilitate the prompt accomplishment of goals (leaving more time for socializing), and grit can help students avoid serious academic pitfalls that may lead to substantial distractions (such as failed assignments, exams, or entire courses). Students with these attributes may also have stronger social relationships, because they may be more reliable when making and keeping plans for socializing, so they may therefore less likely to disappoint their friends and acquaintances.

In contrast to these positive indirect relationships, noncognitive attributes have a negative direct relationship with retention. The explanation for this negative direct effect—which contrasts with a much larger indirect effect—is not clear. Noncognitive attributes predict not only academic achievement and educational attainment, but also outcomes ranging from first impressions made on strangers to retention within a job and performance at that job (e.g., Connelly and Ones 2010; Eskreis-Winkler et al. 2014; Robertson-Kraft and Duckworth 2014). When accounting for other relevant factors that promote retention within the statistical model, the negative direct effect could possibly mean that these noncognitive qualities may lead students to focus diligently on other pursuits, such as starting their own business or non-profit organization, which could cause them to drop out, transfer, or pursue those alternative goals. This possibility is certainly speculative and cannot be examined within the present study. Notably, the raw correlation between noncognitive attributes and college retention is positive, so this negative finding is a suppressor effect that may not have much (if any) substantive meaning (Pedhazur 1997).

It is worth considering that the positive total effect (i.e., direct plus indirect) of noncognitive attributes on retention is comparable in size to that of financial means, which has been the focus of considerable research and policy attention. This total effect is also similar to the corresponding value for social adjustment to college, which clearly plays a role in shaping students' postsecondary attrition, retention, and persistence (see Credé and Niehorster 2012; Mayhew et al. 2016; Robbins et al. 2004). The comparability among these effect sizes provides further credence to the consideration of noncognitive attributes when seeking to understand the factors that predict college student success.

Conclusion and Implications

This study makes several important contributions to the literature. First, it shows that noncognitive attributes potentially influence both social and academic outcomes, which may then lead to greater retention. Second, it illustrates that several key noncognitive attributes identified in previous research are sufficiently related to one another that they may be treated as a global noncognitive construct. Third, in a related point, the study demonstrates that existing classifications of noncognitive variables may be useful conceptually, but these groupings do not necessarily correspond to the strength of relationships among constructs. Fourth, it provides multi-institutional evidence regarding the association between noncognitive attributes and retention (as opposed to previous single-institution studies that mostly examined college grades as the primary outcome).

Promoting Noncognitive Attributes

When considering implications for practice, this observed link with student outcomes leads to an important question: How malleable are noncognitive attributes? Systematic reviews of existing research (Caspi et al. 2005; Farrington et al. 2012; Roberts and DelVecchio

2000) support several broad conclusions: (1) noncognitive attributes are somewhat stable over time, but they often exhibit both overall changes within the population and variation in individuals' trajectories over time, (2) some noncognitive attributes are more malleable than others, whether through maturation or susceptibility to change through specific interventions (e.g., self-perceptions as well as mindsets about intelligence or belonging can be readily changed, whereas grit or academic perseverance seem more stable), (3) such attributes are more malleable during the teenage years and young adulthood than in middle and late adulthood. Thus, well-designed attempts to improve noncognitive attributes may ultimately be successful in promoting short-term and long-term outcomes, especially among traditional-age undergraduates.

Related to this issue of malleability, Walton (2014) provides suggestions for conducting short-term "wise interventions" that can have long-term effects on noncognitive attributes and corresponding college behaviors. First, interventions need to occur early—often just before or soon after a key transition point—to maximize their effects. For instance, it is far easier to change students' perceptions about whether intelligence or college academic performance can be improved over time before those students have encountered substantial academic setbacks in college. Second, actively involving students in the intervention is much more effective than having them passively "receive" information about what they should think or believe. For example, a time management workshop should have students engage with their own schedules and share how they could approach or structure these differently (in ways that are consistent with the intended learning outcomes), as opposed to simply providing a list of time management tips that students may or may not use. Third, any intervention could be undermined if the environment is not conducive to the targeted psychological phenomenon. Attempts to improve students' mindsets about college belonging, for instance, may not work if the campus environment provides few opportunities for students to engage meaningfully with peers, faculty, and staff.

Higher education practitioners and administrators can use these findings in multiple ways. Programs and workshops that are designed to promote noncognitive activities could be administered to students; the design and timing of these activities should follow the advice of Walton (2014). As one notable aspect not mentioned above, the "saying is believing" approach is a time-tested strategy for effecting attitudinal and behavioral change. That is, students should make the case for why the strategies or perspectives offered in the workshop are beneficial, since doing so often leads people to internalize this message that they are personally conveying. This approach is one form of incorporating active learning, which is also a well-established means for enhancing student learning and motivation (see Mayhew et al. 2016; Pascarella and Terenzini 2005). These interventions do not need to be stand-alone workshops; they could occur through a first-year seminar, summer precollege orientation, or in a general education course. In addition, as an implication for college admissions at institutions that are at least moderately selective, applicants' noncognitive attributes could be considered as a factor for determining acceptance. Although administering a self-reported grit scale would certainly not be a good idea in this high-stakes context (see Duckworth and Yeager 2015), grit can be ascertained through resumes or other application materials (Robertson-Kraft and Duckworth 2014).

Future Research on Noncognitive Attributes

The present study also broaches important directions for future research. While this analysis demonstrated a general correspondence among noncognitive attributes, the potential interdependencies among these constructs merit attention. For instance, might self-efficacy be a necessary condition for fostering grit, since students would be reluctant to work hard to accomplish a goal if they did not believe that their hard work will help them achieve this goal? If so, interventions that bolster self-efficacy may be particularly effective for shaping student outcomes. And are self-discipline and time management more strongly related to college outcomes among grittier students (i.e., those that have identified and are maintaining long-term academic and career goals) than among less-gritty students? Although some tentative evidence can be provided with a single survey administration, longitudinal studies that collect noncognitive data at multiple timepoints would serve as the basis for stronger conclusions. Future research could also account for selection bias that might be exacerbated through the use of multiple surveys that therefore have multiple occasions for potential nonresponse.

Moreover, given their predictive utility for various success outcomes, noncognitive attributes may also be important to consider as mediators or moderators in college impact research. For instance, first-year seminars are generally designed to promote college student achievement and retention; are courses that promote students' noncognitive attributes (rather than focusing exclusively on campus resources or academic subject matter) more effective at bolstering student success? Given the simultaneous promise and challenges with promoting academic mindsets and other noncognitive attributes (e.g., Yeager et al. 2013; Yeager and Walton 2011), how can student affairs and academic affairs practitioners bolster these characteristics within large, diverse student populations? Which specific noncognitive attributes might be most susceptible to change and yield the greatest improvements in student success if they are changed? Understanding such issues could provide critical insights for practitioners who seek to promote college student retention, persistence, and graduation.

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