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Development and Validation of ENGAGE™ Grades 6–9

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Abstract

This report details the development and validation of the ENGAGE Grades 6-9, a measure of academic behavior designed to determine students' levels of academic risk. The work presented in this report is part of a comprehensive research program of educational risk assessment based on key academic behavior predictors (also known in the literature as socioemotional or psychosocial factors) of academic success and persistence. ACT researchers modeled early high school GPA based on a prospective sample of 4,660 middle school students from 24 schools and 13 districts. The findings show that (a) prior grades and standardized achievement scores are the strongest predictors of high school academic success, and (b) academic behavior (e.g., motivation, social engagement, and self-regulation) adds substantial incremental validity to the prediction of success. These findings highlight the importance of effective risk assessment based on a combination of achievement and behavior factors amenable to intervention. The discussion focuses on how educators can use such information to identify at-risk students early, assess their strengths and needs, and provide them with interventions designed to facilitate academic success.

Development and Validation of ENGAGE Grades 6-9

High academic failure and dropout rates remain significant issues in the United States, with estimates of over 25 percent of public school students failing to earn a high school diploma (Education Week, 2009; Stillwell, 2009). In some states and communities, these rates exceed 50 percent of all entering 9th-grade students. The No Child Left Behind (NCLB) legislation includes systematic monitoring of student progress through standardized achievement testing, but this alone does not ensure the proper identification of and intervention with at-risk students. We now know that measuring critical noncognitive factors can increase schools' abilities to identify and intervene with students at risk of academic failure and dropout (ACT, 2008; Zins, Bloodworth, Weissberg, & Walberg, 2004). In the psychological literature, noncognitive factors are often referred to as socioemotional learning (SEL) factors, psychosocial factors (PSFs), and behavioral factors. These terms are often used interchangeably to describe "academically and occupationally relevant skills and traits that are not specifically intellectual or analytical in nature" (Rosen, Glennie, Dalton, Lennon, & Bozick, 2010). Noncognitive factors include a range of attitudinal, behavioral, emotional, and personality characteristics that facilitate functioning well in one's environment, including school and work. It is worth noting that some of these factors tend to be more visible to others (e.g., behaviors like completing homework or certain personality traits like extraversion), whereas others are less visible (e.g., attitudes about school, emotions, and the processes by which individuals regulate them). Since this report is geared toward an education audience, we will use the term "academic behavior" as an umbrella that encompasses the full range of noncognitive factors (i.e., attitudinal, behavioral, emotional, and personality).

After reviewing studies of student dropout conducted over the past 25 years, Rumberger and Lim (2008) identified several factors that differentiate students who graduate from those who drop out of high school. Their list includes learning behaviors, attitudes, demographics, and characteristics of family and school. Similarly, the Baltimore Education Research Consortium (Mac Iver, 2010) found that poor grades and course failure is a strong predictor of high school dropout. These findings, among others, point to the importance of including psychosocial and behavioral data when assessing academic risk.

Several single-sample studies have examined the direct and indirect effects of noncognitive factors on academic success and retention rates, highlighting a range of constructs, including self-efficacy, motivation, locus of control, attitude toward learning, attention, and persistence, as well as strategy and flexibility (Grigorenko, Jarvin, Diffley III, Goodyear, Shanahan, & Sternberg., 2009; Yen, Konold, & McDemott, 2004). These findings are consistent with results of a large-scale review of student success research conducted in elementary and middle school, where a range of noncognitive constructs—self- and social-awareness, self-management, relationship skills, and responsible decision-making—were found to be key antecedents of student academic performance (e.g., Payton, Weissberg, Durlak, Dymnicki, Taylor, Shellinger, & Pachan, 2008).

Analogous results have been obtained during the transition to postsecondary education, where a combination of noncognitive factors, academic performance, and standardized achievement factors are highly predictive of first-year college academic success and retention behavior (Robbins, Allen, Casillas, Peterson, & Le, 2006). Using an assessment model based on motivation, social engagement, and self-regulation (see Le, Casillas, Robbins, & Langley, 2005; Robbins, Lauver, Le, Davis, Langley, & Carlstrom, 2004), noncognitive factors made incremental contributions beyond high school grade point average and standardized achievement for predicting college academic performance and persistence behavior (Robbins et al., 2006). Similar findings also have been obtained when predicting graduate school outcomes, where personality and behavioral data provide incremental validity contributions after controlling for college GPA and standardized test scores (Kyllonen, Walters, & Kaufman, 2005).

What is ENGAGE Grades 6-9?

Research suggests that one of the most effective ways to prevent poor academic performance and student dropout is to identify at-risk students early and assist them in their educational development (Balfanz, Herzog, & Mac Iver, 2007). Although standardized achievement tests have been shown to be valid and useful measures for predicting academic outcomes (ACT, 2007; Willingham, Lewis, Morgan, & Ramist, 1990), the utility of these measures for predicting student success and identifying at-risk students can be improved with assessment of academic behaviors.

ENGAGE Grades 6-9 (formerly known as the Student Readiness Inventory—Middle School) is designed to identify youth who are at academic risk by augmenting standardized achievement testing with measures of important academic behaviors. It is a low-stakes, self-report inventory made up of ten scales (106 items, 4th-grade reading level) that can be generally organized into three broad domains shown to be predictive of academic performance and persistence (Robbins et al., 2004, 2006; Robbins, Oh, Le, & Button, 2009):

- **Motivation** includes personal characteristics that help students to succeed academically by focusing and maintaining energies on goal-directed activities.
- **Social engagement** includes interpersonal factors that influence students' successful integration into their environment.
- **Self-regulation** includes the thinking processes and emotional responses of students that govern how well they monitor, regulate, and control their behavior related to school and learning.

ENGAGE captures students' perceptions of themselves, their families' commitment to education, school-related factors, and important behavioral indicators. It is designed for students in grades 6 through 9. Results from ENGAGE are reported as percentile rank scores based on norms from the ENGAGE Grades 6-9 field study (ACT, 2011a) and indicate whether students have developed the academic behaviors necessary to succeed in high school. In addition to individual student and advisor reports, both of which provide a broad profile of students' strengths and needs across the ten scales measured by ENGAGE, the instrument provides an academic success index (included on the advisor report only). This index is based on ACT's research using ENGAGE scales along with other information reported by students (e.g., previous grades, homework completion) to estimate the probability that a student will be academically successful (defined as obtaining a high school GPA of 2.0 or above). Further, ENGAGE provides a roster report, which allows educators to sort, filter, and merge student scores, and it also provides school and district aggregate reports, which allow school administrators to review the academic behaviors of entire groups of students (either at the school or district level). Based on the student-level information provided by ENGAGE, educators can identify students who may be at-risk of experiencing academic difficulties and connect them to interventions based on their areas of need. Further, administrators can use the aggregate-level data to assess whether group-based interventions (in a particular behavior area or at a particular school) may be needed. For more details on how to use ENGAGE and to view sample reports, consult the ENGAGE Grades 6-9 User's Guide (ACT, 2011a).

This report details the development and validation of ENGAGE, as well as its utility for identifying students who are at-risk of poor academic performance. The report concludes with a discussion of practical applications.

Developing a Comprehensive Conceptual Model

Development of ENGAGE followed a construct validation approach (Clark & Watson, 1995; Loevinger, 1957; Nunnally & Bernstein, 1994), a multi-step process by which researchers (a) describe a theoretical model, referred to as the "nomological net" (Cronbach & Meehl, 1955) consisting of one or more hypothetical constructs and their relations with one another and to observable criteria, (b) build measures identified by the theory, and (c) empirically test the hypothesized relations between the constructs and observable criteria. (For a detailed review of the construct validity approach to test construction, see Simms & Watson, 2007.)

The process for developing ENGAGE began with a thorough literature review to identify predictors of student academic performance and persistence in high school. Based on the existing literature, ACT researchers generated a comprehensive conceptual model for assessing middle school academic risk. Developers focused on predictors from five primary categories:

1) prior academic achievement,
2) noncognitive factors including motivation, social engagement, and self-regulatory factors,
3) observable behavioral indicators including time spent on homework and absenteeism,
4) school factors including average class size and percent of students eligible for free/reduced lunch, and
5) demographic factors including gender, race/ethnicity, and parental education.

This model is detailed in Table 1 (see on following page).

Our goal was to assess the relative importance of each category of variables across a large number of independent studies. We relied on effect size, a measure of the strength of the relationship between two variables, to summarize the results. We focused on bivariate relationships. It is worth noting that when these variables are combined into a single model/study (as in ENGAGE) each will likely make a smaller contribution because of intercorrelations. Thus, only articles and chapters containing sufficient information to calculate an effect size (e.g., means and standard deviations or correlations) were included. Key results for the outcomes of persistence and academic achievement are summarized below.

TABLE 1

Predictors Included in the Model of Middle School Academic Risk

Categories	Predictors		
Academic Achievement	▪ school grades ▪ EXPLORE scores		
Psychosocial Factors	<u>Motivation</u> ▪ Academic Discipline ▪ Commitment to School ▪ Optimism	<u>Social Engagement</u> ▪ Family Attitude toward Education ▪ Family Involvement ▪ Relationships w/School Personnel ▪ School Safety Climate	<u>Self-Regulation</u> ▪ Managing Feelings ▪ Orderly Conduct ▪ Thinking Before Acting
Behavioral Indicators	▪ days absent ▪ homework not done ▪ media time	▪ # of times changed schools ▪ time spent on homework	
School Factors	▪ percent free/ reduced lunch	▪ percent minority ▪ average class size	
Demographic Factors	▪ gender ▪ race/ethnicity ▪ parental education	▪ home resources ▪ family education aspirations	

Student Academic Achievement

As predictors of dropout, general academic competence and overall high school GPA varied considerably in terms of effect size, with most of them being small (range d = .14 to .28) (Cairns, Cairns, & Neckersman, 1989). However, specific core academic competencies such as English, math, and reading had higher effect sizes, ranging from moderate to large (range d = .44 to .80) (Fitzsimmons, Cheever, Leonard, & Macunovich, 1969; Kaufman & Bradbury, 1992; Lloyd, 1978). Having been held back in school consistently showed large effects (mean d = .96). This variable was also a good predictor of subsequent academic achievement, with a moderate to large effect size (range d = .39 to 1.00) (Lloyd, 1978; Rumberger, 1995).

Psychosocial Factors

The literature shows that student personality characteristics, student attitudes, and parental/family attitudes are all relevant predictors. Each of these is summarized below.

Student personality. Several personality characteristics have been found to predict both dropout and achievement, with a broad range of effect sizes reported. For example, motivation constructs, such as achievement motivation, academic discipline, as well as disinhibition and impulsivity, have demonstrated moderate effect sizes (mean d = .43) (Lounsbury, Saudargas, & Gibson, 2004; Peterson, Casillas, & Robbins, 2006; Robbins et al., 2006; Watson & Clark, 1993). Emotional stability and related constructs, such as aggression, self-esteem, and academic self-confidence demonstrated small to moderate effect sizes (mean d = .36) (Robbins et al., 2006; Marsh & Yeung, 1997). Further, optimism and self-efficacy showed moderate to large effect sizes (range d = .50 to .75) (Lounsbury et al., 2004; Capella & Weinstein, 2001; Skinner, Wellborn, & Connell, 1990).

Student attitudes. As predictors of dropout, measures of students' general attitude toward school showed small effect sizes (mean d = .26) (Alexander, Entwisle, & Kabbani, 2001), whereas measures of school commitment had a moderate predictive effect (mean d = .52) (Robbins et al., 2006; Vallerand, Fortier, & Guay, 1997). Students' expectations of educational attainment also had a small to moderate effect (mean d = .31) (Rumberger & Larson , 1998). As predictors of academic achievement, both general attitude and commitment to school showed moderate to large effects (range d = .29 to .80) (Marchant, Paulson, & Rothlisberg, 2001; Peterson et al., 2006).

Parental/family attitudes. As predictors of dropout, general parent and family attitudes toward education showed small effect sizes (range d = .06 to .14) (Alexander et al., 2001). However, more specific measures of parental attitudes toward education (e.g., communication with students about school, parental involvement in school activities, and educational expectations for students), evidenced large effects (range *d* = .95 to 1.67) (Jimerson, Egeland, Sroufe, & Carlson, 2000; Kaufman & Bradbury, 1992). These measures also were moderate to strong predictors of achievement (range *d* = .39 to .90) (Jimerson et al., 2000; Marchant et al., 2001; Seyfried & Chung, 2002).

Behavioral Indicators

As a predictor of dropout, disorderly conduct showed moderate effects (mean *d* = .50) (Finn & Rock, 1997; Kaufman & Bradbury, 1992). Further, student absenteeism showed moderate to large effects (mean *d* = .70) (Finn & Rock, 1997; Rumberger, 1995; Worrel & Hale, 2001). Time spent doing homework varied in effect size from small to large (range *d* = .22 to 1.30), depending on the response options (and resulting variance) used in each study. Generally, a greater range of response options led to higher effects (Kaufman & Bradbury, 1992). As a predictor of academic achievement, engaging in disruptive behavior showed moderate to large effects (range *d* = .40 to .80) (Kaufman & Bradbury, 1992), and student absenteeism evidenced moderate to very large effects (range *d* = .50 to 2.00) (Kaufman & Bradbury, 1992; Rumberger, 1995; Worrell & Hale, 2001).

School Factors

As predictors of dropout, a number of school characteristics (e.g., mean achievement scores, size, percent of minority students, percent of students eligible for free/reduced lunch) showed moderate effects (mean *d* = .65) (Kaufman & Bradbury, 1992), whereas measures of school climate showed small effects (mean *d* = .15). However, few studies have included measures of safety, which were reported to be predictive in some qualitative reports (e.g., Bridgeland, DiIulio, & Morison, 2006; Skiba, Simmons, Peterson, & Forde, 2006). As predictors of student academic achievement (e.g., grades), both school climate and mean standardized achievement scores (at the school level) showed moderate effects (mean *d* = .51) (Kaufman & Bradbury, 1992; Marchant et al., 2001; Worrell & Hale, 2001).

Demographic Factors

The research on demographic variables has been primarily used to examine dropout. In this context, age, ethnicity, and socioeconomic status (SES) showed moderate to strong effects (average d = .85, .46, and .64, respectively) (Cairns et al., 1989; Kaufman & Bradbury, 1992; Rumberger, 1995). Further, mobility (i.e., number of school moves) evidenced small to large effects, with larger effects for greater frequency of moves (range d = .14 to 1.21) (Kaufman & Bradbury, 1992; Rumberger, 1995; Rumberger & Thomas, 2000).

Theoretical Context

The aforementioned findings fit well within the broader theoretical literature on psychosocial predictors of academic success and persistence, in particular motivation, social engagement, and self-regulation (cf. Robbins et al., 2004). For example, Kanfer and Heggestad (1997, 1999) illustrated the importance of motivation and self-regulation as proximal determinants of goal-oriented behaviors when examining the effects on learning. Motivation and self-regulation are undergirded by three critical processes: self-monitoring, self-evaluation, and self-reactions (Kanfer & Ackerman, 1989; Kanfer & Heggestad, 1997). These processes are malleable to change through targeted intervention and reflect students' ability to motivate themselves to achieve via self-regulatory processes (Kuhl, 1985) as observed in study habits and skills. Robbins et al. (2009) included social engagement as another key mechanism in student success, especially as it relates to persistence behavior. Social engagement is associated with college retention (Robbins et al., 2006; Robbins et al., 2009) and could also be a mechanism to prevent high school dropout behaviors. Helping students feel connected to their school environment and able to take advantage of family, peer, and school supports can promote feelings of "belonging" in an educational environment, which is necessary for continued persistence behavior.

Inventory Development and Model Refinement

The conceptual model detailed in Table 1 provided the foundation for the ENGAGE scale development process, particularly for measures of student psychosocial characteristics and behavioral indicators. Briefly, ACT researchers developed items targeting the constructs in the conceptual model. These initial items were administered to samples of middle school students and exploratory and confirmatory factor analyses were used to examine the factors underlying these data. Items were screened based on their loadings on the factors. After collecting data from additional student samples, ACT researchers have continued to track these students throughout high school to collect outcome data and refine prediction models. Details about each of these steps are provided below.

Item Writing

A team of four applied psychologists wrote items to represent each of the psychosocial constructs included in the conceptual model. (See Table 2 for scales and definitions.) For each construct, the writers developed a definition and then wrote items to capture the construct. The writers first generated items independently and then met to discuss the items to be retained and/or revised.

TABLE 2

ENGAGE Grades 6-9 Scale Definitions, Sample Items, and Behavioral Indicators[1]

Domain	Scale Name	Definition	Sample Item
Motivation	Academic Discipline	Degree to which a student is hardworking and conscientious as evidenced by the amount of effort invested into completing schoolwork.	I turn in my assignments on time.
	Commitment to School	Commitment to stay in school and obtain a high school diploma.	I am committed to graduating from high school.
	Family Attitude toward Education	Positive family attitude regarding the value of education.	My family supports my efforts in school.
Social Control	Family Involvement	Family involvement in a student's school life and activities.	I talk to my family about schoolwork.
	Managing Feelings	Tendency to manage duration and intensity of negative feelings and to find appropriate ways to express feelings.	I would walk away if someone wanted to fight me.
	Optimism	A hopeful outlook about the future in spite of difficulties or challenges.	I am confident that everything will turn out all right.
	Orderly Conduct	Tendency to behave appropriately in class and avoid disciplinary action.	I have been sent to the principal's office for misbehaving.

[1] Based on research concerning the optimal number of response options in Likert-type scales (Green & Rao, 1970; Matell & Jacoby, 1972), items were set to a 6-point Likert-type response scale, ranging from *strongly disagree* (1) to *strongly agree* (6). The Orderly Conduct items, which use a Yes/No response scale, were an exception.

TABLE 2 (continued)

Domain	Scale Name	Definition	Sample Item
Self-Regulation	Relationships with School Personnel	The extent to which students relate to school personnel as part of their connection to school.	Adults at my school understand my point of view.
	School Safety Climate	School qualities related to students' perception of security at school.	I feel safe at school.
	Thinking Before Acting	Tendency to think about the consequences of one's actions before acting.	I think about what might happen before I act.
Behavioral Indicators	Absenteeism	Number of absences, days tardy, and skipped classes reported by the student over the past month.	How many days were you absent from school in the past month?
	Held back	Having been held back from normal grade progress.	Have you ever been held back from moving to the next grade?
	Homework time	Time spent on homework on a typical school day.	How many hours do you usually spend doing homework on a school day?
	Media time	Time spent watching TV, playing video games, and surfing the Internet (for non-school related purposes) during a typical school day.	How many hours do you usually watch TV on a school day?
	School Mobility	Number of times that the student changed schools since starting elementary school.	How many times have you ever changed schools?

Preliminary Test of Item Clarity

To ensure that the items would be comprehensible to middle school students, we administered the items to a small group of 6th- to 8th-grade students (N = 25; 72% White; 52% female; mean age = 12.3 years, SD = 1.0, range 11 to 14 years). The students were asked to rate the extent to which they understood the meaning of the items using a 5-point Likert-type scale ranging from *very easy to understand* (1) to *very difficult to understand* (5). Based on these mean ratings of item clarity, we deleted or revised items. Subsequently, the revised items were presented to a group of experts in education and communication, who were asked to comment on item clarity. The items were again revised based on this feedback.

Pilot Test

Next, we collected data for a pilot version of ENGAGE items at four middle schools. The pilot study data were used to establish the initial structure and psychometric properties of the scales, as well as to guide item revision for the next phase of research and development.

Advisory Group

Concurrent with the pilot test, ACT staff convened an advisory group composed of a broad range of experts in fields related to K-12 education administration, academic failure/dropout, and secondary school remediation/intervention. The advisory group provided feedback on the model of middle school academic risk, our choice of scales and behavioral indicators, and some preliminary use cases. The general consensus was that this model appropriately captured the constructs theoretically expected to predict high school academic success.

Based on results from the pilot test and the recommendations of the advisory group, ACT researchers made additional modifications to ENGAGE scales in preparation for the field study.

Item Selection and Scale Structure

To identify the factors (scales) underlying ENGAGE items and to identify those items most strongly associated with each scale, ACT researchers conducted both exploratory and confirmatory factor analyses using the pilot test sample (N = 1,664).

Exploratory Factor Analysis

We used exploratory factor analysis to understand the structure of ENGAGE item-level data and to select items. These analyses were carried out on two-thirds of the total sample from the pilot (N = 1,098). We used a “bottom-up” strategy in which we built scales independent of one another. That is, we ran a separate factor analysis for the items written to represent each scale to determine whether they tapped a single dimension (as intended). We specified principal axis factoring as the extraction method and used varimax rotation (cf. Nunnally & Bernstein, 1994; Gorsuch, 1997). In the majority of cases, a single factor solution was clearly indicated. In these cases, items with loadings of .40 or higher on the first principal component were retained for further analysis.

Confirmatory Factor Analysis

Next, we used confirmatory factor analysis to (a) confirm each of the dimensions identified in the previous step and (b) select a final set of items to represent each of the scales. The confirmatory factor analysis was carried out on the remaining one third of the total sample from the pilot (N = 566) using EQS software for structural equation modeling (Bentler, 1995). For each dimension, we specified one-factor solutions using the items that were retained from the exploratory step. The fit of the intended model to the data was assessed using several fit indexes [i.e., Comparative Fit Index (CFI), Global Fit Index (GFI), Root Mean Square Error of Approximation (RMSEA), and Standard Root Mean Square Residual (SRMR); see Hu & Bentler, 1999]. Items that showed clear loadings on their respective dimensions in the results of *both* the exploratory and confirmatory factor analyses were selected for the final versions of the scales. After the exploratory-confirmatory steps described above, approximately 30% of the items were discarded.

The Field Study

Participants

During the Spring and Fall of 2006, ACT staff recruited districts throughout the country to participate in the ENGAGE field study. To be invited to participate, schools needed to: (a) be made up of students representing a broad range of demographic and achievement characteristics, (b) use ACT's EXPLORE program, and (c) agree to provide follow-up data as the students moved into and through high school.

A total of 4,660 students from 24 middle schools from 13 districts participated in the field study. Most participating students spoke English as their primary language (98%) and were Caucasian (62%)[2]. Students' mean age was 13.5 years (*SD* = .7), the sample was evenly split on gender (51% male), and the majority were enrolled in 8th grade (83%), with the remainder enrolled in 7th grade.

Of the initial sample of 4,660 students, 3,757 (81%) also took the EXPLORE assessment, which is typically administered in the 8th grade. Among students who took EXPLORE, 51% were male, 98% spoke English as their primary language, and 64% were Caucasian. Students varied in age from 12 to 16 years old (*M* = 13.6, *SD* = .6). Thus, the subsample of students who took EXPLORE was similar in demographics to the larger study sample.

As part of the study, school districts agreed to provide follow-up information (i.e., enrollment status and high school grades) for the students who participated in the initial phase of the study. Follow-up information was obtained two years later for 3,325 students enrolled in 9th and 10th grade at the time of follow-up, who comprised 71% of the original study sample and 89% of the EXPLORE-tested sample. Demographic characteristics for the subsample of students with follow-up information were similar to those of the original sample (69%

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[2] The remaining race/ethnicity breakdown was: 16% Hispanic/Latino, 10% African American, 3% Multiracial, 2% Asian American/Pacific Islander, 1% American Indian/Alaskan Native, and 7% of "other" or unknown race/ethnicity.

Caucasian; 51% male; 99% spoke English as primary language; mean age = 13.6 years, *SD* = .6). Academic behavior variables also were similar for the original sample and the subsample with follow-up data.

Procedure

ENGAGE was administered to the field test sample in group settings during class time. Students were told that participation was voluntary, their results would be kept confidential, and the questionnaire would require approximately 30 minutes. Participating schools and districts were provided with group-level summaries of their students' results as an incentive for participating. Additional summaries were provided to districts after each follow-up wave of data collection.

Psychometric Properties of ENGAGE Grades 6-9

The following descriptive statistics, reliability estimates, and convergent/discriminant relationships with other scales and constructs were derived from the field study sample.

Scale Reliability

ENGAGE scales are relatively short (range = 9 to 12 items) and have good to excellent internal consistency reliabilities (Crobanch coefficient alpha range = .81 to .90; median = .87; see Table 3).

TABLE 3

Descriptive Statistics and Intercorrelation Matrix for the ENGAGE Grades 6-9 Scales

	Scale Name (# of items)	M	SD	1	2	3	4	5	6	7	8	9	10
1	Academic Discipline (11)	4.80	0.92	*.92*									
2	Commitment to School (10)	5.63	0.60	.53	*.88*								
3	Optimism (10)	4.79	0.93	.54	.50	*.90*							
4	Family Attitude toward Education (10)	5.55	0.67	.46	.63	.44	*.88*						
5	Family Involvement (9)	4.67	1.04	.53	.46	.56	.57	*.86*					
6	Relationships with Sch. Personnel (12)	3.95	1.02	.47	.35	.54	.33	.53	*.90*				
7	School Safety Climate (11)	4.19	0.96	.37	.33	.42	.31	.36	.56	*.84*			
8	Managing Feelings (12)	3.83	1.20	.53	.29	.40	.25	.38	.48	.37	*.90*		
9	Orderly Conduct (9)[a]	0.68	0.30	.55	.29	.32	.25	.32	.38	.34	.62	*.83*	
10	Thinking before Acting (12)	3.91	1.10	.51	.28	.41	.25	.37	.43	.31	.55	.49	*.87*

Note. Range N = 2,982 to 4,646. Cronbach's alphas featured on the diagonal in *italics*. Correlations with absolute value exceeding .05 are significant ($p \leq .01$). [a]Scale scored as Y/N; all other scales scored on a 6-pt Likert scale.

Convergent/Discriminant Validity of ENGAGE Scales

Intercorrelations among ENGAGE scale scores are presented to provide a clear picture as to how the scales of the instrument related to each other. Intercorrelations among the scales show a reasonable convergent/discriminant pattern, with scales generally correlating more strongly with those scales that are conceptually similar than with other scales (see Table 3). For example, the motivation scales (Academic Discipline, Commitment to School, and Optimism) showed generally larger correlations with each other (range r = .50 to .54, median = .53) than with other scales (range r = .28 to .63, median = .44). A similar pattern was seen for the self-regulation scales (Managing Feelings, Orderly Conduct, and Thinking before Acting) in which these scales tend to relate more strongly among themselves (range r = .49 to .62, median = .55) than with other scales (range *r* = .25 to .55, median = .37). Although the social engagement scales (Family Attitude toward Education, Family Involvement, Relationships with School Personnel, and School Safety Climate) also showed a pattern of convergent/discriminant correlations, this pattern was less clear. Nevertheless, these scales still correlated more strongly among themselves (range *r* = .31 to .57, median = .45) than with other scales (range *r* = .25 to .63, median = .38). (See Table 3 for a full intercorrelation matrix of ENGAGE scales.)

Relationships with Other Constructs

ENGAGE scales have the expected relationships with other constructs as well. We examined correlations with behavioral indicators (e.g., absenteeism, times without homework), academic achievement (e.g., prior grades, EXPLORE scores), school-level factors (e.g., percent minority, average class size), and demographic factors (e.g., gender, parental education). The following sections detail these results.

Behavioral indicators. As shown in Table 4, ENGAGE scales are mildly to moderately related to time spent on homework assignments (Hours Spent on Homework; range *r* = .13 to .24, median = .17). In addition, ENGAGE scales are moderately to strongly (negatively) related to frequency of students not having their homework completed (Homework Not Done range *r* = -.19 to -.58, median = -.30). Further ENGAGE scales are mildly to moderately (negatively) related to time spent watching television, playing videogames, or browsing the Internet for nonacademic purposes (Media Time range *r* = -.16 to -.28, median = -.19); times absent, tardy, and/or skipping class (Absenteeism range *r* = -.19 to -.36, median = -.22); and less strongly related to the number of times that a student has changed schools (Times Changed School range *r* = -.07 to -.14, median = -.10). Thus, ENGAGE scales are correlated with several key behavioral indicators that have been linked to academic success in the literature (Kaufman & Bradbury, 1992; Rumberger, 1995; Rumberger & Larson, 1998).

TABLE 4

Correlations between ENGAGE Grades 6-9 Scales and Behavioral Indicators

	Behavioral Indicators				
Scales	**Hours Spent on Homework**	**Homework Not Done**	**Media Time**	**Absenteeism**	**Times Changed School**
Academic Discipline	.24	-.58	-.27	-.36	-.14
Commitment to School	.17	-.27	-.18	-.24	-.08
Family Attitude toward Education	.14	-.23	-.16	-.22	-.07
Family Involvement	.20	-.30	-.19	-.21	-.10
Managing Feelings	.17	-.34	-.28	-.26	-.13
Optimism	.13	-.30	-.17	-.20	-.12
Orderly Conduct	.18	-.36	-.27	-.33	-.14
Relationships with School Personnel	.17	-.28	-.17	-.21	-.09
School Safety Climate	.13	-.19	-.17	-.19	-.08
Thinking Before Acting	.16	-.33	-.24	-.20	-.10
Median	*.17*	*-.30*	*-.19*	*-.22*	*-.10*

Note. Range N = 2,741 to 4,619. Correlations with absolute value exceeding .05 are significant ($p \leq .01$).

Academic achievement. As shown in Table 5, ENGAGE scales are positively associated with indicators of academic achievement. For example, they are moderately related to school grades earned prior to students completing ENGAGE (range r = .15 to .52, median = .30). Based on the literature, the associations of ENGAGE scales with standardized achievement measures, such as EXPLORE scores, are expected to be somewhat lower than those with grades. Measures of academic behavior tap achievement-related content that is expected, and has generally been shown, to be distinct from most cognitive skills and standardized achievement measures (e.g., Lounsbury, Sundstrom, Loveland, & Gibson, 2003; Robbins et al., 2006; Watson & Clark, 1993). Table 5 also shows relationships between ENGAGE scales and EXPLORE scores. As can be seen, these relationships are generally low to moderate and provide further evidence of discriminant validity.

TABLE 5

Correlations between ENGAGE Grades 6-9 Scales and Academic Achievement

	Academic Achievement					
Scales	**Prior Grades**	**EXPLORE Composite [a]**	**EXPLORE English [a]**	**EXPLORE Math [a]**	**EXPLORE Reading [a]**	**EXPLORE Science [a]**
Academic Discipline	.52	.27	.25	.22	.22	.26
Commitment to School	.31	.23	.21	.20	.19	.20
Family Attitude toward Education	.27	.22	.20	.18	.19	.19
Family Involvement	.28	.13	.13	.08	.12	.13
Managing Feelings	.31	.21	.20	.17	.16	.21
Optimism	.31	.14	.13	.12	.11	.14
Orderly Conduct	.37	.28	.26	.22	.23	.27
Relationships with School Personnel	.28	.13	.14	.09	.11	.13
School Safety Climate	.15	.08	.08	.06	.05	.09
Thinking Before Acting	.28	.15	.14	.11	.12	.15
Median	*.30*	*.18*	*.17*	*.15*	*.14*	*.17*

Note. Range N = 2,936 to 4,537. [a] Range N = 2,785 to 3,765. Correlations with absolute value exceeding .05 are significant ($p \leq .01$).

School factors. As expected, ENGAGE scale scores are generally unrelated to school-level factors (see Table 6), including the percent of minority students in a school (range r = .00 to -.17, median = -.08), the percent of free or reduced-lunch recipients (range r = -.05 to -.19, median = -.11), average class size (range r = .01 to .10, median = .06), and student-teacher ratio (range r = .02 to .15, median = .08). These findings are consistent with the literature showing that academic behavior measures are generally unrelated to these types of school factors (Glovinsky-Fahsholtz, 1992; Wyss, Tai, & Sadler, 2007).

TABLE 6

Correlations between ENGAGE Grades 6-9 Scales and School Factors

	School-level Factors			
Scales	**% minority**	**% free lunch**	**Average Class Size**	**Student-Teacher Ratio**
Academic Discipline	-.12	-.14	.08	.08
Commitment to School	-.05	-.11	.05	.10
Family Attitude toward Education	-.02	-.09	.06	.08
Family Involvement	-.08	-.10	.02	.03
Managing Feelings	-.10	-.13	.09	.10
Optimism	-.04	-.05	.01	.02
Orderly Conduct	-.12	-.17	.10	.12
Relationships with School Personnel	-.07	-.08	.01	.07
School Safety Climate	-.17	-.19	.03	.15
Thinking Before Acting	.00	-.06	.08	.03
Median	*-.08*	*-.11*	*.06*	*.08*

Note. Range N = 2,975 to 4,660. Correlations with absolute value exceeding .05 are significant ($p \leq .01$).

Demographic factors. Table 7 features relationships between ENGAGE scales and demographic factors. ENGAGE scales showed low to moderate relationships with demographic factors. Instances in which these relationships were moderate in magnitude (e.g., Orderly Conduct with male gender; Family Involvement with home resources; Commitment to School and Family Attitude toward Education with family educational aspirations) make intuitive sense and are consistent with previous research indicating that males are more likely to engage in disruptive behaviors (e.g., Cohn & Modecki, 2007; Zimmer-Gembeck, Geiger, & Crick, 2005), family resources are related to parental involvement in their children's academic endeavors (Alexander et al., 2001; Desimone, 1999; Sui-Chu & Willms, 1996), and educational achievement is related to family educational aspirations (Fan & Chen, 2001; Hill & Tyson, 2009). Although relationships between academic achievement and academic behaviors may vary somewhat by demographic groups, this study did not address this issue.

TABLE 7

Correlations between ENGAGE Grades 6-9 Scales and Demographic Factors

	Demographic Factors				
Scales	**White**	**Male**	**Parent Education**	**Home Resources**	**Fam. Edu. Aspirations**
Academic Discipline	.13	-.17	.17	.25	.23
Commitment to School	.07	-.16	.16	.22	.30
Family Attitude toward Education	.06	-.08	.20	.26	.30
Family Involvement	.11	-.05	.22	.30	.21
Managing Feelings	.15	-.20	.15	.18	.14
Optimism	.05	-.06	.17	.23	.20
Orderly Conduct	.17	-.25	.13	.18	.14
Relationships with School Personnel	.11	-.10	.10	.19	.15
School Safety Climate	.12	-.06	.04	.08	.06
Thinking Before Acting	.04	-.08	.10	.16	.10
Median	*.11*	*-.09*	*.16*	*.21*	*.18*

Note. Range N = 2,975 to 4,660. Correlations with absolute value exceeding .05 are significant ($p \leq .01$).

Predictive Validity

As stated previously, ACT researchers partnered with the school districts that participated in the field study to follow the 4,660 participating students as they progress through high school. Given the difficulty in studying dropout before the age of 16 due to state mandatory school attendance requirements, we used early high school GPA (during either 9th or 10th grade) as a direct measure of academic performance. Failing one or more courses—and by extension having a low high school GPA—can be considered a proxy of eventual dropout risk (see Mac Iver, 2010; Rumberger & Lim, 2008).

Analyses

Regressions. Linear regression models were run to test our hypotheses that academic behaviors (i.e., psychosocial and behavioral variables) are predictive of high school GPA after controlling for the effects of traditional predictors (school-level, demographic, and academic achievement variables). In model 1, high school GPA was regressed on school and demographic characteristics. In model 2, measures of academic achievement were added to the model, including prior grades earned and EXPLORE Composite score. In model 3, the behavioral indicator variables were added followed by the psychosocial variables in model 4. Multiple R was used to measure the overall predictive strength of the four models. Fitting the models sequentially allows us to measure how much each set of predictors adds to the overall predictive strength.

Capture rates. True positive and capture rates are measures that are meaningful if a model's predicted values are used to identify students who are at high risk of failing academically in the future. Here, we define the true positive rate as the probability of an unsuccessful outcome, given that a student is flagged for intervention. The capture rate is the probability of a student having been flagged, given that they have an unsuccessful outcome. The true positive and capture rates can be calculated as a function of R for linear regression models (Allen, Robbins, & Sawyer, 2010). We assumed that students ranking in the bottom p% of predicted values (p = 5, 10, 25) would be flagged, and calculated true positive and capture rates for identifying students with early high school GPA less than 2.0. Three models for identifying at-risk students were compared for each outcome: (a) random selection; (b) prior grades and EXPLORE Composite scores; and (c) prior grades, EXPLORE Composite scores, psychosocial variables, and behavioral indicators.

Dominance analysis. Because of correlation between and within sets of predictor variables, the relative importance of a set of predictor variables cannot be determined from regression coefficients or beta weights. Moreover, while the sequential regression models allow us to measure how much each set of predictors adds to the overall strength in predicting early high school GPA, they do not allow us to determine the relative importance of each set of predictors.

Accordingly, we used the dominance analysis technique (Azen & Budescu, 2003) to compare the relative importance of each set of predictors. Dominance analysis is based on an examination of the R^2 values for all possible subset models—or all possible models formed by each possible combination of predictor variables. The R^2 attributed to each predictor is determined by analyzing the R^2 values for all subset models to which the predictor belongs. The total amount of variation explained by each set of predictor variables is then obtained by summing the R^2 attributed to each predictor within the set. The dominance analysis technique is attractive in that the importance of each predictor is estimated irrespective of order of model entry. It is also conceptually appealing in that it makes no assumptions about the causal relationships between predictor variables in the model. For example, the dominance analysis technique allows us to measure the importance of academic achievement measures and academic behaviors in predicting early high school GPA, without requiring us to specify a model for the relationship between the psychosocial and academic achievement variables. Such a model would likely need to capture complex relationships—such as the effects that motivation, social engagement, and self-regulation have on academic achievement and subsequent behavior.

Moderation between achievement and psychosocial risk. Finally, we examined the combined effects of achievement and psychosocial risk by sorting our participants into a 3 x 3 matrix of high-medium-low achievement (based on EXPLORE Composite scores) along one dimension and high-medium-low psychosocial scores (based on ENGAGE Grades 6-9) along the other dimension. In addition to examining main effects of these predictors, we explored the possibility of moderation between academic achievement and psychosocial scores.

Results

Prediction of high school GPA. All academic, psychosocial, and behavioral indicators were significantly related (at the bivariate level) to early high school GPA. The bivariate associations of early high school GPA with middle school grades (r = .64) and EXPLORE Composite score (r = .56) were the largest in magnitude. These were followed by the associations of the psychosocial factors (range r = .18 to .48; median = .28), behavioral indicators (range r =|.10| to |.41|; median = |.20|), demographic factors (range r = .05 to .29; median = .19), and finally school-level factors (range r = |.01| to |.21|; median = |.16|) (see Table 8). This table also features the results of the four sequential linear regression models; beta weights for the variables are presented. The first model included school-level and demographic predictors and yielded an R of .397. The second model added academic achievement variables, and this model yielded an R of .711. The third model added the behavioral indicators and yielded an R of .730; the fourth model added the psychosocial variables and yielded an R of .742. F-statistics confirmed that each sequential model's increase in R was a statistically significant increase over the previous model.

TABLE 8

Correlations and Beta Weights for Predictors of Early High School GPA

Predictor	***r***	**Model**			
		1	**2**	**3**	**4**
School-level					
% free lunch	-.16	-.049	-.017	.000	.019
% minority	-.21	-.047	-.054*	-.059*	-.061*
Average Class Size	.01	-.076*	-.112*	-.108*	-.098*
Demographic					
Gender (male)	-.17	-.184*	-.101*	-.083*	-.068*
Race/Ethnicity					
White	.26	.160*	.063*	.052*	.036
Black	-.16	-.061*	-.016	-.025	-.026
Hispanic	-.17	-.017	-.014	-.020	-.023
Asian	.05	.079*	.030	.025	.019
Parent's Education	.29	.211*	.040*	.030	.028
Academic Achievement					
Prior Grades	.64		.431*	.353*	.316*
EXPLORE Composite Score	.56		.302*	.296*	.297*
Behavioral Indicators					
Number of Days Absent	-.22			-.050*	-.041*
Skipped Class	-.22			-.053*	-.023
Homework Not Done	-.41			-.146*	-.102*
Was Held Back	-.20			-.022	-.020
Media Time	-.19			-.007	.011
Psychosocial					
Academic Discipline	.48				.088*
Managing Feelings	.34				.027
Commitment to School	.26				-.054*
Family Attitude toward Education	.26				.046*
Family Involvement	.28				.028
Optimism	.27				-.009
Orderly Conduct	.43				.081*
Relationships with School Personnel	.28				.005
School Safety Climate	.18				.021
Thinking Before Acting	.24				-.049*
Model *R*		.397	.711	.730	.742

Note. n = 3,278 for multiple regression models. Correlations with absolute value exceeding .05 are significant ($p \leq .01$). Predictors marked with an asterisk are significant ($p \leq .01$).

In Table 8, effect sizes are represented by both Pearson's correlations (*r*) and beta weights (*b*). Both metrics can be interpreted as the estimated increase in GPA (in standard deviation units) associated with a standard deviation increase in the predictor. In the final model, prior grades (b = .316) and EXPLORE Composite score (b = .297) remained the strongest predictors, with significant incremental validity added by Academic Discipline (b = .088), Orderly Conduct (b = .081), Family Attitude (b = .046), Homework Not Done (b = -.102), and Number of Days Absent (b = -.041). Interestingly, the psychosocial variables Commitment to School (b = -.054) and Thinking Before Acting (b = -.049) had negative weights in the final model. This is likely a product of model multicollinearity and employing a large number of predictor variables (26 total) in model 4, as the bivariate correlations between Commitment to School and Thinking Before Acting with early high school GPA were positive and significant.

Because students are nested within high schools, we considered using hierarchical linear modeling (HLM; Raudenbush & Bryk, 2002) to model the outcomes of interest. However, we chose to use ordinary least squares regression because it permitted use of the dominance analysis technique (described earlier). To test the sensitivity of our model to school effects, we also modeled early high school GPA using hierarchical linear regression with random intercepts for each high school. Although there was evidence of variation across high schools in average high school GPA (the variance of intercepts across schools was estimated at 0.06, $p < .05$), the HLM model results were very similar to the multiple linear regression results. The regression coefficient estimates for the student-level predictors (demographics, academic achievement, psychosocial factors, and behavioral indicators) differed by 0.02 or less. All student-level variables that were significant in the multiple regression model were significant in the HLM model, and vice-versa. Thus, only the results of the regressions are reported in this document.

Accuracy of classification. Table 9 features accuracy of classification models based on true positive and capture rates. Both rates depend on the percentage of students who are flagged—true positive rates decrease as the percentage of students flagged increase, whereas capture rates increase with an increase in the percentage of students flagged. As shown in Table 9, use of prior grades and achievement score results in substantial increases in accuracy (i.e., increased true positive rate) over random selection for identifying students who subsequently earned a low GPA (i.e., < 2.0) during the 9th or 10th grades (probability increases over random selection by 0.609, 0.543, and 0.391 for 5, 10, and 25% of students flagged). Further, the combination of prior grades, EXPLORE Composite score, and psychosocial and behavioral indicators results in the highest level of accuracy (a 0.609 probability increase over random selection, for a total accuracy of 0.905 when 5% of students are flagged). The capture rates also demonstrate the incremental utility of using psychosocial and behavior measures. When 25% of students are flagged, 55.5% of the students who will struggle academically in high school are included among those flagged based on prior grades and EXPLORE Composite scores. This percentage increases to 58% when psychosocial and behavioral indicators are also used for flagging.

TABLE 9

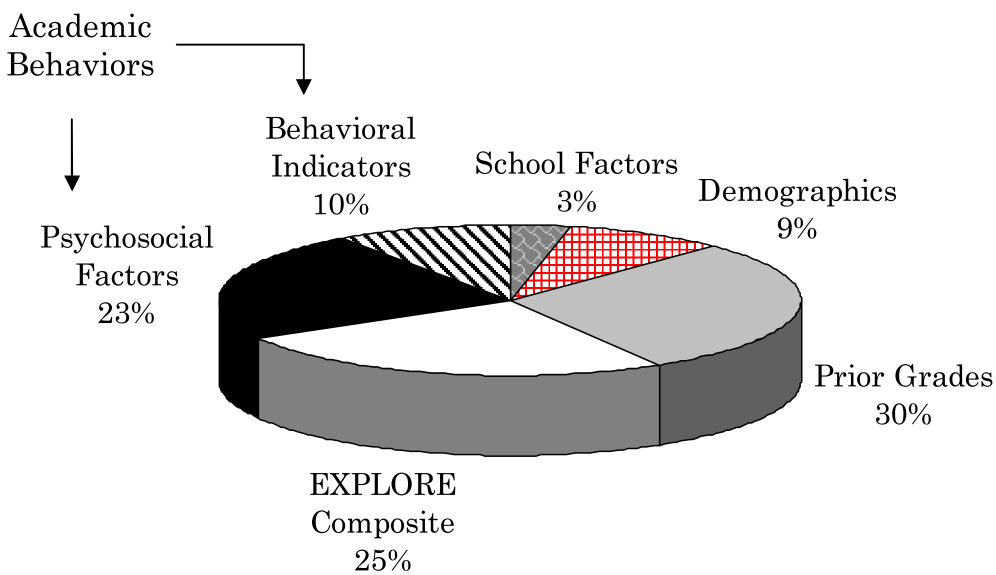
Accuracy of Identifying Students with Early High School GPA < 2.0

Flagging Variables	True Positive Rate	Capture Rate
5% flagged		
1. None (Students Flagged at Random)	0.296	0.050
2. Prior Grades, EXPLORE Composite	0.873	0.147
3. Prior Grades, EXPLORE Composite, psychosocial variables & behavioral indicators	0.905	0.153
10% flagged		
1. None (Students Flagged at Random)	0.296	0.100
2. Prior Grades, EXPLORE Composite	0.804	0.271
3. Prior Grades, EXPLORE Composite, psychosocial variables & behavioral indicators	0.839	0.283
25% flagged		
1. None (Students Flagged at Random)	0.296	0.250
2. Prior Grades, EXPLORE Composite	0.658	0.555
3. Prior Grades, EXPLORE Composite, psychosocial variables & behavioral indicators	0.687	0.580

Note. The true positive rate is the probability of having early high school GPA < 2.0 among students scoring in the bottom p% on the flagging variables (p = 5, 10, 25). The capture rate is the probability of scoring in the bottom p% on the flagging variables among students with high school GPA < 2.0.

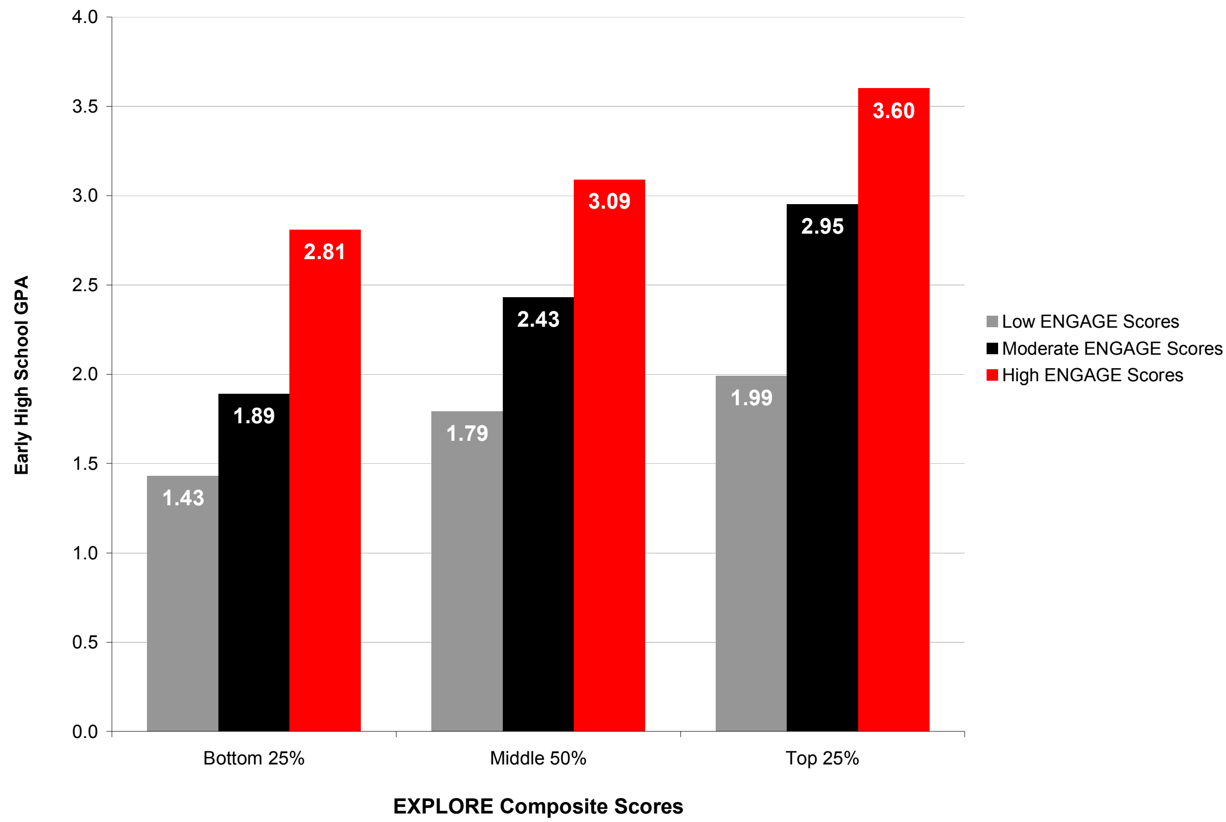
Dominance analysis. Figure 1 reports the relative importance of each set of predictors in predicting early high school GPA using the dominance analysis technique (Azen & Budescu, 2003). One of the primary benefits of using the dominance analysis technique is that the relative importance of sets of predictors are measured, irrespective of sequence of entry into the model and irrespective of theorized directions of causality between predictors. The results in Figure 1 show that prior grades were the most important predictor, with 30% of the explained variation attributed to it. Next, came EXPLORE Composite (25%), psychosocial factors (23%), behavioral indicators (10%), demographic variables (9%), and school characteristics (3%). Although the sequential regression models suggest that academic behaviors (i.e., psychosocial factors and behavioral indicators) add a significant but limited amount of explained variance to the model, the dominance analysis shows that academic behaviors are a key contributor (explaining 33% of variation in early high school GPA) when the sequence of model entry is ignored.

FIGURE 1 Relative Strength of Predictors of Early High School GPA



Interplay of academic achievement and behavior. Another way of presenting our study findings for early high school GPA is illustrated in Figure 2. To create this figure, students were classified into subgroups according to their EXPLORE Composite scores and their average ENGAGE scale scores. For each set of scores, students were classified into one of three groups: lower quartile (lowest 25%), middle quartiles (middle 50%), or upper quartile (highest 25%). On the left side of this figure, the first three bars show students who scored in the lowest quartile of EXPLORE Composite scores. Within this group, students who scored higher on ENGAGE tended to earn higher GPAs. This pattern is consistent across EXPLORE score groups. Thus, Figure 2 illustrates the presence of two main effects on early high school GPA. The first main effect is that of prior academic achievement, as measured by the EXPLORE Composite score $F(2, 3422) = 198.9$, $p < .01$. The second main effect is that of psychosocial factors, as measured by the average rank of the ten scales of ENGAGE $F(2, 3422) = 112.2$, $p < .01$. Further, we tested for moderation (i.e., the interaction in "cell" or column differences between academic achievement and psychosocial factors) and results showed that moderation was indeed present $F(4, 3422) = 4.44$, $p < .01$. The test of moderation suggests that the strength of the effect of the psychosocial scores depends on prior academic achievement, or vice-versa. In particular, the differences between "low" and "medium" psychosocial scores increase as prior academic achievement level increases. This finding suggests that, although students of all achievement levels may benefit from positive academic behavior, students with higher academic achievement tend to benefit the most.

FIGURE 2 Average Early High School GPA by EXPLORE and Average ENGAGE Grades 6-9 Score Groups



Summary and Discussion

ENGAGE was developed to assess a range of academic behaviors believed to be related to academic performance and persistence based on existing theoretical perspectives (i.e., motivational, social engagement, and self-regulatory) and empirical evidence documented in the literature. The set of predictors used to model school success also included a range of more "traditional" variables, such as prior grades, standardized achievement test scores, demographic, and school-level factors. Altogether, the measurement model presented in this report is among the most comprehensive available in the literature.

The field study that served as the final stage of instrument development focused on a large cohort of 7th- and 8th-grade students across 24 middle schools from 13 districts throughout the Midwest and Southern regions of the U.S. ACT researchers have been tracking these students through high school with a fairly high follow-up rate (71% of the original sample).

Based on the field study data, ENGAGE has good to excellent psychometric properties. Specifically, ENGAGE scales have good to excellent internal consistency reliability (median alpha = .87). The instrument showed a pattern of convergent/discriminant relationships with other variables and constructs consistent with the expectation for a measure of academic behaviors. For example, ENGAGE scales were more strongly correlated with prior grades than with achievement test scores. Further, they were strongly correlated with a variety of behavioral markers of academic success, such as regular homework completion and (lack of) absenteeism, and less correlated with school-level and demographic factors. Finally, ENGAGE demonstrated the expected higher-order structure (consisting of three higher-order factors: Motivation, Social Engagement, and Self-Regulation), which parallels that of the college version of ENGAGE (ACT, 2011b; Le et al., 2005).

This report expands previous ACT longitudinal research bridging high school and college (e.g., Robbins et al., 2006), which focused on the effects of achievement and academic behaviors on college academic performance and persistence (and culminated in the development of ENGAGE College). The current report focuses on the development of ENGAGE and its validity for predicting high school academic performance, thus extending ACT's academic behavior research to the transition from middle school to high school. The findings confirm that academic achievement indicators (i.e., prior grades, standardized achievement scores) are the strongest predictors of future academic success. These findings are consistent with those of earlier longitudinal studies, in which course performance during middle school was a key indicator of subsequent academic performance and eventual high school graduation (e.g., Allensworth & Easton, 2005, 2007; Bowers, 2010; Mac Iver 2010).

The findings also show that academic behaviors contribute to the prediction of future academic performance and thus can be useful in identifying middle school students who are at high risk of failing academically and dropping out of high school. This has significant implications for combining academic behavior and achievement information to support the timely identification of at-risk students. As demonstrated in this study, the predictive factors in question were clearly present in middle school and can be assessed and used to help students to better prepare for—and successfully navigate—the transition from middle to high school.

With this enhanced arsenal of information, intervention programs can be more successfully directed toward the students who need help. Compared to early warning systems based on archival data alone (e.g., Balfanz et al., 2007), our findings show that including academic behaviors provides significant (though modest) incremental power for predicting later academic achievement. More important than the improvement in prediction, measuring academic behaviors can help educators understand *why* students are at risk. As the dominance analysis shows (33% of the explained variation in early high school GPA is attributed to the combination of psychosocial factors and behavioral indicators), these factors play a prominent role in understanding students' risk for academic difficulties and will be key in intervening with students who are at risk.

By measuring the range of characteristics related to academic success (or risk), educators can align interventions to students' unique needs and have a better chance of improving their performance. Educators need to be able to address students' academic behavior needs before they manifest in failing grades or dropout. There is some research on the positive effects of self-regulatory, motivational, and social skill training on students (e.g., Pintrich & DeGroot, 1990) and on workers (e.g., Lord, Diefendorff, Schmidt, & Hall, 2010). More research is needed to better map interventions onto students' academic behavior needs and to understand how institutional and family contexts can either facilitate or impede the effectiveness of such interventions.

From an individual student narrative perspective (cf. McAdams & Olson, 2010), understanding the unique interplay of school, family, and individual achievement and academic behavior factors allows schools to better know each student, be able to tell that student's "story," and use the aforementioned factors to make more informed decisions (e.g., Balfanz et al., 2007). For example, in our interactions with school administrators, we have found that those students who are at moderate risk but who are not acting out (and thus not drawing as much attention to themselves) are often missed by school personnel trying to identify students who need additional behavior support or interventions. These students actually may be among the most responsive to intervention and prevention strategies. Thus, we see the use of measures of academic behavior as key to helping tell each student's "story" and to tailoring interventions in order to increase a student's chance of success, whether in core academic areas (e.g., math, English) or in the behaviors and attitudes that support academic performance (e.g., positive attitudes toward education, prosocial behavior, increased engagement, time management, etc.).

At the institutional level, some of the ways that measures of academic behavior can be used include: (a) use in student-level data dashboards and other early warning systems to identify at-risk students, and (b) looking at aggregate data (at the classroom, school, or district level) to monitor student characteristics and plan system-wide interventions and resources. At the family level, measures of academic behavior can be used to (a) provide parents/guardians with information that can facilitate conversations and engagement regarding their students' academic lives, and (b) help them monitor whether their students are developing the characteristics needed for academic success.

Because ENGAGE measures ten different facets of academic behavior, in addition to the behavioral indicators included, it can provide educators with a broader range of information about the reasons students are at risk (i.e., their strengths and weaknesses). ENGAGE scores provide information that educators can use to better target interventions and provide the particular kinds of support students need most. This would allow educators to intervene based on students' attitudes, perceptions, and behavior, and provide interventions designed to increase positive attitudes and behaviors and decrease risk. To help educators take these next steps, user documentation for ENGAGE provides samples of interventions that can be used by educators to help students leverage their areas of strength and develop their areas of need (ACT, 2011c). In addition, ACT has developed a set of behaviorally-anchored rating scales (ENGAGE Teacher Edition; ACT, 2010) that can be used by educators to rate student behavior, track student progress over time, and determine next steps. These scales are designed to complement ENGAGE and assess the same three broad domains important for academic success (i.e., Motivation, Social Engagement, and Self-regulation). By aggregating the behavioral ratings across students (e.g., across those participating in an intervention or across an entire school), educators can assess the effectiveness of interventions, as well as their own progress in improving students' academic behavior. Finally, ENGAGE is part of a suite of academic behavior assessments that measure important predictors of performance and persistence from middle school to college, as well as the workplace.

Understanding student risk and student retention over time is essential if we are to reduce the shockingly high dropout rates and low achievement rates in our K-12 educational system (cf. Balfanz et al., 2007; Rumberger & Lim, 2008). As the research findings presented in this report suggest, good academic behaviors, in combination with academic achievement, provide the foundation for future academic success.

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