BEYOND SCHOOL RECORDS:

THE VALUE OF COGNITIVE AND AFFECTIVE ENGAGEMENT IN PREDICTING DROPOUT AND ON-TIME GRADUATION

Early warning systems use school record data— such as attendance rate, behavior records, and course performance—to identify students at risk of dropping out. These are useful predictors of graduation-related outcomes, in large part because they indicate a student's level of engagement with school. However, these data do not indicate how invested students are in education—information that could help school counselors and other staff understand and intervene when students are falling off the path to graduation. To examine whether student engagement surveys have additional predictive value beyond data readily available in school databases, we followed a cohort of students, who completed a survey of cognitive/ affective engagement as ninth graders, to one year beyond their expected high school graduation. Some engagement factors measured by the survey met rigorous tests of predictive value in terms of identifying which students were falling off the graduation path, even when controlling for other powerful predictors of the outcome.

n the last quarter century, student engagement has emerged as a distinct area of scholarship that crosses disciplines and nationalities (Christenson, Reschly, & Wylie, 2012). Interest in the construct extends well beyond academia, as student engagement has also become a growing area of focus for many educators, practitioners, and policymakers (Appleton, Christenson, & Furlong, 2008; Fredricks, Blumenfeld, & Paris, 2004; National Research Council & the Institute of Medicine [NRC], 2004). Different models of engagement exist, but most scholars agree that engagement involves aspects of students' emotion, cognition, and behavior. The editors of an international volume on student engagement offered the following definition:

> Student engagement refers to the student's active participation in academic and co-curricular or school-related activities, and commitment to educational goals and learning. Engaged students find learning meaningful, and are invested in their learning and future. It is a multidimensional construct that consists of behavioral (including academic), cognitive, and affective subtypes. Student engagement drives learning; requires

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energy and effort; is affected by multiple contextual influences; and can be achieved for all learners. (Christenson et al., 2012, pp. 816-817)

Student engagement is useful for understanding dropout and promoting school completion (Christenson et al., 2008; Finn, 2006). Extensive literature documents predictors of high school dropout (Christenson, Sinclair, Lehr & Godber, 2001), the negative consequences of which are well documented for students, including increased rates of unemployment, poverty, incarceration, and health problems (Freudenberg & Ruglis, 2007; Sum, Khatiwada, & McLaughlin, 2009), and for society, such as lost earnings and higher costs of government assistance programs (Rouse, 2005; Rumberger & Rotermund, 2012). Furthermore, in light of data that suggest postsecondary education is increasingly important for job attainment (e.g., Carnevale, Jayasundera, & Gulish, 2015), educators and support staff within K-12 schools are seeing a shift in focus from high school graduation to college and career readiness, rendering high school graduation a necessary but not sufficient step in preparing students for the future.

Predictors of dropout and completion have been classified in numerous ways (e.g., status vs. alterable; proximal vs. distal; protective vs. risk factors; push vs. pull factors; Reschly & Christenson, 2012). For school personnel, one of the most useful distinctions is demographic vs. functional risk (Christenson et al., 2008). In the U.S., certain demographic characteristics are associated with a greater likelihood of dropping out of school, such as students who are economically disadvantaged; who are American Indian, Hispanic or Black; or who have been identified with limited English proficiency. However, providing intervention services to all of the students who share some of these demographic characteristics would be a waste of time and money. For example, 76.1% of students who are economically

disadvantaged graduate from high school on time (National Center for Education Statistics, 2016). Functional risk, however, builds upon engagement theory and research demonstrating that, in addition to achievement, indicators of engagement (e.g., attendance, behavior, belonging) are among the most powerful predictors of high school dropout (Janosz, 2012; Rumberger & Lim, 2008). Furthermore, engagement differentiates those who are successful from those who drop out within demographically high-risk groups (Finn & Rock, 1997; Reschly & Christenson, 2006). Engagement variables are largely considered to be alterable in nature, rooted in important contexts (e.g., home, school, peers), and directly related to intervention and school success. Therefore, the fact that the most promising dropout prevention strategies are rooted in engagement theory is not surprising (Christenson et al., 2012).

Beyond dropout, however, engagement is associated with academic, social, and emotional learning outcomes for all students (Christenson et al., 2012; Fredricks et al., 2004). A "meta-construct" (Fredricks et al., 2004), engagement offers a unifying frame from which to more fully describe students' school experiences. From this perspective, different types of engagement are interrelated. For example, an intervention that addresses students' self-regulation (cognitive engagement) or relationships/belonging at school (affective or emotional engagement) may also positively affect their behavioral engagement (e.g., participation in class, attendance, positive behavior in class/school). Given this interest and wide applicability of the engagement construct, the number of evidence-based interventions and strategies

for enhancing student engagement is expanding (Christenson et al., 2012).

Measures of Engagement

As interest in engagement has grown among scholars and practitioners, an increasing variety of measures are available for use in both research and school settings (Fredricks et al., 2011). Engagement is a construct that resonates with many educators who see its value and applicability to intervention (Finn & Zimmer, 2012). Therefore, a significant motive for developing engagement instruments is the possibility of using them for data-based decision making within schools (Appleton, 2012). Monitoring engagement also may provide stakeholders with the opportunity to respond to students or school issues most in need of intervention (Reschly, Appleton, & Pohl, 2014).

The gap between research and practice is often lamented within the fields of education and psychology—a criticism that is also applicable to the study of engagement. For example, an instrument that may prove useful in evaluating a scholar's theory may provide little to a practitioner in day-to-day practice or it may prove to be too costly in terms of time and money to be widely used. Thus, a primary impetus for this study was the practical value of including a student engagement survey in data-based decision making in a school setting. The Student Engagement Instrument (SEI; Appleton, Christenson, Kim, & Reschly, 2006) is one measure that is well suited to this purpose. It is one of the few student engagement surveys that is comprehensive (i.e., includes subscales related to both cognitive and affective engagement; Fredricks et al., 2011), grounded in a theoretical model (Appleton et al., 2006; Reschly & Christenson,

BEYOND DROPOUT, HOWEVER, ENGAGEMENT IS ASSOCIATED WITH ACADEMIC, SOCIAL, AND EMOTIONAL LEARNING OUTCOMES FOR ALL STUDENTS.

2012), available for free (published in full in Appleton et al., 2006, and in Betts, Appleton, Reschly, Christenson, & Huebner, 2010), and has shown widespread applicability through its routine use in districts across the U.S. and internationally (Appleton, Reschly, & Christenson, 2013).

Using an engagement survey for data-based decision making raises important validity questions. Although a number of student engagement measures have robust validity research behind them (Fredricks et al., 2011), no studies have looked into the practical value of using such surveys in school settings. A key aspect of validity relevant to this gap in the literature for student engagement measures is *incremental validity*—whether a measure adds to the prediction of an outcome beyond what can be predicted by other sources of data (Hunsley & Meyer, 2003; Sechrest, 1963). Several indices may be used to indicate improvement

this sense, incremental validity is a relatively strict test of a measure because it demands not only that the measure predict an outcome better than what could occur by chance alone, but that it also shows additional explanatory value relative to less expensive sources of information. In terms of dropout and on-time graduation prediction, the objective of this study was to test the incremental validity of cognitive and affective engagement beyond what can already be predicted by commonly available school record data.

METHOD

Participants and Procedures

Data were from a large school district in the Southeastern U.S. The racial-ethnic composition of the district was as follows: 36% White, 27% Black, 22% Hispanic, 10% Asian, and 5% other. Approximately 41% of students

A SIGNIFICANT MOTIVE FOR DEVELOPING ENGAGEMENT INSTRUMENTS IS THE POSSIBILITY OF USING THEM FOR DATA-BASED DECISION MAKING WITHIN SCHOOLS.

in prediction, such as increased power, sensitivity, or specificity (Hunsley & Meyer, 2003). Sechrest (1963) argued that for a measure to have true utility in applied settings, it should demonstrate incremental validity over readily available data (e.g., interviews, case histories). School districts have a number of clearly defined prediction tasks (e.g., dropout risk, postsecondary readiness), an abundance and variety of data at their disposal, and considerable incentives for optimizing the prediction of outcomes (e.g., reducing costs, using resources more effectively, meeting accountability standards). A question facing a school counselor or other staff member might be: Do student responses on an engagement survey tell me anything more about student outcomes than what I could have gathered from information already available in school records? In

were eligible for free or reduced-price lunch, 15% qualified as limited English proficient, and 11% received special education services. The district is suited to studying the incremental validity of cognitive/affective engagement because it has administered the SEI biannually (fall and spring) since September 2007 as part of a district-wide student advisement program developed by the district's counseling office (Appleton, 2012; Appleton & Thompson, 2009). We selected a cohort of first-time ninth graders who had been enrolled in the district the previous year (N = 10,067). Students were included if they were enrolled for ≥ 65% of the academic year (i.e., ≥ 117 days) in 2007-2008. These students represented 15 high schools, with enrollments ranging from 425 to 1,002 students. With four academic years of SEI data available, studying this cohort longitudinally allowed for

analyses of the relationships of various student and school characteristics with dropout and on-time graduation.

Measures and Covariates

Dropout and on-time graduation. Dropout was defined as leaving high school before the end of the observation period (September 2011) for any reason besides graduation, transferring out of the district, or earning a certificate of completion. Students who died or left due to a serious illness or accident were not included in the dataset. On-time graduation was defined as graduating with a full high school diploma by the end of summer 2011. Students who earned a certificate of completion or a special education degree were considered *completers* but not graduates.

Cognitive/affective engagement. We constructed cognitive and affective engagement variables for each semester from student responses to items on the SEI. The SEI is a 33-item Likert-response survey designed to measure student perceptions of the less observable subtypes of the engagement construct: cognitive and affective engagement (Appleton et al., 2006). Consistent with Betts et al. (2010), we used five SEI facets of cognitive and affective student engagement. The five facets of engagement and sample items to illustrate each factor were as follows. Teacher–Student Relationships (TSR; *At my school, teachers care about students*), Peer Support for Learning (PSL; *I have some friends at school*), and Family Support for Learning (FSL; *When I have problems at school my family/guardian(s) are willing to help me*) were formulated to represent affective engagement. Control and Relevance of School Work (CRW; *I feel like I have a say about what happens to me at school*) and Future Aspirations and Goals (FGA; *School is important for achieving my future goals*) represented students' cognitive engagement. Higher SEI scores suggest higher levels of engagement. Standardized procedures for administration include reading the items aloud to students to limit unwanted effects from variation in students' reading levels (Appleton, 2012).

Empirical evidence from validation studies of the SEI support its use as a cognitive and affective student engagement measure. Good internal consistency estimates (α = .72 to .88 across factors) have been reported in two studies (Appleton et al., 2006; Betts et al., 2010). Exploratory and confirmatory factor analysis methods have suggested that the SEI has a meaningful factor structure (Appleton et al., 2006; Betts et al., 2010; Reschly et al., 2014). Furthermore, the SEI shows evidence of convergent and divergent validity with another measure of engagement and motivation (Reschly et al., 2014) and the SEI factors are correlated, as expected, with other measures of school behavior and academic performance (Appleton et al., 2006; Reschly et al., 2014). Finally, structural equation modeling techniques have revealed that the SEI's factor structure is stable across grades 6 through 12 (Betts et al., 2010).

Student data common in school records. We constructed the remaining variables from school record data: demographic characteristics, academic achievement, and behavioral disengagement. These variables were chosen based on available district data and comprehensive empirical evidence on associations between student variables and school completion found in a comprehensive review by Rumberger and Lim (2008). Over-age, an indicator related to retention, is typically defined as being 1 or 2 years older than classmates (Rumberger & Lim, 2008). For this study's cohort, ages were known within a 3-month interval; therefore, over-age was defined as being at least 1.5 years older than the average age of classmates. Several status variables, like ethnicity and special education status, are associated with differences in school outcomes as individual indicators, but these effects have commonly been shown to be insignificant once variables related to achievement, socioeconomic status, and behaviors are taken into account (Rumberger & Lim, 2008). We did include these demographic characteristics in the predictive modeling process,

however, as a check on how well the results of this study match with the literature. Operational definitions and descriptive statistics for all variables are provided in Table 1.

Analysis Procedures

Predictive efficiency of grade 9 indicators. The logic behind these analyses was inspired by the work of Gleason and Dynarski (2002) and Balfanz, Herzog, and Mac Iver (2007), who showed that, to be useful for predicting dropout or on-time graduation, variables of interest need to demonstrate high predictive power and sensitivity. Balfanz et al. (2007) utilized a two-pronged approach, requiring high (a) positive predictive value (PPV) and (b) sensitivity. In the case of graduation predictors, PPV would be the proportion of *predicted graduates* who actually graduated, and sensitivity would be the proportion of *all graduates* who were identified by the predictor. To demonstrate high predictive efficiency, each of the student-level variables involved in this study was subjected to a dual-criterion test:

(a) PPV rate is at least double the cohort dropout/nongraduation rate, and

(b) Identifies a substantial enough portion of dropouts/nongraduates to be valuable in intervention efforts. A sensitivity estimate of at least .05 (i.e., 5% of the total target group) was determined to be a reasonable minimum criterion for a single predictor.

Multilevel logistic regression. The above dual-criterion test was used to explore and assess the predictive utility of individual ninth-grade predictors. However, overlap of the explanatory effect of some of these predictors was

possible. For example, if FGA was to demonstrate predictive utility for identifying on-time graduation, it is possible that every graduate identified by FGA could have already been identified by another variable readily available to schools (e.g., attendance). Multiple regression allowed for analysis of the incremental validity of an SEI factor score over other readily accessible data. We analyzed estimates of student-level and school-level effects on dropout and graduation through multilevel logistical regression modeling using Stata software (StataCorp, 2011). The data had an inherent two-level structure of students (N = 10,067) nested within high schools (n = 15).

In a series of separate, two-level, random-intercept logistic regression models, the response variables for on-time graduation and dropout were each regressed on a variety of student-level variables. For each response variable, we built a series of four primary models, representing (a) an *unconditional model* with no level-one or level-two predictors; (b) a *demographic data model*, with a variety of level-one status variables common in school data (e.g., free/reduced lunch eligibility, ethnicity); (c) a *demographic and academic data model*, with a level-one prior achievement variable added; and (d) a *demographic, academic, and behavior data model*, with level-one indicators for attendance and out-of-school suspensions added. In each step, we ran an additional subset of models, first adding an SEI factor, then removing it and adding another SEI factor, eventually running the model with all SEI factors included. This progression allowed for the assessment of the incremental contribution of new variables, including SEI variables at

TABLE 1 — OPERATIONAL DEFINITIONS AND DESCRIPTIVE STATISTICS FOR VARIABLES STUDIED

Variable		Description	*M*	*SD*	*SE*
Dependent variables (y_{ij})	Dropout	1 = Identified as a dropout; 0 = Not identified as a dropout	.05	.21	.002
	Graduate	1 = Graduated with a full diploma from the district within 4 academic years; 0 = did not	.67	.47	.004
Grouping variables	Contrived_id (*i*)	Unique contrived student identifier			
	School_id (*j*)	Contrived identifier of enrolled high school in 2007-2008			
Independent variables	Female	1 = Yes; 0 = Male	.50	.50	.005
Demographic data	*Race/Eth:* Black	1 = Yes; 0 = No; White was the reference category in regression analyses	.25	.43	.004
	Hispanic	1 = Yes; 0 = No	.21	.40	.004
	Other	1 = Asian/Pacific Islander, Native American/Alaskan, or Multiracial; 0 = None of these	.15	.36	.004
	White	1 = Yes; 0 = No	.39	.49	.005
	FRL	1 = Identified as eligible for free or reduced-price lunch in ninth grade; 0 = Not identified	.37	.48	.005
	Over-age	1 = At least 1.5 years older than typical age at start of ninth grade; 0 = Not over-age	.02	.15	.002
	Special Ed.	1 = Identified as receiving special education services as of start of ninth grade; 0 = Not identified	.13	.33	.003
	Spanish	1 = Primary language is Spanish; 0 = Primary language is another language	.16	.37	.004
	Gifted	1 = Identified in records as Gifted; 0 = Not identified	.19	.39	.004
Academic achievement	Achievement[a]	Prior achievement; mean of z-scores (based on state *M* and *SD*) across Grade 8 CRCTs for Math, Reading, and English/Language Arts	.37 (.34)	.90	.009 (.009)
Behavioral disengagement	OSS	1 = At least 1 out-of-school suspension (OSS) in ninth grade; 0 = No OSS	.14	.34	.003
	Attendance	Percentage of enrolled days attended in ninth grade	96.2	5.10	.051
Cognitive/affective engagement	TSR[a]	Average factor score for TSR on the SEI for Grade 9	2.76 (2.75)	0.48	.005 (.005)
	PSL[a]	Average factor score for PSL on the SEI for Grade 9	3.20 (3.19)	0.45	.005 (.004)
	FSL[a]	Average factor score for FSL on the SEI for Grade 9	3.43 (3.42)	0.48	.005 (.005)
	FGA[a]	Average factor score for FGA on the SEI for Grade 9	3.61 (3.60)	0.43	.004 (.004)
	CRW[a]	Average factor score for FSL on the SEI for Grade 9	2.93 (2.91)	0.45	.005 (.004)

Note. N = 10,067. The superscript [a] denotes variables with missing data; analyses with these variables involved multiple imputation. Mean (*M*), standard deviation (*SD*), and standard error (*SE*) shown for nonimputed data. For any variable involving imputation, *M* and *SE* following multiple imputation are shown in parentheses below the estimates.

each step. As further explained in the results below, we conducted the PPV and sensitivity analyses prior to the inferential analyses to better inform which factors to include in the incremental validity analyses.

We assessed statistically significant incremental validity by examining logistic regression coefficients (exponentiated as odds ratios) and their 95% CIs for each SEI factor included in the model. For effect size of overall model prediction, we calculated a pseudo-R^2 statistic by taking the square of the correlation between the predicted conditional probabilities and the outcome variable (Peugh, 2010). The difference in R^2 after new variables were added was used as an absolute index of effect size of the validity increment. Rather than interpreting this effect in traditional terms, such as by Cohen's (1992) benchmarks, we used guidelines by Hunsley and Meyer (2003) that were proposed specifically for tests of incremental validity. Based on Nunnally and Bernstein's (1994) observation that increases in R^2 are generally small in social science research by the time a third substantial predictor has been entered into a regression, Hunsley and Meyer (2003) suggested that a lower R^2 difference, such as .0225 (square root = .15), would constitute a reasonable contribution to the regression. Although a small effect by traditional standards, these criteria were considered to be stringent in the present study given the many substantial controls at each step.

Because dropout was confined to a strict definition of only those students identified as dropouts by the district, it was relatively rare (< 5%). When rare events are binary they can be difficult to analyze for reasons both practical (e.g., costs of gathering extensive data on thousands of participants to capture rare event data) and statistical (King & Zeng, 2001; Lacy, 1997). Issues related to efficient data gathering obviously did not apply here, but statistical issues were a concern because logistic regression often underestimates event probabilities when nonevents greatly outnumber events

(King & Zeng, 2001). Unbiased estimates can be achieved through careful design and postestimation statistical correction (King & Zeng, 2001). For the dropout models, where ones were greatly outnumbered by zeros, a *case-cohort* design was used, in which we constructed a balanced random sample (*n* = 930) by selecting students on the dependent variable, and then, following estimation, applying prior correction (King & Zeng, 2001) to the intercept to account for the case-cohort sampling design.

RESULTS

Descriptives and Missing Data Analysis

Student outcomes. Four-year outcomes for the cohort were determined at the beginning of the semester after the expected 4-year graduation date: 67.3% were on-time graduates (*n* = 6,770), followed by unknown (10.9%, *n* = 1,098), leavers (8.1%, *n* = 811), still enrolled (8.1%, *n* = 815), dropouts (4.6%, n = 465) and completers (1.1%, *n* = 108). These data indicate that the graduation status of about one fifth of the cohort was unknown at the end of the study, either because the student transferred and never re-enrolled or because there was no record of their graduation status and the student did not re-enroll as of September 2011. Without knowing the outcomes for these students, somewhere between 13.8% and 32.8% of the cohort did not earn a high school diploma within four years.

Missing data. Data on demographics, behavior, and attendance were complete for all cases in the cohort for Grade 9; data for prior achievement and SEI responses were not. The dif-

ference between SEI missingness and the overall leave rate in ninth grade (the expected proportion of missingness) indicated that roughly 10% of SEI data was missing beyond what could be expected due to attrition in the first year. When there is no systematic pattern of missingness, data are considered missing completely at random (MCAR; Schlomer, Bauman, & Card, 2010). A less stringent assumption of missingness is when data are considered missing at random (MAR), referring to systematic missingness that can be accounted for by other data in the dataset. Engagement theoretically should influence a student's propensity to be present to complete a survey of any kind, let alone an engagement survey, and this missingness should be accounted for by covariates in the data. MAR was considered a reasonable assumption for the missingness in the SEI and achievement data because the breadth and completeness of surrounding data allowed for a multiple imputation model that included a wide variety of covariates relevant to potential underlying reasons for missingness (e.g., absences, disciplinary records, prior achievement, graduation, prior and later SEI scores, outcome status). Due to this assumption and the low rate of missingness overall, we used multiple imputation methods (Little & Rubin, 2002) to generate a universe of five complete datasets via the multivariate imputations by chained equations (MICE) procedure in Stata (StataCorp, 2011).

Exploratory Data Analysis

Graphical exploration of the data with respect to associations of SEI factors to 4-year outcomes suggested consistent directional trends (i.e., higher reported engagement associated with

FIGURE 1

RATES FOR DROPOUT AND ON-TIME GRADUATION BY NINTH GRADE SEI FACTOR SCORE.

Categorized into tended to *Disagree* (< 2.5), tended to *Agree* (2.5-3.4), and tended to *Strongly Agree* (≥ 3.5). Error bands represent 95% confidence intervals for the proportion.
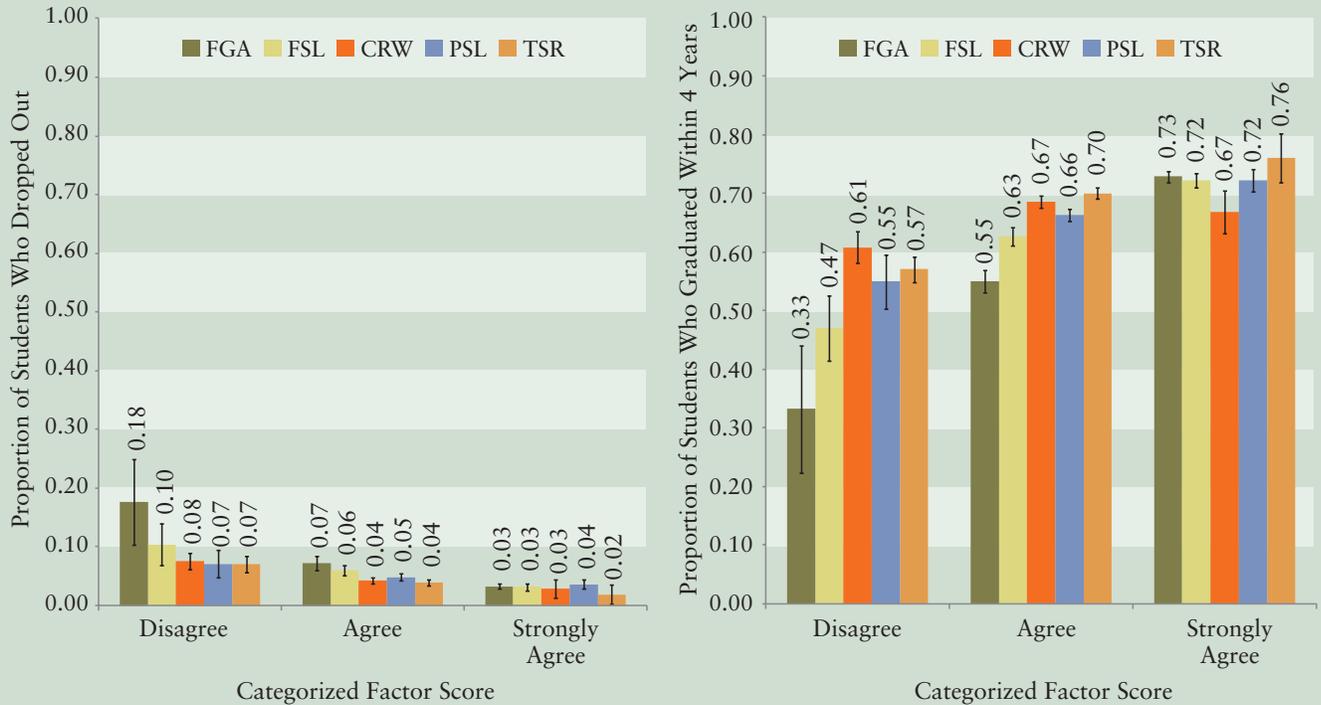
WE ALSO FOUND PRIOR ACHIEVEMENT AND NINTH-GRADE INDICATORS OF BEHAVIORAL ENGAGEMENT AND DISENGAGEMENT TO BE INDEPENDENT AND SUBSTANTIALLY PREDICTIVE OF DROPOUT AND ON-TIME GRADUATION.

higher graduation rates and lower dropout rates) but also varying levels of strength across factors (see Figure 1). The prevalence of dropout among students with lower scores on FGA in ninth grade was roughly five times higher than for students who tended to strongly agree that school was relevant to their future goals, whereas the same comparison for PSL was not as strong. Based on these preliminary graphical explorations, FSL and FGA were considered the only two factors to have the potential to stand up to the rigorous incremental validity tests, a conclusion supported by the PPV and sensitivity tests that followed.

PPV and Sensitivity of Grade 9 Predictors

We next examined PPV and sensitivity for Grade 9 indicators of dropout and on-time graduation. Overall, behavioral indicators, particularly low attendance and out-of-school suspension (OSS), were the most efficient predictors. Students attending less than 90% of enrolled days, for example, were four times more likely than the average student to drop out, and this indicator correctly identified roughly 35% of all dropouts. Further, only 20% of students with low attendance graduated on time and this indicator identified more than 20% of nongraduates. Although less sensitive than behavioral variables, being over-age for grade level stood out as another powerful indicator, with more than 20% dropping out and more than 75% failing to graduate on time. For on-time graduation, low prior achievement was particularly predictive of failing to graduate within four years. Regarding

SEI factors, FGA and FSL met both criteria, albeit less substantially than the previously described predictors. Neither of these factors met both criteria for predicting on-time graduation, although FGA was on the threshold for sensitivity. No other SEI factors met both criteria.

Multi-Level Logistic Regression

To keep modeling, interpretation, and results as elegant as possible, only the SEI factors meeting the predictive efficiency criteria above (FGA, FSL) were included in subsequent analyses. Results for the estimated multilevel models are summarized in Tables 2 and 3, including the estimated change in pseudo-R^2 when SEI factors were added, alone and in combination with each other.

Model 1: Unconditional model. In each model, the dichotomous outcome y_{ij} for student i in school j was modeled with a multilevel logistic regression model with a random intercept for schools. In the notation used by Raudenbush and Bryk (2002) and Rabe-Hesketh and Skrondal (2012), the probability that the response was equal to 1 was modeled using a

TABLE 2

DROPOUT MULTILEVEL MODEL SUMMARIES

Parameters	Model 1: Unconditional	Model 2: Demographic	Model 3: Achievement	Model 4: Behavior
Fixed effects				
Intercept (γ_{00})	0.05 (0.12)	0.04 (0.16)	5.33 (0.70)***	1.29 (0.266)
FGA		0.48 (0.10)***	0.54 (0.11)**	0.64 (0.15)
FSL		0.53 (0.11)**	0.50 (0.10)**	0.48 (0.11)**
Female		0.63 (0.10)**	0.61 (0.09)**	0.49 (0.08)***
Black		1.02 (0.23)	0.85 (0.19)	0.77 (0.19)
Hispanic		0.79 (0.29)	0.67 (0.25)	0.73 (0.30)
Other		0.76 (0.19)	0.70 (0.17)	0.80 (0.21)
ELL		1.40 (0.53)	1.20 (0.46)	0.98 (0.41)
FRL		1.96 (0.34)***	1.74 (0.31)**	1.52 (0.30)*
Over-age		5.32 (2.28)***	4.20 (1.84)**	3.82 (1.73)**
Special Ed.		1.28 (0.26)	0.69 (0.15)	0.61 (0.15)*
Gifted		0.27 (0.08)***	0.55 (0.18)	0.66 (0.23)
Avg. Achievement			0.45 (0.06)***	0.49 (0.07)***
Percent Attendance			0.86 (0.02) ***	
OSS			1.89 (0.43)**	
Variance components				
Intercept (ψ)	.150 (.082)	.045 (.056)	.000 (.015)	.014 (.001)
Conditional ICC (ρ)	.043 (.024)	.013 (.017)	.000 (.005)	.000 (.004)
Pseudo-R^2				
No FGA or FSL	.051	.131	.183	.334
Incremental Difference in Pseudo-R^2				
with FGA		+.057	+.045	+.024
with FSL		+.050	+.045	+.031
with FGA & FSL		+.070	+.058	+.036

Note. Balanced case-control sample (n = 930). Prior correction to level-1 intercept (King & Zeng, 2001). Dropout does not include students who left for unknown reasons or students who earned a certificate of completion or a special education diploma.

*** p < .001 ** p < .01 * p < .05

logit link function with the traditional assumption that y_{ij} has a Bernoulli distribution:

$$\text{logit}(\varphi_{ij}) = \eta_{ij}, y_{ij} \sim \text{Bernoulli}(\varphi_{ij})$$

and the two-level model for Model 1 was:

$$\eta_{ij} = \beta_{0j} \qquad \text{Level 1}$$

$$\beta_{0j} = \gamma_{00} + \mu_{0j} \qquad \text{Level 2}$$

where γ_{00} is the fixed intercept, or the average log-odds of dropout/on-time graduation across schools, while μ_{0j}

and τ_{00} represent the random effects, which were assumed to be normally distributed, independent, identically distributed across schools, and independent of covariates (added in later models). Model 1 results indicated that the level-two variance in the response variable was statistically significant for both dropout (ψ = 0.15, 95% CI = 0.05–0.44) and on-time graduation (ψ = .15, 95% CI = .07–.31). Substituting these level-two variance estimates into a conditional ICC equation:

$$\rho = \frac{\psi}{\psi + \pi^2/3}$$

(Rabe-Hesketh & Skrondal, 2012)

indicated that schools accounted for about 4% of the dropout and graduation variance. Although a variety of studies have found that student-level characteristics commonly account for the majority of the variance in outcomes like dropout (Rumberger & Palardy, 2003), the school-level effects found here are on the low end of estimates reported in the literature.

TABLE 3 ON-TIME GRADUATION MULTILEVEL MODEL SUMMARIES

Parameters	Model 1: Unconditional	Model 2: Demographic	Model 3: Achievement	Model 4: Behavior
Fixed effects				
Intercept (γ_{00})	2.05 (.21)***	2.54 (0.17)***	1.65 (0.11)***	1.82 (0.12)***
FGA		2.42 (0.19)***	2.05 (0.16)***	1.72 (0.14)***
FSL		1.12 (0.07)	1.20 (0.09)*	1.13 (0.08)
Female		1.26 (0.06)***	1.24 (0.06)***	1.38 (0.07)***
Black		0.89 (0.06)	1.15 (0.08)	1.02 (0.08)
Hispanic		0.84 (0.09)	0.96 (0.11)	0.87 (0.10)
Other		1.14 (0.09)	1.34 (0.11)***	1.03 (0.09)
ELL		0.78 (0.09)*	1.05 (0.12)	1.06 (0.13)
FRL		0.58 (0.03)***	0.68 (0.04)***	0.77 (0.05)***
Over-age		0.27 (0.04)***	0.37 (0.06)***	0.48 (0.09)***
Special Ed.		0.40 (0.03)***	0.89 (0.07)	0.94 (0.08)
Gifted		4.13 (0.37)***	1.67 (0.16)***	1.53 (0.16)***
Achievement			2.71 (0.12)***	2.57 (0.11)***
Percent Attendance				1.18 (0.01)***
OSS				0.53 (0.04)***
Variance components				
Intercept (ψ)	.147 (.053)	.024 (.013)	.018 (.010)	.014 (.008)
Conditional ICC (ρ)	.042 (.017)	.007 (.004)	.005 (.003)	.004 (.003)
Pseudo-R²				
No FGA or FSL	.033	.146	.218	.312
Incremental Difference in Pseudo-R²				
with FGA		+.033	+.022	+.010
with FSL		+.012	+.010	+.004
with FGA & FSL		+.033	+.022	+.011

n = 10,067
***p* < .001 ***p* < .01 *p* < .05

Although the estimated school-level effect was small, the estimated design effect D_{eff} (a numerical representation of the effect of independence violations on standard error estimates [Peugh, 2010]) was large. At 26.8 for these data,

$$D_{eff} = 1 + (n_c - 1)ICC = 1 + \left(\frac{10,067}{15} - 1\right).04$$

the D_{eff} suggested the need for a multilevel approach, but the low overall level-two variance suggested that adding school-level variables would not result in better explanatory models.

Models 2 to 4: Progression of conditional models. In Models 2 to 4, nine demographic covariates, followed by an achievement covariate and then two behavior covariates, were sequentially added. Tables 2 and 3 show the estimated conditional odds ratio for the outcome of each covariate in these models when FGA and FSL were also included. A pseudo-R² statistic without FGA or FSL is presented at the bottom of these tables, followed by the incremental difference in pseudo-R² when these variables were added.

Many status variables known to be differentially associated with risk for dropout (e.g., ethnicity, English language learner) were not statistically associated with dropout or on-time graduation when achievement and behavior indicators were added to the model. An exception to this finding was that receiving special education services was estimated to lower the odds of dropout when controlling for achievement, behavior, and cognitive and affective engagement. A few demographic variables remained statistically significant throughout all or most models of dropout and graduation.

Controlling for all other covariates, being female was estimated to halve the odds of dropout and raise the odds of on-time graduation by 38%, whereas being economically disadvantaged raised the odds of dropout by 52% and lowered the odds of on-time graduation by 30%. The most substantial effect among the demographic variables was for over-age students, whose estimated conditional odds of dropout were 3.8 times higher than age-typical peers, whereas the estimated odds of on-time graduation were 2.1 times lower.

We also found prior achievement and ninth-grade indicators of behavioral engagement and disengagement to be independent and substantially predictive of dropout and on-time graduation. All other variables being equal, a one standard deviation increase in academic achievement was associated with a 2.0 times reduction in the estimated odds of dropping out and a 2.6 times increase in the odds of graduating in 4 years. Likewise, higher rates of attendance were associated with lower odds of dropout and higher odds of on-time graduation. Regarding signs of behavioral disengagement, having at least one out-of-school suspension at any time in ninth grade was associated with an 89% increase in the odds of dropout and nearly a 2 times decrease in the odds of on-time graduation.

Incremental validity of FGA and FSL. The odds ratio of the effect of FGA and FSL on dropout and on-time graduation were not always statistically significant across models when both factors were included in the model (Tables 2 and 3), but each factor was significant in all submodels when the other factor was excluded. In these submodels, odds ratios for FGA ranged from 0.34 to 0.43 in models of dropout ($p < .001$ in all cases), indicating that, all other variables being equal, a one-point decrease in FGA was associated with a 2.3 to 2.9 times increase in the odds of dropping out. For models of on-time graduation, odds ratios ranged from 1.8 to 2.6. For FSL, odds ratios were all 0.4 in models for dropout and

ranged from 1.5 to 1.7 for models for on-time graduation ($p < .001$ in all cases). This evidence in combination with the pseudo-R^2 results suggested that FGA and FSL were likely often explaining much of the same variance in the outcome, with FGA tending to add a little more than FSL to overall variance explained. This would indicate that each of these SEI factor scores showed statistically significant incremental validity over other powerful indicators, but not necessarily over each other. Turning attention more closely to the pseudo-R^2 results, SEI factor scores were shown to add much more to overall variance explained by the model in

THE ANALYSES PROVIDE AN INDICATION OF WHAT CAN BE EXPECTED WHEN A STUDENT ENGAGEMENT SURVEY IS USED IN AN APPLIED SETTING.

predictions of dropout than for on-time graduation. In all instances of dropout modeling, these factors—when examined alone or in combination—added enough variance explained to meet Hunsley and Meyer's (2003) criterion. On-time graduation models involving only demographic data met this criterion, but fell just short of it when achievement was added and $\geq 1.5\%$ below the criterion with behavior data.

DISCUSSION

The negative impact of dropout on individuals and society underscores the importance of efforts to raise school completion rates. One necessary component of systematic efforts is effective early warning screening for students at risk (Balfanz, Herzog, & Mac Iver, 2007; Christenson & Thurlow, 2004). No single variable predicts dropout well enough to do the job on its own (Gleason & Dynarski, 2002), but identification of students falling off the graduation path improves when predictive models include a variety of efficient indicators (Balfanz et al., 2007; Gleason & Dynarski, 2002; Rumberg-

er & Lim, 2008). Student engagement is a multifaceted construct, consisting of at least behavioral, cognitive, and affective features (Fredricks et al., 2004); the substantial predictive value of behavioral engagement indicators (e.g., attendance, discipline) is well known (Rumberger & Lim, 2008). However, the practical advantages of measuring cognitive and affective engagement—psychological constructs that typically require the collection of self-report survey data—is less known. The purpose of this study was to investigate the potential of including such measures in risk detection efforts, by testing the associations of cognitive

and affective engagement in the ninth grade with 4-year outcomes.

This study examined the predictive efficiency and incremental validity of cognitive and affective engagement for early identification of students falling off the graduation path. Alongside a variety of data commonly available in schools, indicators of cognitive and affective engagement were subjected to tests of sensitivity and positive predictive value as an individual indicator of dropout and on-time graduation. Although not nearly as efficient in predicting dropout or graduation as behavioral indicators (e.g., low attendance), two factors, FGA and FSL, demonstrated considerable efficiency for a self-report measure in identifying students who were known to drop out within four years of ninth grade. Next, the predictive utility of these SEI factors was further assessed by examining their incremental validity over commonly available school data. This was accomplished by studying their unique contribution to the variance explained in dropout and on-time graduation through a multilevel logistic regression model that controlled

for several well-known predictors of high school outcomes. Here the SEI showed less promise as a predictor of on-time graduation, but in stringent incremental validity tests it performed considerably well as a predictor of dropout, contributing unique variance to models that included 12 other variables, several of which—like prior achievement and student age—were shown to be highly and independently predictive of dropout.

The higher graduation rates and lower dropout rates found here for female students, however, are less representative of findings in the literature. Many studies have found female students to have lower dropout rates and higher graduation rates than male students, but in general the opposite trend has been found when attitudes, behaviors, and achievement are taken into account (Rumberger & Lim, 2008). The positive effects found

ment scores in eighth grade and higher rates of attendance in ninth grade were each independently predictive of a lower likelihood of dropping out and a higher likelihood of graduating on time; whereas receiving at least one OSS in ninth grade greatly reversed the effect. OSS, an indicator of school misbehavior, may be viewed as a behavioral marker of disengagement, which many studies have found to be positively associated with dropout and negatively associated with graduation, even when prior academic achievement and family background were taken into account (Rumberger & Lim, 2008).

In all, the findings from the above analyses fit well with the body of research on the multivariate effects of risk and protective factors on dropout and graduation. But the main focus here was on cognitive and affective engagement. Prior studies of student engagement surveys have tended to focus on their internal consistency, factor structure, and other aspects of reliability and validity (Fredricks et al., 2011), but no studies have assessed the practical value of using such measures in data-based decision making in school settings. This paper adds to this growing body of research on student engagement through an examination of the long-term predictive validity for high school graduation and dropout of a measure of cognitive and affective engagement (the SEI). The analyses provide an indication of what can be expected when a student engagement survey is used in an applied setting, which should be valuable to stakeholders interested in meaningful evidence relevant to screening for risk of school failure.

Similar to the pattern of small correlations reported by Appleton et al. (2006) for SEI factor associations with some relevant outcomes (like grade point average, standardized tests, and suspensions), findings in this study found that some SEI factors did not appear to be meaningfully predictive of on-time graduation, at least in terms of scores representative of a student's self-perceptions of engage-

THIS STUDY DID FIND CLEAR AND CONSIDERABLE LINKS BETWEEN STUDENT RESPONSES ON THE FGA [FUTURE GOALS AND ASPIRATIONS] AND FSL [FAMILY SUPPORT FOR LEARNING] FACTORS AND LATER OUTCOMES.

Dropout and graduation rates are known to differ considerably across various demographic characteristics, but research has shown that such effects often depend on which other variables are included in the study (Rumberger & Lim, 2008). In our multilevel analysis, the effects on the odds of dropping out and on graduating on time of ethnicity and English-language-learner status—two demographic characteristics well-known to associate differentially with these outcomes (Rumberger & Lim, 2008)—were null once achievement, behavior, and engagement indicators were included. Similarly, according to the full model, receiving special education services in ninth grade was shown to reduce the odds of dropping out with no effect on the odds of whether or not a student graduated in 4 years. Such findings are common in the literature. The insignificant effects found here for language status should be interpreted with caution; only the student's native language, not their English proficiency, was known. Other studies (e.g., Griffin & Heidorn, 1996; Lutz, 2007; Perreira, Harris, & Lee, 2006) have found protective benefits of language proficiency when controlling for other background characteristics.

here may be due to characteristics of the district studied—a large suburban school system near a metropolitan city—as some studies have found similar results when looking at gender effects between various subpopulations. For example, similar to findings here that being female is a protective factor, Lichter, Cornwell, and Eggebeen (1993) found lower dropout rates for female students than for male students among those in central cities and suburbs, but the reverse trend in rural areas.

All other variables in the final model that were found to show independent predictive effects were consistent with the literature. Free/reduced-price lunch eligibility, for example, is often used as a proxy for low family financial resources. Most studies have shown that students from lower income households are more likely to drop out and less likely to graduate, even when controlling for all other variables (Rumberger & Lim, 2008). Being over-age for grade level was also found to substantially impact the odds of drop out and graduation. Most studies report similar risk increasing effects for students greater than 1 to 2 years older than their grade-level peers (Rumberger & Lim, 2008). Also found here was that higher achieve-

ment at a single moment in time in ninth grade. Unlike the early findings of Appleton et al. (2006), however, this study did find clear and considerable links between student responses on the FGA and FSL factors and later outcomes. Further, these scores represented the summary of roughly 10 self-report items completed by students at a time in the early days of their high school career—not data from a time- and labor-intensive research initiative.

Future Research

The next step in understanding the practical predictive potential of student engagement measures like SEI might be to examine what early engagement *trajectories* explain about the likelihood of dropping out. Janosz, Archambault, Morizot, and Pagani (2008) found strong relationships between engagement trajectories and dropout, yet engagement in the context of their analyses was largely composed of behavioral measures, and no consideration was given to incremental differences in explanatory power. It will be important to investigate whether understanding factors like FGA or FSL in developmental terms add value to prediction. If so, the incremental validity found in the present study for SEI factors in explaining dropout might be even more pronounced in the early middle school years and when considering trajectories rather than single points in time.

Years of research on dropout indicates that disengagement from school, such as disciplinary problems or low attendance rates, are powerful predictors of dropping out (Rumberger & Lim, 2008). However, disengagement in elementary or middle school years might start with less severe forms of withdrawal. An unstable path of FGA scores, for instance, or perhaps an unusually rapid drop in FGA scores from 6th to 7th grades may predate outward behavioral disengagement for these students. Further, while many students may manifest disengagement through disciplinary problems and low attendance, not everyone who dropped out showed these early signs. Perhaps

early changes in FGA or FSL will help better identify and understand students who fall off the graduation path. Investigating these possibilities is important to understanding the full potential of the measure and for a fuller theoretical understanding of the developmental aspects of engagement.

Implications for Practice

Data that do not inform screening or intervention practices are of little use to educators and no benefit to students themselves. Therefore, evaluations of how engagement data, like those collected in this study, contribute to prediction of student outcomes are important to evaluating the practical utility of the engagement construct. Two subscales (Future Goals and Aspirations and Family Support for Learning) of students' cognitive and affective engagement added to the prediction of long-term outcomes after accounting for data commonly available to school personnel, providing evidence that querying students' cognitive and affective engagement with school may have value. Further, school counselors could use engagement data in concert with academic and behavioral screening and monitoring efforts that are part of comprehensive, tiered models of service delivery (Reschly et al., 2014), such as Response to Intervention, Positive Behavior Intervention and Support (PBIS), or multi-tiered systems of support.

of engagement (cognitive, affective, and behavioral). Therefore, interventions to address one subtype, such as affective engagement (e.g., belonging) may affect another (attendance, class behavior). Further, part of the appeal of student engagement is that it is a meta-construct (Fredricks et al., 2004), allowing for much richer understanding of students' school experiences. In this vein, dropout prevention experts have noted that re-engaging youth at risk of dropping out is more than meeting the academic and behavioral standards of schools, but also requires attention to their affect or emotion and cognitions about school (Christenson & Reschly, 2010). A similar view is espoused in high school reform efforts. In a volume on this topic, the National Research Council concluded that effective school practices addressed adolescents' autonomy, belonging, and competence (NRC, 2004).

The next question, then, is how to effectively link engagement data, such as those collected by the SEI or other engagement surveys, to interventions. Some interventions, such as Martin's (2008) self-directed individual workbook engagement intervention or Check & Connect, an evidence-based dropout intervention program (checkandconnect.umn.edu), are defined specifically as engagement interventions. The recent trend of establishing school- or district-wide

> SCHOOL COUNSELORS COULD USE ENGAGEMENT DATA IN CONCERT WITH ACADEMIC AND BEHAVIORAL SCREENING AND MONITORING EFFORTS THAT ARE PART OF COMPREHENSIVE, TIERED MODELS OF SERVICE DELIVERY.

The real promise of engagement, however, is the presumed link between student engagement and intervention. Although only two subscales were predictive of long-term outcomes, significant, positive relationships exist among the subscales (e.g., FSL, PSL, FGA) and between the broader types

advisement programs wherein a group of students are placed with the same teacher ("advisor") for regular meetings within or across academic years is an example of one way schools are trying to enhance relationships and connections (i.e., student engagement) among students and between students

and staff (Appleton, 2012; Appleton & Thompson, 2009). In line with the meta-construct concept, scholars have begun to compile and classify promising and evidence-based interventions according to engagement subtype and whether each may be thought of as a universal or targeted intervention strategy (Reschly et al., 2014; Reschly, Polh, Christenson, & Appleton, 2017). For example, interventions such as Self-Regulation Empowerment Program (Cleary, Platten, & Nelson, 2008) and Self-Regulated Strategy Development (Harris, Graham, Mason, & Friedlander, 2009) are thought to address students' cognitive engagement (e.g., self-regulation, self-efficacy). Banking Time (Pianta, 1999) and ALAS (Larson & Rumberger, 1995) address affective engagement (relationships with teachers, belonging). PBIS (www.pbis.org), the Good Behavior Game (Bradshaw, Zmuda, Kellam & Ialongo, 2009), and the Behavior Education Program (Hawken & Breen, 2017) are primarily behavioral engagement interventions, although collateral effects on other types of engagement are presumed.

Limitations

An important limitation of this study was the retrospective, observational nature of the methods employed in it, which preclude statements of causal relationships among any of the variables in our analyses. Further, although our sample was large and diverse, it represented one district in the country; further generalizations to nonrepresentative populations may be unfounded. Others are encouraged to replicate these analyses in other districts and across districts, particularly in rural settings or in settings with substantial variability in risk across schools for dropout. The time constraints of our data (i.e., 4 years from Grade 9) as well as missing data should also be noted. Students in the cohort who were still enrolled after the window for on-time graduation may have graduated later. Similarly, other nongraduates may be re-enrolled at a later date or graduated elsewhere

CONCLUSION

The findings of this study suggest that greater confidence may be placed in the interpretation of SEI scores for students in the process of disengaging from school and with long-term educational objectives in mind. Although many previously reported correlations between SEI scores and indicators of behavioral engagement/disengagement and achievement were small to nonsignificant, the results of this study show that—when following students over several years—there are significant, predictable, and educationally meaningful associations between some SEI scores and relevant outcomes. Early screening for dropout risk is a necessary component of systematic, evidence-based prevention programs (Christenson & Thurlow, 2004; Jimerson, Reschly, & Hess, 2008), and while the findings here in no way suggest that the SEI should be used on its own, they do indicate promising potential for the SEI's inclusion in multifactor risk identification efforts. Although student engagement is generally regarded as a multifaceted construct (Fredricks et al., 2004), most engagement studies have involved primarily, or only, behavioral indicators. Data on cognitive and affective engagement may be more challenging to gather than behavioral engagement indicators, but this study found distinct, additive value when incorporated into a multifactor model. ∎

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