Identifying students who are off-track academically in 9th Grade:

The role of social-emotional learning trajectories

By James Soland and Megan Kuhfeld

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Abstract

Research shows that successfully transitioning from middle school to high school is pivotal for students to remain on track to graduate. Studies also indicate that a successful transition is a function not only of how prepared the students are academically, but whether they have the social-emotional learning (SEL) skills to succeed in a more independent high school environment. Yet, little is known about whether students' SEL skills are stable over time, and if they are not, whether a student's initial level of SEL skills at the start of middle school or change in SEL skills over time is a better indicator of whether the student will be off track academically in 9^{th} grade. We use several years of longitudinal SEL data to fit growth models for three constructs shown to be related to successfully transitioning to high school. In so doing, we examine whether a student's mean SEL score in 6^{th} grade (status) or growth between 6^{th} through 8^{th} grade is more predictive of being off track academically in 9^{th} grade. Results indicate that, while status is more frequently significant, growth for self-management is also predictive above and beyond status on that construct.

Keywords: Social-emotional learning, school engagement, dropout, structural equation modeling, growth/development.

Identifying Students Who Are Off-track Academically in 9th Grade: The Role of Social-emotional Learning Trajectories

Social-emotional learning (SEL) is an old concept that is gaining new traction in education practice and policy. SEL is a term that encapsulates a huge swath of research related to educational psychology. Psychological constructs associated with SEL often fall into broad categories like interpersonal, intrapersonal, and deep cognitive competencies (Soland, Stecher, & Hamilton, 2013), and include concepts like grit (Duckworth & Quinn, 2009) and growth mindset (Dweck, 2006). Measures of these constructs are now being used in policy and practice. For example, the California Office to Reform Education (CORE) is a consortium of districts serving over 2 million students that banded together in 2010 to get a waiver of provisions of the No Child Left Behind Act of 2001. Their revised accountability system included measuring outcomes like academic self-management, growth mindset, self-efficacy, and social awareness scores (West, 2016). More recently, the Every Student Succeeds Act (ESSA) of 2015—the main policy mechanism for federal accountability and newest instantiation of the Elementary and Secondary Education Act—requires states to include non-academic indicators, which are often related to SEL, in their accountability plans.

One reason for the renewed interest in SEL is a growing body of research providing evidence on the importance of social-emotional competencies (beyond the effect of cognitive ability) to long-term educational outcomes like high school graduation and workforce outcomes like earnings (Almlund, Duckworth, Heckman, & Kautz, 2011; Belfield et al., 2015; Dweck, Walton, & Cohen, 2011; Heckman & Vytlacil, 2001). In particular, research has shown that students who exhibit behaviors associated with dropping out—including course failures, chronic absenteeism, and suspensions—also have lower scores on measures of SEL constructs like self-management (Soland, Jensen, Keys, Wolk, & Bi, 2018). Students who show several of these behaviors in tandem when they begin high school are more likely to drop out, the ultimate manifestation of academic disengagement (Allensworth, 2013; Allensworth & Easton, 2005; Farrington et al., 2012). Thus, SEL scores are being used increasingly to identify students who may be at risk of dropping out in high school and provide associated supports to get those students back on track (Duckworth & Seligman, 2005; Good & Dweck, 2006; Soland, 2013, 2017).

The transition to high school is an especially pivotal time for academic disengagement. Oftentimes, students who drop out are off track in middle school, but those issues are exacerbated considerably during the transition to high school (Allensworth, 2013). For example, grades and test scores often decline in 9th grade. Students entering high school also show increasing signs of academic disengagement like absenteeism and suspensions (Allensworth, 2013; Farrington et al., 2012). These worrying trends have been connected to students' social-emotional needs. For instance, research suggests that socioemotional functioning at the end of the last year of middle school predicts perceived social support and socioemotional well-being at the end of the first year of high school (Martínez, Aricak, Graves, Peters-Myszak, & Nellis, 2011). Thus, identifying students who are at risk of struggling during the transition to high school while they are still in middle school can be useful in reducing high school dropout rates (Allensworth, 2013; Balfanz, Herzog, & Mac Iver, 2007).

While there is much research on the association between SEL scores and being off track to graduate from high school, most associated studies use SEL scores from a single time point (status). Even when multiple SEL scores are used over time, few if any studies treat related constructs as developmental processes with their own growth trajectories. In practical terms, little is known about how SEL constructs develop during the middle school year, as well as whether SEL developmental trajectories are predictive of being off track to graduate in 9th grade. One could imagine that a steady drop within middle school in a construct such as self-efficacy might predict being off track to graduate above and beyond the student's self-efficacy score at any single timepoint. If true, then educators trying to use SEL scores to support academically disengaged students making the transition to high school would benefit from knowing whether to be most concerned by low SEL status or growth.

This study begins to close the gap in the literature by using longitudinal SEL data to predict whether 9th grade students in our sample meet several indicators of being off track to finish high school, including low GPA, being suspended, and being chronically absent. Using survey results for three SEL constructs—academic growth mindset, self-efficacy, and self-management—utilized often in education accountability and practice (Soland & Kuhfeld, 2018; West, 2016; West et al., 2018), we fit latent growth models with each construct, as well as all constructs jointly modeled in a multivariate structure, to determine whether students' SEL at the start of middle school or change across middle school is more predictive of being off track. Specifically, we examine three research questions:

1. What are the normative pattern of growth in middle school for these SEL constructs, and how similar are the growth patterns across the three SEL constructs studied?
2. For each construct, is status or growth more predictive of being off track in 9th grade for high school graduation?
3. Does combining all three constructs in a single model change which constructs predict whether a student is off track in 9th grade?

In the remainder of the study, we review literature on SEL constructs and early warning systems before describing our sample, measures, and methods. We then present results and discuss their implications for identifying students in need of extra support to finish high school.

Background

The High School Transition

Students who are successful at managing the academic demands of the transition to high school have a high probability of graduating four years later, but those who fail to earn sufficient credits during ninth grade have a substantially elevated risk of dropping out of high school (Neild, 2009). In related work, Neild, Stoner-Eby, and Furstenberg (2008) found that ninth grade outcomes improved dropout predictions, even after controlling for an extensive set of pre-high school controls for family, achievement, aspirations, school engagement, and peer relationships. Beyond graduation, students who enter high school two or more years behind grade level in math and reading have only a 50% chance of on-time promotion to 10th grade (Allensworth, 2013; Balfanz et al., 2007). When students struggle academically, they often begin to disengage further from school (Balfanz et al., 2007). Thus, effectively transitioning students to high school academically has ramifications for their long-term attainment.

Fortunately, research suggests that identifying students who are likely to be off-track in 9th grade while still in middle school can give educators a chance to get those students back on track (Balfanz et al., 2007; Balfanz & Legters, 2004; Heppen & Therriault, 2008). For example, Balfanz et al. (2007) found that focusing on three middle school indicators—poor attendance, misbehavior, course failures—could identify 60% of students who did not graduate from high school. More importantly, pairing students identified by these warning indicators with attendance, behavioral, and academic interventions substantially improved graduation rates, especially when coupled with whole-school reform. Similar studies that paired early identification of students who were off track in 9^{th} grade with appropriate supports and interventions also found reductions in the likelihood of dropout (Carl, Richardson, Cheng, Kim, & Meyer, 2013; Heppen & Therriault, 2008; Mac Iver, 2013).

9^{th} Grade off-track Indicators

Research has identified a range of behaviors indicative of disengagement from school, especially among students transitioning to high school. These behavioral outcomes include poor attendance, suspensions, and low grade-point average (GPA) and were identified due to a strong association with academic disengagement, in particular dropping out of high school (Allensworth, 2013; Balfanz et al., 2007; Heppen & Therriault, 2008; Kennelly & Monrad, 2007; Soland, 2013). For example, low GPA is one of the best predictors of failing to complete high school, in part because getting good grades is partially a function of how hard a student is willing to work (Archambault, Janosz, Fallu, & Pagani, 2009). Chronic absenteeism and suspensions are also warning signs that a student may drop out (Kemple, Segeritz, & Stephenson, 2013).

Together, GPA, attendance, and suspensions account for most of the explained variance in dropout patterns, even when controlling for test scores and other academic measures (Heppen & Therriault, 2008). The association between such behaviors and dropout is strong in part because these behaviors "are the visible, outward signs that a student is [disengaged] and [not] putting forth effort to learn. Because they are observable behaviors, they are also relatively easy to describe, monitor, and measure" (Farrington et al., 2012, p. 8).

SEL Constructs Related to Disengagement in Middle and High School

Research practice and theory suggest that behaviors related to academic disengagement are often manifestations of students' academic mindsets (Farrington et al., 2012). In particular, self-efficacy and growth mindset are two academic mindsets that can start a chain reaction: students with low academic self-efficacy or lacking a growth mindset often do not believe they can successfully complete classroom tasks, which leaves little incentive to undertake those tasks. Lacking an incentive to undertake academic tasks can manifest itself in disengagement behaviors related to low self-management like coming to class unprepared (Bandura, 1993; Yeager & Dweck, 2012). Students with low self-management, in turn, oftentimes develop more serious disengagement behaviors like failing courses and regularly missing school (Farrington et al., 2012). Below, we briefly define the three SEL constructs we focus on within this study and describe their relationship with academic disengagement.

Growth Mindset. Growth mindset measures a spectrum between two extremes of how students view their intelligence (Blackwell, Trzesniewski, & Dweck, 2007; Dweck, 2006). At one extreme, students with a fixed mindset believe intelligence is a static trait: they have a certain amount of intelligence that cannot be changed (Dweck, 2006). By contrast, students with a growth mindset believe they can change their intelligence over time. Having a growth mindset can have a profound impact on whether students exert effort, especially in a schooling context:

> Students with a fixed mindset do not like effort. They believe that if you have ability, everything should come naturally. They tell us that when they have to work hard, they feel dumb. Students with a growth mindset, in contrast, value effort; they realize that even geniuses have to work hard to develop their abilities and make their contributions (Dweck, 2010, p. 16).

Dweck (2010) showed that growth mindset can manifest itself in the behaviors that students exhibit in school, including related to effort. For example, students randomized to receive growth mindset interventions demonstrated higher GPAs than their control-group peers (Aronson, Fried, & Good, 2002). Research also finds that mindset interventions can make students behave differently under academic stress by making them feel less discouraged when faced with challenges (Yeager & Dweck, 2012).

Self-efficacy. Self-efficacy refers to how individuals judge their own abilities to perform certain tasks or actions (Bandura, 1993). The higher a person's self-efficacy, the more that person believes he or she will be able to successfully complete a certain action or perform at a particular level (Bandura, 1993). Bandura (1993, 1997) argued through his body of research that self-efficacy is the foundation of human motivation: without belief in one's ability to accomplish a task, there is little incentive to undertake it. In education, the construct of self-efficacy measures a student's confidence in his or her ability to attain a certain educational goal or outcome, such as the ability to do well on a test or earn good grades in class (Schunk, 1991; Zimmerman, 2000). As an example of this theory in action, Zimmerman (2000) showed that student self-efficacy predicts motivation to learn, including students' activity choices, effort, persistence, and emotional reactions to difficult situations.

Self-management. Though self-management can be defined in several ways (and can be a catch-all for several constructs), the district in our study defined it as the manner in which a student maintains control over his or her thoughts, behaviors, and emotions. The construct captures aspects of self-regulated learning like the ability to stay focused (Pintrich, 1999), as well as classroom behaviors indicative of self-regulation like coming to class prepared (Farrington et al., 2012; Schunk & Zimmerman, 2012; Sperling, Howard, Staley, & DuBois, 2004). Students with less ability or motivation to self-regulate spend less time on academic tasks (Pintrich, 1999; Schunk, 2005). As a result, self-management has been shown to be positively associated with higher report card grades (Duckworth & Seligman, 2005) and higher GPAs, both of which at least partially measure student academic engagement (Tangney, Baumeister, & Boone, 2004).

Growth in All Three Constructs and Academic Disengagement. While much is known about all three constructs, and in some cases how students develop on those constructs over time, little is known about how SEL growth relates to being off-track in 9th grade. Specifically, no research we are aware of has considered whether SEL status or growth is more predictive of being off track, nor have status and growth predictors been compared across subjects. In the following section, we describe our analytic strategy for beginning to close some of those gaps in the literature.

Data, Measures, and Analytic Strategy

Analytics Sample

Our study uses a sample of students from a California district that is urban, high-poverty, and serves a high proportion of English learners. To avoid conflating across-grade differences in test scores with growth on the underlying construct, we follow a single cohort of students from 6th to 9th grade. The cohort was not intact, with approximately half of the students taking the survey at all three time points and half taking the survey during only one or two of the school years. Table 1 presents descriptive statistics for the sample. The sample size for our analyses ranged from 2,319 to 3,266 students depending on the number of complete survey responses for a given year.

Measures Used

Social-emotional Learning. Students in the sample took surveys administered by the district each spring to measure academic growth mindset, self-efficacy, and self-management. Specific items in each survey can be found in the Appendix. Each of these survey scales is measured using five-category Likert items. As described in more detail below, SEL surveys were scored using item response theory (IRT) methods. For each construct, the overall (across-time) mean is 0 and the standard deviation is 1.

Figure 1 displays the linear trends for the three SEL construct scores across the middle school grades. Self-efficacy and self-management show clear negative trends across middle school, with the average student dropping approximately 0.2 standard deviations in self-efficacy and 0.15 standard deviations in self-management. Growth mindset, on the other hand, increases by about 0.25 standard deviations in middle school. Table 2 presents the mean and standard deviations of the IRT scores for the three constructs across the three school years as well as the correlations among the SEL scores and the three off-track indicators. The across-time correlations for each of the three SEL constructs are moderate, ranging from .40 to .57.

One should note that, although the district has been administering the survey for four years, we only use three years of scores in our growth models. This approach was taken because we did not want to include SEL scores in our predictions that were contemporaneous with our 9th grade off-track indicators. That is, we used survey scores collected in middle school to predict being off track as a high school freshman.

Off-track Indicators. We used three 9th-grade indicators that a student may not be on track to graduate from high school: whether the student (a) was ever suspended in 9th grade, (b) was chronically absent (in California, a pupil who is absent on 10% or more of the school days in the school year), and (c) had an average GPA below a C. As discussed in the literature review, all three are strongly associated with academic disengagement, including dropout. As seen in Table 2, only 8% of our sample was chronically absent and 9% were ever suspended in 9th grade. Roughly 28% of students had a GPA below a C.

Ideally, we would have conducted analyses using dropout as the dependent variable in tandem with our 9th-grade indicators. However, the district has not been offering its SEL survey long enough to have students with scores in middle school who have also reached their 12^{th} grade year. Therefore, we focus on only the indicators of being off-track for graduation.

Academic Achievement. In our predictive models, we controlled for math and reading ability in the spring of 8^{th} grade, which was measured by NWEA's MAP Growth assessment. Each test takes approximately 40 to 60 minutes depending on the grade and subject area. Students respond to assessment items in order (without the ability to return to previous items), and a test event is finished when a student completes all the test items (typically 40 items for reading and 50 items for math). Test scores, called "RITs," are scaled from 100 to 300, with the average 8^{th} grade student scoring in the 200 to 250 range.

Student Demographic Characteristics. Our predictive analyses also included indicators for whether a student was male, an English Language Learner (ELL), had an individualized education plan (IEP), and received free or reduced price lunch (FRPL).

General Analytic Strategy

Testing for Measurement Invariance. Before producing scores for our SEL constructs or using them in a growth model, longitudinal measurement invariance tests were conducted to ensure the suitability of the scores for comparisons across grade levels. If the assumption of measurement invariance is violated, the underlying construct as measured by the observed variables is changing over time. Measurement invariance across grade levels was tested through a series of differential item functioning (DIF) analyses. DIF refers to the situation where members from different groups (i.e., sixth and seventh graders) who have the same level of the SEL construct have a different probability of selecting a certain response to a particular item. Items within each construct were evaluated for DIF following the procedure of Hansen et al. (2014) across two age comparisons: (a) sixth versus seventh graders, and (b) sixth versus eighth graders. DIF severity was measured using an index called weighted *a*rea *b*etween the expected score *c*urves (wABC), where wABC values above .35 were deemed problematic DIF (see Hansen et al. (2014) for properties of this index). The SEL items did not show any significant differential functioning across either grade comparison, and so we proceeded with IRT calibration and scoring.

Scoring SEL Surveys. We used an item response theory (IRT) calibration/scoring model to produce scale scores for each construct across the three school years. For each construct, a unidimensional graded IRT model was estimated with the pooled (across three years) item response data using full-information maximum likelihood in flexMIRT® (Cai, 2018). Subsequently, *e*xpected *a p*osteriori (EAP) scores were produced for each construct and year separately.

Growth Models. To understand how students' SEL skills develop over the course of middle school, we fit a series of latent growth curve models (LGCMs, Curran, Howard, Bainter, Lane, & McGinley, 2014). First, we fit a multivariate LGCM that allows for the joint estimation of growth patterns for each SEL construct and to examine the relations among the status and growth of the three constructs. Since we were constrained by only three waves of data, a linear growth trajectory was selected. The path diagram for the multivariate LGCM is depicted in Figure 2. For each construct, the random intercept reflects the average 6th grade score and the latent growth factor represents the linear change between 6th and 8th grade. To account for variance shared among SEL scores measured within a given time point, the within-time residual covariances among the SEL scores were freely estimated.

To answer our second research question (whether status or growth is more predictive of being off track to graduate in 9th grade), we used the structural equation model displayed in

Figure 3 to estimate the relationship between SEL status/growth and the 9th grade indicators. In this model, each 9th-grade off-track indicator of interest, y_j, was regressed on the latent status (α_j) and growth (β_j) variables. Additionally, we controlled for a set of background variables that were hypothesized to be associated with the off-track indicators: FRPL, ELL status, IEP, and gender. Thus, with three SEL constructs and three off-track indicators, we fit a total of nine models. Using these models, we compared the significance and magnitude of the standardized regression coefficients predicting the 9th grade off-track indicator.

As a point of comparison, we also fit three logistic regression models (one for each off-track indicator) without the SEL constructs included to examine the association between achievement and background characteristics independent of the SEL constructs. These models were included in order to compare odds ratios for each background control variable in the absence of SEL to the same odds ratios on SEL constructs in corresponding models. That is, in terms of practical significance, we wanted to be able to compare how much SEL growth changes the odds that a student will, say, have been suspended to the change in odds associated with background covariates like FRPL status.

Lastly, we examined whether jointly modeling the status and growth of the three SEL constructs improved the prediction of whether students were off-track in 9th grade. The conditional multivariate LGCM depicted by the path diagram in Figure 4 was estimated for each off-track indicator separately. All analyses were conducted in Mplus version 7 (Muthén & Muthén, 1998-2017) using full-information maximum likelihood (FIML), which assumes that data are missing at random. As a result, most covariance-based fit statistics are not available.

Results

1. How Strongly Associated are Status and Growth across the Three SEL Constructs Studied?

Before estimating our models using FIML, we first estimated our baseline model in Figure 2 such that correlation-based fit statistics could be generated. The multivariate LGCM in Figure 2 fit the data reasonably well, $\chi2$ (9) = 23.07, p = .006, RMSEA= .026 [90 C.I.: .013, .039]. Turning to FIML estimates, Table 3 presents the estimated mean and variance for each of the status/growth latent variables as well as the correlations among the latent factors. Students who have higher initial levels of self-efficacy and self-management in 6th grade show less steep drops across middle school (correlations between intercept and growth of -.18 and -.35, respectively), whereas higher initials levels of growth mindset are not significantly associated with the growth within middle school.

The results from the multivariate LGCM indicate that initial SEL status and growth are strongly associated across constructs, especially for the self-management and self-efficacy intercepts and slopes. The intercepts (6th grade scores) for self-management and self-efficacy are correlated .74 and the slopes are correlated .95, suggesting these two constructs are highly collinear. Self-efficacy and growth mindset are less strongly related, with intercepts correlated .53 and the slopes correlated .46. Self-management and growth mindset show the least parallel growth patterns, with intercepts correlated .38 and the slopes correlated .28.

2. For Each Construct, is Status or Growth More Predictive of Being off track to Graduate in 9th Grade?

Table 4 presents coefficients (logits) and odds ratios for the background variables we used as covariates when predicting each of the three off-track indicators. These coefficients were produced by fitting a model that regressed the indicator on the six covariates without SEL in the model. Boys are 1.7 times as likely to be suspended and 3.5 times as likely to have a GPA of below a C than girls. The odds of being chronically absent or ever suspended were moderately lower for students with higher math achievement in 8^{th} grade.

Table 5 presents coefficients from the models in Figure 2, which regress observed 9^{th}-grade off-track indicators on each latent variable in the model. Results appear to differ by off-track indicator and SEL construct. Neither the intercept nor growth across middle school for the three SEL constructs were significantly associated with chronic absenteeism in 9^{th} grade after controlling for the background characteristics. However, for GPA, coefficients on the self-efficacy and self-management latent intercepts were significant at the .05 level, as was the coefficient on the self-management growth. For example, covariate-adjusted odds that a student who is one standard deviation above average in self-efficacy has a GPA below a C are about half those of otherwise similar children with average self-efficacy in 6^{th} grade. As a point of comparison, one should note that the decrease in the odds of having a GPA below a C for a one standard deviation increase in self-management (both the intercept and growth), is about equivalent to the increase in the odds of having a GPA below a C if the student is low-income (Table 4). Additionally, the odds of being suspended were significantly lower for students who were above average in self-management at the start of middle school as well as students who showed above-average growth in self-management across middle school.

3. Does Combining all Three Constructs in a Single Model Change which Constructs Predict Whether a Student is off Track in 9^{th} Grade?

As previously described, we began by fitting the multivariate LCM in Figure 4. However, as the results to Question 1 revealed, the slope latent variables for self-management and self-efficacy were correlated .95, and the intercept latent variables for the same constructs were correlated .73. Given this potentially high degree of multicollinearity, we fit an alternative model presented in Figure 5. This model essentially pools the variance of the two intercept and two slope terms for self-efficacy and self-management, then regresses the off-track indicators on those new latent variables. This general approach has been used elsewhere to address multicollinearity in an SEM framework, including by Koufteros, Babbar, and Kaighobadi (2009).

Results from that model are presented in Table 6. As the table shows, none of the parameters are significant when predicting chronic absenteeism. For GPA below a C, the self-management intercept and slope were both significant, with a one standard deviation unit increase in the slope term associated with significantly lower odds that a student had a GPA below a C in 9th grade. For whether the student was ever suspended, the combined self-efficacy/self-management intercept and slope were both significant, with a one standard deviation unit increase in the slope term associated with odds of being suspended that were about 80% lower than students with average growth, controlling for the other background variables.

Surprisingly, the growth mindset intercept is associated with an increase in the odds that a student was suspended. While this finding is counterintuitive, the result appears to occur partially due to the covariates in the model. Growth mindset and test scores are highly correlated (minimum of .45). When the models were fit without control variables like test scores, the coefficients (in logits) for growth mindset were near zero and nonsignificant. Results, meanwhile, for self-management and self-efficacy do not change in significance dependent on inclusion of covariates.

Discussion

Education practitioners, policymakers, and researchers increasingly emphasize students' social-emotional needs. This focus on SEL is driven in part by research connecting related constructs to long-term educational and job market outcomes like college completion and earnings (Dweck et al., 2011; Farrington et al., 2012; J. J. Heckman, Stixrud, & Urzua, 2006). As a result, SEL measures are being used not only in practice, but also in accountability systems (Hough, Kalogrides, & Loeb, 2017; West, 2016). Oftentimes, the purpose of such measures is to identify students who may not be on track to finish high school, and intervene in order to get them back on track (Farrington et al., 2012).

Despite this emphasis on SEL, little is known about the importance of growth on SEL constructs over time, including how that growth may or may not relate to being off track to graduate. We begin to close this gap in the literature by fitting latent growth curve models for three intrapersonal SEL constructs, then regressing 9th grade off-track indicators on status and slope latent variables. In so doing, we provide several pieces of evidence relevant to understanding the role of SEL growth in identifying students who may need extra supports to graduate.

First, we find that growth in all three SEL constructs is highly correlated. For example, the growth latent variables are correlated over .95 for self-management and self-efficacy, and .46 for growth mindset and self-efficacy. Assuming such results are not driven by measurement artefacts, this finding indicates that students' development in these constructs during middle school is highly related. Though debatable, such a finding may also suggest there is some merit to talking about a student's overall SEL when trying to determine whether a student is off track to graduate rather than discuss only individual constructs (Conley, 2007; Dweck et al., 2011). More research to test such a theory is needed.

Second, we show that both SEL scores at the start of middle school and growth in middle school predict being off track in 9th grade. Further, results depend on the construct being measured and the off-track indicator being used. For example, whereas status for self-efficacy is a significant predictor of having a GPA below a C, it is not significantly associated with chronic absenteeism or suspension in 9th grade. Results are similar when fitting models that include growth submodels for all three SEL constructs at once: coefficients that are predictive can shift by model.

Despite these idiosyncrasies across constructs and indicators, one common theme is that status and growth for self-management are associated with decreased odds of having a low GPA and getting suspended, even after controlling for academic achievement and background characteristics. This result holds for models that treat each SEL construct separately, as well as those that include all three constructs. (Though, one should note that the model including all three constructs essentially uses a shared self-efficacy/self-management slope.) Thus, whether discussing status or growth, self-management appears to be the most consistent predictor of being on-track in 9th grade.

In general, these results likely mean that educators could benefit from paying attention to both status and growth when trying to identify and support students who may not graduate from high school. Our findings indicate that growth is often a significant predictor above and beyond status on that construct when a student is in 6th grade. Such a result makes sense given other research showing that improvements on constructs like growth mindset (typically due to an intervention of some kind) can improve outcomes related to graduation like grades and test scores (Dweck, 2006; Yeager & Dweck, 2012).

Limitations

This study has several limitations that bear mention. First, our sample is limited to a single district. The district has a high concentration of low-income and English language learner students. Therefore, our findings may not generalize to other educational settings. Results should be replicated with students of different racial, language, socioeconomic, and geographical backgrounds.

Second, we only had four years of survey data, which meant we could only use three years to predict our outcome of interest. Eventually, with more years of survey responses, we hope to replicate analyses with more years of data. Doing so would mean we could see if models with nonlinear functional forms do a better job of predicting our outcomes of interest.

Third, our SEL measures were student surveys. Thus, they may suffer from self-report and other biases. In fact, one hypothesis might be that growth trends in certain SEL constructs relate to artefacts of the measures themselves, such as changing propensities for social desirability bias over time (Krumpal, 2013). Results should be replicated with SEL scores that do not rely solely on self-reports.

Finally, we wanted to code time in our LGCMs such that the latent intercepts corresponded to mean SEL scores in 8th grade. However, models coding time accordingly would not converge. Therefore, we report only the models that are centered at 6th grade.

Conclusion

While students' SEL scores from a given timepoint have been shown to be associated with being off track to finish high school, little is known about how growth on certain SEL constructs predicts being on course to graduate. In this study, we used survey results for three SEL constructs—growth mindset, self-efficacy, and self-management—to fit latent growth curve models predicting certain 9th-grade off-track indicators established in the literature as being associated with dropping out. In so doing, we found that growth on self-management is associated with lower odds of being off track in 9th grade above and beyond the student's initial SEL score in 6th grade. This finding could mean that practitioners will benefit from factoring in how students are developing on SEL constructs when trying to identify students most in need of extra academic and SEL supports to finish high school.

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Figures/Tables

Table 1
Statistics on Analytic Sample

	6th grade (2014-15)	7th grade (2015-16)	8th grade (2016-17)	9th grade (2017-18)
Prop. Male	0.487	0.492	0.500	0.478
Prop. ELL	0.297	0.289	0.227	0.202
Prop. IEP	0.094	0.110	0.102	0.066
Prop. Hispanic	0.959	0.969	0.957	0.965
Number of students with SEL scores	2,319	3,266	2,842	—
Math percentile (median)	29	31	33	30
Reading percentile (median)	29	25	29	27

Table 2

Descriptive Statistics for SEL Latent Variable Estimates, 9th-grade Off-track Indicators

		Correlations											
	Mean (SD)	GM15	GM16	GM17	SE15	SE16	SE17	SM15	SM16	SM17	GPA	Abs.	S
Growth Mindset 2015	-0.081 (0.815)	1.000											
Growth Mindset 2016	-0.04 (0.836)	0.396	1.000										
Growth Mindset 2017	0.166 (0.872)	0.401	0.485	1.000									
Self-efficacy 2015	0.119 (0.923)	0.261	0.281	0.322	1.000								
Self-efficacy 2016	-0.056 (0.929)	0.238	0.337	0.374	0.467	1.000							
Self-efficacy 2017	-0.108 (0.928)	0.208	0.305	0.417	0.429	0.513	1.000						
Self-management 2015	0.081 (0.904)	0.178	0.228	0.290	0.511	0.354	0.268	1.000					
Self-management 2016	-0.081 (0.895)	0.173	0.232	0.306	0.360	0.557	0.363	0.527	1.000				
Self-management 2017	-0.046 (0.887)	0.118	0.219	0.316	0.271	0.383	0.519	0.417	0.567	1.000			
GPA Below a C 2018	0.280(0.211)	-0.191	-0.257	-0.236	-0.254	-0.254	-0.278	-0.294	-0.323	-0.307	1.000		
Chronically Absent 2018	0.082 (0.186)	-0.013	0.001	0.023	0.029	-0.015	0.009	0.002	-0.004	-0.017	-0.159	1.000	
Ever Suspended	0.091 (0.219)	-0.031	-0.041	-0.068	-0.106	-0.097	-0.103	-0.125	-0.131	-0.150	-0.334	-0.028	1.

Table 3

Correlations among Latent Growth Curve Parameters

Outcome	Latent Variable Means (Variances)	Latent Correlations					
		S.E. - int.	S.E. - slope	G.M. - int.	G.M. - slope	S.M. - int.	S.M. - slope
Self-efficacy - Intercept	0.112 (0.433)	1.000					
Self-efficacy - Slope	-0.131 (0.051)	-0.183	1.000				
Growth Mindset - Intercept	-0.098 (0.255)	0.528	-0.042	1.000			
Growth Mindset - Slope	0.112 (0.033)	0.300	0.458	0.093	1.000		
Self-management - Intercept	0.070 (0.501)	0.737	-0.305	0.381	0.268	1.000	
Self-management - Slope	-0.079 (0.088)	-0.274	0.955	-0.117	0.277	-0.349	1.000

Table 4.
Coefficients for On-track Indicators Regressed on Student Backgrounds Covariates, no SEL in the Model

Chronically Absent	Odds Ratio		Est.	S.E.	P-value
Math Achievement	0.974	*	-0.026	0.009	0.004
Reading Achievement	0.990		-0.011	0.011	0.318
Male	0.787		-0.240	0.228	0.294
English Learner	0.588	*	-0.531	0.281	0.059
FRPL	1.204		0.186	0.604	0.759
IEP	0.709		-0.344	0.413	0.405
GPA below C					
Math Achievement	0.925	*	-0.078	0.006	0.000
Reading Achievement	0.961	*	-0.040	0.007	0.000
Male	3.545	*	1.266	0.129	0.000
English Learner	0.754		-0.282	0.164	0.085
FRPL	1.446	*	0.369	0.107	0.230
IEP	0.427	*	-0.851	0.245	0.001
Ever Suspended in 9th Grade					
Math Achievement	0.975	*	-0.025	0.005	0.000
Reading Achievement	0.974	*	-0.026	0.006	0.000
Male	1.713	*	0.538	0.126	0.000
English Learner	0.520	*	-0.654	0.159	0.000
FRPL	0.805		-0.217	0.294	0.461
IEP	0.560	*	-0.580	0.231	0.012

Note. * p<.05

Table 5.

Coefficients for On-track Indicators Regressed on Individual SEL Intercept, Growth Parameters

Chronically Absent	Odds Ratio		Est.	S.E.	P-value
Growth Mindset - Intercept	1.622		0.484	0.400	0.227
Growth Mindset - Growth	0.208		-1.572	1.762	0.372
Self-efficacy - Intercept	0.717		-0.333	0.206	0.106
Self-efficacy - Growth	0.716		-0.334	1.031	0.746
Self-management - Intercept	0.603		-0.507	0.189	0.007
Self-management - Growth	1.446		0.368	0.611	0.547
GPA below C					
Growth Mindset - Intercept	1.184		0.169	0.213	0.428
Growth Mindset - Growth	0.431		-0.841	1.116	0.451
Self-efficacy - Intercept	0.524	*	-0.646	0.116	0.000
Self-efficacy - Growth	0.520		-0.654	0.561	0.244
Self-management - Intercept	0.493	*	-0.707	0.108	0.000
Self-management - Growth	0.444	*	-0.812	0.366	0.027
Ever Suspended in 9th Grade					
Growth Mindset - Intercept	1.340		0.295	0.199	0.138
Growth Mindset - Growth	0.427		-0.850	0.904	0.347
Self-efficacy - Intercept	0.820		-0.198	0.107	0.064
Self-efficacy - Growth	0.408		-0.896	0.608	0.141
Self-management - Intercept	0.590	*	-0.527	0.102	0.000
Self-management - Growth	0.340	*	-1.078	0.362	0.003

Note. N=2,352. Background covariates included in all models, though coefficients are not reported.

Table 6.
Coefficients for On-track Indicators Regressed on Individual SEL Intercept, Growth Parameters

Chronically Absent	Odds Ratio		Est.	S.E.	P-value
Growth Mindset - Intercept	2.005		0.696	0.387	0.073
Growth Mindset - Slope	0.352		-1.043	2.489	0.675
Self-efficacy/Self-management - Intercept	0.486		-0.722	0.562	0.198
Self-efficacy/Self-management - Slope	1.760		0.565	1.529	0.712
GPA below C					
Growth Mindset - Intercept	1.687		0.523	0.329	0.112
Growth Mindset - Slope	6.691		1.901	1.485	0.201
Self-efficacy/Self-management - Intercept	0.202	*	-1.602	0.394	0.000
Self-efficacy/Self-management - Slope	0.126	*	-2.074	0.956	0.030
Ever Suspended in 9th Grade					
Growth Mindset - Intercept	1.845	*	0.612	0.201	0.002
Growth Mindset - Slope	1.836		0.608	1.220	0.618
Self-efficacy/Self-management - Intercept	0.402	*	-0.911	0.307	0.003
Self-efficacy/Self-management - Slope	0.202	*	-1.601	0.787	0.042

Note. N=2,352. Background covariates included in all models, though coefficients are not reported.

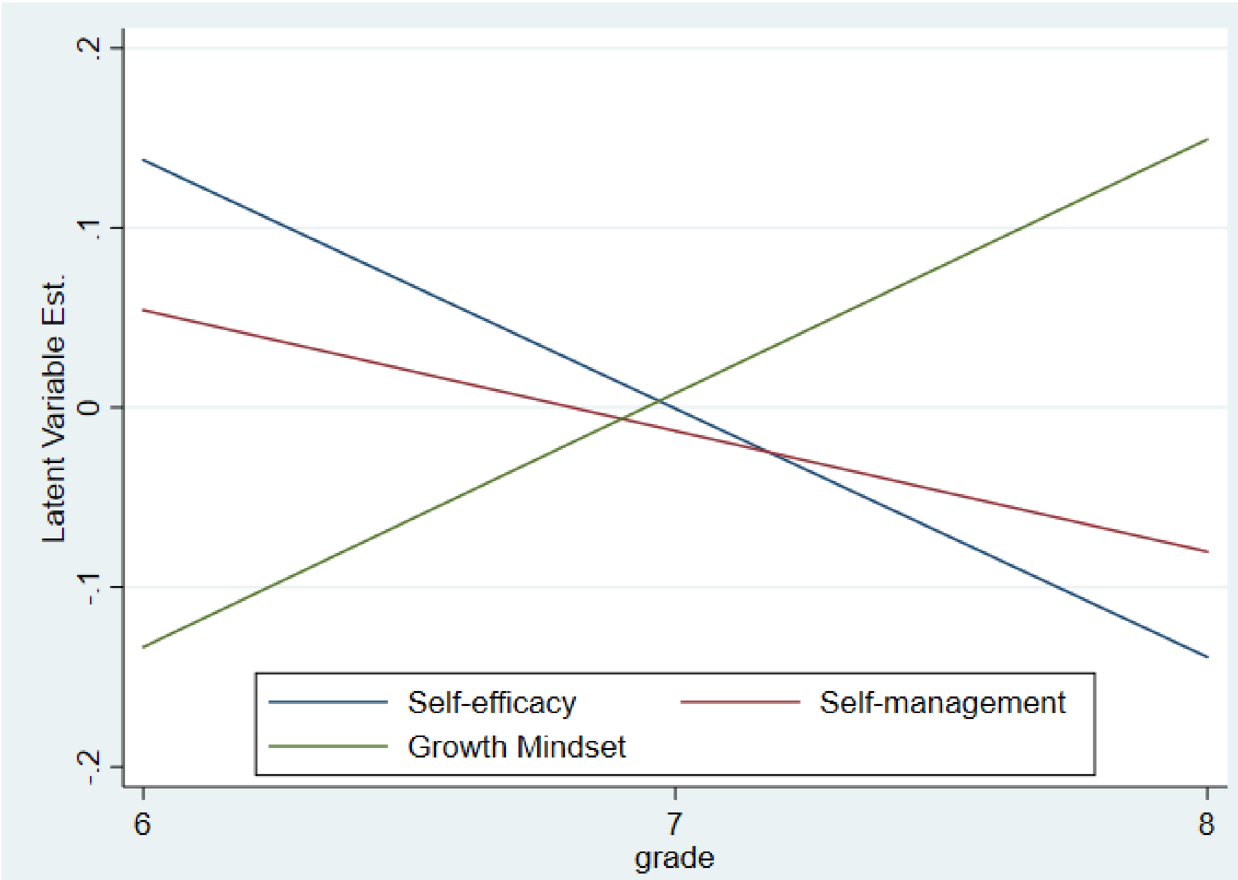

Figure 1. Trends in the SEL IRT scores across middle school.

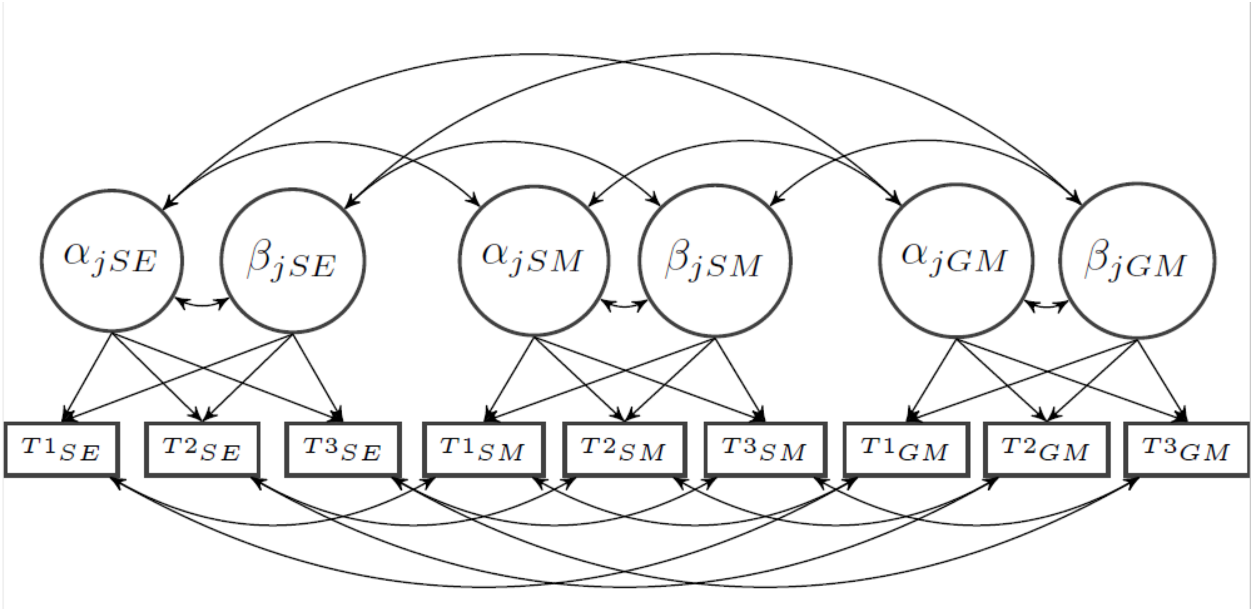

Figure 2. Path diagram for LGCMs.

Note. α_j is the latent intercept, and β_j the latent slope. T1 is the latent variable estimate (EAP score) for a given SEL construct at Time 1 (Spring of 2015). All paths from the α_j's to EAP estimates were constrained equal to 1. All paths from the β_j's to EAP estimates were constrained equal to 0 (Time 1), 1 (Time 2), and 2 (Time 3).

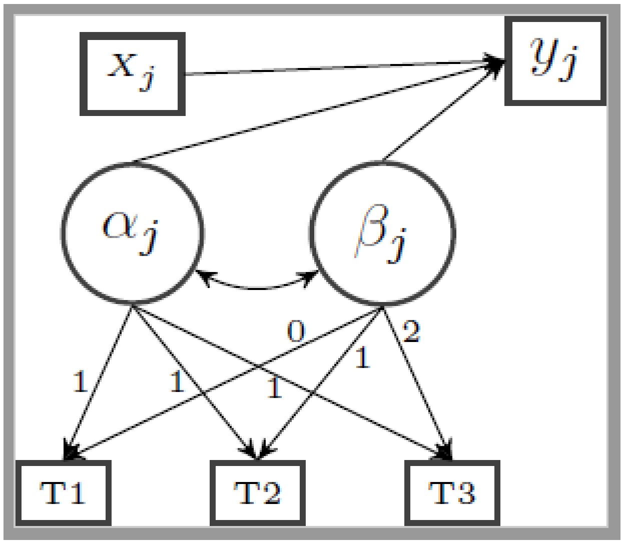

Figure 3. Path diagram for models with 9th-grade on track indicator regressed on latent intercept and slope parameters for a single SEL construct.

Note. y_j is the on-track indicator for person j, α_j is the latent intercept, and β_j the latent slope. T1 is the latent variable estimate (EAP score) for a given SEL construct at Time 1 (Spring of 2015).

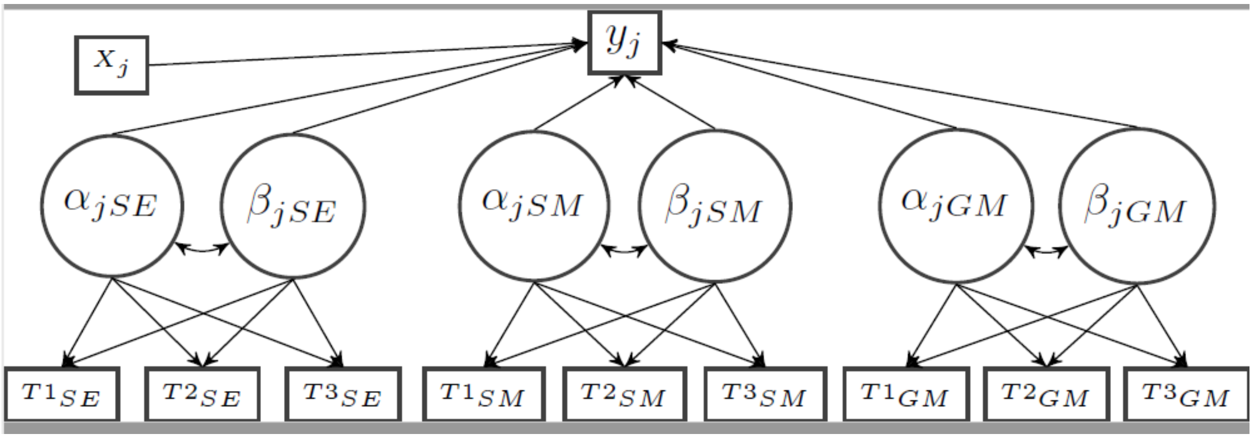

Figure 4. Path diagram for models with 9th-grade on track indicator regressed on latent intercept and slope parameters for all three SEL constructs.

Note. y_j is the on-track indicator for person j, α_j is the latent intercept, and β_j the latent slope for a given SEL construct, each of which is identified by the second subscript. $T1_{SE}$ is the latent variable estimate (EAP score) for self-efficacy at Time 1 (Spring of 2015). For parsimony, correlations among latent variables across constructs are omitted from the path diagram but are estimated in the model. For example, there is an estimated correlation between α_{j1} and α_{j3}. Correlations among EAP scores for different constructs in the same time period are also omitted but estimated in the model. For example, there is an estimated correlation between $T2_{SE}$ and $T2_{SM}$.

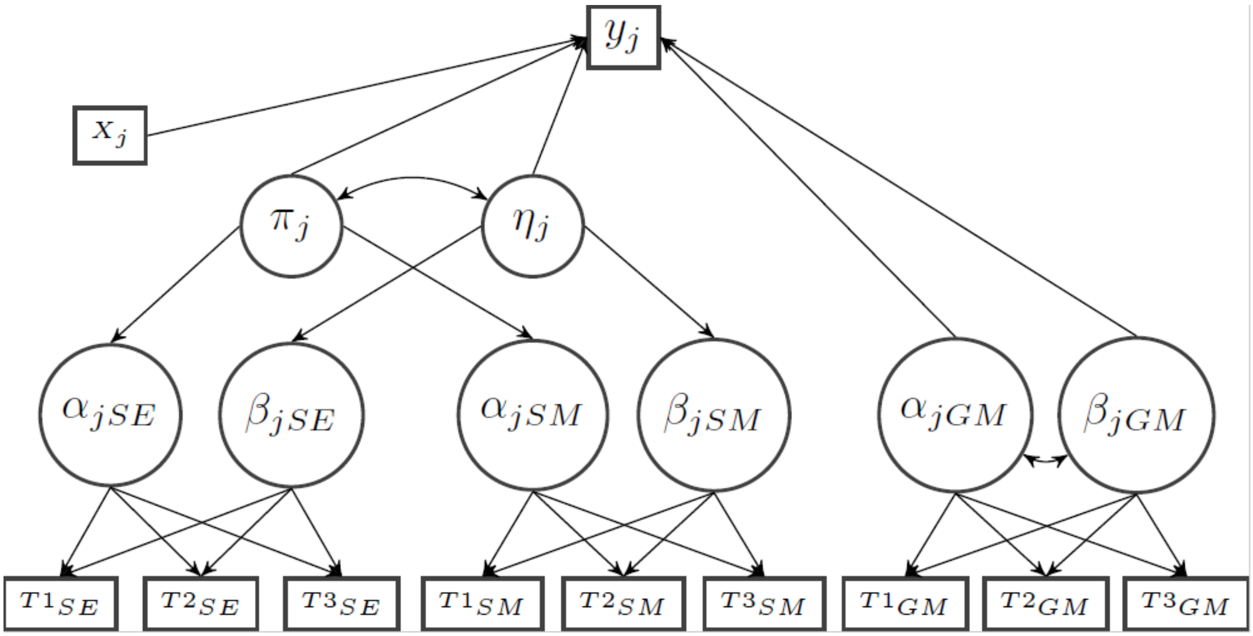

Figure 5. Path diagram for models with 9th-grade on track indicator regressed on latent intercept and slope parameters, accounting for multicollinearity.

Note. y_j is the on-track indicator for person j. α_{jSE} is the latent intercept for self-efficacy, β_{jSE} is the latent slope for self-efficacy, α_{jSM} is the latent intercept for self-management, and β_{jSM} is the latent slope for self-management. $T1_{GM}$ is the latent variable estimate (EAP score) for growth mindset at Time 1 (Spring of 2015). The only correlations allowed among latent variables are between α_{jGM} and β_{jGM} (intercept and slope for growth mindset, depicted), π_j and η_j (higher-order intercept and slope parameters for self-efficacy and self-management, depicted), and α_{jGM} and β_{jGM} with π_j and η_j (not depicted for parsimony). Correlations among EAP scores for different constructs in the same time period are also omitted but estimated in the model. For example, there is an estimated correlation between $T2_{SE}$ and $T2_{SM}$.

Appendix

Table A1

Items from District Surveys

Agree or disagree with the following (5 point Likert scale)
Growth Mindset
My intelligence is something that I can't change very much.
Challenging myself won't make me any smarter.
There are some things I am not capable of learning.
If I am not naturally smart in a subject, I will never do well in it.
Self-efficacy
I can earn an A in my classes.
I can do well on all my tests, even when they're difficult.
I can master the hardest topics in my classes.
I can meet all the learning goals my teachers set.
Self-management
I came to class prepared.
I remembered and followed directions.
I got my work done right away instead of waiting until the last minute.
I paid attention and resisted distractions.
I worked independently with focus.

ABOUT THE COLLABORATIVE FOR STUDENT GROWTH

The Collaborative for Student Growth at NWEA is devoted to transforming education research through advancements in assessment, growth measurement, and the availability of longitudinal data. The work of our researchers spans a range of educational measurement and policy issues including achievement gaps, assessment engagement, social-emotional learning, and innovations in how we measure student learning. Core to our mission is partnering with researchers from universities, think tanks, grant-funding agencies, and other stakeholders to expand the insights drawn from our student growth database—one of the most extensive in the world.

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