PRELIMINARY DRAFT
NOT FOR DISTRIBUTION
DO NOT CITE

Predicting Academic Performance from Social-emotional Learning Scales

Tara Chiatovich, Ph.D.
Panorama Education

Abstract

Using methods that accounted for the nesting of students within schools, this study predicted student GPA, ELA post-assessment scores, and math post-assessment scores from third- through twelfth-grade student responses to social-emotional learning surveys. The scales from the surveys included Emotion Regulation, Growth Mindset, Grit, Social Awareness, Self-Efficacy, and Self-Management. For all three academic outcomes, analyses controlled for student background characteristics, and for ELA and math post-assessment scores, they also controlled for pre-assessment scores. Sample sizes differed across analyses, ranging from 1,081 to 2,797 students for GPA and from 123 to 3,005 students for post-assessments. The six SEL topics were all positively associated with GPA such that higher self-reported SEL skills were linked to higher GPAs, with moderate effect sizes for Self-Efficacy and Self-Management and small effect sizes for Emotion Regulation, Growth Mindset, Grit, and Social Awareness. Students reporting higher levels of Emotion Regulation, Growth Mindset, and Self-Management earned higher ELA post-assessment scores overall, but the effect sizes were notably smaller than for GPA. When predicting math post-assessment scores, only Grit emerged as a significant predictor, with higher self-reported Grit corresponding to higher math post-assessment scores. As with ELA post-assessments, effect sizes were small. Implications for the relative contributions of the SEL topics to academic performance are discussed.

Introduction

Many schools are choosing to focus on students' social-emotional learning (SEL), which the Collaborative for Academic, Social, and Emotional Learning (CASEL, 2019) defines as "the process through which children and adults understand and manage emotions, set and achieve positive goals, feel and show empathy for others, establish and maintain positive relationships, and make responsible decisions." Not only is SEL associated with school success, but it is also seen as a key aspect of student's development (see Zins & Elias, 2007). Although research has demonstrated a link between SEL and academic performance (e.g., Schonfeld, et al., 2015; Taylor, Oberle, Durlak & Weissberg, 2017), rarely does an individual study address the wide range of topics that fall under SEL or evaluate their relative associations with different measures of academic performance. This study uses 2017-2018 data on self-ratings of SEL by third-twelfth-graders from schools across the country to predict their grade point average (GPA) and ELA and math post-assessment scores for the same academic year. Included were the following scales: Emotion Regulation, Growth Mindset, Grit, Social Awareness, Self-Efficacy, and Self-Management. The self-ratings came from Panorama Education's SEL Surveys, which have demonstrated reliability and validity and are administered directly by school and district personnel (Panorama Education, 2015; Panorama Education, 2016). Data on students' grade point average, assessment scores from both ELA and math pre- and post-assessments, and demographic information were from administrative records for the same year.

Multi-faceted SEL

SEL encompasses many related skills, attitudes, and behaviors that are nevertheless distinct from each other. The current study focuses on six specific topics within SEL, which are reviewed below.

Emotion regulation.

As the term itself suggests, emotion regulation is the ability to regulate one's emotions. In the classroom, emotion regulation involves dealing with emotions as they arise so that the student can function academically (Graziano, et al., 2007).

Growth mindset.

Growth mindset is the belief that intelligence and ability are not innate but rather malleable features that individuals can themselves change (Dweck, 2008). A growth mindset shapes one's response to failure, with a focus on increasing effort or changing strategy (see Dweck, 1986, for a review of the literature). Thus, growth mindset presents an adaptive path to success in the long-term even as students face setbacks.

Grit.

Duckworth and colleagues (2007) offer this simple definition of grit: "perseverance and passion for long-term goals" (p. 1087). Underlying this definition is the element of time. Grit as a concept is not something an individual can demonstrate merely in a given moment but rather requires a continued focus over prolonged periods.

Social awareness.

Social awareness, as defined by the Collaborative for Academic, Social, and Emotional Learning (CASEL, 2019), centers on empathy and respect for others. Perspective-taking is also a key skill for social awareness.

Self-efficacy.

The term self-efficacy, as summarized by the scholar who made it popular, "…centers on people's sense of personal efficacy to produce and to regulate events in their lives" (Bandura, 1982, p. 122). As it relates to students in classrooms, self-efficacy reflects students' confidence in their ability to direct their own learning and succeed academically (Zimmerman, Bandura, & Martinez-Pons, 1992).

Self-management.

The SEL skill of self-management involves the ability to focus one's attention, manage one's impulses, and work toward desired outcomes (CASEL, 2019). Relatedly, students' organizational skills and ability to resist distraction both reflect their level of self-management.

Research Questions

Despite the distinctions between the above topics, rarely do studies look across multiple SEL topics within the same data. The research presented here provides an opportunity for a detailed examination of SEL and its relation to important academic outcomes. It addresses the following research questions:

1. How do SEL topics relate to students' GPA, after controlling for student background characteristics?
2. How do SEL topics relate to students' ELA and math post-assessment scores net of their pre-assessment scores and background characteristics?
3. What are the relative contributions of each SEL topic to predictions of the different measures of academic performance?

Given that many prior studies have not only demonstrated that students with higher levels of SEL skills tend to evidence stronger academic performance but also that interventions to improve SEL skills boost academic performance (e.g., Durlak, et al., 2011; Schonfeld, et al., 2015; Sisk, et al., 2018; Taylor, Oberle, Durlak & Weissberg, 2017; Zimmerman, Bandura, & Martinez-Pons, 1992), I hypothesized that any associations between SEL and both GPA and post-assessments scores would be positive; higher SEL skills would be linked to higher GPA and post-assessment scores. However, the varying magnitudes of effects of SEL on academic outcomes in the research literature combined with adjusting for pre-assessment scores when assessing the associations between SEL topics and post-assessment scores suggests that those associations would show smaller and/or fewer effects for SEL. Finally, regarding the relative contributions of each SEL topic, evidence that course grades reflect not only academic skills but also students' ability to navigate the social environment of the classroom point to the relative importance of social awareness when predicting GPA (Bowers, 2009). Growth mindset and grit both involve the element of time—in responding to prior setbacks for growth mindset and persevering toward long-term goals in the case of grit. Therefore, these two SEL topics are expected to be especially important when predicting post-assessment scores adjusting for pre-assessment scores. I hypothesized that the remaining topics of emotion regulation, self-efficacy, and self-management would figure prominently both in the classroom and in assessments. Emotion regulation would correlate to GPA as well as to post-assessment scores because of emotion's ability to distract from learning in the day-to-day of the classroom and because of the need to manage one's emotions in the pressure of a testing situation. Since both self-efficacy and self-management tie directly into academics and beliefs and behaviors conducive to learning, these SEL topics are expected to be linked to both measures of academic performance.

Method

Data

All data used in analyses come from the Panorama Education Student Success platform. Schools and districts that are Panorama clients have agreed to the use of non-personally identifiable data for research purposes. Typically, schools and districts that use Student Success work with Panorama Education to integrate their coursework, assessment, and/or other data into the platform, making data across numerous schools and districts that span multiple dimensions of student development available for research purposes. Additionally, some schools and districts partnering with Panorama Education use its survey platform as well as Student Success, and a portion of those elect to have students complete surveys on their own SEL skills. In these cases, students' ratings of their SEL skills become available alongside data on their coursework and assessments. Which SEL topics schools and districts select for their surveys differs. This study made use of data from six of the most commonly selected SEL topics among schools and districts that use the Student Success platform, with varying sample sizes for each topic.

In partnering with Panorama Education, most schools integrated data on students' race and ethnicity, gender, grade level, whether students were English language learners, and special education status. Together, these data provided the following covariates:

- Grade level;
- English language learner (ELL);
- Special education;
- Male; and
- Under-represented minority (URM), defined as any students not identified as White or Asian.

From these, I calculated the percentage of students belonging to each dichotomous category (e.g., ELL, special education) at the school level so that school-level information on student demographics could complement individual-level demographics in the analyses. Many schools also included data on free/reduced-price lunch (FRPL) eligibility, but this variable suffered from missing data, with over 2/5 of the sample missing; I excluded it from the predictive models despite being reported in descriptive statistics.

Overall Sample

I limited the sample to students who had non-missing responses to at least half of the items in at least one of the six SEL topics for the study. By default, this step also limited the sample to students in third through twelve grade since students in second grade or earlier are not eligible to complete Panorama's self-rating surveys of SEL. Below, I give further exclusion criteria for the GPA, ELA post-assessment, and math post-assessment analyses, though ultimately the number of observations for models using SEL topics to predict each of the academic outcomes depends of the availability of data for the specific SEL topic for the model. Thus, the number of students reported for the GPA, ELA assessment, and math assessment samples below do not match the number of observations for each model.

GPA sample.

For the GPA sample, I also restricted the sample to students who were not missing data on GPA or on any of the following demographics, all of which were significantly associated with GPA even after controlling for each other:

- URM;
- Male;
- Special education; and
- Grade level.

After applying these exclusion criteria, the GPA sample included 3,423 students in 27 schools in 10 districts.

ELA post-assessments sample.

For the ELA post-assessment sample, similar to the GPA sample, I excluded students who were missing ELA pre- or post-assessment scores and students who were missing data on either ELL or special education. Additionally, a small proportion of students had an ELA pre-assessment date that was close in time to their ELA post-assessment date. To ensure that the ELA assessments could function as a pre- and post-assessment, I further excluded any students whose two ELA assessments were less than 90 days apart from each other. These exclusion criteria resulted in an ELA post-assessment sample with 3,042 students in 32 schools in 7 districts.

Math assessments.

Finally, for the math assessment sample, I excluded students who were missing math pre- or post-assessment scores and who were missing data on either URM or special education. As with ELA assessments, a few students took their math assessments fewer than 3 months apart from each other, so I excluded any students who had fewer than 90 days separating the two math assessments. The resulting math post-assessment sample had 2,389 students in 31 schools in 7 districts.

Measures

Social-emotional learning topics.

Measures for all six SEL topics come from third- through twelve-grade student responses to Panorama Education's SEL surveys. The surveys have students rate themselves on the topics Emotion Regulation (e.g., "How often are you able to control your emotions when you need to?"), Growth Mindset (e.g., "In school, how possible is it for you to change how intelligent you are?"), Grit (e.g., "If you have a problem while working towards an important goal, how well can you keep working?"), Social Awareness (e.g., "During the past few weeks, how well were you able to describe your feelings?"), Self-Efficacy (e.g., "When complicated ideas are discussed in class, how sure are you that you can understand them?"), and Self-Management ("How often did you get your work done right away, instead of waiting until the last minute?"). For each item for each SEL topic, students select between five Likert-type response options that best describe them. Panorama's SEL surveys use best practices in survey design and have demonstrated reliability and validity (Panorama Education, 2015; Panorama Education, 2016). The number of survey items for each topic ranged from 5 items (for Self-Efficacy and Grit) to 10 items (for Self-Management), and all items are scored such that 1 reflects the least positive response and 5 represents the most positive response. All survey content is available for download and use free of charge from the Panorama Education website (https://www.panoramaed.com/resources).

Estimates of theta scores for the six SEL topics provided the measures for analyses. From responses to the most recent survey data available, I fit a separate item response theory (IRT) model for each topic using graded response models (grm) from the ltm package in R (see Rizoploulus, 2006). The reason for using all available data, and not merely data from samples analyzed in the current study, was to base the IRT on a larger and more diverse set of students and schools than would be possible if I had limited the sample to only students with GPA or assessment data. I computed estimated theta scores to measure students' latent trait for each of the topics (e.g., students' level of Emotion Regulation and Growth Mindset) based on all available data, then used response patterns to all items within a given SEL topic and their associated theta score estimates to match theta scores produced from the IRT models to response patterns from students in the sample for the current study. In the larger sample on which the IRT models were based, the theta scores for each SEL topic had a mean of 0 and a standard deviation of 1. Prior to computing theta score estimates, I confirmed that the assumptions for item response theory were met.

GPA.

Students' GPA for the 2017-2018 school year were available in Panorama's software platform. Since the scale for GPA differed greatly between individual schools, I computed z-scores within each school by subtracting off the mean GPA and dividing by the standard deviation of GPA at the school level. Any school with GPA values for fewer than 25 students had GPA set to missing. After standardizing, the distribution of students' GPA was symmetric about 0 (the school-level mean) and resembled a normal curve, suggesting that this variable was appropriate to use in analyses.

ELA and math assessment scores.

Scores on ELA and math assessment scores came from school- or district-administered assessments from the following makers:

- FastBridge;
- NWEA MAP; and
- STAR.

To put the assessments on the same scale, I computed the z-score for each assessment, grouping together students who took the same assessment and were in the same grade. If any group contained fewer than 25 students, the assessment z-score was set to missing. Thus, across the assessment makers, a score of 0 represents the mean for the particular assessment and grade level, and each unit represents the standard deviation within the same group. Once on a common scale, the distribution of both ELA and math assessments appeared symmetric about 0, suggesting that the z-scores of assessments did make it feasible to include students who took different assessment in the same analyses. For students who had assessment scores at more than two time points, analyses used the scores from the earliest and latest date within the 2017-2018 school year. Table 1 below presents descriptive statistics on each of the three analytic samples (GPA, ELA assessments, and math assessments).

Table 1. Descriptive statistics for the analytic samples used to predict ELA assessments, math assessments, and GPA.

	ELA assessments	Math assessment	GPA
Percent URM	48.21%	45.04%	42.42%
Percent special education	15.91%	15.49%	15.60%
Percent ELL	8.51%	3.90%	5.43%
Percent male	52.04%	51.61%	52.85%
Percent FRPL	53.56%	58.33%	47.64%
N students	3042	2389	3423
N schools	32	31	27
N districts	7	7	10

Analytic approach

The general analytic approach for models predicting GPA, ELA post-assessments, and math post-assessments was to:

1. Build a control model with all relevant covariates predicting the academic outcome of interest.
2. Employ backwards elimination on the control model, removing the predictor with the lowest p-value one at a time until all remaining covariates in the model were statistically significant.
3. Add the SEL topic to the control model, with one SEL topic per model, resulting in six models.

The models predicting GPA were linear regression models with cluster-robust standard errors to account for the clustering of students within schools. I initially fit an unconditional multi-level model for GPA, but since GPA was standardized at the school level, the clustering of students within schools did not contribute to their GPAs, as evidenced by the small intra-class correlation coefficient. I examined the data and assured that the assumptions for linear regression appeared to be met.

Models predicting ELA and math post-assessment scores were multi-level models where individual students represented level 1 and schools represented level 2. Unconditional multi-level models showed the substantial effects of clustering, with an intra-class correlation coefficient (ICC) of 0.154 for ELA and 0.168 for math. The ICCs reveal that 15.4% of the variance in ELA post-assessment scores and 16.8% of the variance in math post-assessment scores can be attributed to students being nested within schools. Visual inspection of the data revealed that the assumptions for multi-level models were appropriate.

The covariates examined when building the control model for GPA included:

- URM;
- ELL;
- Male;
- Special education; and
- Grade level.

For ELA and math post-assessments, the covariates for the control models included:

- Pre-assessment score;
- URM;
- ELL;
- Male;
- Special education;
- School-level percent URM (i.e., the percentage of students at each school who identified as URM);
- School-level percent ELL;
- School-level percent male; and
- School-level percent special education.

The ELA and math post-assessment control models did not examine grade level since the assessment scores were standardized separately by grade level, resulting in grade level explaining virtually none of the variance in either assessment. Unlike the GPA models, the assessment models examined whether school-level percentages for each demographic group contributed to post-assessment scores. These additional covariates are typical within multi-level models and allow for an examination of not only the contribution of individual student characteristics to post-assessment scores but also that of the overall makeup of each school analyzed (see Bryk & Raudenbush, 2002). The models specified random intercepts at the school level to allow for variation in post-assessment scores between schools.

An important addition to the ELA and math post-assessment models is pre-assessment score. Unlike GPA, which had only one value for the 2017-2018 school year, the ELA and math assessments had scores at two points in time. By including the pre-assessment score as a covariate in the math and ELA post-assessment models, analyses can examine the association between each SEL topic and post-assessment score net of a student's pre-assessment score. In other words, setting up the models so that pre-assessment score served as a covariate examines whether students with higher SEL skills earn higher post-assessment scores among students whose pre-assessment scores were the same. In this manner, the analyses speak to SEL skills' links to *gains* in assessment scores.

Results

GPA models

The control model for GPA included the covariates URM, special education, male, and grade level. To this control model, I added each SEL topic in turn as the predictor of interest, resulting in six final models presented in Table 2 below showing the association between the SEL topic and GPA holding constant URM, special education, male, and grade level. (Grade level is not shown in the table to conserve space.) All SEL topics were statistically significant and positive predictors of GPA, with what are considered moderate effects for Self-Management and Self-Efficacy and small effects that in some cases approached moderate for the remaining SEL topics (Cohen, 1988). Across all SEL topics, higher SEL ability in the topic (as gauged by the estimated theta score) was linked to a higher GPA. The coefficients for the SEL topics give the magnitude of the difference in GPA standard deviation units that is associated with each standard deviation difference in the given SEL topic, holding constant URM, special education, and male. For example, each positive difference of 1 standard deviation in Self-Management was linked to a GPA that was 0.409 standard deviation higher overall. For Self-Efficacy, each positive difference of 1 standard deviation corresponded to a GPA that was on average 0.330 standard deviation higher. Figures 1 and 2 below provide a graphical representation of the models for Self-Management and Self-Efficacy predicting GPA.

The negative coefficients for URM, special education, and male all signal that these groups on average earned lower a GPA than their peers. URM students had GPAs that were overall between 0.229 standard deviation and 0.429 standard deviation lower than their White and Asian peers. Special education students on the whole had GPAs that were between 0.603 standard deviation and 0.840 standard deviation lower than their peers in general education. And male students had GPAs that ranged from 0.245 standard deviation lower to 0.448 standard deviation lower than female students on average.

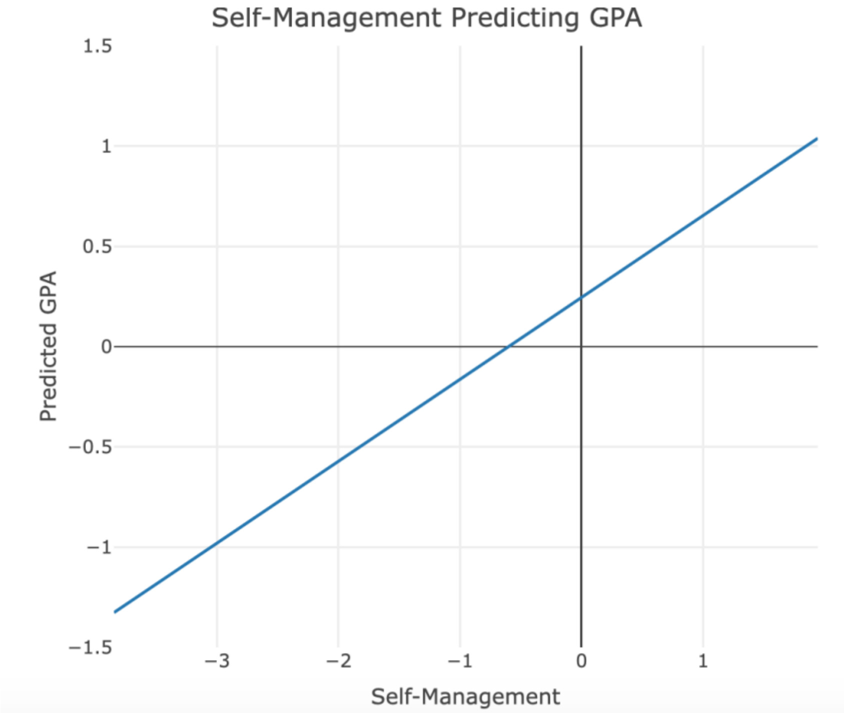
Table 2. Results from regression models with cluster-robust standard errors for schools, with SEL topics predicting GPA z-scores.

Predictors	**Emotion Regulation**	**Growth Mindset**	**Grit**	**Social Awareness**	**Self-Efficacy**	**Self-Management**
(Intercept)	1.139*	0.552**	0.638***	1.019*	1.066*	0.656
URM	-0.402**	-0.376**	-0.385**	-0.429***	-0.229	-0.386*
Special education	-0.840***	-0.632**	-0.603**	-0.702***	-0.686***	-0.679*
Male	-0.438***	-0.420***	-0.448***	-0.353***	-0.397***	-0.245**
SEL topic	0.206***	0.118**	0.244***	0.217***	0.330***	0.409**
Observations	2797	2354	2302	3029	1281	1815
R^2 / adjusted R^2	0.210 / 0.206	0.156 / 0.153	0.186 / 0.182	0.197 / 0.194	0.227 / 0.220	0.253 / 0.249

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

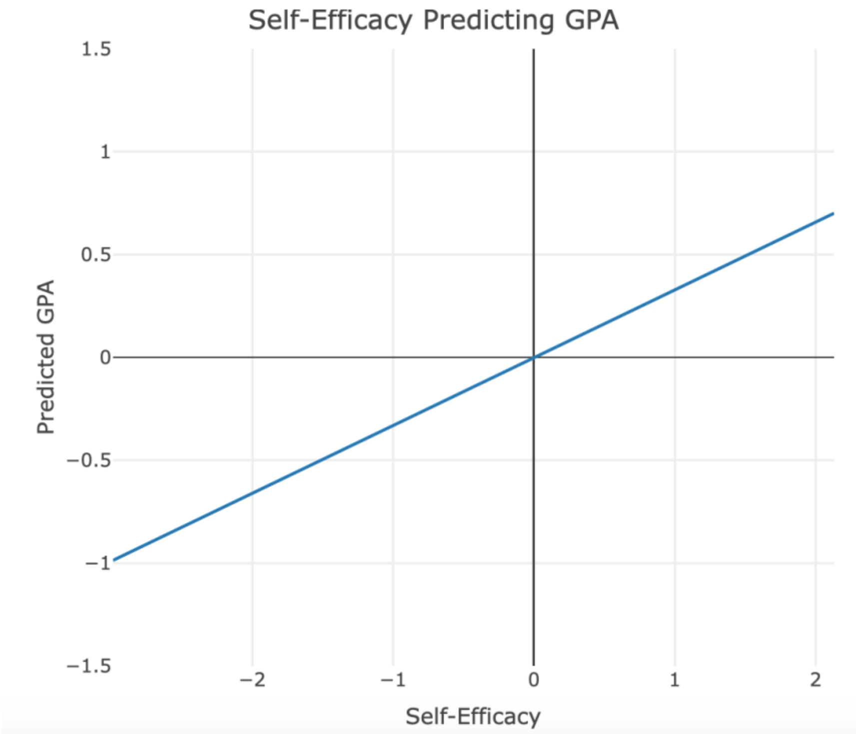
Note: All models above include grade level as a covariate, holding it constant at the earliest grade level present in the sample (grade 3 for Emotion Regulation, Social Awareness, and Self-Efficacy; grade 6 for Growth Mindset, Grit, and Self-Management). For URM, 1 = URM, 0 = other race/ethnicity. For special education, 1 = special education, 0 = general education. For male, 1 = male, 0 = female.

Figure 1. Plot of Self-Management and predicted GPA values from model



Note: The above visualization of the association between Self-Management and GPA holds male, special education, and URM constant at the mean and grade level constant at grade 6.

Figure 2. Plot of Self-Efficacy and predicted GPA values from model



Note: The above visualization of the association between Self-Efficacy and GPA holds male, special education, and URM constant at the mean and grade level constant at grade 6.

ELA post-assessment models

For multi-level models predicting ELA post-assessment score, the control model included ELA pre-assessment score, special education, ELL, and the number of months between pre- and post-assessment administrations. I added each SEL topic, one per model, to create the six models shown in Table 3 below. Emotion Regulation, Growth Mindset, and Self-Management were all statistically significant and positive predictors of ELA post-assessment score after controlling for ELA pre-assessment score, special education, ELL, and the number of months between the pre- and post-assessment administrations. Specifically, each positive difference of one standard deviation in Emotion Regulation, Growth Mindset, and Self-Management was linked to a respective ELA post-assessment score that was 0.031, 0.029, and 0.038 standard deviation higher on average controlling for all covariates in the model. Figures 3, 4, and 5 provide visualizations of these associations. The magnitude of these effects is notably small based on guidelines for interpreting effect sizes (Cohen, 1988).

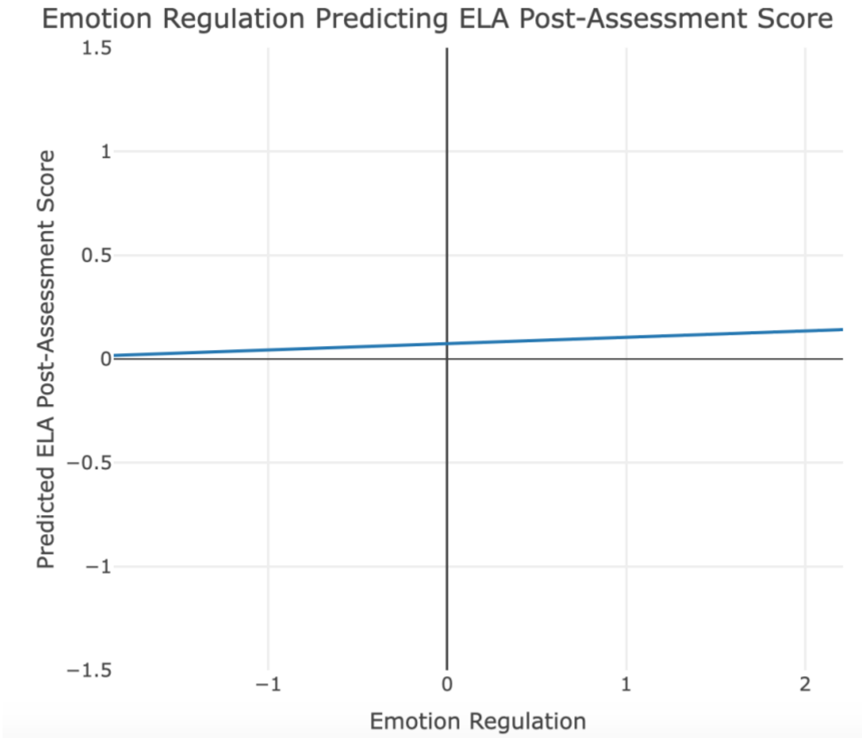
The coefficients for the covariates, which remained statistically significant in all models with the exception of ELL in the Emotion Regulation model, indicate that a higher ELA pre-assessment score and a greater number of months between pre- and post-assessments are linked to a higher ELA post-assessment score after controlling for other predictors in each model. ELA pre-assessment scores that were 1 standard deviation higher corresponded to an ELA post-assessment score that was on average between 0.793 and 0.850 standard deviation higher. For each additional month that separated the pre- and post-assessments, ELA post-assessment scores were between 0.026 and 0.057 standard deviation higher on average. Holding constant other predictors in the model, both special education and ELL students tended to earn lower scores on the ELA post-assessment, specifically, from 0.097 to 0.284 standard deviation lower for special education students compared to their peers and from 0.086 to 0.156 standard deviation lower for ELL students compared to their peers on average. Note that ELL students' ELA post-assessment scores did not differ significantly from those of their peers in the Emotion Regulation model.

Table 3. Results from multi-level models of SEL topics predicting ELA post-assessment score with school-level random intercepts.

Predictors	**Emotion Regulation**	**Growth Mindset**	**Grit**	**Social Awareness**	**Self-Efficacy**	**Self-Management**
(Intercept)	-0.061	-0.040	-0.004	-0.039	-0.018	-0.014
ELA pre-assessment score	0.795***	0.823***	0.821***	0.807***	0.793***	0.850***
Special education	-0.202***	-0.097**	-0.100***	-0.171***	-0.284***	-0.102*
ELL	0.059	-0.092*	-0.099**	-0.086***	-0.156**	-0.134**
No. of months between pre- and post-assessments	0.057***	0.051***	0.050***	0.051***	0.032*	0.026*
SEL topic	0.031**	0.029*	0.015	0.016	0.020	0.038*
Random Effects						
σ^2	0.29	0.24	0.24	0.27	0.33	0.20
τ_{00}	0.03 school	0.03 school	0.03 school	0.03 school	0.01 school	0.01 school
ICC	0.08 school	0.12 school	0.11 school	0.10 school	0.02 school	0.05 school
Observations	2393	2793	2799	3005	935	730
Marginal R^2/ Conditional R^2	0.678 / 0.704	0.713 / 0.749	0.712 / 0.744	0.696 / 0.725	0.709 / 0.715	0.792 / 0.803

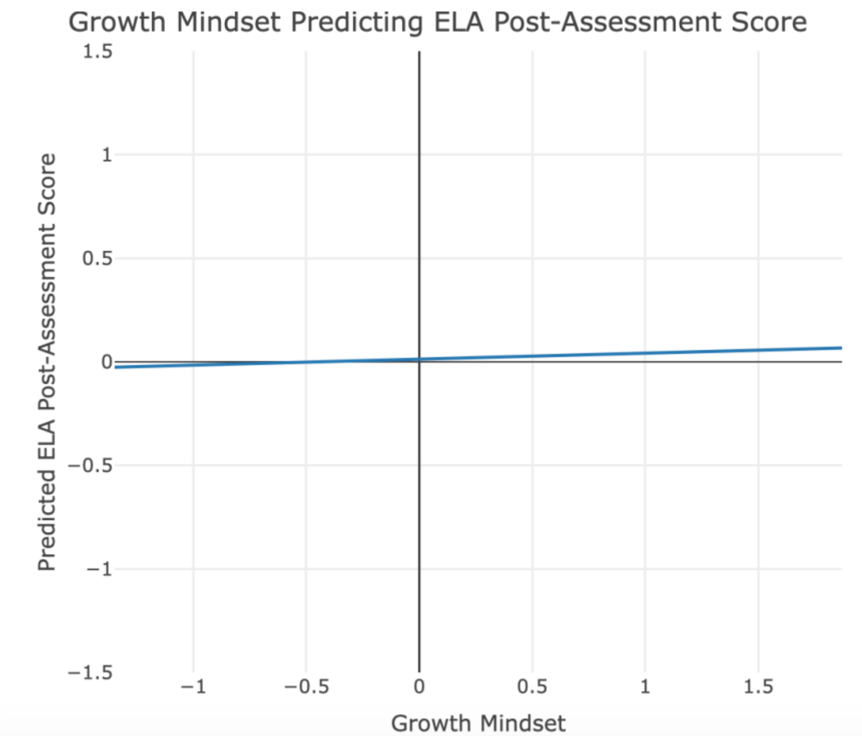
**p* < .05, ***p* < .01, ****p* < .001
Note: For special education, 1 = special education, 0 = general education. For ELL, 1 = ELL, 0 = English proficient.

Figure 3. Plot of Emotion Regulation and predicted ELA post-assessment score from model



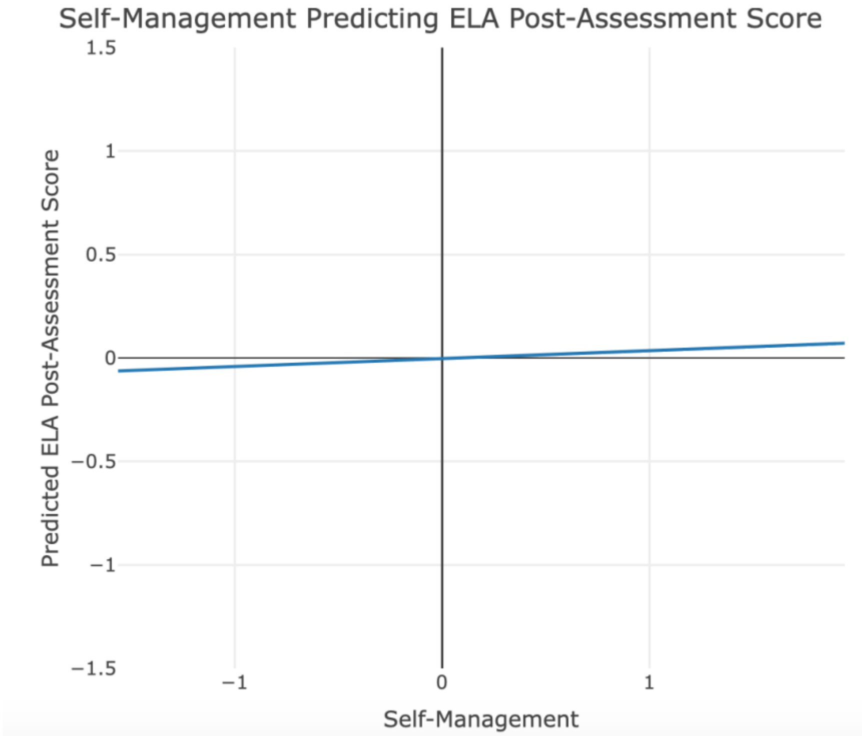
Note: In the above figure, the predictors ELA pre-assessment score, the number of months between assessment administrations, special education, and ELL are all held constant at the mean.

Figure 4. Plot of Growth Mindset and predicted ELA post-assessment score from model



Note: In the above figure, the predictors ELA pre-assessment score, the number of months between assessment administrations, special education, and English language learner are all held constant at the mean.

Figure 5. Plot of Self-Management and predicted ELA post-assessment score from model



Note: In the above figure, the predictors ELA pre-assessment score, the number of months between assessment administrations, special education, and English language learner are all held constant at the mean.

Math post-assessment models

For models predicting math post-assessment score, the statistically significant covariates retained from the control models were math pre-assessment score, URM, special education, and number of months between pre- and post-assessment administrations. As shown in Table 4 below, the only SEL topic that significantly predicted math post-assessment score after controlling for covariates in the models was Grit, with each positive difference of 1 standard deviation in Grit associated with a math pre-assessment score that was overall 0.024 standard deviation higher, making for a small effect according to effect size guidelines (Cohen, 1988). Figure 6 below shows this association graphically. Note that the model for Self-Efficacy is not shown due to its small number of observations and singular model fit; however, in that model, Self-Efficacy was non-significant.

The covariates predicting math post-assessment score overall indicate higher post-assessment scores for students who had higher pre-assessment scores and more months separating their pre- and post-assessment while URM and special education students earned lower post-assessment scores after adjusting for all other predictors in the models. Each positive difference of 1 standard deviation on the math pre-assessment score was linked to a math post-assessment score that was on average between 0.710 and 0.919 standard deviation higher. Regarding the demographic variables, differences ranged from 0.073 to 0.282 standard deviation lower on the post-assessment for URM students compared to their peers and from 0.120 to 0.354 standard deviation lower on the post-assessment for special education students compared to their peers.

Note that the number of months between math pre- and post-assessments was not significantly associated with math post-assessment score in the Self-Management model, which had a particularly low number of observations and so suffered from a lack of statistical power.

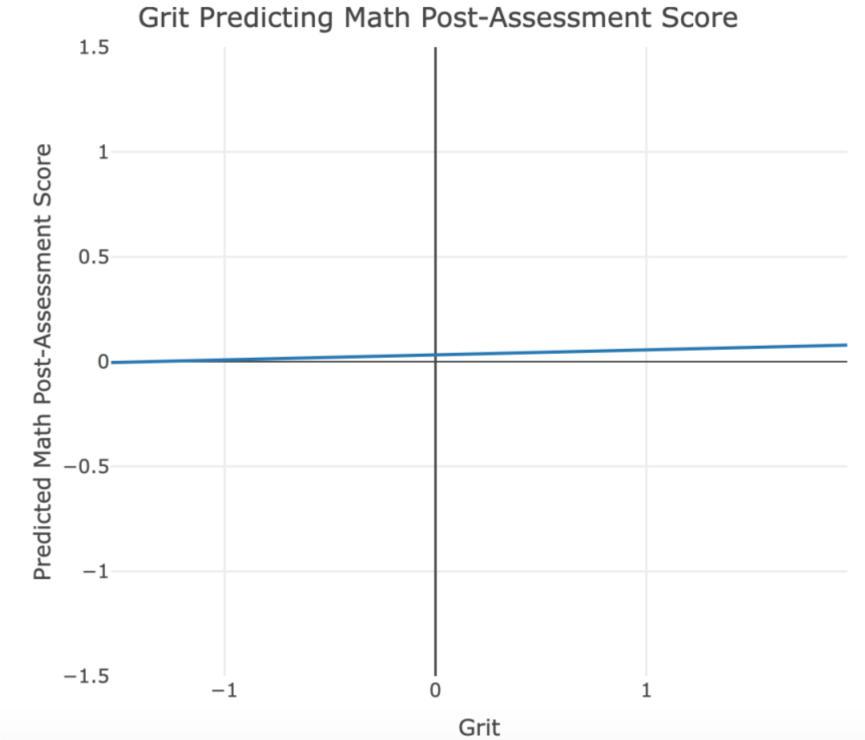
Table 4. Results from multi-level models of SEL topics predicting math post-assessment score with school-level random intercepts.

Predictors	**Emotion Regulation**	**Growth Mindset**	**Grit**	**Social Awareness**	**Self-Management**
(Intercept)	-0.374***	-0.423***	-0.412***	-0.348***	0.159
Math pre-assessment score	0.915***	0.916***	0.917***	0.919***	0.710***
URM	-0.077***	-0.076***	-0.073***	-0.074***	-0.282*
Special education	-0.151***	-0.120***	-0.123***	-0.157***	-0.354**
No. of months between pre- and post-assessments	0.134***	0.150***	0.149***	0.132***	0.024
SEL topic	0.000	0.010	0.024*	-0.006	-0.066
Random Effects					
σ^2	0.22	0.20	0.20	0.22	0.34
τ_{00}	0.07 school	0.05 school	0.05 school	0.07 school	0.00 school
ICC	0.25 school	0.22 school	0.21 school	0.25 school	0.01 school
Observations	2340	2130	2148	2362	123
Marginal R^2/ Conditional R^2	0.724 / 0.792	0.747 / 0.801	0.751 / 0.803	0.724 / 0.793	0.653 / 0.658

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

Note: For URM, 1 = URM, 0 = other race/ethnicity. For special education, 1 = special education, 0 = general education. Model information for Self-Efficacy not shown due to low number of observations and singular model fit; the coefficient for Self-Efficacy was non-significant in that model.

Figure 6. Plot of Grit and predicted math post-assessment score from model



Note: In the above figure, the predictors math pre-assessment score, the number of months between assessment administrations, URM, and special education are all held constant at the mean.

Discussion

SEL Topics and Academic Performance

The analyses presented above, in support of other research findings, show many positive associations between SEL skills and academic outcomes (Schonfeld, et al., 2015; Taylor, Oberle, Durlak & Weissberg, 2017). Looking to GPA first, all six SEL topics—Emotion Regulation, Growth Mindset, Grit, Social Awareness, Self-Efficacy, and Self-Management—were statistically significantly and positively linked to students' GPA for the 2017-2018 school year. In all cases, higher SEL skills corresponded to higher GPAs, and lower SEL skills corresponded to lower GPAs. The effects for Self-Management and Self-Efficacy were moderate whereas for the remaining topics the effects were small or approaching moderate.

The analyses involving assessment scores focused on a slightly different question than those for GPA. Instead of asking which SEL topics were associated with performance, they asked which SEL topics were associated with performance toward the end of the academic year net of earlier performance. By using SEL topics to predict students' post-assessment score after controlling for their pre-assessment score, each SEL topic could only be statistically significant if it explained variance in post-assessment score over and above the variance already explained by how students performed on the same assessment of the same subject area only a few months prior. Nevertheless, Self-Management, Emotion Regulation, and Growth Mindset all statistically significantly and positively predicted ELA post-assessment score after adjusting for pre-assessment score, though the size of these effects were notably small. In essence, these results indicate that students with higher skills in these SEL topics tend to evidence higher gains on ELA assessments, and conversely, students with lower skills in these areas showed lower gains on their ELA assessments. These links also adjusted for important student background characteristics, specifically, special education and ELL status, as well as the amount of time between pre- and post-assessment administrations.

For math, only Grit statistically significantly predicted students' post-assessment score after controlling for their pre-assessment score and other important factors. As with ELA assessments, this effect was small but merits attention as it speaks to the potential role of Grit in student gains in math assessments. Students with higher levels of self-reported Grit generally had higher gains as measured by math pre- and post-assessments. The inverse is also true, where students with lower Grit showed lower gains on math assessments.

Relative Contributions of Different SEL Topics to Predictions of Academic Performance
Viewed on the whole, the results align in some cases, and diverge in others, with expectations for the relative importance of certain SEL topics for course versus assessment performance. Given that course performance as measured by GPA is a mix of not only academic skill but also the ability to navigate the social environment of the classroom (Bowers, 2009), the hypothesis was that Social Awareness would predict GPA but not assessment score gains; the results conformed to that view. However, I also hypothesized that both Grit and Growth Mindset would be linked to gains is assessment score more so than to students' GPA. Growth Mindset involves the ability to reflect on performance and alter one's strategies while Grit relies heavily on persistence and continued focus (Duckworth, et al., 2007; Dweck, 1986; Dweck, 2008), both of which involve an element of time that was present in the pre- and post-assessment scores but not in the single measure of GPA. Although the results provided some support for this conceptualization of Growth Mindset and Grit, with Growth Mindset predicting ELA assessment gains and Grit predicting math assessment gains, both SEL topics also predicted the single measure of GPA.

Finally, I theorized that the SEL topics of Emotion Regulation, Self-Efficacy, and Self-Management would be equally pertinent to the classroom as measured by GPA and a testing situation as measured by assessment score gains, which was partially supported by the results. In the case of Emotion Regulation, emotion's propensity to distract from learning in the classroom and the need for students to contain their anxiety to perform well on an assessment, I argued, would make it relevant to both settings, and the attitudes and behaviors that underlie Self-Efficacy and Self-Management would support learning in the classroom, which both assessment score gains and GPA would likely reflect. Self-Management and Emotion Regulation were associated with both GPA and with ELA assessment score gains, but neither was linked to math assessment score gains. Further, while Self-Efficacy predicted GPA, it did not predict ELA gain scores, and the model for Self-Efficacy predicting math gain scores could not speak this focus due to a small sample size and poor model fit.

Limitations
Across all the SEL topics, lack of statistical power was a larger problem for analyses involving assessment scores than analyses involving GPA, and this was especially true for Self-Efficacy and Self-Management. Additionally, controlling for pre-assessment scores in the assessment analyses, but with no similar prior measure held constant in the GPA analyses, limits the ability

to compare findings for SEL topics across the two types of academic outcomes. Nevertheless, an exploration of which SEL topics were significantly associated with the different academic outcomes is worthwhile at this stage in the project's development, with the understanding that it merits another look once I have access to data on more students with a potentially richer list of academic outcome variables.

An important direction for future research is to attend to causality. Nothing in the analyses speaks to whether a change in SEL skills would result in a change in academic outcomes. The inverse may be true, with academic performance leading students to develop the skills, behaviors, and attitudes inherent in the SEL topics examined, or a confounding variable could help explain both students' levels of SEL skills and their academic outcomes. Although the analyses controlled for some important student background characteristics and, in the case of assessments, the time in between assessment administrations, ruling out these factors as confounders, the analytic design used here does not lend itself to causal conclusions. Analyses that look across multiple points in time, not just the two points in time available for assessments, would make possible an approach such as structural equation modeling that could examine whether early SEL skills are more predictive of later academic outcomes or whether the evidence supports the opposite, with early academic outcomes doing a better job of predicting later SEL skills.

Conclusion

As with prior research (e.g., Durlak, et al., 2011; Schonfeld, et al., 2015; Sisk, et al., 2018; Taylor, Oberle, Durlak & Weissberg, 2017; Zimmerman, Bandura, & Martinez-Pons, 1992), this study demonstrated a link between high SEL skills and strong academic performance. It adds to the literature by looking across specific areas of SEL and different measures of academic performance within the same source of data. In so doing, it addresses how the many facets of SEL may contribute separately to both learning in the classroom as reflected by students' grades and as evidenced in the highly controlled and more objective context of an assessment. In this manner, the study can offer insights to those in the field of education as they seek to support students' overall development.

References

Bandura, A. (1982). Self-efficacy mechanism in human agency. *American Psychologist, 37*(2), 122-147.

Bowers, A. J. (2009). Reconsidering grades as data for decision making: More than just academic knowledge. *Journal of Educational Administration*, *47*(5), 609-662.

Bryk, A. S., & Raudenbush, S. W. (2002). *Hierarchical linear models: Applications and data analysis methods* (2nd ed.). Thousand Oaks, CA: Sage.

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences.* New York, NY: Routledge Academic.

Collaborative for Academic, Social, and Emotional Learning (CASEL). (2019). Core SEL competencies. Retrieved from https://casel.org/core-competencies/.

Duckworth, A. L., Peterson, C., Matthews, M. D., & Kelly, D. R. (2007). Grit: perseverance and passion for long-term goals. *Journal of personality and social psychology*, *92*(6), 1087.

Durlak, J. A., Weissberg, R. P., Dymnicki, A. B., Taylor, R. D., & Schellinger, K. B. (2011). The impact of enhancing students' social and emotional learning: A meta-analysis of school-based universal interventions. *Child development*, *82*(1), 405-432.

Dweck, C. S. (1986). Motivational processes affecting learning. *American Psychologist*, *41*, 1040-1048.

Dweck, C. S. (2008). *Mindset: The new psychology of success*. Random House Digital, Inc..

Graziano, P. A., Reavis, R. D., Keane, S. P., & Calkins, S. D. (2007). The role of emotion regulation in children's early academic success. *Journal of school psychology*, *45*(1), 3-19.

Panorama Education. (2015). Validity brief: Panorama Student Survey. Retrieved from https://panorama-www.s3.amazonaws.com/files/panorama-student-survey/validity-brief.pdf.

Panorama Education. (2016). Reliability and validity of Panorama's Social-Emotional Learning measures. Retrieved from https://panorama-www.s3.amazonaws.com/files/sel/SEL-Validity-Report.pdf.

Rizoploulus, D. (2006). ltm: An R package for latent variable modeling and item response theory analyses. *Journal of Statistical Software*, *17*(5), 1-25. Retrieved from

Schonfeld, D. J., Adams, R. E., Fredstrom, B. K., Weissberg, R. P., Gilman, R., Voyce, C., ... & Speese-Linehan, D. (2015). Cluster-randomized trial demonstrating impact on academic achievement of elementary social-emotional learning. *School Psychology Quarterly*, *30*(3), 406.

Sisk, V. F., Burgoyne, A. P., Sun, J., Butler, J. L., & Macnamara, B. N. (2018). To what extent and under which circumstances are growth mind-sets important to academic achievement? Two meta-analyses. *Psychological science*, *29*(4), 549-571.

Taylor, R. D., Oberle, E., Durlak, J. A., & Weissberg, R. P. (2017). Promoting positive youth development through school-based social and emotional learning interventions: A meta-analysis of follow-up effects. *Child development*, *88*(4), 1156-1171.

Zimmerman, B. J., Bandura, A., & Martinez-Pons, M. (1992). Self-motivation for academic attainment: The role of self-efficacy beliefs and personal goal setting. *American educational research journal*, *29*(3), 663-676.

Zins, J. E., & Elias, M. J. (2007). Social and emotional learning: Promoting the development of all students. *Journal of Educational and Psychological Consultation*, *17*(2-3), 233-255.