Early Assessment of Cognitive Skills, Self-Regulated Learning Skills, and Attitudes toward Education Predict University Success at Graduation

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Abstract

Considerable research has been conducted on the incremental or individual influences of cognitive skills, self-regulated learning skills, and attitudes toward education on the success of learners in many levels of educational inquiry. In addition, much work has been focused on predicting student success in the first year of college, or examining factors that promote retention only for the second semester or second academic year. In this study, we expand this focus by examining the interactive nature of these three domains of student characteristics over the course of the entire students’ experience in higher education. Specifically, using seven years of institutional data, we explored the predictive utility of measures of students’ cognitive skills, self-regulated learning skills, attitudes toward education, and academic anxiety prior to the start of their first semester on graduating grade point average for anyone completing a degree within six years of matriculation. Review of the results demonstrates that while all of the variables were instrumental in explaining university success, the best explanation

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of the data was achieved through a partial moderated mediation model. Furthermore, the patterns of these relationships for first-generation and non-first-generation students differed. We interpret the results in support for a model of early assessment to identify areas of need for learners to promote more adaptive coping strategies at the start of the university experience to support optimal graduation outcomes for both first-generation and non-first-generation learners.

*Keywords:* university success, academic anxiety, self-regulated learning, attitudes toward education, cognitive skills, university admissions
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In today’s educational landscape, considerable attention is devoted to the identification of strategies that promote retention and success among university students (Aljohani, 2016; Chipchase et al., 2017). At the most fundamental level, the impetus underlying these efforts is to identify educational settings and situations that will provide the greatest positive outcomes for learners. There is a long-standing focus by educators and researchers to identify features that may present barriers to learners successfully completing their educational goals, aiming to identify interventions or adaptations that support success (Heller & Cassady, 2017). Unfortunately, there is also a tradition of using student profiles to determine selection standards for academic programs or decisions, under a misguided or ill-informed presumption that some characteristic or skill set determines with great precision the “potential” a student may have in a given setting (Allensworth & Clark, 2020). A growing recognition of the failures of individual achievement or aptitude measures to effectively predict the performance of learners in university settings has recently led to significant changes in admissions practices for institutions of higher education, recognizing that performance on a specific test (e.g., SAT, ACT), high school grade point average (GPA), gender, or race are biased and inappropriate measures to determine admission (Allensworth & Clark, 2020; Rothstein, 2004). The historic—and flawed—strategy of determining likely success in college based on a single achievement test taken by adolescents is rapidly fading as more schools adopt “testing optional” strategies for admissions (Bennett, 2021; Schultz & Backstrom, 2021).

As an alternative to this dated approach to college admissions and advisement, we support a multidimensional assessment strategy that examines students’ abilities, skills, and needs in affective and cognitive domains (see also Kitsantas et al., 2008). This proposed strategy is not offered as a new litmus test for admission, but as a mechanism to identify individual characteristics that can be supported by institutional programs and practices designed to maximize performance for all learners. As such, we advocate for a universal assessment methodology in higher education that is aligned with the model we support for K-12 environments (Cassady & Thomas, 2020). Universal assessment methodologies examine learner behaviors, beliefs, skills, and abilities collectively—recognizing the multidimensionality of human learners (Glover & Albers, 2007). From a pragmatic level, this work can augment higher education institutions’ ability to meet their targets as they grapple with strategies to enhance retention rates and on-time graduation.

The purpose of this investigation was to test the utility of a model exploring multiple domains of student ability and skill for predicting university retention and graduation trends. Specifically, this study explores the interactive influences of entering college students’ cognitive skills, self-regulated learning (SRL) strategies, and attitudes/beliefs toward education on graduation success measures for a large sample of university students. The purpose is to identify factors present in initial enrollment college students that
were most influential in eventual student success so that individuals who demonstrate initial concerns can be offered supports to bolster their skill sets. Furthermore, this investigation focused on the differential utility of this assessment process for students who identified as first-generation (FG) and those who were not first-generation (NFG).

**Literature Review**

**Cognitive Skills and Academic Success**

Historical arguments supporting college entrance exams were placed on notions of “aptitude”—with claims that performance on those measures were strong and valid indicators of likely academic success in the first year of college (e.g., Hezlett et al., 2001). However, research has repeatedly demonstrated that standardized admissions assessments in isolation are relatively ineffectual in determining first year performance (Hannon, 2014; Heller, 2015), and biased against traditionally underserved populations—illustrating that the scores on these aptitude measures are largely a function of the high schools the students attended or more strongly correlated with socio-economic status than ability (Allensworth & Clark, 2020; Zwick & Green, 2007). In line with this, there is a growing body of research demonstrating that measures of learning strategies and attitudes are more predictive of performance in university settings than “ability” indicators in the form of entrance exams (Crede & Kuncel, 2008; Kitsantas et al., 2008).

While traditional standardized measures of college readiness have contributed to biased admissions processes and perpetuated an implicitly racist and sexist system of access to education (Allensworth & Clark, 2020; Buchmann et al., 2010), superior cognitive processing skills and abilities are beneficial to learners engaged in academic tasks (Hannon, 2014). The work that focused on “grit” as more instrumental in determining student outcomes (e.g., Duckworth & Seligman, 2005) maintained that cognitive skills or intelligence were instrumental as well. Recent replications of that work have re-opened the debate over which is more important (self-control/grit vs ability; see Vazsonyi et al., 2022), but this debate maintains the important result that both cognitive abilities and SRL skills (discussed later) are instrumental in determining academic performance in college.

The academic advantage afforded by strong cognitive processing skills is rooted in evidence connecting academic success to superior executive function (Baars et al., 2015), general intelligence (Coyle & Pillow, 2008), or neuropsychological features tied to working memory operation (D’Esposito & Postle, 2015). A comprehensive review of cognitive skills related to academic performance is beyond the scope of this investigation, but we offer that a simple representation of processing efficiency or cognitive load captures the essence of this argument effectively. Consistent with dominant cognitive models of learning and memory (e.g., Baddeley & Hitch, 2019; Mayer, 2019), a cognitive load or processing efficiency perspective asserts that the ability to process content...
with greater fluidity minimizes the “cognitive effort” required to complete a given task (Sweller, 2015; van Merriënboer & Sweller, 2005). At the most basic level, cognitive load theory (CLT) explains that learning events (e.g., reading, listening to lectures, working on problems) tap our limited processing capacity in working memory through three types of load (Moreno & Park, 2010). Intrinsic load is the necessary processing effort required by the task, influenced by the complexity of the content—which is unique to each learner based on experience and ability. Extraneous load is any irrelevant or distracting aspect of the learning task that draws resources away from the actual task—either poor instructional design or intruding distractions (DeLeeuw & Mayer, 2008). Finally, germane load is the proportion of working memory capacity devoted to generative learning or “deep processing” that promotes long term memory storage strength or conceptual change (Fiorella & Mayer, 2016; Wittrock, 2010).

In agreement with the CLT framework, research on achievement emotions (e.g., Eysenck et al., 2007) has implicated processing efficiency as a key aspect that differentiates outcomes for learners who are negatively impacted by negative affective stimuli (Eysenck & Calvo, 1992). Put simply, these models hold that learners with greater cognitive skills and background knowledge in domains are able to more efficiently process the intrinsic load required by tasks and thereby have a greater reserve of available working memory capacity that can promote generative processing (i.e., germane load) or tolerate extraneous load imposed by distractions, poor instructional design, or perseveration on negative affective stimuli (Eysenck et al., 2007; Moreno, 2009; Sweller, 2015). Naturally, limiting being “overloaded” improves the ability to select, organize, and integrate learning content effectively, supporting academic success (Fiorella & Mayer, 2016).

Self-Regulated Learning and Student Success Outcomes
As students proceed through academic levels, external support and control of study behaviors and operations is decreased. In essence, the educational model generally anticipates progressively higher expectations of independent learning skills to be demonstrated by students as they advance from elementary programs through post-secondary education. However, in the first year of university or college, many students lose a significant portion of their academic support network that was built over their elementary and secondary education careers (Heller & Cassady, 2017). During that transitional phase in education, student achievement has been reliably and repeatedly tied to their SRL strategies (Crede & Kuncel, 2008; Weinstein & Palmer, 2002; Weinstein et al., 1987). Similarly, intervention studies focused on promoting SRL strategies for learners have translated effectively into enhancing both student skills and student outcomes (Cleary & Platten, 2013).

Self-regulated learners effectively monitor and control cognitive, motivational, and emotional processes to learning to support their academic success (Lens & Vansteenkiste, 2012). Instead of viewing themselves as passive receivers of information, self-regulated learners perceive themselves as agentic (Bandura, 2008) and in control of their
learning outcomes (Zimmerman et al., 2017). Given the centrality of self-monitoring and adjustment to meet their short- and long-term academic goals, learners with high SRL skills effectively recognize performance-inhibiting and maladaptive strategies (e.g., procrastination, distractibility), address environmental demands (e.g., time and resource management), and monitor strategy effectiveness (Kitsantas & Cleary, 2016; Zeidner & Matthews, 2005; Zimmerman et al., 2017). As a core conceptual framework within educational psychology, SRL skills consistently predict significant variations in student performance across disciplines (Kitsantas & Cleary, 2016; Zimmerman & Kitsantas, 2014), and is often attributed as a principal feature differentiating high and low achieving students with otherwise similar backgrounds (Zimmerman et al., 2017).

Student Affect and Emotionality Influences on Performance

In addition to the impacts outlined above that student affect has on cognitive efficiency and SRL skills, the literature has identified that students’ affective (sometimes termed emotional or attitudinal) orientations to academic content may be a direct predictor of success and retention (Crede & Kuncel, 2008; Pekrun, 2006; Pekrun et al., 2007). Student affect can be represented as either state (fluid) or trait (dispositional) dimensions with positively (interest, enthusiasm) or negatively (distress, irritability) valued emotional responses (Boekarts & Pekrun, 2015; Eschleman et al., 2012). Contemporary literature frequently highlights the influence affect maintains over long-term performance within academic settings; positive affect is generally associated with academic success whereas negative affect is linked to reductions in working memory capacity, processing efficiency, or adopting behaviors (e.g., avoidance, procrastination, withdrawal) that promote academic self-handicapping (Eysenck et al., 2007; Zeidner & Matthews, 2005).

The influence attitudes and emotions have on academic success and performance has been explained through the Emotional Information Processing model (EIP; Cassady & Boseck, 2008; Cassady & Thomas, 2020). Building upon constructivist principles of individualized representations of contextual cues, emotion regulation strategies, and SRL models with iterative feedback loops, the EIP seeks to explain how students navigate emotionally challenging events in a recursive cycle. Put simply, the EIP postulates that individuals identify and interpret situational challenges and establish goals that are either growth-oriented (generally positive) or ego-preserving (generally maladaptive) before envisioning and enacting solutions or strategies in contexts where they are emotionally charged (Cassady & Thomas, 2020).

As such, when learners’ conceptions of academic contexts center on perceived threats, goals and strategies tend to be more maladaptive or protective—focused on reducing the perceived threat of the situation rather than activating coping mechanisms to “solve the problem” at hand (Lazarus, 2006). Conversely, learners with a generally positive affective orientation toward academic contexts are characterized by positive attitudes, interest in learning, and curiosity for the topics (Alexander & Grossnickle,
In those settings where the learner maintains the more positive affective orientation, the range of responses tend to be focused on adaptive coping strategies and engagement with the content (Cassady & Thomas, 2020).

**Generational Status and Higher Education Success**

One key learner characteristic that is commonly discussed in relation to retention and success in higher education is generational status. Applied research and institutional analyses of higher education success have centered on the unique challenges navigated by many FG college students as compared to their NFG peers. Studies have attributed a general trend of lower outcome achievement for FG students to issues including financial challenges (Cho et al., 2008), familial support (Saenz & Barrera, 2007), prior academic preparation (Atherton, 2014), mismatch in social or cultural norms (Stephens et al., 2012), and a range of emotional responses that orient toward a perception of the university setting as more threatening than NFG learners (Harackiewicz, et al., 2014; Woosley & Shepler, 2011).

While we agree that attention to FG students is critical to support long term success for a growing population of higher education learners, it is important to recognize Woosley and Shepler’s (2011) assertion that there is wide diversity within the broad population of FG students, and overgeneralization of findings in the literature is a perilous error. To that effect, the purpose of this direct focus on FG and NFG populations is to explore if there are aspects of higher education entry factors that appear to be more influential in predicting performance trends for students in these two broad groups. The benefit of this focus is the potential to identify domains of influence in postsecondary success that are unique for FG learners, leading to potential intervention developments to meet needs for FG learners (see Goldman et al., 2020; Harackiewicz et al., 2014).

**Current Study**

Using data captured from an institutional perspective, this study employed a predictive model determining long-term student performance outcomes in a traditional four-year university located in the Midwest United States. Using institutional data collected from all incoming first year students over a seven-year period, this study explores a model of long-range student success examining key characteristics at the point of university matriculation. Specifically, using data from the Learning and Study Strategies Inventory—High School Edition (LASSI-HS), this study explores the relative and combined influences of four primary dimensions on student success over the course of their college careers (as measured by graduating GPA). The four contributing features of interest were basic cognitive skills, SRL strategies, affective responses to educational settings, and anxiety toward academic contexts. In addition, the study focused on generational status to identify if there were differential patterns of influence for these key variables on graduating GPAs for learners who were FG and NFG learners.
Methods

To enable this investigation, our study focused on institutional data collected from incoming first year students using the LASSI-HS (Weinstein & Palmer, 2002; Weinstein et al., 1987), which assesses three broad domains of student strategic learning deemed beneficial to performance in higher education settings: strong SRL strategies, sufficient cognitive skills to comprehend academic content, and positive affective orientation toward educational tasks and settings. The LASSI-HS data were drawn from all incoming first-year students over a seven-year span at a midsize university in the midwestern region of the United States and subsequently connected to student retention and graduation data (allowing for six years to complete a degree). Collectively, complete data were available from approximately 40,000 students.

Measures

Learning and Study Styles Inventory—High School Edition

The LASSI-HS (Weinstein et al., 1987) is a 76-item survey intended for individuals who have not yet started a postsecondary program. The LASSI-HS was originally validated with 10 subscales that address three primary domains of academic functioning referred to by the original authors as “skill, will, and self-regulation.” Subsequent research on the factor structure of the scale has generated several different representations for the structure of the scale (Cano, 2006; Finch et al., 2016; Olaussen & Bråten, 1998; Weinstein & Palmer, 2002). Regardless of the primary subscale structure offered in those studies, the notion of a hierarchical representation with three overarching categories of functioning tends to be maintained. In our presentation of these data, we label the broad categories SRL, Cognitive Skills, and Affect.

The SRL component includes 26 items (Finch et al., 2016), drawing primarily from the original LASSI-HS subscales titled Information Processing, Elaborative Rehearsal, Study Aids, Self-Testing, and Time Management (Weinstein & Palmer, 2002). The focus of the SRL component is activities that promote regulated learning behaviors (e.g., self-testing, visualizations) and skills in managing their academic challenges. Items address time management strategies and skills, use of active study behaviors that promote regulated learning behavior (e.g., self-testing, visualizations), and skills in maintaining attention (or concentration) while working on academic tasks.

The Cognitive Skills component includes 10 items (Finch et al., 2016), drawing from subscales Selecting Main Ideas, Test Strategies, and Information Processing. This construct is similar to Weinstein and Palmer’s (2002) “Skill” domain or Cano’s (2006) “Comprehension” domain. In essence, this scale differs from the SRL category by focusing on the perceived ability in primary academic tasks such as reading comprehension or understanding and thinking about content deeply. By contrast, the SRL component is more focused on activities the learner activates or regulates to support performance.
Finally, the Affect component, which was represented by 14 items, is aligned with LASSI’s “Will” (Weinstein & Palmer, 2002) or general “Affective/Goal Orientation” components (Cano, 2006; Olaussen & Bråten, 1998). This factor includes items originally labeled as Attitude, Motivation, and Anxiety in the LASSI-HS. The Affective subcomponents provide indicators of both positive and negative affect, which precludes an overall “Affect” score that is not influenced by this directional modification. To overcome this limitation, in this investigation we examined Affect after removing the Anxiety subcomponent to empirically explore the relative influences of positive and negative Affect in the long-term thriving and performance of university students (see also Cassady et al., 2019).

Fong et al.’s (2021) recent meta-analysis examining the utility of the LASSI for predicting academic outcomes revealed consistent evidence that it generates predictive validity for near-term and longer-range academic performance (e.g., GPA) as well as academic resilience indicators. Furthermore, Khalil and colleagues (2020) illustrate success in differentiating high and low performing students in medical school using the LASSI subscales.

**Student Characteristics and Outcomes**

As an exploration of institution-wide performance, the data available for this study was limited to the information that was linked to the initial LASSI-HS variables and cleared by the local IRB for investigation. In this study, we had access to student-level data documenting student GPA at graduation (for all students who graduated within six years of starting their academic programs), which served as the primary outcome of interest, and first-generation college student status. The selection of graduating GPA was prompted largely by prior work with a similar sample of students in which first-year GPA (a common variable used in prediction studies of this nature) was only weakly related to any prediction variables (including the variables in this study as well as traditional measures of “entry exams”) and did not provide meaningful insight to long term university success (defined as retention and graduation; Heller, 2015). Furthermore, merely knowing how they perform at the end of the first year fails to examine the impact of these “entry” variables in determining success as defined as retention to graduation.

**Data Analysis**

In order to address the research questions of interest, four separate structural equation models (SEMs) were fit to the data. The models we explored were founded on the theoretical notion that cognitive skills and SRL influenced long-term performance (i.e., graduating GPA), but that the relationship was potentially mediated by attitudes and beliefs about education (i.e., “affect”). Furthermore, our focus on anxiety as a moderating variable required removing that component of affect. The four models reflected a fully mediated model (Figure 1, Panel A), a partially mediated model (Figure 1, Panel B), a moderated fully mediated model (Figure 1, Panel C), and a moderated partially mediated model (Figure 1, Panel D). The optimal model was determined based on the AIC, BIC, and sample size adjusted BIC (aBIC), with smaller values indicating overall better models.
Once the optimal model was identified, multiple group SEMs were used to ascertain whether there were differences in structural coefficients between FG and NFG students. Two such models were fit, one in which the structural coefficients were allowed to vary between the groups and the other in which the coefficients were constrained to be equal across groups. The fit of the two models were compared by using a Chi-square difference test for which the null hypothesis was that the models allowed structural coefficients to vary across groups and that constrained them to be equal by group yield equivalent model fit. Therefore, a statistically significant result for the Chi-square statistic indicates that the structural coefficients differed between groups. Finally, prior to fitting the aforementioned SEMs, measurement models for each of the factors were fit to ensure that the hypothesized factor structure fit the data appropriately. Fit of these models was ascertained using commonly used fit statistics, including CFI, TLI, and RMSEA. Values of CFI and TLI ≥ 0.95 and RMSEA values ≤ 0.05 were taken to indicate acceptable fit (Kline, 2015). All model parameter estimation was carried out using maximum likelihood with Mplus, version 8.6 (Muthén & Muthén, 2020).

Results

Descriptive Statistics
The disaggregated means, standard deviations, 95% confidence intervals, and Cohen’s *d* values for specific means comparisons appear in Table 1. The focus of those explorations was centered on comparisons among FG and NFG students as well as those who ultimately graduated within six years and those who did not. Based on Cohen’s (1992) guidelines, the mean differences between FG and NFG students on Cognitive Skills (COG), SRL, Affect, and Anxiety were all negligible. The difference in mean graduating GPA between the groups fell into the small range (Cohen, 1992), with NFG students having a higher mean GPA than FG students. With respect to graduation status, mean differences were negligible with the exception of Affect, for which the difference was small in magnitude. Students who ultimately graduated had a higher mean Affect score than did those who did not graduate within six years of matriculation.

Measurement Models
Measurement models for each of the factors were fit to the data, and yielded evidence that the hypothesized latent structure did in fact fit the data, with each being represented by a single factor. The model fit statistics for the individual factor models were: SRL (RMSEA=0.031, CFI=0.97, TLI=0.96), COG (RMSEA=0.038, CFI=0.96, TLI=0.95), Affect (RMSEA=0.029, CFI=0.97, TLI=0.97), and Anxiety (RMSEA=0.034, CFI=0.95, TLI=0.95). Given these positive results for model fit, it was possible to continue with the SEMs.
Table 1. First-Generation Status and Graduation Status Group Comparisons on Primary Variables

| Group (N)            | Mean  | SD   | 95% CI       | d    |
|----------------------|-------|------|--------------|------|
| Cognitive Skills (COG) |      |      |              |      |
| First gen (3,651)    | 3.64  | 0.68 | 3.62, 3.68   | 0.04 |
| Non-first gen (8,366)| 3.69  | 0.68 | 3.67, 3.70   |      |
| Graduated (12,071)   | 3.67  | 0.68 | 3.66, 3.68   | -0.08|
| Did not graduate (16,193) | 3.61 | 0.70 | 3.60, 3.62   |      |
| Self-Regulated Learning (SRL) |      |      |              |      |
| First gen (3,651)    | 3.24  | 0.53 | 3.22, 3.26   | 0.03 |
| Non-first gen (8,366)| 3.27  | 0.52 | 3.26, 3.28   |      |
| Graduated (12,071)   | 3.26  | 0.52 | 3.25, 3.27   | -0.11|
| Did not graduate (16,193) | 3.20 | 0.53 | 3.19, 3.21   |      |
| Affect               |       |      |              |      |
| First gen (3,651)    | 4.14  | 0.52 | 4.12, 4.16   | -0.03|
| Non-first gen (8,366)| 4.13  | 0.53 | 4.12, 4.15   |      |
| Graduated (12,071)   | 4.13  | 0.53 | 4.12, 4.14   | -0.25|
| Did not graduate (16,193) | 3.99 | 0.56 | 3.98, 4.00   |      |
| Anxiety              |       |      |              |      |
| First gen (3,651)    | 3.42  | 0.76 | 3.39, 3.45   | 0.05 |
| Non-first gen (8,366)| 3.47  | 0.77 | 3.45, 3.48   |      |
| Graduated (12,071)   | 3.45  | 0.77 | 3.43, 3.46   | -0.04|
| Did not graduate (16,193) | 3.42 | 0.79 | 3.41, 3.43   |      |
| Graduating GPA       |       |      |              |      |
| Total (12,071)       | 3.22  | 0.44 | 3.22, 3.23   |      |
| First gen (3,651)    | 3.16  | 0.43 | 3.15, 3.17   | 0.20 |
| Non-first gen (8,366)| 3.25  | 0.44 | 3.24, 3.26   |      |

Note. SD = standard deviation; CI = confidence interval.

Identification of Optimal Model Structure
As described in the methods section, four structural models were considered, and their fit was compared using the AIC, BIC, and sample size adjusted BIC (aBIC). These models were full mediation (Figure 1, Panel A), partial mediation (Figure 1, Panel B), full mediation moderated by Anxiety (Figure 1, Panel C), and partial mediation moderated by Anxiety (Figure 1, Panel D). AIC, BIC, aBIC, and model fit statistics appear in Table 2. The moderated partial mediation model (Panel D) had the smallest AIC, BIC, and aBIC values, indicating that it yielded the best fit.
Figure 1. Proposed Models

A

B

C

D

Note. Panel A: Full mediation model. Panel B: Partial mediation model. Panel C: Moderated full mediation model. Panel D: Moderated partial mediation model. SRL = self-regulated learning; COG = cognitive skills; GPA = graduating grade point average.

Table 2. Model Fit Comparisons

| Statistic | Full mediation | Partial mediation | Moderated full mediation | Moderated partial mediation |
|-----------|----------------|-------------------|--------------------------|---------------------------|
| AIC       | 299315.09      | 289991.61         | 275339.80                | 262668.54                 |
| BIC       | 317322.98      | 298700.39         | 282619.74                | 264218.27                 |
| aBIC      | 314277.25      | 292322.44         | 280173.05                | 263271.66                 |
| CFI       | 0.90           | 0.93              | 0.94                     | 0.96                      |
| TLI       | 0.89           | 0.91              | 0.94                     | 0.95                      |
| RMSEA     | 0.08           | 0.06              | 0.05                     | 0.03                      |
| (90% CI)  | (0.07, 0.09)   | (0.05, 0.07)      | (0.04, 0.06)             | (0.02, 0.04)              |
| GPA $R^2$ | 0.14           | 0.16              | 0.15                     | 0.20                      |

Note. AIC = Akaike information criterion; BIC = Bayesian information criterion; aBIC = adjusted Bayesian information criterion; CFI = comparative fit index; TLI = Tucker-Lewis index; RMSEA = root mean square error of approximation; GPA = grade point average.
among the candidates. In addition, the CFI, TLI, and RMSEA values for this model were all in the good fit range based on commonly used cut-values (Kline, 2015). Therefore, it was concluded that the moderated partial mediation model was optimal among those considered and provided good fit to the data. The proportion of variance explained \((R^2)\) by the models was also largest for the moderated partially mediated model, for which 20% of the variability in graduating GPA was accounted for by the model. Given these findings, this model will be the focus of discussion throughout the remainder of the results.

**Multiple Groups SEM: Generational Status**

In order to assess whether the structural coefficients (direct and indirect) were invariant between the FG and NFG students, two models were fit to the data. The first model constrained all model parameters to be equal across groups, whereas the second model allowed the structural coefficients to differ between them. The optimal model was determined using a Chi-square difference test, along with the aBIC. The Chi-square test comparing the models for which the structure coefficients were allowed to differ between groups and the model for which they were constrained to be equal across groups was statistically significant \((\chi^2 = 75.33, p < 0.00001)\), indicating that the structural coefficients differed between the two groups. In addition, the aBIC for the fully constrained model was 576003.24 whereas the BIC for the unconstrained coefficients model was 521375.08, providing further evidence that the model in which the structural coefficients were allowed to differ between FG and NFG students yielded better fit than the group equality constrained model. In brief, these analyses confirm that there were differential patterns of relationships among the predictor variables in determining graduating GPA.

Table 3 includes the standardized coefficients and standard errors for the main effects and interactions associated with the moderated mediation model for FG and NFG students, respectively. For each term in the model, an * indicates that the parameter differed from 0, and the final column of the table includes the results of a test comparing the values between the two groups (identifying variables where differences in relationships were noted between FG and NFG students). These \(p\)-values reflect the adjustment for Type I error control.

The results in Table 3 reflect that COG and SRL were both positively related to Affect for both groups; however, only the relationship between COG and Affect revealed a difference based on generational status (NFG showed a stronger relationship value than FG). As expected, Anxiety had a statistically significant negative relationship with Affect for both groups. The interaction effects for the Anxiety and the COG/SRL variables demonstrated that only the NFG students demonstrated a significant value for COG, but both groups shared similar values for SRL. In the bottom half of Table 3, the relationships of these variables with graduating GPA are presented. Those results demonstrate that both groups had significant positive coefficients for Affect and Anxiety, and a significant negative coefficient for COG. However, the coefficient
for SRL as well as the interactions between Anxiety and SRL/COG were found to be statistically significant for the NFG group, but not for FG students. This complex pattern of interactions initially represents that (a) the Affect variable was a key and influential predictor of college completion success indicators, (b) COG and SRL were mediated through Affect and moderated by Anxiety, and (c) there were differences among FG and NFG students in the contributions the measured variables made in predicting graduating GPA.

To more fully explore these patterns, the total effects for the mediated coefficients (SRL and COG) for students based on the moderating variable (Anxiety) at one standard deviation below the mean (low), at the mean (medium), and one standard deviation above the mean (high) appear in Table 4 (see also Figures 2 and 3). These coefficients are presented for both groups, along with an indication of group differences.

Among NFG students, COG was more strongly associated with GPA for individuals with higher levels of Anxiety, whereas for FG students the level of Anxiety did not impact the relationship between COG and GPA. In addition, the total effect of COG on GPA was significantly larger for the NFG group at medium and high levels of Anxiety.

### Table 3. Standardized Model Coefficients by First-Generation Status, and Comparison across Groups

| Variable          | $\beta$ (SE) not first gen | $\beta$ (SE) first gen | P for comparing coefficients |
|-------------------|---------------------------|------------------------|-----------------------------|
|                   | Affect                    |                        |                             |
| COG               | 0.80* (0.01)              | 0.76* (0.02)           | 0.04**                      |
| SRL               | 0.70* (0.01)              | 0.68* (0.01)           | 0.08                        |
| Anxiety           | -0.36* (0.01)             | -0.35* (0.02)          | 0.67                        |
| Anxiety X COG     | 0.03* (0.01)              | -0.01 (0.01)           | 0.002**                     |
| Anxiety X SRL     | -0.05* (0.01)             | -0.06* (0.01)          | 0.24                        |
|                   | Graduation GPA            |                        |                             |
| Affect            | 0.40* (0.01)              | 0.31* (0.02)           | 0.00003**                   |
| COG               | -0.06* (0.02)             | -0.07* (0.03)          | 0.39                        |
| SRL               | -0.07* (0.02)             | -0.02 (0.03)           | 0.92                        |
| Anxiety           | 0.10* (0.02)              | 0.08* (0.03)           | 0.29                        |
| Anxiety X COG     | 0.03* (0.01)              | -0.01 (0.02)           | 0.04**                      |
| Anxiety X SRL     | 0.05* (0.01)              | 0.02 (0.02)            | 0.09                        |

Note. COG = cognitive skills; SRL = self-regulated learning; GPA = grade point average; SE = standard errors.

* Coefficient is statistically different from 0. ** Coefficients are statistically significantly different between groups.
Anxiety. The total relationship (accounting for all direct, mediated, and moderated effects) between the standardized COG score and graduating GPA by level of Anxiety for both student groups appears in Panels A and B of Figure 2. For FG students, there was a positive relationship between COG and GPA, and this relationship was equivalent across levels of Anxiety, as is evidenced by the complete overlay of the lines. In contrast, for NFG students, the relationship between COG and GPA was strongest for students with high levels of Anxiety, followed by a somewhat weaker relationship at moderate Anxiety, and the weakest relationship when Anxiety was low.

A similar pattern of group-specific effects was present for the total effect of SRL on GPA as mediated through Affect (Figure 3). For NFG students, the total effect of SRL on GPA as mediated through Affect was stronger for students with higher levels of Anxiety, followed by a somewhat weaker relationship at moderate Anxiety, and the weakest relationship when Anxiety was low. For FG students, the relationship between SRL and GPA did not differ based upon levels of Anxiety. In addition, the total relationship between SRL and GPA was significantly larger at the highest level of Anxiety for NFG than for FG students. Figure 3 displays the lines linking standardized SRL scores and GPA for NFG (Panel A) and FG (Panel B) students. As was true for COG, there was no difference in this relationship influenced by the degree of Anxiety for FG students. However, among NFG students, the relationship between SRL and GPA was stronger as the level of Anxiety increased.

### Table 4. Total Effects by Levels of Anxiety and First-Generation Status

| Effect          | Coefficients (SE) | $P$ for comparing coefficients |
|-----------------|-------------------|--------------------------------|
|                 | NFG               | FG                             |
| Total COG: LA   | 0.09* (0.01)      | 0.08* (0.01)                   | 0.24                          |
| Total COG: MA   | 0.11* (0.01)      | 0.08* (0.01)                   | 0.02**                        |
| Total COG: HA   | 0.13* (0.01)      | 0.07* (0.01)                   | 0.00001**                     |
| Total SRL: LA   | 0.09* (0.01)      | 0.08* (0.01)                   | 0.24                          |
| Total SRL: MA   | 0.10* (0.01)      | 0.08* (0.01)                   | 0.08                          |
| Total SRL: HA   | 0.11* (0.01)      | 0.08* (0.01)                   | 0.02**                        |

* Coefficient is statistically different from 0. ** Coefficients are statistically significantly different between groups.

Note. LA = low anxiety (1 standard deviation below the mean); MA = moderate anxiety (at the mean); HA = high anxiety (1 standard deviation above the mean); COG = cognitive skills; SRL = self-regulated learning; NFG = non-first-generation students; FG = first-generation students.
Figure 2. Total Relationship between Cognitive Skills and GPA at Low, Moderate, and High Anxiety

A

COG: Non-First Generation

GPA

Standardized Cognitive score

Note. Panel A: Non-first-generation students. Panel B: First-generation students. COG = cognitive skills; GPA = graduating grade point average.
Figure 3. Total Relationship between SRL and GPA at Low, Moderate, and High Anxiety

A

SRL: Non-First Generation

B

SRL: First Generation

Note. Panel A: Non-first-generation students. Panel B: First-generation students. SRL = self-regulated learning; GPA = graduating grade point average.
Discussion

The primary goal for this study was to examine the relationships among key variables that have been repeatedly demonstrated to influence student success in higher education settings. Rather than merely identifying that each of these key variables (cognitive skills, SRL skills, attitudes toward education, and anxiety) contribute to student success in university settings in an iterative or progressive fashion, this study was designed to explore the interconnections among the variables and specifically identify interactions and overlaps. Building from the framework outlined in Credé and Kuncel’s (2008) meta-analytic study of the instrumental contribution of study habits, skills, and attitudes on predicting academic success in university students over and above traditional measures of readiness (e.g., high school GPA, college entrance exams), this study focused specifically on graduating GPA for two reasons. First, prior work with a similar sample (Heller, 2015) demonstrated relatively low success in predicting success with first-year GPA. Second, our work is primarily interested in examining factors leading to student retention and graduation, suggesting a “long view” was warranted. Beyond the focus on graduation GPA (within six years of matriculation), the additional focus of this study was the explicit test of both moderation and mediation models for these variables as well as specific attention to variations observed for students who were identified as FG as compared to those identified as NFG.

Initial analyses demonstrated that first-generation status was not instrumental in the responses offered for the LASSI-HS factors (COG, SRL, Affect) collected at the point of entering the university. However, the data did indicate that there was a small difference in graduating GPA based on identified first-generation status, such that NFG students enjoyed a slight advantage. The preliminary analyses also demonstrated one difference in the LASSI-HS subscale scores when comparing those who graduated to those who left the university. While there were no identifiable differences in anxiety, SRL skills, or cognitive skills, there was a small effect demonstrating that those individuals who graduated within six years started their university experience with a higher Affect score than those who left before graduating. This primary finding is consistent with the prevailing viewpoints on affective responses to academic settings such that positive emotional orientations toward the learning environment support learners’ positive appraisals of the learning context (Lazarus, 2006), development of positive growth goals (Dweck, 2007), maintenance of higher degrees of perceived control and value for the educational setting (Pekrun, 2006), and selection of more adaptive coping strategies that preserve their performance potential (Cassady, 2022; Pekrun, 2006).

The study’s main results demonstrated that the moderated partial mediation model (Figure 1, Panel D) provided a good fit to the data. That model demonstrated that graduating GPA was predicted by SRL and cognitive skills as partially mediated through affect toward education, and moderated by degree of anxiety. To unpack these complex mediated-moderation effects, a progressive approach to recounting the results and connecting them to theoretical and practical orientations follows.
Affect Mediates Self-Regulated Learning and Cognitive Skills

As expected, both SRL and cognitive skills had a measurable, direct influence on graduating GPA. However, those relationships were also primarily transmitted through the educational attitudes (cf. “Affect”) they maintained at the point of university entry (see Table 2). Interpretation of these effects for the total sample are somewhat premature given the unique interaction identified based on first-generation status (discussed below). However, the generalized pattern demonstrates that simple analyses exploring the influence of cognitive abilities and/or SRL skills on student performance outcomes without including measures of learner affect (i.e., achievement emotions, attitudes toward education) oversimplify the relationships. This finding reinforces work illustrating the importance of examining academic achievement within a complete context with attention to the interactions among learners’ cognitive and affective responses in academic settings (Cassady & Thomas, 2020; Pekrun, 2006). It is worth noting that a simple representation of these data of merit is that attitudes and beliefs learners hold toward education at the university level were the most powerful predictor of graduation and graduating GPA in our sample.

Academic Anxiety Moderates Self-Regulated Learning and Cognitive Skills

After accounting for the influence of general Affect in the model, the data also demonstrate that the influence of Anxiety (as measured by the LASSI-HS) moderates the influence of cognitive skills and SRL on GPA. This effect indicates that for individuals with high Anxiety, the influence of cognitive skills on graduating GPA is significantly greater than for learners with moderate and low Anxiety. This relationship essentially demonstrates that the range of graduating GPA is greatest for the high Anxiety learners, and high Anxiety learners with the lowest levels of cognitive skills demonstrate the lowest levels of GPA over time. Conversely, learners reporting high levels of Anxiety with high cognitive skills had the highest overall GPAs at graduation (see Figure 2). The same moderation effect was noted for the influence of SRL skills on graduating GPA.

The results demonstrate that high levels of Anxiety reported on the LASSI-HS scale do not directly translate to lower performance over time—the true impact of anxiety is only realized when examining how anxiety interacts with a student’s cognitive skills and SRL skills (Zeidner & Matthews, 2005). These patterns align with models identifying the potential facilitative elements of academic anxieties, where it serves as an “activating” stimulus within a transactional processing model (Lazarus, 2006). As illustrated in Figures 2 and 3, the presence of anxiety functions positively for those learners with more confidence in their cognitive and SRL skills. For those learners with low cognitive abilities and SRL skills, the pattern was reversed. From a basic transactional processing framework, these data would be explained as demonstrating that when faced with an academic stressor (perceived threat appraisal), learners with high levels of cognitive and SRL skills are likely to identify and employ more effective—or
adaptive—coping strategies leading to success (see also the EIP; Cassady & Thomas, 2020). Conversely, anxious learners with lower skills faced with perceived threats in academic settings are more likely to adopt failure predictions, avoidance behaviors, and employ ineffective coping strategies (leading to eventual performance declines; Thomas et al., 2017).

The moderating effects highlight the importance of explicitly acknowledging the bidirectional and interactive nature in the relationships among learners’ affective and cognitive constructs (Pekrun, 2006). The results of the moderation analyses may also be explained through a buffering effect, consistent with the Processing Efficiency Theory (PET; Eysenck & Derekshan, 2011). The PET (and related Attention Control Theory [ACT]) predicts that learners with higher cognitive and SRL skills dealing with anxiety may not perform at optimal efficiency, but they may not be disrupted enough to show performance declines (Wong et al., 2013). Examining academic anxiety as extraneous cognitive load (Plass & Kalyuga, 2019), the PET (and ACT) would predict that those with high levels of skill will have a higher degree of tolerance to the distracting anxiety stimuli (Pekrun, 2006; Pekrun et al., 2007).

First-Generation Status and Predicted Graduation Outcomes

An additional extension of this analysis was to explore the differential effects demonstrated in the data when examining those students identified as FG learners as compared to NFG. The results demonstrated that there was a significant difference in the relationships among the study variables for the two groups, calling attention to the importance of examining student success models in higher education institutions with attention to academic generational status.

More specifically, the results indicate that the Anxiety effects discussed in the “total sample” model were only present for the NFG students. That is, when we disaggregated the data set and examined the influence of Anxiety as a moderating variable for FG and NFG learners separately, the moderation effect did not hold for the FG students. As shown in Panel B of Figures 2 and 3, FG students with high, moderate, and low Anxiety all reported the same degree of relationship between cognitive skills and GPA (as mediated through Affect) and between SRL and GPA. However, the NFG learners demonstrated that the moderating influence of Anxiety was present.

Similarly, the results demonstrate a significant difference in the predictive power of Affect on graduating GPA when comparing FG and NFG learners. The influence of Affect on graduating GPA was significantly stronger for NFG students than FG students. The attitudes, interests, and motivation toward education held by NFG learners was the strongest predictor of graduating GPA (see Table 2)—and the difference in the magnitude of the coefficients reflecting those relationships was approximately 25%.

This pattern of results raises questions regarding why FG students and NFG students had differential experiences with the importance of anxiety on eventual graduating
GPA. Examination of the overall group values demonstrate similarity in both mean and standard deviations in the Anxiety measure for both groups, discounting a simple measurement explanation. One explanation for this may rest in the differential focus of academic anxiety for the NFG and FG students. While FG students demonstrated similar levels of anxiety reported at the point of college entry when compared to their NFG peers, that anxiety was not instrumentally related to their confidence in the COG and SRL domains. As such, it is possible that the source of academic anxiety was attached to a broader uncertainty of what their college experience may entail or require. Given the lower degree of familial experiences with university life for FG learners as compared to the NFG population, the anxiety over success and thriving in school may have been focused more on external threats (finances, housing, transition) than on the features examined by the LASSI (Cho et al., 2008; Saenz & Barrera, 2007; Stephens et al., 2012). Conversely, NFG students’ anxiety appears to be directly connected to their perceived abilities in COG and SRL, reflecting a more internal source of their uncertainty about outcomes (and subsequently reflected in overall performance levels).

Limitations and Extensions
As with any institutional dataset, limitations to the study are to be noted. This study was limited in the ability to explore the degree to which learners over the seven years sought and received support for initially-identified limitations in cognitive, self-regulatory, or affective orientations to education. Programs of support exist in most postsecondary education settings that provide training on study skills, counseling support, and engagement in their fields of study (see Kitsantas et al., 2008). These factors are likely to promote optimal performance, and were inaccessible on the individual level for these analyses. However, given the large sample, we propose that these effects were likely distributed across our sample and did not pose a significant threat to validity in our findings. Furthermore, specific demographic information was not available for these analyses. As such, the data do not provide the opportunity to explore variations among learners from diverse populations (beyond the simple FG vs NFG variable). The university in this study serves a primarily White population drawn largely from the Midwestern United States, leaving the question of whether these patterns are fully representative of a more diverse population. Finally, we were unable to control for program majors in these analyses. While all students were in a four-year program with a common core set of liberal arts content for all majors, there are possible variations across programs (e.g., STEM vs the Arts) that would provide insights into support services for students in diverging areas of study.

Conclusions
The conclusions from this large-scale study of student success and retention illustrate that early identification systems (i.e., universal assessment) can provide critical information relevant to the success of students in higher education. While there is considerable evidence that cognitive skills, SRL skills, and affective dispositions toward
education are all meaningful predictors to success, this study provides a clear test of the relative and interactive influences of these features in determining factors instrumental in predicting long-range success (as measured by graduating GPA) at the university level. Overall, the results demonstrated that while confidence in cognitive skills and strong SRL habits at the start of postsecondary education have a measurable influence on graduating GPAs (4–6 years later), these factors are heavily influenced by affective variables (both positive affect and anxiety). This finding highlights the importance of early identification of learners with maladaptive attitudes toward education (e.g., academic anxiety) to provide institutional support to mitigate negative influences on performance and support optimal outcomes. While this study was focused only on the entry point of college, we believe that ongoing and iterative assessments of student attitudes, anxiety, and skills are a simple solution to provide universities with systemic data addressing the changing needs of their student populations. This universal assessment strategy provides the opportunity to more directly target supports for all learners, isolating those individuals who may differentially benefit from support programs focused on affective interventions (e.g., positive self-care, mindfulness training, emotional reframing), proactive coping strategies focused on SRL skills (e.g., study strategies, time management, planning), or both, depending on the profile of needs demonstrated.

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