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Abstract: Student retention models were tested via structural equation modeling to examine the interrelations and predictability among socioeconomic status, psychosocial, and student success variables with a sample of 445 undergraduate students attending a large Hispanic serving institution. The proposed theoretical model included socioeconomic status (generational status & Pell grant eligibility), psychosocial (academic efficacy, problem solving, connectedness to professors and college), and student success variables (SAT scores, college GPA, intent to remain, and retention). Results provided support for the proposed model and showed that the psychosocial variables examined herein play an important role in predicting connectedness and student success variables. Implications for institutions are discussed.

A Structural Model for Predicting Student Retention

Undergraduate student retention and degree attainment is vital to student, institutional, and societal success (Cardy, Lengnick-Hall, & Miller, 2010), which explains enduring interest in the determinants and predictors of postsecondary academic achievement (Robins, Trzesniewski, Tracy, Gosling, & Potter, 2002; Robbins et al., 2004). Though meta-analytic research has identified some of the most salient variables related to postsecondary academic achievement, results have also revealed complex interrelationships among important variables often rendering different pathways for different groups (Al-Harthy, Was, & Isaacson, 2010; Tinto, 1993). Multiple factors correlate with degree attainment and are often described in terms of student, pre-college, and college level variables (Hsieh, Sullivan, Sass, & Guerra, 2012; Tinto, 1987; 1993). Thus, while undergraduate retention and completion is a national concern, some institutions struggle with retention and graduation rates more than others (Astin & Oseguera, 2005).

To provide some context, the 6-year graduation rate for full-time students seeking a bachelor's degree was 58%, 65%, and 32% for public, private nonprofit, and private for-profit institutions, respectively (National Center for Education Statistics, 2015). These statistics necessitate the need for predictive models of student success and the implementation of effective interventions (Robins et al., 2002; Robbins et al., 2004). At present there is little integration of the educational and psychological literatures when looking at postsecondary success, especially with respect to socioeconomic status, psychosocial, and student success variables. Consequently, a model examining the interrelations among these variables is necessary to understand the unique and combined contribution of these variables when predicting undergraduate student success. While these variables have not previously been explored in combination, the amalgamation of research suggests these variables may be critical when developing and testing a theoretical model for undergraduate retention.

THEORETICAL FRAMEWORK

In the proposed model (see Figure 1), we examine the relative predictive ability among socioeconomic status (generational status & Pell grant eligibility), psychosocial (academic efficacy, problem solving, connectedness to professors and college), and student success variables (SAT scores, intent to remain, college GPA, & retention). While research exists regarding traditional predictors of college retention and degree attainment, theoretical models focused on the above mentioned variables are limited (Cabrera, Nora, & Castaneda, 1993).

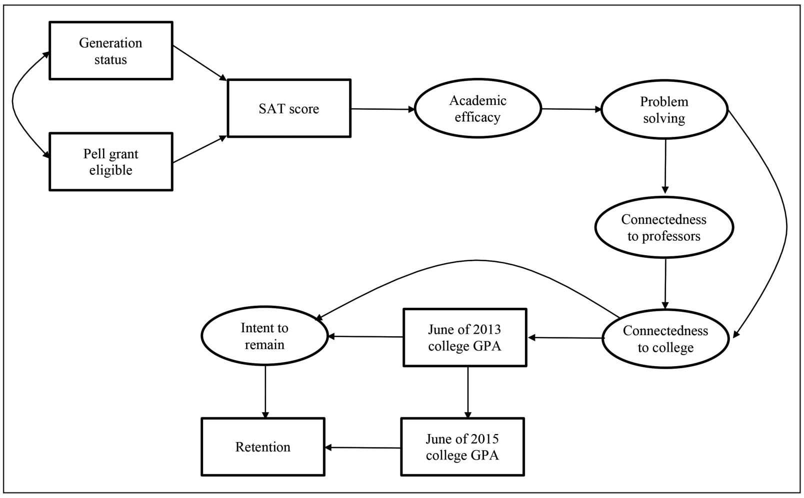

Figure 1. Provides our hypothesized model based on theory and previous research.

Socioeconomic Status

Socioeconomic status (SES) is often a significant predictor of standardized test performance (e.g., SAT scores) and academic achievement (Crisp, Taggart, & Nora, 2015; Nandeshwar, Menzies, & Nelson, 2011; Sciarra & Whitson, 2007; Willingham, 1985). For example, generational status (i.e., being a first generation college student) is often inversely related to college GPA (Fisher, 2007). In fact, it is estimated that 1 in 10 students who come from the bottom income quartile graduate from college versus an estimated 8 out of 10 who comprise the upper income quartile (Walpole, 2003).

In this study, rather than focusing on the direct link between SES (recall, generation status and Pell grant eligibility served as a SES proxies) and college success (i.e., college GPA & student retention), we propose these relationships are mediated by SAT scores and several psychosocial variables (see Figure 1). Our reasoning is that in spite of the odds, many low SES students succeed in college. Moreover, it is clear that the relationship between these variables is complex and other variables contribute to college success. In our model, SAT score was selected as the proceeding variable for chronological reasons (i.e., students grow-up in a certain SES with parents that either did or did not attend college and then students take the SAT) and students with greater economic advantages should theoretically perform better on the SAT.

SAT Scores

SAT scores often emerge as a strong predictor of college degree attainment (Lee, Olson, Locke, Michelson, & Odes, 2009), with a significant body of research (Astin & Oseguera, 2005) showing the relation between cognitive ability (often measured by SAT scores) and academic achievement (i.e., high school graduation, college enrollment, college GPA). For example, in a national study by Astin and Oseguera (2005), students earning a SAT score of 1300 or higher were three times more likely to earn a Bachelor's degree than students earning a SAT score of 700 or lower, thus SAT score should be a driving factor when predicting college student success. With that said, the SAT, and other tests like it, are not without their controversy (Zwick, 2007).

Most models, however, omit an important link between SAT and academic efficacy when predicting college success (Brown et al., 2008; Castro-Villarreal, Guerra, Sass, & Hseih, 2014; Hseih, Sullivan, & Guerra, 2007; Robbins et al., 2004). For example, a recent investigation of the influence of cognitive motivational variables on academic performance show academic efficacy as mediating academic outcomes (Brown et al., 2008). That is, students who perform well academically do so because they have developed strong academic efficacy beliefs that influence outcome expectations and lend to approaching challenging academic tasks (Brown et al., 2008). Thus, it is hypothesized that SAT scores directly relate to academic efficacy and indirectly relate to student achievement (e.g., college GPA & retention).

Psychosocial Variables

Academic Efficacy. Academic efficacy refers to confidence in one's ability to successfully complete academic tasks (Costello et al., 2008; Zajacova, Lynch, & Espenshade, 2005) and has been found to relate directly and indirectly to academic outcomes (Al-Harthy et al., 2010; Brown et al., 2008; House, 2000; House & Prion, 1998; Sciarra & Whitson, 2007). Indeed, a wealth of literature on academic efficacy has repeatedly shown its predictability with grades and persistence in college (Crisp et al., 2015; Zajacova et al., 2005). Academic efficacy has also emerged as central to persistence and self-regulation when faced with challenges or when problem solving (Al-Harthy et al., 2010; Brown et al., 2008). In this respect, studies of academic efficacy suggest that self-referent thoughts and beliefs play a central role in goal directed behavior and academic achievement.

Academic efficacy beliefs are also purported to relate to student's performance goals, with higher academic efficacy working towards more challenging academic goals. Recent meta-analytic research showed academic efficacy as having the strongest effect on academic outcomes (Brown et al., 2008; Hseih et al., 2007; Robbins et al., 2004). Therefore, we chose to focus on academic efficacy as playing a central role in our model, where students' academic efficacy predicts problem solving and indirectly connectedness to professors.

Problem Solving. Academic problem solving is frequently discussed in reference to the attributes of high achieving students (Robbins et al., 2004) and, therefore, often a central component of academic interventions (Ferret, 2000; Noble, Davenport, Schiel, & Pommerich, 1999). Academic behaviors, such as problem solving, have also been shown to mediate goal directedness and its relation with academic performance, with productive study and learning habits being correlated with academic achievement (Zajacova et al., 2005). In fact, academic problem solving skills were found to be predictive of college GPA (Robbins et al., 2004); however, the connection with other psychosocial variables, such as professor and college connectedness, is relatively unexplored.

Due to the established association with academic performance and amenability to intervention, we examined problem solving and its relation with academic performance via professor and college connectedness. For our model, problems solving was strategically placed after academic efficacy as belief in one's academic ability is hypothesized to undergird persistence in problem solving and to mobilize self-regulation skills central to goal directed behavior (Hseih et al., 2012). Problem solving is hypothesized to predict connectedness, as students with strong efficacy beliefs and good problem solving skills are more inclined to approach challenging tasks and seek out professors as one aspect of effective problem solving (Brown et al., 2008; Robbins et al., 2004).

Connectedness to Professors. While many factors relate with undergraduate student retention, recently faculty-student relationships have been recognized as a critical influence (Pazos & Micari, 2012) and to have direct bearing on students' persistence, experiences, and learning (Komarraju, Musulkin, & Bhattacharya, 2010). For example, reasons for withdrawing from college include unsatisfactory academic experiences, lack of social integration, and few meaningful connections (Crosling, Heagney, & Thomas, 2009). Moreover, similar psychosocial constructs, such as students' sense of belonging, have been shown to be more predictive of academic success than aptitude alone (Anderman, Jenson, & Freeman, 2007; Laskey & Hetzel, 2011). Professor variables, such as encouragement, positive instructor-student interactions, instructor warmth, and well-designed instruction, were correlates of students' sense of class belonging and predicted course grades and course confidence (Pazos & Micari, 2012). Such variables appeared to foster meaningful relationships that functioned to make students feel more at home and want to stay at their institution (Crisp et al., 2014).

Notable salient psychosocial variables for predicting student Bachelor's degree attainment are locus of control and parental support (Sciarra & Whitson, 2007). Factors, such as these, point to the importance of emotional, relational, and interpersonal support in academic achievement. In this investigation, connectedness to professors speaks to students' beliefs about their relationships with professors (not specific to one professor, but as a whole), specifically their perception of professors' availability, belief in their ability, and quality of relationships, and for this reason, we predict a direct link between connectedness to professors and college. As a result, our model (see Figure 1) theorizes that students who seek greater professor and college connectedness will predict current college GPA, which ultimately predicts their intent to remain, future GPA, and retention.

Connectedness to College. A sense of belonging and connection to school has been extensively researched at the primary and secondary levels (Hausmann, Schofield, &Woods, 2007; Pazos & Micari, 2012). Findings at this level have shown positive associations between students' sense of belonging and connection and various academic outcomes. At the college level, however, research in this area is just beginning to emerge and has been discussed as involvement or engagement (Hurtado & Carter, 1997; Johnson et al., 2007; Tinto, 2007). One study found students' sense of belonging and institutional commitment to be positively associated with intent to remain (Crisp et al., 2015; Hausmann et al., 2007); however, meaningful relationships and perceived support appear to be intricately related to one's sense of belonging or school connectedness (Crisp et al., 2014). For example, researchers (Pittman & Richmond, 2007) found students with higher reported university belonging had better grades, higher levels of perceived academic competence, and reported more positive perceptions of their university environment (Gloria et al., 2005).

Institution type is also important to student's sense of belonging and achievement, as Latino students attending college with a large percentage of Latinos tend to perform better academically (Crisp et al., 2015). These findings suggest a need for continued empirical study of how belonging and connectedness variables function in relation to college persistence and retention (Tinto, 1987; 1993). In light of previous research, we hypothesized that connectedness to college would be directly associated with both college GPA and intent to remain. Despite research showing association between school climate, institution type, and retention, the connectedness construct has yet to be systematically examined with college age students.

Academic success

Educational persistence models (Tinto, 1993) have shown intent to persist predicts retention through the degree of students' integration in college. Specifically, the literature shows academic goals and/or students' determination for staying in college correlates positively with retention (Robbins et al., 2004). Based on the notion that academic achievement in college should predict retention, we combine expectancy-value theory (i.e., academic goals or intent to remain) and academic achievement and predict these two variables to correlate strongly with retention (Robbins et al., 2004).

Research questions

Based on the above literature, there appears to be theoretical and empirical support for our hypothesized model (see Figure 1). While there has been a fair amount of research focusing on the direct effect, less research has focused on the indirect effects and testing models that include SES, psychosocial, and academic achievement. Moreover, psychometrically sound instruments to assess constructs purportedly related to student success are also insufficient. Therefore, the current study seeks to fill these gaps guided by the following research questions: 1) Do the psychosocial and intent to remain measures possess adequate factorial validity, internal consistently reliability, and predictive validity (tested via the measurement and structural models)? and 2) Does the proposed theoretical model (see Figure 1) provide adequate model fit, along with significant structural coefficients and R^2 statistics?

METHODS

Sample

Participants included undergraduate students from a large urban Hispanic-serving university, with an overall enrollment of approximately 30,000 students. Of the 1,470 students enrolled in the five introductory biology courses sampled, 555 (or 37.8%) attended class the day the survey was administered and of those 498 (90%) completed the survey. While there was variation in attendance rate across the five sections (35.0%, 36.5%, 47.4%, 30.1%, & 57.6%), both instructors indicated these percentages were typical. Nevertheless, these rather poor attendance rates are a limitation, as the results might not generalize to those not in attendance.

Sixteen surveys were removed due to insufficient/invalid data (e.g., either most of their data were missing or they provided invalid responses, such as the same response option for all items) and another 37 students were omitted because they were seniors. Seniors were removed because other factors (e.g., being so close to graduating) are likely driving factors to remain at the university rather than those other variables investigated in this study (see Figure 1). Note, no graduate students were sampled, thus our model results may not generalize to the graduate level.

The final sample of 445 was composed of slightly more females (53.3% females, 46.3% males, 0.4% missing), with ages ranging from 17 to 51 (M = 19.63, SD = 2.32, M_d = 19). Participants self-identified as 44.7% Hispanic, 27.9% Caucasian, 13.9% African-American, 7.4% Asian, 3.8% Biracial, 1.8% Other, and 0.4% missing. Most participants were underclassmen (Freshmen, n = 230; Sophomore, n = 154; Junior, n = 59) and were retained (i.e., still enrolled or graduated) at the university 27 months later (Enrolled, n = 316, 71.0%; Not Enrolled, n = 118, 26.5%; Missing, n = 11, 2.5%). Academically, student's mean cumulative GPA (collected June of 2013) was 2.78 (SD = 0.60) following the semester of survey data collection (April of 2013), with an average student credit hours earned of 32.75 (SD = 21.10). Student mean GPA, along with the standard deviation, was nearly identical (two to decimal points) at follow-up two years later (June of 2015). Additional participant demographics are provided in Table 1, with additional information related to the influence of these variables on our theoretical model available from the corresponding author[2].

Measures

The survey, which included 13 subscales (70-items) and 13 demographic items, was group administered to five large sections of an undergraduate course. The first portion of the survey measured various educational, psychosocial, and business related subscales. However, this study focused only on the educational and psychosocial variables, thus only five subscales/latent factors (problem solving, academic efficacy, connectedness to college, connectedness to professors, & intent to remain) were evaluated in our proposed model (see Figure 1). The remaining subscales, which focused more on business related constructs, were not of theoretical interest for this study.

[2]The decision to include demographic variables into our model as control variables was considered; however, these variables were excluded for two reasons. First, these variables (i.e., gender, marital status, child status, parents pay, live on campus, first generation status, Pell grant eligibility, & year in school) were not strong predictors of the endogenous variables in the model. Using these demographic variables as predictors, the largest R^2 was .06 for the June of 2015 college GPA variable, with the only significant predictor variables being Pell grant eligibility and gender. Two, adding these variables to the model would significantly increase model complexity and distract from the primary study purpose. However, additional analyses were conducted and are available from the corresponding author.

TABLE 1
SAMPLE STATISTICS CORRESPONDING TO EACH STUDENT VARIABLE.

	n (%)
Parents help pay for college	
Yes	144 (32.4%)
No	291 (65.4%)
First generation student	
Yes	190 (42.7%)
No	195 (43.8%)
First person to graduate from college	
Yes	152 (34.2%)
No	285 (64.0%)
Pell Grant Eligibility	
Yes	196 (44.0%)
No	190 (42.7%)
Married	
Yes	8 (1.8%)
No	429 (96.4%)
Has children	
Yes	7 (1.6%)
No	431 (96.9%)
Lives on campus	
Yes	132 (29.7%)
No	305 (68.5%)
Academic College/Discipline	
Architecture	1 (0.2%)
Business	53 (11.9%)
Education and Human Development	59 (13.3%)
Engineering	19 (4.3%)
Liberal and Fine Arts	71 (16.0%)
Public Policy	26 (5.8%)
Sciences	72 (16.2%)
University College	85 (19.1%)
Missing	59 (13.3%)

Note. Sample sizes or percentages that do not sum to 445 or 100%, respectively, represent missing data.

The demographic portion of the survey inquired about their gender, ethnicity, age, classification, familial and educational history, employment status, time spent studying, marital status, living status (on- or off-campus), and college major. Additional student data (e.g., student retention, SAT scores, GPA, Pell grant eligibly, generation status, major, hours earned) were collected from university records. Below we outline the variables used in the current study.

Each subscale included 3 to 7 items that were rated on a 6-point scale from 'strongly disagree' to 'strongly agree,' with several items reverse worded to ensure students were carefully reading and responding to each statement. To reduce concerns associated with common method variance and students responding to items based on previous responses, item were systemically, yet randomly, ordered. In other words, items from the same subscale were internationally placed as far apart as possible in a random order. While several of the subscales were created by previous researchers, others were created or modified specifically for this study. Nevertheless, the results provided here (see *Confirmatory factor analysis* and *Internal consistency reliability* results below) provide evidence of these subscales psychometric properties.

Academic efficacy. Five academic efficacy items were adapted from Patterns of Adaptive Learning Scales (PALS; Midgley et al., 2000) to measure students' sense of academic competency and belief in their ability to be successful with academic college coursework. To make the scale more compatible with the current survey and study purpose, item stems were slightly revised (i.e., focus changed to college coursework) and the response scale was change from 1 (Not at all true) to 5 (very true) to our standard 6-point scale above. While the original version of the PALS has been evaluated for various forms of reliability ($\alpha = .78$) and validity in the past (Midgley et al., 2000), this slightly revised set of items (see Table 3) has not been investigated to date. However, our analyses provide positive findings related to the subscale's psychometric properties as demonstrated below.

Problem Solving. This subscale is a measure of academic goal setting and self-reported problem solving skill, with higher scores indicating better problem solving. While Heppner and Peterson (1982) developed a 35-item Problem Solving Inventory (PSI) to measure Problem Solving, Approach-Avoidance, and Personal Control, this study only used the 7-items from the Problem Solving subscale. The logic was to reduce the survey length and only include subscales of interest to our theoretical model. Nevertheless, psychometric research using the PSI has been promising (Heppner & Peterson, 1982) and the Problem Solving subscale performed well with our sample. The list of items, along with factorial validity evidence, are provided in Table 3.

Hemmingway Measure of Connectedness. Previous research using the Hemmingway Measure of Connectedness with college students provided mixed results in terms of its psychometric properties (Karcher & Wallace, 2003). Via personal communication with Dr. Karcher, we revised these subscales to measure the following three connectedness subscales: connectedness to college, professors, and advisors. Although all three subscales were administered, only the connectedness to college and professors were theorized and included in the proposed model. For the Connectedness to College subscale, 7 items (see Table 3) were used to assess student's connection and loyalty to their university. Connectedness to Professors, which also had 7 items (see Table 3), assessed student connection and relationship with university professors. Factorial validity and internal consistency reliability analyses indicated here provide evidence for the use of these two subscales for research purposes.

It is critical to recognize that this is a general (or average) measure of professor connectedness (see items in Table 3) and not associated with a specific professor. Consequently, the theory is that students who seek a connection with their professors (e.g., maybe they interact more with them outside of class), or simply just feel more connected to their professors (e.g., get the feeling their professors care about their success) are more likely to connect with their college/university and eventually increased academic successful.

Intent to Remain. This 3-item (see Table 3) subscale measured students' perceived benefits of completing a college degree at their current university versus transferring to a different university. Specifically, two of these items focus on whether the student anticipated graduating from either their current or another university. Based on the analyses conducted here, this subscale appeared to have reasonably good psychometric properties and was a strong predictor of whether students remained enrolled at their current university.

Student characteristics. To accompany the latent variables/scales above, several observed variables were used to understand those factors influencing student retention. Starting with the exogenous variables, generation status and Pell grant eligibility were used as measures of socioeconomic status (SES). Generation status was coded as zero for first generation students and one for not first generation students, with first generation student classification being based on the federal guidelines of 1) neither of their natural, adoptive, or custodial parents received a baccalaureate degree, 2) they were foster care youth, or 3) an individual who is homeless. This SES proxy variable was selected as a parents earning potential measure. Moreover, this variable provides an indirect measure of students' familiarity with college (via the parents) and purportedly the importance placed on a college education. Pell grant eligible, which provides an estimate of parent income and SES, was coded as 0 (not eligible, thus having a higher SES) and 1 (eligible, thus having lower SES).

Student success. SAT scores were used as a measure of college readiness and general "aptitude," with the general premise that these areas should be a driving factor when predicting other variables in the model (e.g., academic efficacy, student connectedness, & student success). One measure of student academic success is student's college GPA, which was measured at two time points (June of 2013 & 2015). The final measure of student success, and variable of primary interest, was retention (collected June of 2015 or 27 months after survey data were collected). The retention variable measured whether the student remained enrolled, or graduated from, the university were where survey data were collected.

Procedures

Five sections of an undergraduate biology course, with three sections taught by a full professor and two sections by a senior lecture, were identified as a subject pool. This course was selected for three reasons: 1) there was a large number of students ($N = 1{,}470$) in these five sections, 2) most students were posited to be either freshmen or sophomores (we did not want a large proportion of transfer students or those that would be graduating in the near future, as we sought to evaluate retention and not graduation), and 3) this course tends to have students with majors across a wide range of academic colleges and disciplines (see Table 1).

Student survey data collection occurred during April of 2013. Three Ph.D. researchers and three graduate assistants visited each class and gave a survey packet to every student in attendance during the first 20 minutes of the course. Prior to completing the survey, one of the Ph.D. researchers stated the purpose of the study, explained that the information collected would remain confidential (as required by our approved university IRB protocol), and informed the students that their participation was voluntary.

In addition to the demographic and subscales questions of interest, the survey packet also contained a form to provide students' identification number that allowed the researchers to gather pertinent student information (SAT/ACT scores, student major, current cumulative and semester GPA, Pell grant eligibility, etc.) and retention information from university records. These university data were collected during June of 2013 and 2015, which allowed us to assess retention longitudinally over the course of 27 months.

STATISTICAL ANALYSES

While Frequentist (e.g., maximum likelihood) factor analysis and structural equation modeling (SEM) approaches are generally well understood and documented, Bayesian approaches have received relatively little attend until recently due to software and computing resources. For this reason, we first provide a brief comparison of these estimation methods and references for interested readers before discussing how our models were estimated. While a brief comparison is included here, Muthén and Asparouhov (2012), Van de Schoot et al. (2013), and Zyphur and Oswald (2013) provide a more detailed comparison between these approaches.

Frequentist vs. Bayesian

Frequentist and Bayesian approaches are not different statistical models per se, but instead different estimation procedures that make different data and model assumptions. Unlike Frequentist approaches, Bayesian statistics do not rely on large sample normal theory, can better accommodate non-normal parameter distributions, provide increased performance with smaller sample sizes, and can estimate underidentified, more complex models (Muthén & Asparouhov, 2012). Perhaps more importantly, Frequentist approaches apply unnecessarily strict model assumptions (e.g., all cross-loadings, residual variances, & non-theorized structural coefficients are often fixed at zero), thus often resulting in a less than desired model fit and requiring later model modifications. However, Bayesian methods are not limited by these restriction/identification rules and allow researchers to test more complex and realist models (e.g., it does not require the strict assumption that all cross-loadings are zero in the population) that would otherwise be under-specified with Frequentist/traditional SEM methods. That is, a traditional CFA model with all the cross-loadings and residual covariances estimated could not be estimated/identified; however, this is not a problem for Bayesian estimation.

Another difference between Frequentists and Bayesians is the *p*-value interpretation. Frequentists interpret the *p*-value as "the probability of observing the same or more extreme data assuming that the null hypothesis is true in the population," whereas Bayesians interpret it as "the probability of the (null) hypothesis" (Van de Schoot et al., 2013, p. 844). The interval estimates are also interpreted differently due to prior distributions[3]. For Frequentists, the 95% confidence interval is interpreted as "over an infinity of samples taken from the population, 95% of these contain the true population value," whereas the Bayesian interpretation for the credibility interval is "a 95% probability that the population value is within the limits of the interval" (Van de Schoot et al., 2013, p. 844). Relatedly, Bayesians assume random model parameter with values reflecting parameter uncertainly rather than fixed (i.e., assume there is one true value) as perceived by Frequentists.

[3]Although priors are an extremely important part of Bayesian inference (see Muthén & Asparouhov, 2012), due to space constraints this topic is not discussed in significant detail here. However, it is critical to note that priors provide information related to the model parameters (e.g., a factor loading or structural coefficient) uncertainty and is used in combination with the data to estimate the posterior distribution. Typically, a prior distribution mean is selected based on previous research or one's theorized estimated value, with the variance determined based on the degree of parameter uncertainly.

Another major difference between Frequentist and Bayesian estimation is how model misfit is determined. For Frequentists (or CFA or SEM model estimation), modification indices are used to determine those paths that differ significantly from the fixed value (often set at zero) and would improve the model fit. However, this approach is often considered problematic in that multiple model changes can produce the same change in model fit and this practice often results in elevated Type I error rates (MacCallum, 1986; MacCallum, Roznowski, & Necowitz, 1992) and can produce incorrect models (Spirtes, Scheines, & Glymour, 1990). Conversely, Bayesian estimation allows the estimation of all model parameters simultaneously, thus eliminating the need for modification indices. As a result, one could argue that Bayesian models allow a simpler procedure for testing the significance of cross-loadings, correlated residuals (a.k.a., residual covariances), and structural coefficients traditionally fixed at zero because all parameters are estimated simultaneously.

Unlike traditional model fit statistics (e.g., χ^2; Comparative Fit Index, CFI; Normed Fit Index, NFI; Root Mean Square Error of Approximation, RMSEA) used for Frequentist estimation, Bayesian estimation assesses the predictive accuracy of the model via the *posterior predictive checking* method (Gelman, Carlin, Stern, & Rubin et al., 2004). The general premise of this procedure is to evaluate the degree of discrepancy between data generated by the model and the actual data itself, with any difference between these results suggesting possible model misspecification. Specifically, Bayesian model fit is assessed using the posterior predictive p-value (PPP) and the associated 95% credibility interval (CI) around the model fit statistic. The fit statistic, *f*, is calculated using the likelihood-ratio χ^2 of an H_0 model compared to the unrestricted H_1 model. To calculate the 95% CI, Mplus takes the difference in the *f* statistic for the data generated by the model and the actual data over each of the 10th iterations (Asparouhov & Muthén, 2010). Therefore, the PPP measures the proportion of χ^2 values obtained in the simulated data that exceed that of the actual data. A well-fitting model is expected to have a PPP around .5 and a symmetric 95% CI centered at zero. However, Asparouhov and Muthén (2010) stated that PPP of .10, .05, or .01 appear reasonable for most applied applications, as this would indicate there is not a significant difference between the simulated and actual data. While estimated and interpreted differently from a χ^2 from a traditional CFA or SEM model, obtaining a PPP $< .05$ is equivalent to having a *p*-value from a $\chi^2 < .05$.

Bayesian Model Estimation

For this study, statistical analyses were conducted using Bayesian estimation in Mplus 7.3 (Muthén & Muthén, 1998–2015), with the latent factor variances set to one for the purposes of latent variable scaling. Setting the scale in this fashion also made the prior distributions more intuitive, thus producing comparable unstandardized and standardized results. Using a polychoric correlation and different starting values, the posterior distributions were estimated using two Markov Chain Monte Carlo (MCMC) chains with 30,000 iterations and Gibbs sampler with the random walks algorithm (Muthén & Asparouhov, 2012). The first half of the chains was discarded as a burn-in phase, with the second half used to estimate the posterior distributions (Muthén, 2010). Model convergence was assessed with the Gelman–Rubin convergence diagnostic, which takes into account the potential scale reduction factor (PSR; Gelman et al., 2004; Gelman & Rubin, 1992). The PSR was used to assess model convergence, with values between 1.05 (or intraclass correlation, ICC, = 0.09) and 1.10 (or ICC = 0.17) considered acceptable for model interpretation. Models that did reach an acceptable PSR were revised and re-run.

Normal priors were used for the cross-loadings [N(0,.02), thus the 95% CI was ± .28], residual covariances [N(0,.02)], and non-theorized structural coefficient effects [N(0,.02)]. All other parameter estimates used default priors in Mplus. Note, cross-loadings, residual covariances, non-theorized structural coefficients, and other model prior distributions were rather non-informative given the lack of previous research in this area. To assess prior distribution sensitivity, alternative priors were also evaluated to assess the impact the results. However, changing these priors did not significantly alter the model fit or parameter estimates.

Estimated Models

Deviating slightly due to the estimation method and model estimated, but still following the general premise recommended by Anderson and Gerbing (1988), this study took a sequential approach to understand model misfit and model specification. Specifically, we started with a very restrictive measurement and structural model and continued to relax model constraints until an acceptable model was obtained.

To understand the measurement model's factor structure (i.e., only the latent factors) and investigate issues related to misfit, the succeeding Bayesian confirmatory factor analysis (BCFA) modeling approach was followed (see Table 2). The first BCFA model (i.e., BCFA Model 1) tested whether it was statistically appropriate to fix all the cross-loadings and residual covariances at zero, which is the typical practice for Frequentist CFA. If the BCFA Model 1 did not produce an acceptable model fit, BCFA Model 2 tested the impact of allowing the cross-loadings to be estimated with the residual covariances remained fixed at zero. If BCFA Model 2 still produces model misfit, BCFA Model 3 also estimated the residual covariances. Once an acceptable model fit was obtained, the parameter estimates were then assessed for practical and statistically significance to better understand the cause of any model misfit.

Table 2.
Model fit statistics for each model BCFA and BSEM model estimated.

Model	*95% CI*	*PPP*	*# of free parameters*
Measurement models			
BCFA Model 1: No cross-loadings or residual covariances	179.81 to 350.37	> .001	170
BCFA Model 2: Cross-loadings, but no residual covariances	78.31 to 243.58	> .001	278
BCFA Model 3: Cross-loadings and residual covariances	-104.36 to 52.63	.775	629
Structural models			
BSEM Model 1: Theorized model, but no cross-loadings or residual covariances	325.79 to 521.77	> .001	179
BSEM Model 2: Theorized model with cross-loadings, but no residual covariances	196.16 to 392.73	> .001	287
BSEM Model 3: Theorized SEM model with cross-loadings and residual covariances	19.740 to 212.93	.009	644
BSEM Model 4: Exploratory SEM model with cross-loadings and residual covariances	-39.98 to 151.43	.124	651

As demonstrated in Table 2, the Bayesian structural equation models (BSEMs, which included latent and observed variables of interest, see Figure 1) followed a similar approach to that of the BCFA models. In other words, BSEM Model 1 made the traditional assumption that the cross-loadings and residual covariances were fixed at zero when estimating the SEM model. BSEM Model 2 and 3 sequentially relaxed the assumptions that the cross-loadings and residual covariances were fixed at zero, respectively. The final model, BSEM Model 4, also relaxed structural coefficients that were theorized to be zero, thus testing a more complex (but less parsimonious) structural model. For SEM Model 4, structural coefficients were relaxed (i.e., not fixed at zero) serially based on theory until the model fit was acceptable (i.e., there was no difference between the simulated and actual data). As with the BCFA models, these BSEM models were tested sequentially to better understand model misfit and the impact of relaxing model constraints. All covariance and correlation matrices used to estimate the model may be obtained from the corresponding author.

Missing Data

Although Little's Missing Completely at Random (MCAR) test indicated that data were not missing completely at random, χ^2 (2003) = 2137.62, p = 0.018, the data are purportedly missing at random (MAR) due to the strong relationship between the items and factors, as well as the relatively high correlations between factors. Stated differently, the strong correlations between items and factors should allow for a good prediction of missingness, thus making it MAR. Moreover, the percent of overall missing data was minimal (2.9%), thus missingness should not have a significant impact of the parameter estimates. As a result, missing data were treated within the Gibbs sampler (for more details see Asparouhov & Muthén 2010) in Mplus.

It is important to note that most of the missing data were present on the first generation status (13.5%), Pell grant eligibility (13.3%), retention (13.3%), and SAT (22.3%) variables. The reason being that these data were obtained through university records and some students 1) did not provide their student IDs to allow for student identification, or 2) the university did not have this data on record. As a result, readers might elect to interpret the relationships associated with these variables slightly more tentatively.

RESULTS

Measurement Models/Confirmatory Factor Analyses

Before evaluating the SEMs, we first tested a series of BCFAs using only the latent variables (i.e., excluding generation status, Pell grant eligible, SAT scores, college GPAs, & retention) to explore the latent variable's measurement qualities. These models are critical to evaluate the factorial validity and understanding any model misfit related to these latent variables before proceeding to the BSEM. Moreover, many of these scales were created or modified specifically for this study and, therefore, have never been explored in combination.

The BCFA (see Table 2) results suggest that making the assumption that all cross-loadings and residual covariances are zero (typical assumption when conducting Frequentist CFAs[4]) is unrealistic given than the PPP was statistically significant (i.e., PPP < .05) and did not reach an optimal (PPP < .05) value until all cross-loadings and residual covariances were estimated. An evaluation of these parameter estimates revealed that no cross-loadings were statistically significant at the .05 level; however, several residual covariances were statistically significant at this level[5]. Nevertheless, many of these residual covariances were rather small in magnitude and did not exceeded |.20|. Overall, the results provided relatively strong support for the overall measurement model quality, as the primary loadings were relatively large ($\lambda > .40$), the cross-loadings were relatively small ($\lambda < |.20|$), and the residual covariances were generally small ($\Theta\delta < |.20|$) in magnitude. These results suggest the measurement model has adequate factorial validity and it is appropriate to evaluate the BSEM models.

Internal Consistency Reliability

For each subscale, internal consistency reliability was estimated using the traditional Cronbach's α and the arguably more appropriate McDonald's (1999) ω coefficient. Reliability coefficients were as follows for each scale: Problem solving $\omega = 0.78$ (95% CI 0.75 to 0.82) and $\alpha = 0.82$, Academic Efficacy $\omega = 0.80$ (95% CI 0.77 to 0.84) and $\alpha = 0.79$, Connectedness to professors $\omega = 0.75$ (95% CI 0.71 to 0.79) and $\alpha = 0.76$, Connectedness to

[4]A more detailed description and interpretation of the results is available from the corresponding author. However, it is worth nothing that when the Frequentist CFA (i.e., all the cross-loadings and residual covariance fixed at zero) model was estimated using a weighted least squares means and variance adjusted estimation procedure a good model fit was obtained based on the CFI, TLI, and RMSEA, χ^2 (314) = 886.41, $p < .001$, CFI = .950, TLI = .945, RMSEA = .064. As expected, there was model misfit based on the χ^2 statistic.

[5]These included i27 with i60 ($\Theta\delta = -.16$, $p = .013$), i6 with i7 ($\Theta\delta = .16$, $p = .007$), i18 with i29 ($\Theta\delta = -.12$, $p = .010$), i11 with i50 ($\Theta\delta = .15$, $p = .005$), i11 with i29 ($\Theta\delta = .13$, $p = .020$), i11 with i33 ($\Theta\delta = -.13$, $p = .025$), i11 with i47 ($\Theta\delta = .22$, $p = .004$), i33 with i58 ($\Theta\delta = -.19$, $p = .019$), i6 with i55 ($\Theta\delta = -.14$, $p = .019$), i50 with i55 ($\Theta\delta = -.17$, $p = .002$), i37 with i60 ($\Theta\delta = -.15$, $p = .017$), i37 with i50 ($\Theta\delta = .12$, $p = .010$), i2 with i27 ($\Theta\delta = -.15$, $p = .021$), i2 with i33 ($\Theta\delta = .14$, $p = .019$), i14 with i29 ($\Theta\delta = .17$, $p = .002$), i14 with i35 ($\Theta\delta = -.18$, $p = .021$), i14 with i59 ($\Theta\delta = -.20$, $p = .007$), i5 with i11 ($\Theta\delta = -.14$, $p = .006$), and i5 with i37 ($\Theta\delta = -.19$, $p = .002$).

TABLE 3.
PROVIDES THE STANDARDIZED FACTOR LOADING CORRESPONDING TO THE STRUCTURAL MODEL IN FIGURE 3 (I.E., MODEL 4).

Item	*PS*	*Efficacy*	*Profs*	*College*	*I2R*
I6. I am usually able to think up creative and effective alternatives to solve a problem.	**0.71***	0.02	-0.06	-0.04	-0.01
I13. When I make plans to solve a problem, I am almost certain that I can make them work.	**0.80***	0.03	-0.05	0.04	0.00
I27. Given enough time and effort, I believe I can solve most problems that confront me.	**0.79***	-0.05	0.00	0.07	0.05
I38. When faced with a novel situation, I have confidence that I can handle problems that may arise.	**0.93***	-0.05	-0.01	-0.12	-0.04
I44. I trust my ability to solve new and difficult problems.	**0.80***	0.03	0.05	0.03	-0.04
I50. When confronted with a problem, I am unsure of whether I can handle the situation.	**0.44***	0.04	-0.08	-0.11	0.05
I60. I have the ability to solve most problems even though initially no solution is immediately apparent.	**0.80***	0.05	0.06	-0.19*	-0.03
I7. I'm certain I can master the skills taught in my college coursework.	0.16	**0.49***	0.01	0.12	0.03
I18. I'm certain I can handle most difficult college coursework.	0.00	**0.61***	0.07	0.14	-0.06
I29. I can perform well in my college coursework if I don't give up.	0.14	**0.38***	0.04	0.26*	0.03
I41. Even if the college coursework is hard, I can learn it.	0.04	**0.73***	0.04	0.08	-0.06
I54. I can do even the hardest college coursework if I try.	0.06	**0.80***	0.01	0.03	-0.01
I11. I feel no sense of connection to my professors.	-0.11	-0.01	**0.51***	0.02	0.04
I22. Earning my professors' respect is important to me.	0.02	-0.04	**0.58***	0.12	0.06
I33. I seek out my professors outside of class.	-0.14	-0.02	**0.72***	0.01	-0.08
I37. I dislike having to talk one-on-one with my professors.	0.01	0.05	**0.56***	0.10	0.12*
I47. I enjoy interacting with my professors in class.	0.06	-0.01	**0.33***	-0.07	0.00
I55. I feel good about the relationships I have with my professors.	0.02	0.04	**0.76***	-0.04	0.03
I58. I feel comfortable discussing my future with my professors.	0.12	0.00	**0.72***	0.01	-0.05
I2. I take full advantage of all that college has to offer.	-0.02	-0.08	0.09	**0.65***	-0.04
I14. Being a student is a positive part of my life.	0.12	0.01	0.03	**0.61***	0.05
I35. I work hard in college to be successful.	0.07	0.09	-0.01	**0.71***	0.08

Table 3, cont.

Item	*PS*	*Efficacy*	*Profs*	*College*	*I2R*
I49. I like being a college student.	0.11	0.05	-0.01	**0.53***	0.11
I59. I put as little effort into my academics as I can get away with.	0.08	0.05	0.00	**0.39***	-0.01
I5. I anticipate graduating from *insert university name*.	0.00	0.01	0.05	0.18*	**0.70***
I17. I anticipate transferring to another university.	-0.01	-0.02	-0.03	-0.01	**0.92***
I40. I anticipate graduating from another university.	0.01	0.02	0.01	-0.02	**0.93***

Note. PS, Efficacy, Profs, College, and I2R correspond to the Problem solving, Academic efficacy, Connectedness to professors, Connectedness to college, and Intent to remain factors. Bolded coefficients indicate primary factor loading (i.e., the factor they are theorized to measure), with statistically significant coefficients at the .05 level marked with an asterisk.

college $\omega = 0.66$ (95% CI 0.61 to 0.71) and $\alpha = 0.69$, and Intent to remain $\omega = 0.85$ (95% CI 0.82 to 0.89) and $\alpha = 0.83$.

Structural Equation Modeling

Summary of Model Fit Results. Model fit results differed greatly depending on the model estimated (see Table 2), which was expected based on the BCFAs. It is clear from the BSEM Model 1, BSEM Model 2, and BSEM Model 3 results that fixing the cross-loadings and residual covariances at zero is statistically inappropriate. Based on the 95% CI and larger PPP, fixing all the non-theorized structural coefficients at zero also appears statistically unjustified (see Table 2, BSEM Model 3). With that said, the model fit did not deviate considerably from the .05 level (PPP = .009). Nevertheless, additional non-theorized structural coefficients were added based on theory (e.g., rather than estimating a full mediation model a partial mediation model was estimated) to improve the overall model fit. After adding additional structural coefficient estimates, the BSEM Model 4 revealed an acceptable model fit.

BSEM Measurement Results. Given that the measurement portion of model (i.e., factor loadings, residual variances, & residual covariances) were nearly identical across the four BSEM model, the measurement model results associated with BSEM Model 4 are only presented here. The measurement model results for the other three BSEM are available from the corresponding author. As seen in Table 3, the estimated primary factor loadings were generally large ($\lambda > .40$) in magnitude and loaded on the theorized factor. While four statistically significant cross-loadings emerged at the .05 level, these coefficients were rather small in magnitude ($\lambda < |.30|$). As found with the BCFAs, residual covariances were a concern. In fact, 13 statistically significant residual covariances emerged, with these results available from the corresponding author. However, only one residual covariance was greater than .20 (i27 with i29, $\Theta\delta = .20$), which suggests from a practical standpoint these are of relatively little concern. Overall, these results provide relatively good evidence of factorial validity, as the primary factor loadings remained large, the secondary/cross-loadings were small, and the residual covariances were generally small.

Structural Model Results for BSEM Model 3. Despite some structural model misfit as indicated by the PPP (see Table 2, BSEM Model 3), results revealed relatively good support for our theorized model. However, several structural coefficients (β or γ) and R^2 were relatively small in magnitude and/or non-significant at the .05 level. Effect size standards used here followed those tentatively proposed by Cohen (1988, pp. 413–414): small ($R^2 = .02$; β or $\gamma = |.15|$), medium ($R^2 = .13$; β or $\gamma = |.36|$), and large ($R^2 = .26$; β or $\gamma = |.51|$). Recall, an endogenous variable's R^2 corresponds to the percent of variance explained by those variables with arrows going into that endogenous variable.

Starting with the exogenous SES variables (i.e., Generation status & Pell grant eligible), both variables were statistically significant predictors of SAT scores and displayed medium effect sizes. Therefore, one could conclude that these SES proxies predict academic readiness and ultimately their likelihood of being accepted into college (i.e., higher SAT scores should produce a higher likelihood of college acceptance). While statistically significant at the .05 level, the effect of SAT scores on academic efficacy was relatively small, suggesting that higher "college readiness" or "aptitude" was not a very strong predictor of academic efficacy (i.e., their perceived ability to do well in an academic setting). Nevertheless, academic efficacy was a very strong predictor of problem solving (i.e., their perceived ability to solve difficult problems).

Continuing with the flow to the connectedness variables, problem solving was a strong predictor of connectedness to professors and college, with connectedness to professors partially mediating the relationship between problem solving and connectedness to college. These results imply that students with higher perceived problem solving skills tended to connect more with their university/college via their professors. With that said, the level of connectedness to college was not a very strong predictor of their June of 2013 college GPA, but instead a stronger predictor of whether the student intends to remain at their current college/university.

For the academic/student success portion of the model, there was a very strong association between student's June of 2013 GPA and June of 2015 GPA as expected. However, the prediction of June of 2013 GPA on their intent to remain at their current university was much smaller than expected and, in fact non-significant. This finding suggests that their current GPA had little impact on their desire to return or graduate from their current academic institution. On a positive note, both their June of 2015 GPA and intent to remain were strong predictors on retention (i.e., whether the student graduated or remained at the university). Moreover, these two variables explained 46% of the variance in the retention variable, with their June of 2015 GPA being a slightly better predictor of retention based on the structural coefficients.

Structural Model Results for BSEM Model 4. Despite the improvement in model fit compared to BSEM Model 3, BSEM Model 4 results were generally comparable (i.e., the structural coefficients and R^2 statistics) and unchanged from the BSEM Model 3 results. A few exceptions are worth discussing. First, there was a strong association between SAT scores and June of 2013 GPA, which considerably improved the R^2 statistic (BSEM Model 3 R^2 = .04 to BSEM Model 4 R^2 =.15). While small, SAT scores also displayed a statistically significant association with connectedness to professors and connectedness to college, but not with problem solving or retention. Notice that the R^2 statistics for problem solving and retention were already relatively high, so it is not unexpected that SAT scores did not explain any additional unique variance. In addition, neither $\gamma_{4,2}$ or $\gamma_{6,4}$ were statistically significant and confirmed the full mediation effects of problem solving and connectedness to college, respectively.

From an effect size standpoint, most variables were relatively strong predictors of the endogenous variables based on the structural coefficients (i.e., β or γ), with many of the R^2 being medium to large effect sizes based on Cohen's (1988) standards for BSEM Model 3 (see Figure 2) and BSEM Model 4 (see Figure 3). The exceptions were academic efficacy, June of 2013 GPA (more so for BSEM Model 3), and intent to remain. Recall, due to the additional structural coefficients estimated, the R^2 statistics tended to be a slightly larger for BSEM Model 4.

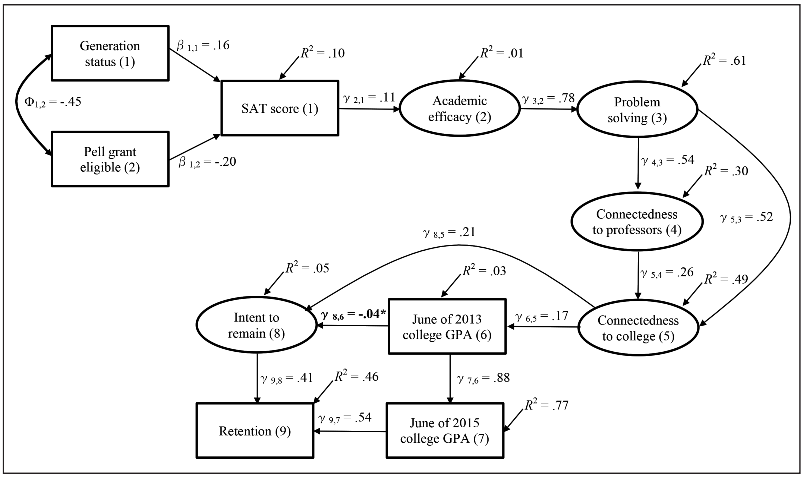

Figure 2. Displays the standardized structural coefficient results for SEM Model 3. With the exception of the one coefficient in bold and marked with an "", all other coefficients were statistically significant at the .05 level.*

DISCUSSION

The present investigation was twofold: 1) evaluate the psychometric properties of several scales designed to predict retention and 2) estimate an undergraduate student retention model. From a psychometric standpoint, the measurement model and internal consistency reliability results provided relatively strong support for the combined use of these scales. While misfit occurred without estimating the cross-loadings and residual covariances, these statistics were often small in magnitude based on conventional criteria. Moreover, the rather large primary factor loadings, and relatively clean fac-

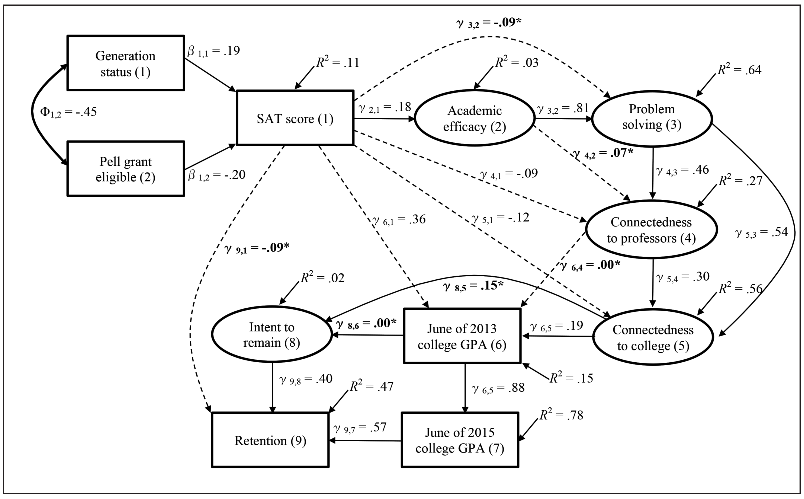

Figure 3. Displays the standardized structural coefficient results for SEM Model 4, where bolded lines were hypothesized and dashed lines were included to improve overall model fit. With the exception of those six coefficients in bold and marked with an asterisk, all other coefficients were statistically significant at the .05 level.

tor structure, support our argument for the factorial validity of the scales. The internal consistency reliability estimates were also acceptable based on established criteria, and this suggests these scales are appropriate for research purposes and continued exploration of the examined variables.

The structural equation model results for BSEM Model 3 indicated that psychosocial variables, which include problem solving, academic efficacy, connectedness to professors and college, were often good mediating variables when predicting student GPA and eventual retention. Perhaps more importantly, most of the structural and R^2 statistics were medium to large in magnitude and significantly predicted the desired endogenous variables. However, several variables (i.e., Academic efficacy, June of 2013 college GPA, & Intent to remain) were not predicted well.

Overall, the BSEM Model 3 model results generally showed support for our theorized model despite some concerns related to model misfit and a few non-significant structural coefficients. Consequently, the alternative model (i.e., BSEM Model 4) may provide more promise, as the additional paths (especially SAT scores on June of 2013 College GPA) produced an improved model. With that said, additional research is needed to identify those variables that predict the endogenous variable's unexplained variance, especially the intent to remain variable. In general, these results provide promise and offer institutions guidance on efforts and initiatives to improve undergraduate retention. One unique finding is the relation between problem solving and connectedness and that connectedness to professors predicts connectedness to college, which is associated with student's intent to remain and eventually retention. Consequently, greater awareness of the role of psychosocial variables (e.g., academic efficacy & problem solving) in academic achievement and the potential returns on investment in school climate and university branding may enhance college connectedness and intent to remain at that university.

Policy and Practice Implications

Contrary to our hypotheses, a student's generation status, Pell grant eligible, and SAT scores did not directly or indirectly predict academic efficacy and become strong driving factors when predicting other academic and connectedness related variables. Instead, our models only hinted that SAT scores might relate to several variables in the model and provide an overarching connection with the other variables of interest. These findings imply that one's SES (as measured by generation status and Pell grant eligible) and previous success on standardized tests (SAT score) do not dictate one's perceived academic ability, connectedness to school and professors, and eventual probability of graduating or remaining enrolled at a university.

On the contrary, students' perceived academic efficacy was a very strong predictor of perceived problem solving and indirectly predicted connectedness to professors and college. Moreover, perceived problem solving mediated the relationship between perceived academic efficacy and connectedness to professors. Findings suggest the higher student's academic efficacy, the higher their sense of problem solving ability. Notably, psychosocial variables such as academic efficacy, problem solving, and connectedness can be cultivated. That is, these variables are fluid (e.g., instructor and student interactions can influence student's academic efficacy and students can work to develop effective problem solving skills; Hseih & Schallert, 2008), whereas SAT scores are relatively fixed. This suggests that problem solving and academic efficacy needs to play a more prominent role in the instructional curriculum, which indeed has a long history in medicine and is making its way into education (Macpherson, 2002). Once a student successfully and effectively completes a complex task, Macpherson's (2002) research suggests students feel that they can master and solve similar challenging tasks. Effective problem solving can be developed over time, and effective tools can be used to empower the problem solver and boost their belief that they can solve complex problems (Guerra, Castro-Villarreal, Cheatham, & Claeys, 2014).

One suggestion is to introduce a systematic problem-solving model in institutions' freshman experience or introduction to college courses. Another evidence-based recommendation is the utilization of problem based learning techniques across curricular areas like what is currently being used in medical training (Basile & Nathenson-Mejía, 2003). Academic advisors also are well positioned to model and teach effective problem solving approaches with advisees. For example, some institutions have adopted advising models where advisors not only recommend that undergraduate advisees visit their professors, but they prepare advisees through role-play and practice to facilitate and enhance professor-student communication.

For practice, this means instructors would do well to engage in explicit instruction in problem solving for academic achievement. For example, students should be taught systematic problem solving methods, algorithms for problem solving, and steps for effective problem solving. Some disciplines have taken to problem based learning where students are taught to problem solve using complex problems in which they implement a systematic model (Hseih & Schallert, 2008). Other research has shown those who prescribe to the belief that intelligence is fluid and malleable are more likely to persist in challenging situations versus those who believe cognitive ability to be fixed (Heppner & Peterson, 1982). As such, it may behoove instructors to discuss research that supports the importance of academic efficacy as part of the idea that intelligence is not fixed and that alterable psychosocial factors serve to enhance and maximize academic potential. Specifically, a student should develop academic self-efficacy (ASE) rather than generalized self-efficacy, as this research and others have (Zajacova et al., 2005) found that ASE predicts grades and persistence. Research shows professors can foster ASE through incorporating evidence-based practices into their teachings, such as increased opportunities to practice, diverse assessment methodologies, setting realistic but high expectations in the classroom, and showcasing success stories of similar peers (House, 2000; Tough, 2014). Another method to enhance ASE is peer mentoring, where high achieving undergraduates are paired with incoming freshman to teach effective problem solving, time management, and the importance of persistence and motivation in academic achievement.

At the policy and institutional level, these findings tentatively support a transition away from highly emphasizing test scores in the administration criteria. This recommendation is not new and is consistent with GRE research and other standardized measures that do not predict graduate school GPA and degree completion (Kaplan & Middleton, 2002). Further, this research reinforces the development of freshman orientation and seminar courses focused exclusively on problem solving, study skills, and time management, along with the restructuring of academic advising departments via retraining of advising personnel to address the idea of teaching academic efficacy and effective problem solving for academic success.

As theorized, connectedness to college mediated the relationship between connectedness to professors and intent to remain, with intent to remain predicting actual retention. These findings underscore the importance of building meaningful relationships with professors and one's university as these variables either directly or indirectly predict college GPA, intent to remain, and retention. The more connected one feels to professors or the university, the more loyal they become which then directly relates with intent to remain (Crisp & Cruz, 2009).

It is interesting to note that while June of 2013 college GPA significantly predicted June of 2015 college GPA and eventual retention, one's June of 2013 college GPA did not significantly predict one's intent to remain. Collectively, these findings suggest that one's grades only predict actual retention and not one's intent to remain and further infers that connectedness may offset other academic risk factors. However, it is also possible that an important moderator (e.g., desire to earn a college degree) was omitted from the model, thus suggesting that college GPA only predicts intent to remain for some students. In addition to these relationships, our findings underscore the importance of the college climate to college connectedness. College connectedness can be promoted in many ways; one such way is through frequent advertisement and promotion of community events both social and academic. From another perspective, the continuous effort to build the brand is also critical to building connectedness and loyalty, which ultimately relates with intent to remain. In efforts to develop connections upon college enrollment, some institutions have adopted mandatory academic advising and mandatory admission to "general" college/major for the first two years of admission before graduating/applying to college/major of their choosing.

Limitations and Future Research

Despite the positive findings, several limitations and areas of future research need to be addressed. Related to model utility, additional predictor and moderator variables need to be included to improve model prediction, especially for those endogenous variables with lower coefficients of determination (i.e., R^2 statistics). For example, the fact that our model explains nearly half of the variance in student retention is certainly a positive finding; however, the fact remains that the other half of the variance remains unexplained. Along a similar vein, this study only tested one configuration of the variables explored, thus alternative models based on our variables is certainly possible.

Related to sampling, the high absentee rate the day of data collection was certainly a limitation. Despite the high response of those students in attendance, it is unknown whether the model results will generalize to those students not in attendance. It is possible that only those more dedicated students attended class and they are fundamentally different from absentee students. Along a similar vein, the fact that data were only collected from a single course could also be a limitation if our sample differs significantly from the typical undergraduate student. Relatedly, this model needs to be evaluated with a larger sample that allows for multi-group (e.g., structural invariance) analyses. For example, it would be interesting to determine whether the model fits and predicts equally well across different student (e.g., different racial groups, student majors, generation status, year in school) and school (e.g., academic college, university tier) characteristics.

When related specifically to connectedness to professors, the effect of this variable on connectedness to college (i.e., the mediating variable), and eventually on college success, was lower than anticipated. Consequently, it would be interesting to determine the individual professor connectedness effects (i.e., use professor specific measures, rather than a general measure of professor connectedness) as a predictor of student success in particular and whether different subdimensions of college connectedness (e.g., students connectedness to various academic, athletic, and social school components) better predict college success. In other words, multi-level models might detect significant variation within professors and, thus, result in a significantly better prediction of college connectedness and college success. For example, a student may be very connected to their algebra professor, thus earning a high course grade, whereas the same student the following semester is unconnected to their calculus professor and earn a very poor grade. Relatedly, students who are more connected to their professors may have higher academic college collectedness, whereas professor connectedness may not be predictive of other forms of college connectedness (e.g., connectedness to college social events).

Another limitation and area for future research is the exploration of student graduation rather than retention, while also evaluating these variables longitudinally. In other words, it would be preferable to sample freshmen entering the university and track their perceptions of these psychosocial and retention variables over time to identify those variables associated with graduation. This would also solve our sampling problem (i.e., not all students were freshmen and attended class the day of data collection) and allow for more specific tests of group differences. Similarly, the intent to remain variable was not ideal in that it composed of three items. Perhaps if a better more robust measure were used other significant predictors would have emerged.

CONCLUSIONS

Concerns associated with low graduation rates and high student turnover remain major concerns for university administrators, students, parents, and state policy makers. Findings from the present study have implications for policy development, along with institutional and instructional improvement. Findings also support the use of several promising practices (Gansemer-Topf

& Schuh, 2006), including instructional practices to enhance problem solving, academic efficacy, and relationship building to foster professor and college connectedness. Perhaps more importantly, results revealed student connectedness to professors and college indirectly affect student retention, thus suggesting the importance of formal professor-student advising, developing a working alliance with students, and conveying warmth and fairness in the classroom. Overall, the findings are consistent with previous research, but uniquely show the mediating effects of problem solving and academic efficacy to professors and college connectedness, which is promising considering the amenability of such variables. Moreover, the direct relationship between connectedness to professors and college and intent to remain and retention is a unique contribution of the present study to the area of undergraduate student retention.

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