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Malleable and Immutable Student Characteristics: Incoming Profiles and Experiences on Campus

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ABSTRACT

Our predictive models of student success provide evidence that students' incoming profiles do not define their destiny. We have found that the learning and developmental experiences that they have after enrollment are far more important in predicting persistence, academic achievement, and graduation. In contrast to immutable student demographic characteristics, we have found that malleable characteristics among students (such as academic habits of mind, sense of belonging, and future orientation) predict student success. Paying attention to students' development does not detract from their learning. In fact, promoting the highest levels of development among students seems to be what helps them reach high academic goals. *Keywords: predictive modeling, student success, longitudinal, cohort study, malleable characteristics, learning and development*

Introduction: Malleable and Immutable Characteristics of Students

Immutable characteristics among students include high school records, precollegiate developmental experiences, ethnicity, and socioeconomic status during childhood. These student characteristics are unalterable or are not amenable to change after enrollment in college. In contrast,

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malleable characteristics are amenable to change after students enroll in college. Malleable characteristics include students' commitment to college, intention to graduate from a specific university, orientation to the future, academic habits of mind (including self-regulation, competency to work autonomously, time management, study skills, and the process of inquiry that is common to all academic disciplines), self-limiting beliefs ("I'm just not good at math"), and sense of belonging. The developmental sciences (Comer, Joyner, & Ben-Avie, 2004) inform whether a characteristic is malleable. To be deemed malleable, the competency (or aspect of development) must intertwine with learning. This criterion considerably narrows the aspects of development under consideration to only those that are relevant in an educational context.

The relationship between development and learning may occur in two ways: (1) schooling may influence the competency, or (2) the competency may impact learning. Consider, for example, students' competency in self-regulation, an aspect of development. Universities have the potential to impact students' levels of self-regulation because a sense of belonging or connectedness to the university is a reason to self-regulate (Baumeister, Bauer, & Lloyd, 2010, p. 74). With this, self-regulation impacts learning, according Pintrich and Schunk (2003). They observe that successful self-regulation leads to high academic performance as well as effective social relations with peers, teachers, and family members; and to optimal life opportunities. Thus, self-regulation is deemed malleable. The focus on that which is changeable among students stands in contrast to the substantial attention paid to the impact of students' past development, unchangeable demographic characteristics (e.g., ethnicity), and precollege on performance in higher education in typical predictive models of student outcomes. Although it is commonly expected that students' collegiate academic paths are determined by unchangeable demographic characteristics and precollege experiences, this expectation downplays the influence of students' experiences while in college.

Understanding which factors are the most critical to students' achievement and graduation may inform the nature and quality of interventions targeted at improving students' learning, development, persistence, and graduation. In a recent paper, "Predicting students' graduation outcomes through support vector machines," we describe our use of these to predict students' graduation (Pang, Judd, O'Brien, & Ben-Avie, 2017). Up to about 100 features, including a set of psychological-educational factors, were employed to construct the predictive model. We evaluated the proposed model using data taken from a state university's longitudinal datasets from the incoming classes of students from 2011–12. The experimental results demonstrated the effectiveness of the model, with considerable accuracy, precision, and recall. These models incorporated the results from our *Academic Habits of Mind and College Success Inventory* (*AHM-CS*) and *Sophomore-Junior Survey* (*SJS*) that are described below. Both of these measure students' levels of learning and development.

In the models, for example, a feature selection routine identified students' response to the following item, which made the largest impact on the classification of on-time graduation: "I expect to graduate from this university." In SPSS Statistics, five groups were identified: (1) students who did not expect to graduate and did; (2) students who expected to graduate and did not; (3) students who did not expect to graduate and did not; (4) students who expected to graduate and were still enrolled; and (5) students who expected to graduate and did so. Students who did not expect to graduate and did so experienced an intentional veer in their developmental trajectories, which provides evidence that universities may influence students' expectations and intentions. According to Pintrich and Schunk (2003), students' motivations, expectations, and aspirations are malleable as a result of interacting with the college environment.

Future orientation is defined as the ability to conceive of one's own development and take actions in the here-and-now to achieve one's hoped-for future (Ben-Avie et al., 2003). The extent to which students are oriented to the future (instead of the past and present) is malleable after they enroll in college. Students' level of their future orientation and cumulative grade point average (GPA) served as the keystone in another model used for predicting the probability of students staying at the university (Ben-Avie et al., 2013). The overall chi-square for the retention model was 94.612 with a p-value < 0.001, meaning that the model was statistically significant for predicting the probability of students staying. The Nagelkerke R^2 value was 0.406. For students who stayed, the model was 93% accurate (that is, of the students whom the model predicted would stay, 93% actually stayed). Of particular note were the following odds ratios: The odds ratio for cumulative GPA was 5.624, meaning that, holding other variables constant, the odds of a student staying at this regional public university increases 5.624 times for each increase of 1 point in cumulative GPA. The odds ratio for future orientation was 4.315, meaning that holding other variables constant the odds of a student staying at the university increases 4.315 times for each increase of 1-point score in future orientation. Students' personal engagement with professors and staff on campus promote their levels of future orientation. Professors and staff are able to frame the learning and reframe students' energy from negative to positive, outcome-oriented thoughts, feelings, and behavior. In other words, the nature and quality of relationships that students form on campus with others have the potential to stretch their thinking and planning for the future.

Psychological-education items dealing with future orientation and academic habits of mind were found to be the most important predictors of retention after cumulative GPA. Another predictive model was developed using a cohort dataset of the incoming class of 2010 to predict students' persistence (Ben-Avie, Iben, & Judd, 2016). The logistic regression model was statistically significant, showing the model was better than chance in classifying whether students would be retained. The overall chi square for the model was 222.735 with a p-value < 0.001. The Nagelkerke R^2 value was 0.686. For students who persisted, the model was 92.9% accurate (that is, of the students whom the model classified would stay, 92.9% actually stayed). For students who withdrew, the model accurately classified 76.7% of the cases. This model was subsequently tested on all remaining cohorts starting with the incoming class of 2007 through the incoming class of 2011. All models were statistically significant. A key component of academic habits of mind is self-regulation.

With self-regulation, success depends on having awareness of a problem and of an ideal outcome, skills to map out a strategy to solve the problem, and having a willingness and skill in persisting at and refining the strategy until a positive outcome is achieved. Students strengthen their self-regulation when they have an orientation to the future and engage in goal setting as a way of articulating ideal outcomes. Once students have set a goal in their mind, it will be "shielded" or protected from distraction and derailment (Shah, Friedman, & Kruglanski, 2002).

College students' instrumental actions in the here-and-now to achieve desired future goals enable them to effectively navigate on campus and take advantage of the education afforded to them by the university. On one side of the equation are "Instructional activities that allow students opportunities to share and defend their ideas for solving particular problems prior to actual solving help develop self-advocacy in students and contribute to a proactive sense of agency" (Cifarelli, Goodson-Espy, & Chae, 2010, p. 227). On the other side of the equation are the actions of the students.

Maladaptive behaviors emerge, in part, when students have yet to develop the level of self-regulation necessary for consistently practicing academic habits of mind (e.g., competency in working autonomously and other aspects of self-regulation). Effective, conscious self-regulation is the ability to overcome obstacles and focus on tasks using proactive and deliberative self-management (Schmeichel & Baumeister 2007). The extent to which students set goals is malleable (Lawley & Tompkins, 2000) as well as other aspects of academic habits of mind.

The ability to handle cognitive complexity emerges from well-formed academic habits of mind and developmental experiences that demonstrated to students that they are, indeed, able to deal with complicated situations and constant change. Developmental experiences are the building blocks of students' competencies, including the ability to handle cognitive complexity. They are characterized by cognitive processing that leads to a sense of well-being that, in turn, promotes future interest (Comer, Haynes, Joyner, & Ben-Avie, 1996). Even though the process may at first be painful, developmental experiences eventually produce a sense of psychological pleasure once the individual realizes that he or she can deal with complexity (Ben-Avie et al., 2003).

The competency to handle cognitive complexity and persist until a positive outcome is achieved is more likely in students who have been exposed to many kinds of experiences, who have been encouraged to see the world metaphorically as well as concretely, who have the ability to create flexible internal images, and who have the linguistic skills to share them. Knauff and Wolf (2010) explain that "we talk about 'complex cognition' when thinking, problem solving, or decision-making falls back on other cognitive processes such as 'perception,' 'working memory,' 'long-term memory,' 'executive processes,' or when the cognitive processes are in close connection with other processes such as 'emotion' and 'motivation'" (p. 99). Baker (2014) writes, "With the development and flourishing of academic intelligence, traditional mental skills such as recitation, disputation, memorization, formalistic debate, formulae application, rote accuracy, and authoritative text reading and exegesis have been pushed aside as mental problem-solving and the active use of intelligence take center stage" (p. 190). Mental problem solving and the active use of intelligence characterize competency in handling cognitive complexity.

In terms of measuring students' attainment of competency in handling cognitive complexity, students' responses are measurable when they encounter unanticipated challenges during internships, when solving novel problems, analyzing unknown pieces of art, and navigating unfamiliar settings. Do they demonstrate skills to map out a strategy to solve a problem as well as willingness and skill in persisting at and refining the strategy until a positive outcome is achieved? Building competency in handling these encounters with the unforeseen prepares students to handle unanticipated challenges in their future careers. Problem solving in mathematics, for example, is an indicator of competency in handling cognitive complexity because students are expected to solve problems, particularly those where prior solution methods are not known. It is for this reason that mathematics was included in the predictive models described below.

Dealing with cognitive complexity is a crucial component of problem solving, particularly mathematical problem solving. Schoenfeld (2013) describes "problem solving" in the most general sense as trying to achieve some outcome, when method for doing so is not known in advance. This describes the experience of students solving problems in academic disciplines other than mathematics as well as those in their personal life and navigating the world around them. Moreover, behaviors of mathematical problem solving that may relate to the solving of any general problem include "making plans, selecting goals and subgoals, monitoring and assessing solutions as they evolve, and revising or abandoning plans when the assessments indicate that such actions should be taken" (Schoenfeld, 1985). This quote also succinctly describes competencies embedded within academic habits of mind. Planning, monitoring and assessing, decision-making, and conscious metacognitive tasks, which Schoenfeld describes as "control," is also an apt description of future orientation.

Developing the capacity to carry out goal-directed behavior emerges from an orientation to the future. The orientation of students placed at risk of failure is marked by magical thinking ("Somehow, the project will get done in time"), by hoping for an external intermediary ("I'll win the lottery"), and/or by the expectation that the future will remain largely the same as the present ("I'll always live in a dangerous neighborhood"; "I wouldn't know how to behave in such a fancy office"). All these beliefs can support academic habits of mind antithetical to academic excellence. In order for students to change, and in order for the faculty and staff who guide them to help them change, the students must have and must demonstrate thoughts, feelings, and behaviors that support a positive attitude about the long-distant future and about themselves as successful learners in the here-and-now.

A goal-directed behavior is a product of thought on the level of consciousness. Dilts (1999) describes self-limiting beliefs that undermine goal-directed behavior (p. 116):

> Hopelessness: . . . "No matter what I do it won't make a difference. What I want is not possible to get. It's out of my control. I'm a victim."
>
> Helplessness: . . . "It's possible for others to achieve this goal but not for me. I'm not good enough or capable enough to accomplish it."
>
> Worthlessness: . . . "I am a fake. I don't belong. I don't deserve to be happy and healthy. There is something basically and fundamentally wrong with me as a person and I deserve the pain and suffering that I am experiencing."

To be successful, students need to shift these types of limiting beliefs to those involving hope for the future, a sense of capability and responsibility, and a sense of belonging. Smart, Feldman, and Ethington noted in the paper they delivered at the 2006 National Symposium on Postsecondary Student Success that the advice provided to students need not be constrained by students' past or present personality profile. Instead, guidance can be grounded in a "futuristically-oriented perspective" based on the broad repertoire of competencies and interests that students desire to develop as a result of their collegiate experiences: "Focus on what they hope to be rather on what they presently are" (p. 17).

This is not to say that students' past experiences and demographic characteristics are not important predictors of student success. They are pivotal in understanding students' success in college. Cole, Kennedy, and Ben-Avie (2009) explain that precollege data can be used in "understanding student backgrounds, experiences, and expectations so that institutions can minimize unmet expectations and increase student engagement, learning, satisfaction, and persistence" (p. 67). Precollege data are also profitably used when contextualizing strategic plans with entering student characteristics that are relevant for designing effective teaching and learning practices. Precollege data help faculty better understand who their students are in order to modify curricular materials and teaching practices. However, Cole et al. noted that "at the same time, past behavior is not a perfect predictor of future behavior. The environment has an important inhibitory or facilitatory role in shaping behavior" (p. 56).

Far more important than students' pre-college learning and immutable demographic characteristics are the experiences that they have on campus. Baumeister, Bauer, and Lloyd (2010) write, "We suggested that expending limited resources for the sake of self-control is the price people pay to gain acceptance in society and thereby satisfy their fundamental need to belong. Put simply, people exert self-control for the rewards it can bring them in return. . . . Belongingness motivates self-control and virtuous choices" (p. 78). This self-identification strengthens students' resolve to follow the standards and customary ways of behaving in class and while studying—even at the cost of impulsive behaviors that give them great pleasure in the here-and-now. For example, whether first-year students settle for just passing courses is within the control of the university to impact because it's all about relationships, to quote Comer et al. (2004). Knowledge of the developmental sciences enables us to see that supportive relationships enhance students' engagement and motivate students to continue to study and learn. Whenever instructional activities become too abstract, whenever students become disinterested and disillusioned, the generative relationships that students have with others—and with themselves—have the power to sustain them in the learning process. Gradually, they can reorganize their everyday experiences under the rubric of academic or scientific concepts (see Vygotsky, 1978), incorporating ever-more-abstract notions in this incremental way.

A focus on students' malleable characteristics represents a major shift in mindset away from talking about "underprepared" students. Were the focus on students' unchangeable demographics or past learning, some may reach the conclusion that students' incoming profiles alleviate them from the responsibility of preventing student failure. According to Ann Rancourt (2010),

> Many faculty in higher education have indicated for many years that they feel students are coming to college underprepared. Whatever knowledge and skills students are entering college with, the primary task of college faculty is to move students' skills in analysis and application to a much higher level. . . . It is our responsibility to identify our expectations and to find strategies that will move students to higher skill levels irrespective of the level at which they enter. (p. 3)

Methodology

Overall Research Question and General Null Hypothesis

Are malleable characteristics among students more important predictors than immutable characteristics of persistence, academic achievement, and graduation? Immutable characteristics are not amenable to change or are unalterable after enrollment in college. Malleable characteristics are amenable to change after enrollment in college. To be deemed malleable, the competency (or aspect of development) must intertwine with learning. This relationship between development and learning may occur in two ways: (1) schooling may influence the competency, or (2) the competency may impact learning. Malleable characteristics include students' sense of belonging and self-limiting beliefs.

Students' academic habits of mind are malleable (self-regulation, the competency to work autonomously, time management, study skills, the process of inquiry that is common to all academic disciplines, and the self-advocacy that is the result of an orientation to the future). Students' levels of future orientation are also malleable. Future orientation is the ability to conceive of one's own development and take actions in the here-and-now to achieve one's hoped-for future. An orientation to the future and goal setting are important predictors of college success because some students find the present so overwhelming that they cannot focus on the future and other students, those who have experienced trauma, need the university's help to change their orientation from the past to the future.

The dependent variables in the study were students' persistence, academic achievement, and graduation. The immutable independent variables were gender, ethnicity, high school GPA, and SAT scores. The malleable independent variables were first college math course grade, college GPA, and competencies that are familiar from the developmental sciences (future orientation, sense of belonging, academic habits of mind, self-limiting beliefs). The research can be thought in comparison to a general null hypothesis: immutable characteristics are stronger predictors of student outcome measures than malleable characteristics.

Sample

All undergraduate students at a regional public university were included in longitudinal, within-sample change studies that started with the incoming class of 2007 (n = 16,263). The students were followed from new student orientation through graduation from the university, or subsequent enrollment in other colleges and universities. As each incoming class entered the university, a cohort dataset was established. A cohort dataset initially contained demographic information from the university's Banner Student Information System (high school rank, high school GPA, SAT scores, gender, ethnicity, residential status, registration with Veterans Services and the Disability Resource Center, and English and mathematics placements). Each year, new data were added (earned credits, cumulative GPA at time of graduation or withdrawal, registration status, and scores on surveys and performance-based assessments). Students' unique identification numbers were used to link their demographic characteristics with their scores from surveys and performance-based assessments to create comprehensive datasets. There are now 10 longitudinal datasets and each one contains over 1.9 million individual data points.

Data Collection

The *Beginning College Survey of Student Engagement* (BCSSE), the *Academic Habits of Mind and College Success Inventory* (*AHM-CS*) and the *Sophomore-Junior Survey* (*SJS*) were administered each year of the longitudinal, cohort study. The surveys are comprised of items that measure both malleable and immutable characteristics.

Chronologically, the first survey administered to students was the *Beginning College Survey of Student Engagement* (*BCSSE*). *BCSSE* was developed by the Center for Postsecondary Research at Indiana University for incoming students. It is a companion survey to the *National Survey of Student Engagement*, which is typically administered to first-year students and seniors. Since the *BCSSE* was administered to students on campus during their new student orientation, they were a captive audience and thus the response rate was exceedingly high. *AHM-CS* was administered to all first-year students in their required First-Year Experience (FYE) course. *SJS* was administered to students in their required capstone courses. An online version was also administered to students who had yet to enroll in capstone courses.

The scales of the *AHM-CS* were derived by factor analysis. Each item response was a five-point Likert scale in which 1 meant "strongly disagree" and 5 meant "strongly agree." Factor analysis was conducted with a Varimax rotation. The KMO measure of sampling adequacy of .74 and the Bartlett's test of sphericity at p <.001 indicated that the data were suitable for factor analysis. Five scales, with acceptable reliability measures (Cronbach alpha), eigenvalues of 2 or higher, and total variance explained of about 24%, were identified. The five scales were:

Sense of Belonging (Cronbach alpha of .85)
Academic Habits of Mind (Cronbach alpha of .88)
Future Orientation (Cronbach alpha of .74)
Obstacles to Academic Success (Cronbach alpha of .75)
Overall Learning and Development (Cronbach alpha of .92)

In order to determine whether the self-assessment met statisticians' criteria for a reliable instrument, internal consistency reliability analyses were conducted (see Ben-Avie et al., 2013, for a description of the development of this self-assessment as well as its psychometric properties). The analyses showed that the overall self-assessment was reliable and, thus, could be used for analyses (Cronbach's alpha = .926).

The scales of the *SJS* were derived by factor analysis. Factor analysis was conducted with a Varimax rotation. The KMO measure of sampling adequacy of .840 and the Bartlett's test of sphericity at p <.001 indicated that the data were suitable for factor analysis. Six factors, with acceptable reliability measures, were detected.

Academic Habits of Mind (Cronbach's alpha = 0.86)
Obstacles to Academic Success (Cronbach's alpha = 0.79)
Future Orientation (Cronbach's alpha = 0.85)
Sense of Belonging (Cronbach's alpha = 0.82)
Interpersonal Relationships (Cronbach's alpha = 0.85)
Confidence of Choice in Major (Cronbach's alpha = 0.82)

SJS items that were not part of variables:

It will take me longer to graduate than I expected.
I made the right decision in choosing this institution.
My family would be disappointed if I were not to graduate.
To improve my performance in class, I use campus resources such as the Academic Success Center.

In 2016 an additional factor analysis was conducted after new items were added to the *SJS* mirroring the methods applied to the ***AHM-CS***.

Maximum likelihood factor extraction with a direct oblimin rotation was used. The KMO measure of sampling adequacy of .825 and the Bartlett's test of sphericity at $p < 0.001$ demonstrated that the data was susceptible to factor analytic techniques. An analysis showed that the survey was reliable (alpha = .879), and thus could be used for analyses.

AHM-CS is comprised of 90 items and *SJS* is comprised of 102 items. The following items appear on both surveys.

Future Orientation

I have a fairly clear idea of what I need to study now in order to have the career that I want.
Thanks to this university, I have a clear idea of what I will be doing in five years.

Academic Habits of Mind

I study regularly to be successful in college.
I have different "game plans" for tackling homework assignments, and I know which strategy would be the most effective for each type of assignment.
I often play catch-up in my classes.

Self-limiting Beliefs

I fear that if I ask for help, my professor will think less of me.

Sense of Belonging

I feel that I belong here.
Generally, I am only on campus when I have class.
My social life tends to be off campus.
The way I'm treated by other students makes me rethink my decision to stay here.

Developmental Experiences

In my classes, I am exposed to ideas so interesting that I talk about them with friends.
What I read for class makes me more interested in what I'm studying.

Relationships

If I have some type of crisis, I know that there is a faculty or staff member at the university who will help me.

Anxiety

My anxiety tends to become amplified when presented with stressful situations in my courses (e.g., answering questions during lectures, receiving negative feedback on papers).
I often get distracted during class by feelings of anxiety.

Validity

The *SJS* emerged during meetings of the university's Student Success Taskforce. The core of the survey was developed by students in a research methods course under the guidance of the same team that developed the *AHM-CS*. A taskforce, comprising faculty and staff, then refined the survey. The *SJS* was designed to complement the *AHM-CS*, which was developed in a similar manner. The full description of *AHM-CS*' psychometric properties, including validity, have been previously published in this journal (Ben-Avie et al., 2013).

Results

Organization of the Results

To identify the most important predictors of persistence, academic achievement, and graduation, analyses were conducted using IBM Watson™ Analytics, a cognitive data discovery platform, SPSS Statistics, which was used to conduct linear and binary logistic regression analyses, and AMOS, which was used to conduct structural equation modeling. The aim of using different analytic approaches was to confirm the research findings. The more that the same findings emerge from different analytic platforms and techniques, the more confidence we have in the findings.

1. The longitudinal cohort study was launched in 2007. The outcomes from the first two years were previously reported in this journal (Ben-Avie et al., 2013).

2. The cohort dataset from the incoming class of 2009 was analyzed in SPSS when all the students had either graduated or withdrew from the university. In this analysis, malleable characteristics were analyzed in conjunction with students' achievement in mathematics, an indicator of the competency to handle cognitive complexity.
3. The cohort dataset from the incoming class of 2010 was analyzed to see the predictive strength of items from both the *AHM-CS* and the *SJS*.
4. The cohort dataset from the incoming class of 2011 was analyzed using IBM's Watson Analytics. This section is brief because this cohort was used to predict students' graduation outcomes through support vector machines and the results appear elsewhere (Pang et al., 2017).
5. The cohort dataset from the incoming class of 2012 was analyzed using SPSS AMOS.
6. As not all the students from the incoming classes of 2013 and 2014 have yet to graduate, the datasets from these classes were analyzed in SPSS to predict academic achievement, as measured by cumulative GPA. This section is also brief as the results from the analyses were already published elsewhere (Ben-Avie and Darrow, 2018). Moreover, these cohort datasets were merged with students' critical thinking, quantitative literacy, and written communication scores from AAC&U's VALUE Institute (Ben-Avie et al., 2019).

The advantage of this strategy is that it rules out a cohort effect, that is, an experience that is distinctive to a particular cohort. The strategy also takes into consideration the benefits and limitations of different statistical procedures. Watson Analytics, for example, does not expect that different subgroups are comprised of an equivalent number of students. This platform for cognitive analytics is also not limited by the conventional threshold of statistical significance ($p \leq .05$).

Incoming Class of 2009: Malleable Characteristics Were Strong Predictors

To determine the extent to which malleable characteristic among students were important predictors of academic achievement, a longitudinal "within sample change" analysis was conducted on first-time, full-time students from the incoming cohort of 2009. The 2009 cohort was chosen for analysis because data had been collected for each of the 1,237 first-time full-time students over the course of seven years, which allowed for the study of retention and graduation over time. Additionally, the data contained information about students' precollege academic experiences as well as their placement and performance in their first mathematics courses in college. Prior to this study, rigorous analyses of students' performance in required university mathematics courses had not yet been conducted.

Students' score on the mathematics section of the SAT was used for students' initial placement into mathematics courses upon entry to this public university. Although the mathematics SAT score emerged as a statistically significant predictor of students' first math course grades, the analysis suggests SAT score alone is a poor predictor [$F(1,1076) = 72.321$, $p < .001$; adj. $R^2 = .063$] and therefore provides evidence to suggest that it is an inappropriate placement technique. Furthermore, the SAT mathematics section score alone only explains 6.3% of the variance in students' first mathematics course grades, which by institutional, behavioral, and educational research standards is considered low. As an additional analysis, a linear regression analysis was conducted to determine if the combined SAT score (math and verbal) predicted overall academic success at the university as measured by cumulative GPA at time of graduation or withdrawal. The combined SAT score was a statistically significant predictor but only explained 5.8% of the variance in cumulative GPA, suggesting it is a poor predictor of overall academic success.

To determine if students' precollege and first-year data better predicted students' performance in mathematics courses, a multiple regression analysis was conducted. The model, where each of the predictors were statistically significant, explained 24.5% of the variance in students' grades [$F(10,662) = 30.970$, $p < .001$; adj. $R^2 = .245$], which was nearly four times that of the model using the established placement method described above. In addition to high school grades, the following *AHM-CS* were included in the analysis:

I have gained confidence in my ability to defend my position on an issue.
I settle for just passing courses.
I study regularly to be successful in college.
I have developed effective strategies for managing my time.
I have a fairly clear idea of what I need to study now in order to have the career that I want.
My confidence in my academic skills and abilities has increased this semester.

Two items from the *Beginning College Survey of Student Engagement* (*BCSSE*) were also included in the equation: "How prepared are you to analyze math or quantitative problems?" and "In high school, did you earn a passing grade in pre-calculus/trigonometry?" All of the predictors are listed in Table 1.

A multiple regression analysis was also conducted to predict students' cumulative GPA at time of graduation. The model included the items listed above as well as first college mathematics course grade, placement into the entry-level mathematics course (e.g., developmental mathematics), high school grades, and first-generation college student status. The model explained over 50% of the variance in cumulative GPA, a complex outcome variable that serves as a measure of students' overall academic achievement at the university [$F(9, 592) = 61.018$, $p < .001$; adj. $R^2 = .503$]. All the items included in the model were statistically significant. The novelty of

TABLE 1. Predicting Students' First Mathematics Course Grades

Variable Description	β[a]	T	Significance
BCSSE			
Item 1: In the coming college year: How prepared are you to do the following in your work: Analyze math or quantitative problems.	.106	2.837	.005
Item 2: In high school, did you earn a passing grade in pre-calculus/trigonometry?	.296	8.129	< .001
High school GPA	.119	−3.027	.003
Number of math courses students took in high school	.096	2.839	.005
Placement			
Into MAT095 (developmental math) or MAT100 (Dichotomous, 0 = MAT095, 1 = MAT100)	−.113	−2.702	.007
Into MAT102 (Dichotomous, 0 = No, 1 = Yes)	−.083	−2.055	.040
Into MAT103 or above (Dichotomous, 0 = No, 1 = Yes)	−.061	−1.338	.181
AHM-CS			
Item 1: I have gained confidence in my ability to defend my position on an issue.	−.70	−0.070	< .001
Item 2: I settle for just passing my courses.	.170	3.254	.001
Item 3: I study regularly to be successful in college.	.125	−1.955	.051

[a] Standardized

the predictive model is that it combines measures of students' early academic experiences at the university, learning, and development, and predicts students' overall academic performance at the university better than immutable measures (e.g., SAT scores).

It is important to note that an interaction term was included in this model to account for the phenomenon that high school GPA (HSGPA) influences cumulative GPA at time of graduation or withdrawal differently depending on students' first math course grade. A quadratic term for HSGPA was also

TABLE 2. Regression Independent Variables and Description

Variable Description	β[a]	T	Significance
BCSSE Item 1: In the coming college year: How prepared are you to do the following in your work: Analyze math or quantitative problems.	−0.159	−5.088	< .001
HSGPA	0.754	2.276	.023
First college math course grade	0.891	6.148	.000
Quadratic term for HSGPA	−0.383	−1.126	.261
Placement into MAT095 (Dichotomous, 0 = No, 1 = Yes)	0.149	4.688	< .001
Whether or not a student is a first-generation college student (Dichotomous, 0 = No, 1 = Yes)	−0.080	−2.732	.006
AHM-CS			
Item 2: I settle for just passing my courses.	0.096	3.031	.003
Item 4: I have developed effective strategies for managing my time.	0.091	2.646	.008
Item 5: I have a fairly clear idea of what I need to study now in order to have the career that I want.	−0.063	−1.904	.057
Item 6: My confidence in my academic skills and abilities has increased this semester.	0.107	3.238	.001
Interaction term between HSGPA and students' first math course grade.	−0.499	−3.062	.002

Note: Standardized regression coefficients, t-test statistics, and significance value at the ∝ = .05 level.

[a] Standardized

included since it was found that the relationship between students' HSGPA and college GPA is quadratic. Due to the addition of this term in the model, the standardized β values cannot be interpreted directly. For example, it has been found that students who agreed to the item "I settle for just passing my courses" (*AHM-CS*, item 2) have lower cumulative GPAs compared to their peers. However, in the model below the β is positive, suggesting the opposite: this is due to the quadratic HSGPA term.

It is worthwhile to note that several of the items measure students' growth in their first year in terms of both their learning and development (for example, settling for just passing courses, time management, and perceived academic growth). Since it was found that the combination of measures of students' learning and development predicted academic performance, logistic regression analyses were conducted to determine if they also predicted graduation from the university. These *AHM-CS* items were included in the model: "I expect that I will graduate from the university," "Compared to the start of the semester, I now have a clearer sense of what I need to do in order to succeed academically," and "My confidence in my academic skills and abilities has increased this semester." In addition, students' first mathematics course grade and cumulative GPA were included. The model was statistically significant and correctly classified students who in fact graduated from the university with an overall 84.1% accuracy. The table of predictors is included below:

An interpretation of these findings is that students' first semester, and the growth they exhibit in these malleable characteristics, determines in part their long-term success at the university. These findings, combined

TABLE 3. Logistic Regression Independent Variables and Description

Regression Variable and Description	Significance	Exp(B)
First math course grade	.001	0.772
Cumulative GPA	.000	20.075
AHM-CS		
Item 6: "My confidence in my academic skills and abilities has increased this semester."	.004	0.688
Item 7: "Compared to the start of the semester, I now have a clearer sense of what I need to do in order to succeed academically."	.016	1.425
Item 2: "I settle for just passing my courses."	.024	0.813
Item 8: "I expect that I will graduate from the university."	.000	2.015

with those from the previous analysis predicting cumulative GPA, provide a context for predicting student success that is not based on immutable academic metrics and precollege experiences alone. The results suggest that students who engage in developmental experiences on campus and who manage and improve the ways in which they tackle their workload; engage in goal-directed thinking and actions; and build academic confidence thrive academically in comparison to their peers.

Incoming Class of 2010: Another Rejection of the General Null Hypothesis

Research question: Are malleable characteristics among students more important predictors than immutable characteristics of persistence and graduation?

Academic Habits of Mind and College Success

A regression analysis on the incoming class of 2010 was conducted to predict students' persistence and graduation (n = 1248). Entered into the equation were both immutable and malleable characteristics from the *AHM-CS*.

The immutable characteristics were SAT scores, gender, ethnicity, age, and residential status. The malleable characteristics were the *AHM-CS* scales that deal with Academic Habits of Mind and Obstacles to Academic Success as well as cumulative GPA. A significant regression equation was

TABLE 4. Predicting Persistence and Graduation

Variable	B	Std. Error	β	t	*p*-value
(Constant)	.610	.321		1.898	.058
Ethnicity	.013	.038	.023	.344	.731
Gender	−.007	.040	−.012	−.173	.863
SAT Verbal	.000	.000	−.070	−1.143	.254
SAT Math	.000	.000	−.022	−.365	.715
Cumulative GPA	.346	.040	.468	8.694	.000
Obstacles to academic success	−.147	.049	−.155	−3.028	.003
Academic habits of mind	.131	.050	.150	2.619	.009

Note: AHM CS malleable characteristics were significant; immutable characteristics were not significant.

found ($F(1, 1247) = 8.145$, $p < .001$), with an adjusted R^2 of .205. The malleable characteristics were significant, but the immutable ones were not.

Sophomore-Junior Survey

A regression analysis on the incoming class of 2010 was conducted to predict students' persistence and graduation (did not graduate, left university; did not graduate, still enrolled; graduated). Entered into the equation were both immutable and malleable characteristics from the *SJS*, which was completed by 578 students. The immutable characteristics were SAT scores, gender, ethnicity, high school GPA, residential status, parental income, and honors college placement (based on precollege academic achievement). The malleable characteristics were overall *SJS*, cumulative GPA at time of graduation or withdrawal, and individual items that were not part of variables (taking advantage of campus resources to improve academic performance, sense that the right choice was made to attend the university, intentionality to graduate from the institution, expectation of on-time graduation, family would be disappointed if withdrew and did not graduate). A significant regression equation was found ($F(1, 577) = 7.420$, $p < .001$), with an adjusted R^2 of .301. The malleable characteristics were significant, but the immutable ones were not.

Students' gender, ethnicity, high school GPA, SAT scores, residential status, and family income were not influential predictors of students' persistence and graduation. By way of contrast, characteristics that are amenable to change after they enroll in college were important predictors. The results from this analysis provide further evidence to reject the null hypothesis.

Incoming Class of 2011: Cognitive Analytics Reveal the Same Pattern

The first step in the analyses was to determine whether the immutable independent variables were important predictors. Analyses conducted in IBM Watson Analytics on the data collected from the *SJS* showed that the predictive strength of the following metrics of precollege learning were weak predictors of persistence, academic achievement, and graduation. In Watson Analytics, predictive strength is the proportion of correct classifications and uses the same algorithm as in SPSS Modeler (a predictive strength of above 90% is considered noteworthy). The strength of the predictors from students' incoming profiles were as follows: high school GPA (44% predictive strength), SAT Math and Verbal Scores (18%), and a

TABLE 5. Predicting Persistence and Graduation with Sophomore-Junior Survey

	B	Std. Error	β	t	Significance
(Constant)	.074	.357		.207	.836
Overall *SJS*	.019	.005	.202	4.049	.000
Gender	.113	.060	.086	1.872	.062
Ethnicity	.022	.023	.042	.944	.346
SAT Verbal	.000	.000	.032	.584	.560
SAT Math	.000	.000	.010	.188	.851
Residential status	−.036	.122	−.030	−.296	.767
Expectation of on-time graduation	.229	.058	.179	3.930	.000
Using campus resources to improve academic performance	−.040	.020	−.091	−1.964	.050
Cumulative GPA	.107	.054	.115	1.988	.048
Intentionality to graduate from institution	.086	.039	.119	2.184	.030
Right decision in choosing institution	−.093	.034	−.167	−2.733	.007
Family disappointment with withdrawal	−.092	.030	−.143	−3.099	.002
HS GPA	−.003	.004	−.031	−.714	.476
Parental income	.000	.000	.076	1.650	.100
Honors	.234	.147	.081	1.594	.112

Note: SJS malleable characteristics were significant; immutable characteristics were not significant.

combination of SAT Verbal Scores and high school GPA (20%). Ethnicity and age were also weak predictors (17% predictive strength). In terms of predictors of college cumulative GPA at time of graduation or withdrawal, high school GPA was a weak predictor (31% predictive strength).

In contrast, the malleable experiences that students had while in college were important predictors. For example, *AHM-CS* items that measure the extent to which students had developmental experiences in the college classroom were important predictors (e.g., "In my classes, I am exposed to ideas so interesting that I talk about them with friends"). Items that deal with self-limiting beliefs were also important predictors of persistence, academic achievement, and graduation (e.g., "I fear that if I ask for help, my professor will think less of me"). Developmental experiences and self-limiting beliefs are amenable to change after college enrollment. Additional items that had 94% predictive strength were “At the end of the class period, after I close my notebook, I don’t think about the material until I have to,” “A large part of my success will depend on whether the rest of my life (e.g., work, family, friends) will allow me to dedicate enough time for my studies,” “I have developed effective strategies for managing my time,” and “I settle for just passing courses.”

Watson Analytics identified an important predictor of students’ withdrawal from higher education. The dependent variable (withdrew, still enrolled, graduated) was gleaned from the university’s enrollment outcomes provided by the National Student Clearinghouse (StudentTracker). The predictor was an item on the *AHM-CS*: “Compared to the start of the semester, I now have a clearer sense of what I need to do in order to succeed academically,” an indicator of future orientation. Combined with students’ math achievement, the predictive strength was 98%.

Incoming Class of 2012: A Similar Pattern Observed with AMOS

To confirm the findings that students’ unchangeable demographic characteristics were weak predictors, an additional analysis was conducted that included both immutable (e.g., ethnicity) and malleable independent variables (“Obstacles to Academic Success,” which was referred to in the chart below as “Barriers to Study”). The analysis was conducted in collaboration with Christine Unson, a faculty member from Public Health who received reassigned time to work on the analysis. Using SPSS AMOS, the longitudinal dataset from the incoming class of 2012 (n = 1,166) was analyzed. Enrollment retention, the dependent variable, was measured by the number of semesters, including summer semesters. Student achievement was measured with the cumulative GPA.

The exogenous variables of the model, obtained from their college applications and testing, were immutable characteristics: high school class rank percentile and placement in remedial math courses. The intermediary variables (i.e., are both predictors and dependent) were derived from the *AHM-CS*.

Structural equation modeling (IBM SPSS AMOS, v. 20) was used to assess direct and indirect causal relationships among the dependent and independent variables. The analysis began with a saturated model in which all possible paths were specified. Nonsignificant paths were eliminated subsequently. Modification indices were used to identify unspecified paths that needed to be included to improve goodness-of-fit. This use required the imputation of missing values via regression. Also, a multiple group analysis classified for gender and ethnicity was conducted and determined significant differences through pairwise comparisons (Byrne, 2000). The indicators of goodness-of-fit between the observed and hypothesized model are a nonsignificant chi-square, a Tucker-Lewis Index between 0.90 and 0.99, and RMSEA of 0.05 or less (Arbuckle, 2011).

The strongest direct predictors of student persistence were GPA (β = 0.51) and Sense of Belonging or Fits in University (β = 0.37). Both of these are amenable to change after enrollment in college. A weak predictor was immutable high school class rank (β = .23). Another weak predictor was students' placement in math remedial courses based on their performance in math prior to college. Math placement overall had a small and negative total effect on number of semesters attended by students. All the other predictors were small (< .1).

A Sense of Belonging was mainly predicted by Academic Habits of Mind ("Learned Study Skills") and the scale that measured whether students took advantage of campus resources to receive help with learning (β = .27). The more students developed their academic habits of mind over time and the more campus support that they received, the stronger was their Sense of Belonging. Feelings of not being prepared for college (adj. R^2 = .21) were

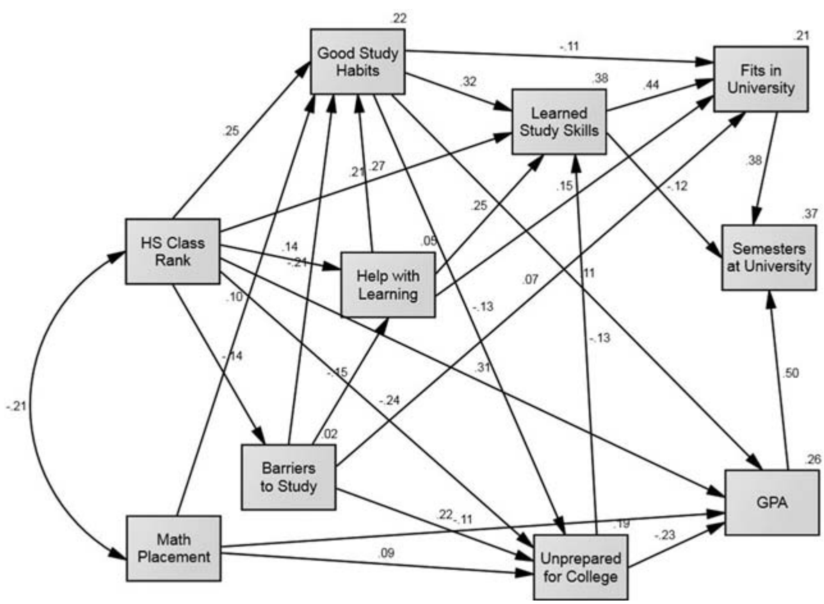

FIG. 1 Predicting Persistence through Structural Equation Modeling.

mainly predicted by the *AHM-CS* variable called "Obstacles to Academic Success" ($\beta = .25$) and negatively predicted by their study habits ($\beta = -.13$). The more they encountered obstacles to academic success and the lower their levels of academic habits of mind, the more they perceived themselves as underprepared for college.

Incoming Class of 2013–2014: Predicting Academic Achievement

In terms of predicting students' academic achievement, a regression analysis was conducted. Entered into the equation were both immutable and malleable characteristics. The immutable characteristics were SAT scores, gender, and ethnicity. The malleable characteristics were scores on the *SJS*'s scales for Academic Habits of Mind and Future Orientation. Cumulative GPA at time of graduation or withdrawal, a malleable characteristic, was also added to the equation. A significant regression equation was found [$F(1,414) = 142.780$, $p < .001$] with an adjusted R^2 of .786. The malleable characteristics were significant, but the immutable ones were not.

To confirm these findings, the cohort datasets from the incoming classes of students from 2007–15 were merged and analyzed. Each individual cohort dataset had about 1,300 variables. Students' enrollment status was categorized in this way: (1) student did not graduate, left the university; (2) student did not graduate, still registered at the university; and (3) student graduated.

Students' levels of future orientation ("I have a fairly clear idea of what I need to study now in order to have the career I want") were markers

TABLE 6. Predicting Academic Achievement

	B	Std. Error	Wald	df	Significance	Exp(B)
SAT Verbal	−.003	.002	2.277	1	.131	.997
SAT Math	.000	.002	.001	1	.982	1.000
Academic habits of mind	−.870	.264	10.894	1	.001	.419
Future orientation	.677	.284	5.682	1	.017	1.968
Cumulative GPA	1.833	.246	55.552	1	.000	6.255
Ethnicity	.059	.115	.259	1	.611	1.061
Gender	−.324	.271	1.438	1	.231	.723
Constant	−4.022	1.775	5.132	1	.023	.018

Note: Academic habits of mind and future orientation predicted academic achievement; immutable characteristics did not.

of future graduation. The students who did not graduate and left the university had nonchance lower scores than the students who graduated and those still registered at the university [$F(2, 6536) = 59.385$, $p < 0.001$.]. The students who left the university had nonchance lower scores than the graduates and those still registered at the university on this item: "I am able to spread out the work on a long-term assignment, and not wait until the last minute to complete it" $F(2, 6678) = 35.721$, $p < 0.001$. Students' levels of academic habits of mind were also important: "When I am studying or doing my homework, I take the time to get it right" [$F(2,6690) = 23.964$, $p < 0.001$]; and "At the end of a class period, after I close my notebook, I don't think about the material until I have to"—[$F(2, 7073) = 4.934$, $p = 0.007$].

The longitudinal, cohort study reinforced the importance of following students over time. As learning and development are incremental processes, short-term or point-in-time studies may not yield information that is useful for decision making. Consider that the implications of a low retention rate for universities include a limited ability to offer upper-level courses to seniors and financial stress due to fewer students paying tuition. Knowing the reasons why students stay or leave may influence which prospective students to recruit and what to ask on the admissions application form. So, too, the information gleaned from longitudinal, cohort studies may inform the design of interventions once the students are on campus. In particular, longitudinal studies that focus on that which is amenable to change yield more useful and actionable data than studies that focus on students' immutable demographic characteristics (e.g., ethnicity) and pre-college learning (e.g., high school GPA, SAT scores), which cannot be changed.

Discussion

The analytic strategy was to determine whether a consistent pattern related to students' persistence, academic achievement, and graduation would emerge across multiple longitudinal, cohort studies and through the use of diverse statistical procedures. A consistent pattern was observed: characteristics that were amenable to change after students enrolled in college were found to be important predictors of persistence, academic achievement, and graduation. The null hypothesis was rejected because, collectively, the different analyses provided evidence that malleable characteristics among students were more important predictors than immutable ones.

The results indicate that universities have the potential to impact students' developmental trajectories. A developmental trajectory is the lifepath of the student that has been influenced by the past, present, and image of the future. Hence the importance of stretching students' future orientation. Developmental trajectories are intentional veers from that which immutable demographic characteristics and prior learning alone might have predicted. Longitudinal studies that focus on that which is amenable to change yield more useful and actionable data than studies that focus on students' characteristics prior to college enrollment. Labeling students as "underprepared" or "at risk" upon entry to college does not necessarily compel action on the part of the university.

Students' intention to graduate from the university more than doubled the odds that they would actually do so, suggesting that students' orientation to the future impacts their graduation. Students' intention to graduate is malleable. As with the prediction of cumulative GPA, students' within-semester growth of confidence and academic habits of mind (*AHM-CS* items) also contributed to the prediction of graduation. Intentionality to graduate, perceived growth of confidence, and academic habits of mind are aspects of development that are intertwined with learning. In other words, there is more to the story of persistence and graduation than just unchangeable pre-college experiences, demographic characteristics, high school grades, and SAT test scores—all of which are immutable or cannot be influenced after enrollment in college.

The finding that immutable demographic characteristics and precollege learning were weak predictors is significant as a great deal of research in higher education relies on students' SAT scores, ethnicity, and gender as important indicators of whether students will be successful. While psychological-educational factors are harder to measure than such measures as SAT and high school academic achievement, these factors are directly related to teaching and learning in and out of the college classroom.

A shift to focusing on malleable characteristics among students provides universities with actionable information. For example, the strongest direct predictors of student persistence were GPA (which has been meaningfully predicted with other malleable student characteristics) and sense of belonging for the incoming class of 2012. A sense of belonging or connectedness to the university provides student with the commitment that they need to override self-absorbed and self-indulgent behaviors (i.e., self-regulation). This finding is consistent with the evidence that competencies familiar from the developmental sciences (e.g., academic habits of mind) are important predictors of student persistence, academic achievement, and graduation. An orientation to the future and related instrumental actions in the here-and-now to achieve the desired future are important predictors of future success because some students find the past or present so overwhelming that they cannot focus on the future.

Paying attention to students' development does not detract from their learning. In fact, promoting the highest levels of development among students seems to be what helps them reach high academic goals. In essence, students who develop well, learn well.

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