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EXAMINING THE PREDICTORS OF STEM DEGREE OBTAINMENT WITHIN SOCIAL COGNITIVE CAREER THEORY FOR NATIVE AMERICAN UNDERGRADUATE STUDENTS

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EXAMINING THE PREDICTORS OF STEM DEGREE OBTAINMENT WITHIN SOCIAL COGNITIVE CAREER THEORY FOR NATIVE AMERICAN UNDERGRADUATE STUDENTS

A DISSERTATION APPROVED FOR THE
DEPARTMENT OF PSYCHOLOGY

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To my family, without whom I would never be here.

To Emily, who gave me endless light.

To my friends, for an unforgettable journey.

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Abstract

This dissertation examines the predictors of STEM degree attainment among Native American undergraduate students using the Social Cognitive Career Theory (SCCT) framework. Leveraging a longitudinal dataset comprising Native American, Asian American, and White undergraduates, this study identifies the SCCT constructs most predictive of educational outcomes, including graduation with a STEM degree, graduation with a non-STEM degree, and earning no degree. Using elastic net multinomial regression, the analysis evaluates the influence of self-efficacy, outcome expectations, supports, barriers, and other SCCT components on these outcomes. The methodology incorporates measurement invariance testing to ensure the validity of cross-group comparisons of SCCT constructs. By integrating institutional records and self-reported survey data, this research addresses critical gaps in understanding the factors that facilitate or hinder STEM success for Native American students. The findings provide actionable insights for developing targeted interventions to support STEM persistence among underrepresented groups, with implications for broader educational policies and practices.

Introduction

Science, Technology, Engineering, and Mathematics (STEM) professionals will be important for addressing many of the complex issues the global community will face in the coming decades, such as climate change, pandemic mitigation, and the use of artificial intelligence (e.g., Bauchner & Sharfstein, 2020; Turner et al., 2022). The Bureau of Labor Statistics projects significant growth in STEM occupations over the next decade, highlighting the necessity for educational systems to prepare students for these roles (U.S. Bureau of Labor Statistics, 2021). Additionally, STEM degree recipients earn more income than non-STEM degree recipients, regardless of the jobs they hold, meaning disparities in STEM achievement between gender and racial/ethnic groups may impede progress towards economic equity for these underrepresented groups (Chen, 2013; US Department of Commerce, 2011). These facts have made the cultivation of a skilled STEM workforce a national priority (Trapani & Hale, 2022).

The quality of the STEM workforce is dependent on maximizing the quality of STEM graduates (Olszewski et al., 2024). Disparities in STEM degree attainment across racial and ethnic groups present concerns that potential talent in these groups is underutilized, likely due to economic disparities impacting access to opportunities in these fields, differential treatment of individuals who belong to marginalized groups in higher education, and cultural differences that may impact the interest in pursuing certain careers (Chakraverty, 2022; Smith et al., 2014; Stevens et al., 2016; S. L. Turner et al., 2022; Williams & Shipley, 2018). Studies have documented that underrepresented minorities, including Native American, Black, and Hispanic students, face significant barriers to entering and completing STEM programs, such as financial constraints, lack of role models, and insufficient academic preparation (Lent et al., 2018; Trapani & Hale, 2022). Additionally, experiences of bias and discrimination can create a hostile learning environment, leading to decreased persistence and engagement in STEM fields for marginalized groups (McGee & Bentley, 2017). Addressing these disparities likely requires a multifaceted approach that includes improving educational access, creating inclusive learning environments, and fostering cultural competence among educators and students (A. Byars-Winston & Rogers, 2019).

The population that presents the largest disparities in STEM degree attainment is the Native American population. Native American students have consistently shown the lowest levels of college enrollment and completion, particularly in STEM disciplines, compared to other racial and ethnic groups (De Brey et al., 2019). Cultural disconnects, limited access to resources, and the absence of representation in STEM fields contribute to the lower participation rates observed among Native American students (Reyes & Shotton, 2018). Moreover, recent studies indicate that tribal identity and community values play a critical role in educational choices, with many Native students expressing a desire to pursue careers that allow them to give back to their communities, which may not always align with traditional STEM career pathways (Windchief & Brown, 2017). Addressing these unique cultural and structural challenges is vital to improving STEM degree attainment among Native American students. Research that explores factors contributing to STEM disparities for Native American students has been limited, often due to low sample sizes for this group in larger research projects, resulting in exclusion of Native American students from some analyses or their aggregation into broader racial groups (Shotton et al., 2013). Even more lacking in this literature is research that explores predictors of STEM achievement for Native American students during college.

While many factors could be influential in the lower STEM participation among certain populations/groups, it is particularly important to identify what factors influence STEM persistence in undergraduates. Undergraduate students experience many academic and personal changes during their time in university which may impede their progress towards a STEM degree (Foltz et al., 2014). Earning a STEM degree is a key outcome of interest for research that explores STEM achievement as it represents success over the obstacles that many STEM majors encounter during college and allows the degree recipients to pursue STEM-related careers. Admitting undergraduates constitutes a significant investment for the university, meaning there is a financial incentive for universities to understand what may impede their undergraduates' persistence in their degree programs. Additionally, universities often have resources they can provide to promote student achievement but must know where to direct those resources so that they are maximally effective. Persistence in STEM is not solely a matter of academic or financial resources but also relates to students' sense of belonging, self-efficacy, and the availability of support systems (Lent et al., 2013). Universities can implement targeted interventions, such as mentoring programs, research opportunities, and inclusive curricula, to encourage retention and success among STEM students, particularly those from underrepresented backgrounds (Graham et al., 2013). Furthermore, fostering a supportive campus climate that emphasizes collaboration and inclusion can help in retaining students who might otherwise switch out of STEM programs (Estrada et al., 2016). Thus, identifying the factors that contribute to the success of certain undergraduate populations can be critical for deploying institutional efforts to enhance persistence that maximize the return on investments of those efforts.

A framework that is often used to begin identifying the factors that are most relevant for individuals' persistence in STEM is the Social Cognitive Career Theory (SCCT) framework. SCCT, grounded in Bandura's Social Cognitive Theory, provides a comprehensive model for understanding how self-efficacy, outcome expectations, and personal goals influence career development and decision-making (Lent et al., 1994). The framework has been widely used to examine educational and career outcomes across diverse populations and settings, including STEM fields (Lent et al., 2008). SCCT posits that self-efficacy and outcome expectations are shaped by learning experiences, and these factors, in turn, inform interest and career-related goals (Garriott et al., 2013). This model is particularly useful for understanding the complex interplay of personal, social, and environmental factors that contribute to STEM persistence among underrepresented groups. The SCCT framework has been used to guide research into underrepresented minority participation in STEM. Empirical research has supported many of the relationships found in the model, including the positive effects of self-efficacy on interest, intentions, and persistence in STEM (A. M. Byars-Winston & Fouad, 2008). However, a limitation of the existing research is the focus on solely pre-college experiences which does not fully capture how STEM education trajectories develop into a STEM career (Fouad et al., 2002). This limitation is especially the case regarding the research on Native American STEM achievement. Additionally, most studies are cross-sectional, providing only a snapshot of student experiences, while longitudinal data are necessary to understand how SCCT variables change over time and influence long-term outcomes (Lent et al., 2018). By addressing these gaps, researchers can develop a more nuanced understanding of the factors that promote STEM persistence and success.

Many of the factors in the SCCT may be important for predicting the attainment of a STEM degree. Research suggests that self-efficacy, outcome expectations, and goal setting each play critical roles in students' persistence and success in STEM (Garriott et al., 2013; Lent et al., 2008). Validated measures of SCCT constructs, such as the Career Decision Self-Efficacy Scale, have been instrumental in examining these relationships (Betz, 2007). While the SCCT framework is useful for conceptualizing individuals' career development and the predictions of the model have been validated by many studies, there remains a gap in identifying specific predictors of graduation with a STEM degree. Moreover, it remains unclear how these factors change and interact over time and across different stages of a student's undergraduate career. Therefore it is essential to identify the influence of time on SCCT variables and how they predict undergraduate achievement in STEM (Sheu et al., 2010). A comprehensive analysis that considers the timing of these predictors could provide deeper insights into effective interventions for STEM education. In order to identify the predictors of Native American undergraduate achievement in STEM, a grant from the National Institutes of Health (NIH) was awarded to collect and analyze data from undergraduates at a university with a large Native American population. The participants completed measures that assess constructs within the SCCT model and institutional records from the university were collected to assess outcomes such as GPA and what degrees participants earned at the university. These data provided the foundation for the present study.

The present study addresses several gaps in the literature on Native American undergraduate student achievement in STEM by providing the first empirical evidence linking SCCT variables to graduation outcomes (obtained via university records) for Native American college students. This direct connection will enhance research on STEM persistence and achievement. Leveraging longitudinal data, the study offers a more valid link between predictors and outcomes while identifying critical time points during students' undergraduate careers when these variables are most influential. By developing a novel, comprehensive model of SCCT predictors, this research guides future studies and informs institutional tools and resources to support Native American students' success in STEM.

Additionally, this study employs an Elastic Net multinomial regression model to analyze a large, longitudinal dataset comprising Native American, Asian American, and White undergraduate students, to determine which SCCT predictors are most effective at different stages of university education. This approach allows for the identification of interactions and non-linear relationships often missed by traditional regression models (Zou & Hastie, 2005). The findings contribute to educational policies and practices that support Native American students in STEM while offering insights that may improve outcomes for other underrepresented groups. Given the limited application of the SCCT model to this population (A. Byars-Winston & Rogers, 2019), this research fills a critical gap in the field and advance understanding of STEM persistence and degree completion.

Native American Achievement in STEM

Research on STEM achievement for Native American students has highlighted significant disparities when compared to other racial/ethnic groups. Native Americans remain one of the most understudied populations in higher education, especially in STEM fields. According to data from the National Science Foundation (Trapani & Hale, 2022), Native Americans represent a very small fraction of those earning Science and Engineering (S&E) degrees, with American Indians or Alaska Natives earning only 0.5% of science and 0.3% of engineering bachelor's degrees in 2016. This low representation persists despite Native Americans comprising approximately 0.7% of the U.S. population (Trapani & Hale, 2022). Native American students are also less likely to graduate high school and attend college compared to other racial/ethnic minorities (De Brey et al., 2019), and they face substantial challenges in persisting in STEM majors.

Much of the research on disparities in Native American student achievement focuses on identifying factors that contribute to their underrepresentation in STEM. Studies suggest that tribal identity and cultural values play a significant role in shaping Native American students' educational trajectories, including their pursuit of STEM fields. Tribal identity, which refers to a student's connection to their tribal community, traditions, and language, has been linked to both positive and negative educational outcomes. Some studies show that strong tribal identity is associated with better educational outcomes, such as higher academic achievement and enhanced well-being (Huffman, 2001; Kulis et al., 2016; Whitbeck et al., 2002). However, other research suggests that strong tribal identity may create challenges for students as they navigate the often individualistic and competitive culture of higher education institutions, particularly in STEM fields (Waterman, 2012). Native American students may struggle with the cultural disconnect between the collectivist values of their communities and the values espoused in many STEM programs (Smith et al., 2014; Windchief & Brown, 2017).

Another key factor is the presence of barriers and supports within the educational environment. Research shows that Native American students often perceive a lack of institutional support and experience culture shock in predominantly White universities (Gloria & Robinson Kurpius, 2001; Waterman, 2012). Moreover, Native American students' desire to "give back" to their communities, a fundamental tribal value, can conflict with the individualistic focus of STEM disciplines, which often emphasize personal achievement over communal benefits (Khupe, 2014). This lack of alignment between Native American students' values and the culture of STEM fields may contribute to their higher rates of attrition from these programs. In addition to cultural factors, prior preparation in mathematics and science is another critical influence on Native American students' STEM achievement. Students who take more advanced math and science courses in high school are more likely to pursue and persist in STEM degrees (Shoffner & Dockery, 2015; Tyson et al., 2007). However, Native American students often have less access to advanced coursework, particularly in rural or reservation schools (Betz, 2007), further limiting their preparation for STEM fields. Research on other underrepresented groups in STEM, including African American and Hispanic students, has identified similar challenges. These students also face barriers such as financial constraints, stereotype threat, and limited access to resources, which negatively impact their STEM participation and achievement (Bottia et al., 2015; Wang, 2013). However, there are important differences between groups. For instance, while African American and Hispanic students may face cultural and structural barriers, research suggests that Native American students also contend with additional cultural dissonance related to the unique values of their tribal communities (Smith et al., 2014). Despite these challenges, there are promising avenues for increasing Native American participation and success in STEM. Programs that foster a sense of belonging and respect for tribal identity, as well as those that provide mentorship and community support, have been shown to improve retention rates for Native American students in higher education, including in STEM fields (Khupe, 2014; Windchief & Brown, 2017).

Social Cognitive Career Theory

The Social Cognitive Career Theory (SCCT) framework, developed by Lent, Brown, and Hackett (1994), is grounded in Bandura's (1986) social cognitive theory and was designed to provide a comprehensive understanding of the processes through which individuals develop academic and career interests, make choices, and achieve success in these domains. This framework integrates the roles of self-efficacy, outcome expectations, and goal setting, all key constructs from Bandura's work, to explain how individuals are guided by personal agency in their career development (Lent et al., 1994).

Bandura's Social cognitive theory posited that individuals' psychosocial functioning is the result of a triadic, reciprocal causal process wherein individuals' personal attributes such as affective, cognitive, and physical states bidirectionally relate to the individuals' external environmental factors and to their overt behaviors which both bidirectionally relate to each other (Bandura, 1986). This theory was novel in the way it emphasized self-referent thinking in the processes of motivation and behavior and in the way it models overt behaviors as co-determinants rather than products of individuals' personal attributes and their environment. Lent and colleagues (1994) emphasized three social cognitive mechanisms within Bandura's personal attributes domain that are important for career development: self-efficacy beliefs, outcome expectations, and goal representations. Self-efficacy refers to individuals' beliefs about their capabilities in a given domain and are thought to be the most important predictor of what behaviors and environments an individual will choose, as well as the effort and persistence the individual will demonstrate in those decisions. These beliefs are posited as dynamic and incrementally important for predicting performance beyond skill alone. Outcome expectations refer to individuals' beliefs about the probable outcomes of their decisions. Individuals may anticipate certain physical outcomes such as money or rewards, social outcomes such as approval from others, and self-evaluative outcomes such as feeling happy or satisfied. In line with Vroom's (1964) expectancy theory, both self-efficacy and outcome expectations contribute to individuals' motivation to engage in certain behaviors. However, scholars posit that self-efficacy is likely a more substantial predictor of behavior because individuals may believe a course of action will benefit them, but not engage in that action due to their lack of confidence in their abilities (Lent et al., 1994). The final dimension of personal attributes are goals which are symbolic representations of desired future outcomes. Goals are posited by Lent and colleagues to be a ubiquitous element of career development that allow for motivation to be sustained for a long period of time while progressing towards the desired outcome.

Lent et al. (1994) aimed to address the gap in career theories by focusing not just on career choice but also on how interests evolve and how people perform in their chosen fields. The authors took a cognitive constructivist approach to career development whereby career interests and decisions are not simply the result of an accumulation of positive feedback, but also the result of a feed-forward mechanism whereby individuals anticipate, forecast, and construct meanings which then interact with environmental events. This approach acknowledges individuals as proactive agents in shaping their environment while accounting for bidirectional relationships between the person, their environment, and their behavior. The SCCT framework emphasizes the dynamic interplay between personal, contextual, and behavioral variables, building on existing career theories while incorporating new elements, such as the impact of personal beliefs and social influences on career behavior (Bandura, 1986; Lent et al., 1994). Another key innovation in SCCT is its emphasis on environmental and contextual factors that interact with personal variables to influence career development. Lent et al. (1994) highlighted that individuals' experiences of barriers and supports in their environment are critical in shaping their career paths, a notion that expanded previous theoretical models (Betz & Hackett, 1981). Overall, SCCT provided a more integrative and dynamic model of career development, blending cognitive, behavioral, and environmental considerations, thus making it applicable across diverse populations and settings (Lent et al., 1994). The final conceptual scheme, referred to as the SCCT model, presented by Lent and colleagues proposes relationships between ten interrelated aspects or categories of predictors resulting in a framework for career development (see figure 1). The SCCT model is not a strict prescription for how the constituent variables relate to each other, as explained by the authors, but rather emphasizes certain relationships (those depicted by the arrows in figure 1) that contribute to career development. The authors posit that many of the relationships are likely bidirectional and the entire model is reciprocal in order to reflect the constant shifting of individual's beliefs, interests, and behaviors.

Person Inputs

Person inputs in the SCCT framework refer to individual characteristics such as gender, race/ethnicity, disabilities, and personality traits that may influence career and academic choices. These inputs can affect how individuals perceive their abilities and interests, as well as the opportunities available to them (Lent et al., 1994). In studies on SCCT, researchers often measure person inputs using demographic surveys or psychometric assessments of traits like openness or conscientiousness. For example, a student's interest in STEM might be shaped by early exposure to STEM-related activities or cultural expectations related to their gender or ethnicity.

Background Contextual Affordances

Background or contextual affordances encompass the broader environmental factors that can support or hinder an individual's career development. This can include family socioeconomic status, educational resources, or community support systems (Lent et al., 1994). In empirical studies, these are often assessed through questionnaires that explore factors such as parental support, the availability of mentors, and access to educational resources. For instance, a student from a lower socioeconomic background may face challenges accessing advanced STEM courses, which can limit their academic choices and career trajectories.

In the present study, the SCCT construct of background contextual affordances is represented through measures of Previous Math and Science Courses, Tribal Engagement, Concern with Finding Job Locally, Family Structure and Dependency, Family and Community Attitudes Toward Education, Subtle Discrimination, Explicit Discrimination Towards Native Americans, Non-Discriminatory Campus Climate, Incivility, Perceived Individual Mobility, and Hours of Employment per Week. Each measure captures unique dimensions of the latent construct of environmental factors. For example, prior coursework reflects exposure to foundational STEM learning opportunities, while tribal engagement captures cultural connectedness and its influence on decision-making. Measures of subtle and explicit discrimination assess the frequency of negative experiences, quantifying barriers that impede academic persistence. Together, these measures provide a comprehensive view of the external supports and constraints influencing participants' pathways.

Learning Experiences

Learning experiences in SCCT are defined as the direct and vicarious experiences that shape an individual's self-efficacy and outcome expectations. These experiences are critical because they influence how a person perceives their competence in certain activities (Lent et al., 1994). Measurement of learning experiences can involve self-reported surveys that capture the extent of exposure to specific activities or courses. For example, hands-on laboratory sessions or participation in science fairs can strengthen a student's belief in their scientific skills, thereby encouraging them to pursue a STEM career.

To operationalize learning experiences, this study employs measures of Learning Experiences, Experiences with Faculty, Undergraduate Research Experience, and Quality of Mentoring Relationship. Learning experiences reflect direct exposure to STEM-related tasks, providing concrete evidence of engagement with discipline-specific activities. Faculty interactions assess the frequency and quality of academic guidance, while mentoring relationships reflect deeper supportive connections that shape skill development and professional identity. Undergraduate research involvement quantifies participants' active participation in generating and interpreting knowledge, operationalizing the construct as both experiential learning and developmental feedback within STEM contexts.

Self-Efficacy

Self-efficacy, a core concept in SCCT, refers to an individual's belief in their ability to successfully perform specific tasks. High self-efficacy can lead to greater persistence and resilience when facing challenges (Lent et al., 1994). Researchers typically measure self-efficacy using scales that ask participants to rate their confidence in completing tasks in a given domain. For undergraduate students, self-efficacy might be reflected in their confidence to solve complex math problems or conduct experiments, influencing their decision to major in fields like engineering or biology.

The SCCT construct of self-efficacy is measured using Math Self-Efficacy, Science Self-Efficacy, Leadership Efficacy Scale, and Identity as a Scientist. Math and science self-efficacy measures reflect confidence in completing domain-specific tasks, serving as operational proxies for perceived competence in STEM fields. The leadership efficacy scale extends this construct by assessing participants' belief in their ability to influence and guide others, representing self-efficacy in interpersonal and collaborative contexts. Identity as a scientist measures the degree to which participants internalize the role of a scientist, capturing how their self-concept aligns with professional norms and expectations.

Outcome Expectations

Outcome expectations are the beliefs about the consequences or outcomes of engaging in specific activities. These expectations can be related to tangible rewards, such as job stability and income, or intrinsic rewards, like personal satisfaction and fulfillment (Lent et al., 1994). Measurement of outcome expectations often involves surveys that explore what students perceive as the benefits of pursuing certain academic paths. For example, a student who expects that a degree in computer science will lead to high-paying job opportunities may be more likely to choose that field.

Outcome expectations are represented in this study using the Outcome Expectations measure. This scale captures participants' beliefs about the potential benefits of earning a STEM degree, including financial rewards, career opportunities, and contributions to community well-being. The measure operationalizes the latent construct by asking participants to evaluate the personal and societal value of academic success in STEM, reflecting SCCT's emphasis on anticipated rewards as motivators for career decisions.

Interests

Interests in SCCT are defined as enduring preferences for particular activities. These interests are shaped by past learning experiences and influence career and academic choices (Lent et al., 1994). To measure interests, researchers often use interest inventories that assess preferences across various domains. For undergraduate students, developing an interest in coding through early exposure to computer programming can lead to sustained engagement in related coursework and extracurricular activities.

The SCCT construct of interests is assessed through Research Interests and STEM Interests measures. Research interests reflect participants' attraction to investigative activities and problem-solving, while STEM interests gauge enthusiasm for specific disciplines such as math and science. These measures operationalize the construct of interests as preferences for particular academic domains, shaped by prior learning experiences and aligned with career aspirations.

Choice Goals

Choice goals refer to the aspirations or decisions individuals make regarding their educational and career pursuits. These goals are a reflection of their self-efficacy, interests, and outcome expectations (Lent et al., 1994). Researchers measure choice goals through surveys that ask participants to articulate their academic and career aspirations. For instance, an undergraduate student's decision to double major in biology and chemistry could be driven by their long-term goal of becoming a medical researcher.

Intention to Major in STEM is used to measure choice goals within the SCCT framework. This scale captures participants' stated academic aspirations, operationalizing the latent construct of goal-setting. By reflecting intentions to pursue STEM majors, the measure links self-efficacy and outcome expectations to tangible academic commitments, aligning closely with the theoretical model's emphasis on aspirational decision-making.

Choice Actions

Choice actions are the specific steps or actions individuals take toward achieving their choice goals. These include enrolling in courses, seeking internships, or applying for jobs that align with their career interests (Lent et al., 1994). In research, choice actions are often measured by tracking participants' academic and career-related behaviors, such as course selection patterns or participation in field-specific internships. For example, a student who actively seeks out summer research programs is engaging in choice actions that reflect their interest in a career in academia.

Choice actions are represented in this study through participants' enrollment in STEM courses and persistence to graduation with a STEM degree. These behaviors are direct operationalizations of the SCCT construct, reflecting the translation of intentions into observable steps toward achieving career goals. By tracking these actions, the study provides empirical evidence of how career-related decisions manifest as measurable outcomes.

Performance Domains and Attainments

Performance domains and attainments in the SCCT model refer to the specific areas of achievement and success that result from sustained engagement in a field of interest. These attainments can reinforce self-efficacy and further shape career choices (Lent et al., 1994). Performance is often measured through academic grades, standardized test scores, or completion of specific projects. For instance, a student's consistent high performance in mathematics courses may encourage them to pursue further studies in engineering.

The construct of performance domains and attainments is captured using measures of academic performance, including STEM course grades and completions. These indicators quantify achievement, serving as operational proxies for sustained engagement and success in STEM disciplines. By linking performance to career trajectories, the study aligns with SCCT's emphasis on the feedback loop between attainments, self-efficacy, and future goals.

Contextual Influences Proximal to Choice Behavior

These influences are the immediate environmental factors that can impact decision-making at the point of choice, such as financial constraints, social support, or the availability of educational resources (Lent et al., 1994). Researchers assess these influences by exploring variables such as access to scholarships, family expectations, and the presence of role models. For undergraduate students, having a supportive mentor who encourages exploring different career paths can play a crucial role in the decisions they make about their major or career.

This study measures contextual influences proximal to choice behavior through Perceived Supports, Perceived Barriers, Coping Efficacy for Barriers, Educational Supports, and Career Barriers. Perceived supports assess participants' access to resources and encouragement, while perceived barriers quantify anticipated obstacles such as financial constraints or discrimination. Coping efficacy evaluates confidence in overcoming challenges, operationalizing resilience within the SCCT framework. Together, these measures reflect the immediate environmental factors shaping critical academic and career decisions.

Method

Participants and Procedures

The longitudinal study is a multiple-cohort, online survey investigating Native American students' interest, persistence, and success in STEM fields. Asian American and White students were selected as the comparison groups due to their consistent representation in STEM fields. Following successful completion of an initial survey, students were invited to complete subsequent surveys each semester. Each survey took about 30 to 45 minutes to complete. Participants were compensated with a $20 gift card for every survey that they completed. The survey included measures outlined in the SCCT framework, including background/contextual affordance variables, learning experiences, interest in STEM fields, intention to major in a STEM field, etc. The data collection process started in the spring semester of 2014 and ended in the spring semester of 2022.

The larger survey consisted of three forms (Pre-A, B, and A) designed to assess constructs relevant to the Social Cognitive Career Theory (SCCT) framework. Participants first completed Pre-A upon agreeing to participate. If they continued their participation, they completed B for their next survey (the following semester at the earliest), then A for their subsequent survey, alternating between A and B each time they agreed to participate until they were no longer undergraduates. The purpose of having two survey versions (A and B) was to capture a large number of variables over time, while ensuring that the time to complete any one survey was minimized to the extent possible. Participants could begin participating at any point during their university career, were invited to complete one survey per semester, and were re-invited at the start of each new semester. The timing of data collection for each measure varied across participants based on when they began participation and how long they remained in the study. Because the measures used in the present study could be completed at any point during each student's enrollment, the timing of the acquisition of each indicator variable varies for each student. A description of what surveys are included in each survey is included in Table 1.

There were 1,577 Native American, Asian, and White undergraduate students (55.8% women; 37.7% Native American) majoring in STEM by the beginning of their second year of enrollment who participated in a longitudinal student achievement study from Spring 2014 to Spring 2022. In order for participants to have the opportunity to complete all study measures (contained in each of the three forms of the survey), only participants with at least three completed surveys were included in the sample for the present study. After Identifying the participants meeting these criteria, 11 were still enrolled at the end of 6 years, which was an insufficient sample size for a separate outcome category. Therefore, these participants were removed and the final number of participants was 928 (see Table 3 for sample descriptives).

Based on the Native American sample demographics, the largest group of respondents (29.55%) grew up in medium-sized towns with populations under 10,000 people, followed by those from medium-sized cities with over 100,000 people (18.18%) and small cities (16.19%). Additionally, 12.78% came from small towns, 11.65% from rural areas outside of towns, and 9.09% from big cities with populations exceeding 200,000 people. This distribution indicates that the sample predominantly consists of individuals who spent their formative years in smaller communities, with nearly 60% growing up in towns or rural areas with populations under 10,000. Almost the majority of Native American participants (48.30%) reported that they go back to their tribal community less than once every two years, and only 4 participants (1.14%) reported that they are currently living there. The next-largest pluralities of Native American participants reported that they went back to their tribal community once a year (11.08%), once every semester (6.82%), once every two years (6.25%), and once a month (5.11%). Only 3.69% of Native American participants reported they engage in tribal government quite often or very often, and 70.46% reported they never participate in tribal government. Overall, these characteristics suggest that Native American participants in the sample come from primarily smaller towns with populations under 10,000 people and are somewhat split in terms of their physical involvement in their tribal community (i.e., almost half visit less than once every two years).

Measures

Person Inputs

Socioeconomic Status and Parental Education. Socioeconomic status (SES) and parental education were assessed using a series of 7 items designed to capture various aspects of participants' backgrounds. Items from this measure are used as independent predictors in order to assess the importance of all dimensions of SES without losing potentially important variance by aggregating the data. In the present study, SES predictors are father/male guardian level of education, mother/female guardian level of education, combined income of parents/guardians, student income from all sources, and the size of town in which the student spent the majority of their time growing up. These items were each rated on a multiple-choice scale with higher responses indicating higher SES person inputs. Additionally, this measure included an item asking whether the participant went to a school on a reservation or other tribal land, and an item asking for how many years the participant attended this school. These items were answered by all participants and used as independent predictors when exploring predictors of STEM degree obtainment for Native American students.

Goal orientation. The goal orientation was measured using a adapted from VandeWalle's (1997) Goal Orientation for Work scales. The original scale contains 13 items assessing three goal orientations, learning (5 items), prove (4 items), and avoid (4 items). Items were adapted for use in the present study by replacing "work" with "school" or "academic", depending on the context of the item. Sample items include I am willing to select a challenging assignment that I can learn a lot from (Learning), I try to figure out what it takes to prove my ability to others at school (Prove), and I would avoid taking on a new task if there was a chance that I would appear rather incompetent to others (Avoid). Participants rated items on a 7-point Likert scale (1 = Strongly Disagree, 7 = Strongly Agree), with higher scores indicating greater identification with the goal orientation subdimension.

Implicit theories of math and science ability. Implicit theories of math and science ability were measured using a modified version of Dweck's (2013) 8-item measure of implicit theories of intelligence. Similar to Chen and Usher (2013), the measure was modified to reflect "math ability" and "science ability" instead of general intelligence, resulting in an 8-item measure assessing math and an 8-item measure assessing science. Participants rated the items using a 5-

point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). Sample items include "You can learn new things, but you can't really change your basic math ability" (fixed belief) and "No matter how much math ability you have, you can always change it quite a bit" (malleable belief). Higher scores on the subscales indicate stronger belief that math and science ability is fixed.

Background/Contextual Affordances

Previous math and science courses. Previous math and science courses were measured with check-all-that-apply items. Participants were asked to select all of the math classes that they have taken from a list of eight classes, Pre-Algebra, Algebra, Geometry, Trigonometry/Algebra II, Pre-Calculus, Calculus I, Calculus II, and Statistics. Similarly, participants were asked to select all of the science classes that they have taken from a list of five classes, Biology, Chemistry, Physics, Environmental Science, and Computer Science. Higher numbers of classes taken indicate that participants have greater exposure to math or science in high school.

Tribal Engagement. Native American participants received questions assessing their participation in their tribe and tribal activities. Questions were generated by the research team asking participants in focus groups about their connection and involvement in their tribe, as well as their knowledge of tribal history and tradition and tribal language. Results of a prior exploratory factor analysis using data from the same longitudinal study suggest that a 5-item version of this measure may reflect a latent construct of Tribal Engagement. These items were measured on a four-point Likert scale (not at all involved = 1, very involved = 4). Items include: "How would you rate your involvement in your Tribal community?"; "How would you rate your connection to your Tribal community?"; "How would you rate your involvement in your Tribal community?"; "How would you rate your connection to your Native American culture?"; and

"How connected are you to a Native American community on campus?" Higher scores indicate greater engagement in one's Tribe.

Concern with Finding Job Locally. Concern with finding a job locally was assessed using 4 items focusing on the importance of family and community ties when considering future living arrangements. Participants rated how essential factors like "Living close to your relatives" were in deciding where to live after college on a 5-point Likert scale, with higher scores suggesting a stronger preference for staying local.

Family Structure and Dependency. Family structure and dependency were measured using a set of 12 items. Similar to SES, the items of this measure are treated as separate predictors in order to capture the unique variance that may be explained by each component of participants' family structures. Items assessed marital status, romantic relationships, children, siblings, and parental dynamics. Items included "Are you currently married?", "How many children do you have?", and "What percentage of time do you have custody of your children?" Participants' responses helped establish a broader understanding of their family dependencies and support structures.

Family and Community Attitudes Toward Education. This measure consisted of 24 items asking participants to assess how important doing well in school, getting good grades, staying close to home after high school and making college education a top priority in my life are to the participant's parents, siblings, close relatives, community in which they grew up, and spouse/romantic partner. Participants rated how important they perceived each group viewed academic success on a scale from 1 (Not Important) to 5 (Very Important), with higher scores indicating more positive attitudes toward education from these groups. The items were aggregated for each referent in order to obtain 5 predictors from this measure.

Subtle Discrimination. This measure developed by Snyder and colleagues (2010) consisted of 8 items evaluating the frequency of subtle discrimination experienced by undergraduates. Participants reported how often they encountered scenarios like "That your contribution during a discussion was discounted" on a scale from 1 (0 times) to 11 (10 or more times). Higher scores indicated a greater frequency of perceived subtle discrimination.

Explicit Discrimination Towards Native Americans. For Native American participants only, explicit discrimination was measured through 10 items specifically targeting experiences of discrimination toward Native American undergraduates. Participants indicated how many times during college they had encountered behaviors such as being asked, "If you live in a teepee?" on a scale from 1 (0 times) to 11 (10 or more times). Higher scores reflected a higher frequency of explicit discriminatory experiences.

Non-Discriminatory Campus Climate. The Non-Discriminatory Campus Climate measure developed by Dugan and colleagues (2012) included 5 items assessing participants' perceptions of discrimination on campus. Participants rated their agreement with statements like "I have observed discriminatory words, behaviors, or gestures directed at people like me" using a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). Higher scores indicated perceptions of a more discriminatory campus climate.

Incivility. Incivility among undergraduates was measured using an adapted version of Cortina's (2001) incivility scale. The measure included 7 items that asked participants to report how often they encountered various forms of incivility, such as rude or dismissive behavior from others. Items were adapted by changing the wording/context of the items to be about university experiences rather than work experiences. Participants rated how often they experienced each behavior on a scale from 1 (Never) to 4 (Most of the time). Higher scores indicate more experiences of incivility.

Perceived Individual Mobility. This measure consisted of 4 items designed to assess participants' perceptions of the ability to move up socioeconomically, regardless of ethnicity. Participants were asked to indicate their agreement with statements such as “America is an open society where individuals of any ethnicity can achieve higher status” and “Individual members of certain ethnic groups are often unable to advance in American society.” Responses were given on a 7-point Likert scale ranging from 1 (Strongly Disagree) to 7 (Strongly Agree). Higher scores on this measure indicated a greater belief in the possibility of mobility across socioeconomic classes, while lower ratings on reverse-coded items (e.g., “Individual members of certain ethnic groups are often unable to advance”) also reflected higher perceived mobility. The measure was adapted from Major et al. (2002) and utilized reverse coding for two of the items to ensure accurate assessment. Scores were calculated by averaging across the four items, with appropriate recoding applied to ensure consistency.

Hours of Employment per Week. To assess the impact of holding a job while pursuing a degree, participants’ responses to the question “Are you currently employed” and (if participants indicated yes to that item) “On average, how many hours do you work per week?” were used as independent predictors. Participants who are currently employed could indicate their hours of employment per week on a 40-point scale ranging from 1 (1 hour) to 41 (“40+” hours).

Learning Experiences

Learning experiences. The present study directly assessed learning experiences via the Learning Experience Questionnaire (LEQ; Schaub, 2004; Schaub & Tokar, 2005). The present study utilized only Realistic and Investigative subscales due to their link to STEM occupations.

The LEQ assesses the extent to which individuals are exposed to and competent with activities that are specific to Holland's (1997) RIASEC (Realistic, Investigative, Artistic, Social, Enterprising, Conventional) occupational themes. Each occupational theme was assessed with 20 items reflecting the extent to which participants were exposed to, have past accomplishments in, or have negative experiences with activities in that RIASEC domain. The LEQ also assesses Bandura's (1986) sources of self-efficacy, performance accomplishments, vicarious learning, verbal persuasion, and emotional arousal. Thus, each 20-item subscale contains four 5-item subscales of sources of self-efficacy for the RIASEC domain (e.g., Realistic performance accomplishments, vicarious learning, verbal persuasion, and emotional arousal). Participants rated the items using a 6-point Likert scale (1 = Strongly Disagree, 6 = Strongly Agree). Higher scores on Demonstrated Abilities or Learning Influences indicate higher learning experiences, whereas higher scores on the emotional arousal subscales indicate lower levels of emotional arousal in the relevant domain.

Experiences with Faculty. The Experiences with Faculty measure consisted of 10 items designed to assess the frequency of interactions between students and faculty members. Participants were asked to reflect on their experiences at their institution and indicate how often they engaged in activities such as "Talking with your instructor about information related to a course you were taking (grades, make-up work, assignments)" and "Discussing your academic program or course selection with a faculty member." Responses were collected on a 4-point Likert scale ranging from 1 (Never) to 4 (Very Often), with higher scores indicating more frequent and varied interactions with faculty. The measure was adapted from the College Student Experiences Questionnaire (Gonyea et al., 2003), with modifications to better align with the survey's objectives.

Undergraduate Research Experience. The Undergraduate Research Experience measure was adapted from Chemers et al. (2011) and consisted of 14 items designed to assess the extent of research experience gained by participants during their undergraduate studies. Participants were asked to reflect on their involvement in various research-related activities and rate their engagement on a 5-point Likert scale ranging from 1 (Not at all) to 5 (A lot). Higher scores indicated a greater amount of research experience. Sample items included “I had the opportunity to generate my own research question to answer” and “I created my own explanation for the results of a study/research project.”

Quality of Mentoring Relationship. The Quality of Mentoring Relationship measure was adapted from Noe (1988) and Chemers et al. (2011) and comprised 18 items designed to assess the extent to which mentors provided meaningful support and opportunities to their mentees, specifically targeting freshmen participants. Participants were asked to describe their experiences with their mentors using a 5-point Likert scale ranging from 1 (Not at all) to 5 (To a very large extent). Higher scores indicated a higher quality of the mentoring relationship. Sample items included “My mentor gave me the impression that s/he believed in me” and “My mentor earned my trust.”

Self-Efficacy

Math self-efficacy. Math self-efficacy was assessed via a modified version of Usher and Pajares’ (2009) Sources of Middle School Mathematics Self-Efficacy Scale. The original measure contained 24 items reflecting four sources of self-efficacy, mastery experience (6 items), vicarious experience (6 items), social persuasions (6 items), and physiological state (6 items). Vicarious experience items were excluded for the present study as these items reflected vicarious experiences of middle school students rather than college students. Participants rated the extent to which statements were true or false for them using a 6-point Likert scale (1 = Definitely False, 6 = Definitely True). Higher scores indicate greater self-efficacy in the math domain.

Science self-efficacy. A modified version of Usher and Pajares' (2009) Sources of Middle School Mathematics Self-Efficacy Scale (as described above) was used to measure science self-efficacy. Items were changed to refer to "science" instead of "math", and instructions listed science as referring to biology, chemistry, Earth science, geology, and computer science. Participants rated the extent to which statements were true or false for them using a 6- point Likert scale (1 = Definitely False, 6 = Definitely True). Higher scores indicate greater science self-efficacy.

Leadership Efficacy Scale. The Leadership Efficacy Scale includes 4 items measuring participants' self-confidence in leadership skills. Participants were asked to rate their confidence in scenarios such as "Leading others" and "Taking initiative to improve something," using a 5-point scale ranging from 1 (Not confident at all) to 5 (Very confident). Higher scores reflect greater self-efficacy in leadership roles.

Identity as a Scientist. The Development of Identity as a Scientist measure consisted of 6 items designed to assess how much participants identified with the role of a scientist. Participants rated their agreement with statements such as "I am a scientist" and "I have come to think of myself as a 'scientist'" on a 5-point Likert scale, ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). Higher scores indicated a stronger identification with the role of a scientist. This measure was based on work by Chemers et al. (2010), examining the role of self-efficacy and identity in supporting science-related pursuits.

Outcome Expectations

Outcome expectations. Outcome expectations were assessed via an adapted version of Byars-Winston et al.'s (2010) 18-item Outcome Expectations scale, which itself was adapted from Lent et al. (2001). The version of the scale used in the present study removed negatively worded items resulting in a 12-item scale. Participants indicated the extent to which "graduating with a bachelor's degree with a major in a science, technology, engineering, or mathematics field" would allow them to meet specific financial, career, and other expectations. Sample items include receive a good job offer and increase my sense of self-worth. The version of the scale used in the present study included two additional items reflecting experiences relevant to Native American undergraduate experiences, help the community that I grew up in and help the community where I will be living in the future. The resulting 14 items were rated on a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree), with higher scores indicating more positive internal and external outcome expectations.

Interests

Research interests. The measure for research interests adapted from Bishop and Bieschke's (1998) Interest in Research Questionnaire. The original scale contained 16-items designed to assess graduate and postdoctoral samples and was modified to address undergraduate students (Bishop & Bieschke, 1998). Six of the items were deemed inappropriate or irrelevant for undergraduate students and were removed. The final 10-item scale asked participants to rate the extent to which they were interested in a list of research-related activities on a scale from 1 (Very Uninterested) to 5 (Very Interested), with higher scores indicating greater research interest.

STEM interests. Lent et al.'s (2001) 8-item interest in science and math measure was used to assess interest in STEM. The measure asks participants to rate the extent that they are interested in science or math subjects (e.g., Statistics and Chemistry) on a 5-point Likert scale (1 = Strongly Dislike, 5 = Strongly Like). Higher scores indicated greater interest in STEM subjects.

Choice Goals

Intention to major in STEM. The measure for intentions to major in STEM was an adapted version of Lent et al.'s (2003) educational goals measure. The items of the original measure were adapted from focusing on engineering to focus on "science/technology/engineering/math." The measure contained three items on which participants indicated their agreement with statements such as "I intend to major in a science/technology/engineering/math field" using a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). Higher scores reflect a stronger intention to major in STEM fields.

Contextual Influences Proximal to Choice Behavior

Perceived supports. Participants perceptions of the support they receive for pursuing a STEM major was assessed using the 15-item supports subscale of Lent et al.'s (2001) Perceived Contextual Supports and Barriers to the Pursuit of Math- and Science-Related Educational Options measure. The original measure includes items assessing four sources of support, social support and encouragement, instrumental assistance, access to role models or mentors, and financial resources. The original scale's instructions were modified to ask participants to assume they were majoring in a STEM-related college major, so participants rated the extent to which they would experience various supports in a STEM major on a 5-point Likert scale (1 = Not at All Likely, 5 = Extremely Likely). Higher scores reflect stronger positive expectations of the pursuit of a STEM major.

Perceived barriers. Perceived barriers for pursuing a STEM major were measured via the 21-item barriers subscale from Lent et al.'s (2001) Perceived Contextual Supports and Barriers to the Pursuit of Math- and Science-Related Educational Options measure, which included four sources of barriers, social or family influences, financial constraints, instructional barriers, and gender and race discrimination. As mentioned above, the instructions of this scale were modified to focus on perceptions of barriers in STEM degrees. Participants rated the extent to which they would experience various barriers on a 5-point Likert scale (1 = Not at All Likely, 5 = Extremely Likely). Higher scores reflect greater expectations of barriers in the pursuit of a STEM major.

Coping efficacy for barriers. Coping efficacy for barriers was assessed using 18 items adapted from Lent et al. (2001) that measured participants' confidence in their ability to handle challenges that might arise while pursuing a math or science-related major. Although participants may have declared different majors, they were asked to assume they were pursuing a STEM major for this assessment. Participants responded on a 9-point Likert scale, ranging from 1 (No Confidence at All) to 9 (Complete Confidence), with higher scores indicating greater perceived ability to overcome obstacles in STEM fields. Sample items include "Succeed in a math or science course despite having a poor instructor" and "Deal with unfair treatment you might receive because of your gender."

Educational Supports. The Educational Supports measure included 44 items designed to gauge the extent of awareness of and engagement with financial support for participants' educations. Sample items include "I know where to search for scholarships" and "Have you completed a Free Application for Federal Student Aid (FAFSA) either last year or this year?" Responses varied from Yes/No questions to Likert scales. Similar to measures of SES and family structure, each item of this measure are treated as an independent predictor in order to capture the potentially unique influence of each aspect of awareness of and engagement in financial support opportunities.

Career Barriers. The Career Barriers measure consisted of 35 items adapted from Byars-Winston & Fouad (2008) and Swanson & Tokar (1991) and was designed to assess the perceived likelihood of encountering obstacles related to career progression within a STEM field. Participants were asked to think about each potential barrier, such as "Lacking information about possible jobs/careers" and "Being limited to certain career choices because of my gender," and indicate how likely they thought it was that they would experience each one if they pursued a STEM major. Responses were given on a 7-point Likert scale ranging from 1 (Very Unlikely) to 7 (Very Likely), with higher scores reflecting a greater perceived likelihood of encountering these barriers. Subdimensions included likelihood and hindrance, with separate items assessing how likely barriers were to occur and the extent to which they might hinder career progress.

Outcome Measure

Student degree outcomes were used as the outcome measure for the present study. The degree status of each participant was obtained from university records which detailed the specific degree that was obtained (e.g., Bachelor of Science in Psychology, Master of Science in Economics, etc.) and the semester in which the degree was conferred. Student degree outcomes were recorded at the end of the sixth year since each participant's enrollment at the university. Students who obtained no degree were coded as 0 in the outcome measure; students who obtained a non-STEM degree were coded as 1; and students who obtained a STEM degree were coded as 2. See Table 4 for the demographic distributions of participants in each outcome category. It is important to note that while students who were coded as obtaining no degree left the university before obtaining a degree, they may have obtained a degree at a different university. In other words, the no-degree outcome can also be considered as “exited from the university before obtaining a degree” to be more specific.

Survey Design and Data Management

The present study defines time as the number of years since initial college enrollment at the time of survey completion for each participant. That is, if a participant completes a survey during their first year of enrollment, that survey was considered occurring at time zero for that participant. I constrained the data to be only that which is collected during the first 6 years of enrollment at the university as this reflects a timeframe that would allow for most students to achieve a baccalaureate degree. The project was originally designed to include all items from the SCCT predictor measures at each of the 6 time points throughout the duration of the study. In this plan, each SCCT construct is measured longitudinally, allowing for the assessment of temporal influences. To account for the repeated measures, my intention was for the elastic net multinomial regression to treat the data at each time point as separate predictors, enabling the identification of SCCT items whose influence on the outcome variable is different depending on when it is measured. A table describing the number of each survey form collected during each year for the sample is presented in Table 2.

However, to ensure the robustness of the analyses and mitigate the effects of missing data over time, the present study implemented an inclusion threshold for predictor variables based on response rates at each time point. Given that participant responses are expected to decrease over successive survey waves, only predictor variables for which at least 80% of the total sample provided responses at a given time point were included in the analyses. This criterion helped maintain consistency in the data structure and reduce potential biases introduced by varying sample sizes across time points. By establishing this threshold, the study enhanced the reliability of the elastic net multinomial regression results while preserving the integrity of longitudinal assessments of SCCT constructs.

Upon examination of the data provided by the participants, no predictor variables that were collected in a given year satisfied the 80% completion threshold. This is likely because participants could complete any of the survey forms at any point during their undergraduate career (e.g., Pre-A as a freshman or a senior). Thus, the completion of predictor measures in a given year ranged from 30% to 50% due to these very ragged arrays of data. In order to obtain the most complete and consistent dataset, the first observation of each predictor variable was compiled for each student, which resulted in a dataset that was largely satisfactory for the 80% completion criteria of predictor measures. All analyses were thus conducted with this set of first observations of each predictor, and the temporal influence of predictors was not examined beyond the first observation.

Analyses

To examine the factors most predictive of educational outcomes for undergraduate students, the study employed elastic net multinomial regression using the *glmnet* package for R (Friedman et al., 2010). This method allowed for the simultaneous analysis of multiple predictor variables, helping to determine which components of the SCCT model are most relevant for predicting whether students graduated with a STEM degree, graduated with a non-STEM degree, or earned no degree after 6 years. Models for only Native American participants and models with all participants were tested. The Native-American-only model included predictors asked to only Native American students as well as the other measures, whereas the model for all participants excluded measures/items that are only asked to Native American participants.

Elastic Net Multinomial Regression

Elastic net is a regularization technique that was developed to address some of the limitations of traditional regression models, particularly when dealing with high-dimensional datasets where the number of predictor variables may be greater than, or comparable to, the sample size (Zou & Hastie, 2005). Unlike traditional regression, which can become unstable and prone to overfitting in such scenarios, elastic net introduces penalty terms that help to shrink coefficients, thereby mitigating multicollinearity and improving the model's generalizability. Specifically, elastic net combines the penalties of both Lasso (L1) and Ridge (L2) regression, allowing it to perform variable selection and regularization simultaneously (Hastie et al., 2015). The elastic net approach is particularly useful for datasets with high multicollinearity among predictors because it tends to retain groups of correlated predictors (Zou & Hastie, 2005).

Multinomial regression is an extension of logistic regression used when the dependent variable is categorical and has more than two possible outcomes. By using elastic net regularization within a multinomial regression framework, the analysis accommodated the complexity of the educational outcomes, which are treated as a categorical variable with five levels. The *glmnet* package in RStudio facilitates this by implementing the elastic net penalty and providing efficient algorithms for estimating the parameters of the model (Friedman et al., 2010). The elastic net method helps identify which items from SCCT measures (e.g., self-efficacy, outcome expectations, interests, goals, supports, and barriers) are the most predictive of students' educational pathways.

Analytical Approach

I tested models where indicators are aggregated at the scale level in order to identify which constructs of the SCCT are the most important predictors of student degree obtainment.

Conducting a regression analysis at the construct level provided easily interpretable information for researchers using the SCCT model to predict student outcomes. Before conducting the regression analysis, all predictor variables that reflect latent constructs were analyzed for reliability by obtaining omega coefficients. Additionally, I conducted a CFA on and check evidence of metric measurement invariance for the a-priori factor structures of the measures using all available data from participants on those measures. This process allowed for problematic items to be removed before conducting subsequent analyses.

The fit indices of each CFA were evaluated according to traditional criteria for fit indices (CFI > 0.95; RMSEA < 0.08; SRMR < 0.06; Hu & Bentler, 1999). For measures without an a-priori factor structure from the literature, data were randomly divided into two datasets to conduct an EFA using promax rotation with one half of the dataset. The other half of the data was then used to fit a CFA model to the factor structure obtained through the EFA. Missing data during this stage of the analyses were modeled using Full Information Maximum Likelihood (FIML) estimation. Missing data during the elastic net regression analyses were addressed through the implementation of the inclusion criteria described above. However, in order to assess potential patterns of missingness, the demographic data (e.g., gender, race/ethnicity, etc.) of responders to certain items were compared to that of non-responders using a chi-square test. If, for example, a demographic group had significantly more non-responders than another group, data for that item may be missing not at random (MNAR) which would bias the results. If an item presents this significant difference in responding, it was noted in the results and discussion of the present study. Models for Native American, White, and Asian American students combined were tested and models using data from only Native American students (including two unique measures assessing tribal engagement and explicit discrimination) were tested separately.

To ensure the validity of comparisons across Native American and all student samples, I tested for measurement invariance of the study measures. Measurement invariance determined whether the same construct is measured equivalently across groups, thereby supporting the validity of cross-group comparisons. This process involved a series of nested confirmatory factor analyses (CFAs) using maximum likelihood estimation with robust standard errors (MLR) in Rstudio. The analyses followed the first two stages of a four-stage process consistent with best practices for testing measurement invariance (F. F. Chen, 2007; Putnick & Bornstein, 2016). Only minor invariance is necessary for the present study because the goal is primarily to identify highly problematic measures that should likely not be compared across demographic groups in any way. First, I evaluated configural invariance to determine whether the same factor structure holds across groups. This model allowed all parameters to vary freely across groups and served as the baseline for comparison. Then, I tested metric invariance by constraining factor loadings to equality across groups while allowing intercepts and residuals to vary. Model fit at each stage was assessed using conventional indices, including the Comparative Fit Index (CFI), the Tucker-Lewis Index (TLI), the Root Mean Square Error of Approximation (RMSEA), and the Standardized Root Mean Square Residual (SRMR). A decrease in CFI $\leq .01$ between nested models was considered evidence of invariance provided that other fit indices remain within acceptable ranges (Cheung & Rensvold, 2002). These analyses provided evidence for the extent to which the results of the elastic net models for each group are appropriate to compare.

The regression analysis used cross-validation to determine the optimal values of the penalty parameters (alpha and lambda), which control the balance between L1 and L2 penalties and the degree of shrinkage applied to the coefficients, respectively (Friedman et al., 2010). A stratified 10-fold cross-validation approach was implemented, where the training dataset is divided into 10 subsets (folds). The model was trained on nine of these folds while the remaining fold is used for validation, repeating this process across all folds. This ensures that the model is evaluated across multiple iterations, reducing the risk of overfitting to any single subset of the training data. The selected model was the one that minimizes prediction error on a separate validation dataset.

To ensure the validity and generalizability of the elastic net multinomial regression model, I included a hold-out dataset for prediction purposes. The dataset was split into training, validation, and testing subsets. Cross-validation was conducted within the training dataset to optimize model parameters before final testing. The training dataset comprised approximately 60% of the total data and was used to fit the elastic net multinomial regression model. The validation dataset, comprising about 20% of the data, was used for hyperparameter tuning, where the 10-fold cross-validation process was applied to systematically assess different values of alpha and lambda. The optimal penalty parameters were those that minimize prediction error across all validation folds, ensuring stability in parameter selection. The testing dataset (hold-out), which consisted of the remaining 20% of the data, was not used during model training or validation. The random splitting process was stratified by the outcome variable (educational status categories: graduated STEM, graduated non-STEM, and no longer enrolled) to ensure that each subset has proportional representation of the outcome categories. This stratification ensures that all categories are adequately represented in the hold-out dataset, providing a reliable basis for evaluating the model's performance across all outcome levels.

Once the optimal hyperparameters are identified through cross-validation, the final model was trained on the full training dataset using these parameters and then evaluated on the unseen hold-out dataset. By keeping model selection (via cross-validation) and model evaluation (via hold-out testing) as separate steps, this approach minimizes the risk of overfitting and improves the model's ability to generalize to new data. The hold-out dataset served as an independent set of observations to evaluate the final model's predictive accuracy and generalizability. This approach aligns with best practices in machine learning, ensuring that the final performance metrics truly reflect the model's real-world predictive capability rather than its ability to fit the training data. Additionally, by reserving a portion of the data solely for testing, the risk of overfitting to the training or validation datasets is minimized, further enhancing the reliability of the findings.

Model performance was assessed at multiple stages, first through cross-validation error metrics for model selection, and finally on the hold-out dataset for independent evaluation. Accuracy (percentage of correctly predicted outcomes) was the primary performance metric. This measure provides a straightforward and interpretable assessment of the model's ability to classify students into the five educational outcome categories (graduated STEM, graduated non-STEM, no degree). Additionally, I reported confusion matrices to provide a breakdown of correct and incorrect predictions for each outcome category, offering insight into where the model performs well or struggles. Metrics such as the macro-averaged F1 score or log-loss were also reported to provide a more comprehensive evaluation of model performance, particularly in cases of class imbalance.

After examining the results of the multinomial models, I then tested two distinct binary models in an effort to understand the influence of SCCT predictors on more narrow outcome distinctions. Binary model 1 examined the ability of the data to predict whether students graduated with a non-STEM degree or graduated with a STEM degree (excluded students who did not obtain a degree). Binary model 2 combined non-STEM and STEM degree outcomes into a single class and explored how well the data predicted whether students obtained no degree or obtained any degree. Each binary model was tested for all students and then for Native American students separately. The results of these models provide a better understanding of the ability of SCCT constructs to predict student outcomes under different conceptualizations of outcome categories, and provide additional information regarding how influential certain SCCT factors are when predicting more narrowly defined pathways of STEM majors.

Interpretation of Results

The results of the elastic net multinomial regression were interpreted by examining the coefficients of the selected model. Non-zero coefficients indicate variables (i.e., specific SCCT variables) that are predictive of the different educational outcomes. Given the regularization properties of elastic net, predictors that consistently contribute to the model and show stability across cross-validation folds were deemed particularly important. Additionally, by examining the direction and magnitude of the coefficients, insights can be gained into how different SCCT variables (e.g., self-efficacy, supports) influence the likelihood of a student's persistence and success in STEM versus non-STEM fields.

The use of elastic net regularization enhanced the model's ability to handle the large number of predictors and reduce the risk of overfitting, leading to more robust and generalizable conclusions about which factors are most critical for supporting Native American students in STEM fields. This approach aligns with recent applications of elastic net in educational research, where it has been used to analyze complex, multidimensional data to identify key predictors of student outcomes.

The elastic net regression results were interpreted both in terms of variable selection and overall model performance. While the primary goal is to identify the most predictive SCCT components and items, the predictive strength of each model must also be compared. The use of regularization helps identify stable, non-zero coefficients that consistently contribute to the model across cross-validation folds. These coefficients were interpreted as indicators of the importance of specific SCCT variables. Furthermore, the models' overall performance metrics, including accuracy and potential validation against the hold-out datasets, provided evidence for the predictive power of each model.

Results

Prior to conducting machine learning analyses, several preparatory steps were undertaken to ensure data quality and measurement validity. First, comprehensive measure refinement was conducted, including evaluation of alpha and omega reliability coefficients for all study variables according to their a priori factor structures (see Table 7). Confirmatory factor analyses were performed for each variable to identify problematic items with poor factor loadings, and theoretically justified residual covariances were specified to address local dependencies not fully explained by the latent constructs alone (see Table 8). These covariances reflected shared content themes, similar phrasing, method effects, and domain-specific response patterns that improved model fit while preserving the conceptual integrity of the unidimensional factor structures.

Prior to conducting elastic net regression modeling on the multi-ethnic STEM education dataset, a comprehensive missing data analysis was performed to assess potential bias from differential missingness patterns across ethnic groups (Native American, Asian American, and White). Chi-square tests were conducted to examine whether missingness on 63 predictor variables differed systematically by ethnicity and gender (see Table 5). Based on these analyses, the primary imputation strategy employed group-stratified Multiple Imputation by Chained Equations (MICE), conducting separate imputation models within each ethnic group using 50 iterations. This approach was designed to preserve group-specific distributional properties and correlational structures while avoiding potential bias from pooled imputation that could impose overall sample characteristics on groups with distinct missingness patterns. For each missing value, MICE used the other available variables to build predictive models and selected the predicted value as the imputed estimate, cycling through this process iteratively up to 50 times to refine and stabilize the imputations. Only the final, most refined estimate from the last iteration was retained as the single imputed value for each missing data point. This approach differs from full multiple imputation, which would typically draw random samples from predicted distributions and create multiple complete datasets rather than using point predictions to generate a single dataset.

Measurement invariance testing was then conducted across the three ethnic groups (Native American, Asian American, and White students) for 47 latent constructs using a hierarchical approach that evaluated configural invariance followed by metric invariance. Group-stratified multiple imputation using the MICE algorithm was employed rather than pooled imputation to prevent bias from response patterns dominated by groups with more complete data. Sensitivity analyses confirmed that complete case analysis would have introduced selection bias due to differential attrition rates across ethnic groups. These preparatory analyses established the psychometric foundation and data quality necessary for subsequent machine learning model development and evaluation.

To identify the best predictors of STEM degree attainment for Native American students, I report the results of several Elastic Net models' performances in predicting the outcomes of students in the hold-out dataset. The alpha hyperparameters of models were obtained through optimization on the validation split of the training data, while lambda hyperparameters were derived from cross-validation within the training subset. The optimal models were then tested using the hold-out dataset. The use of the hold-out dataset for reporting model performance allows for the models' performances to be reflective of novel data and thus provide evidence of generalizability. All predictor variables were standardized prior to analysis, allowing coefficient magnitudes to be directly compared across variables to assess relative predictor importance.

I first report the results of the multinomial logistic regression models for all students, then for Native American students only. The multinomial models will compare the ability of the data to predict the participant's degree attainment based on three outcome levels (0 = No Degree, 1 = Non-STEM Degree, and 2 = STEM Degree). Model performance is reported via multiple evaluation metrics (see Tables 9 and 16) as well as confusion matrices (see Tables 10 through 15). The coefficients of predictors for each optimal multinomial model are reported and reflect the log-odds of outcome category membership relative to the reference category (no degree), with positive coefficients indicating increased likelihood of the respective degree type and negative coefficients indicating decreased likelihood (see Tables 17 through 22).

I then report the results of binary models that examine two distinct educational pathways. Binary Model 1 compares non-STEM degree attainment versus STEM degree attainment among participants who obtained any postsecondary degree, excluding those with no degree. Binary Model 2 compares any degree attainment (STEM or non-STEM) versus no degree attainment using the full sample. These binary models provide complementary insights by separately examining degree type selection among degree holders and overall degree attainment likelihood. For both multinomial and binary models, cost-sensitive class weighting was applied during training to address outcome class imbalances. Model coefficients represent the effect of one standard deviation change in each standardized predictor variable.

Sample Identification

To obtain the full dataset, I identified all participants in the larger longitudinal study who were STEM majors by the beginning of their second year of enrollment. For these participants, I obtained all observations of the study variables provided by these participants during a six-year period from the time they first enrolled at OU. Then, I separated observations for participants into separate datasets based on the year in which the data were provided. When data were divided into separate time points (year since enrollment) no variable at any one year was 80% complete. That is to say, when looking at data from any one year, the measures and survey forms completed by participants during that year since their enrollment varied so much that each variable was at most completed by only 60% of participants who had observations during that year.

To obtain a usable dataset of the study variables for the models, I chose to compile the earliest observations of each variable provided by participants during their 6-year period of undergrad. Additionally, because some measures of study variables were only present in Survey A, which was only offered to participants who had successfully completed surveys Pre-A and B, I constrained the inclusion criteria to be only participants who had provided at least 3 surveys. These changes resulted in a much more complete dataset with completion ranging between 80% and 95% for most variables. There were a few variables that still did not meet the threshold for imputation due to them having been added later in the data collection period of the larger study and their being present in only one, later form (A or B) of the survey since they were added (see Table 6). These variables were thus removed from the analyses.

The average age of participants at the time of their first observation was 19. The average number of months between observations for participants was 7.2 months (approximately one semester). The average amount of time between participants' first and last observations was 3 years and 5 months.

Due to the very small number of participants who were still enrolled at the end of six years, participants who had earned no degree but were still enrolled were removed and the outcome variable was recoded to only include Unenrolled with no Degree, Graduated with Non-STEM Degree, and Graduated with STEM Degree. This was done due to glmnet requiring a minimum of eight observations per class in the outcome variable to produce statistically stable results.

The final analytic sample consisted of 928 undergraduate students across three ethnic groups: Native American (*n* = 352, 37.9%), Asian American (*n* = 347, 37.4%), and White (*n* = 229, 24.7%). The oversampling of Native American participants was intentional due to the focus of the larger longitudinal research study which sought to ensure adequate representation of Native American students for the primary research questions. Educational outcomes were distributed as follows: 25% received no degree, 21.1% received a non-STEM degree, and 53.9% received a non-STEM degree after six years.

Measure Refinement

There were 31 SCCT factors in the dataset. Five factors contain multiple scales. These scales were treated as individual predictors, resulting in a total of 61 variables. Five of these variables were measures assessing non-latent variables (e.g., check box questions), and seven variables were removed due to low completion. This resulted in a total of 49 scales used as predictors in the present study.

Alpha and omega reliability coefficients were obtained for the study measures according to their a priori factor structures (see table 7). Most variables had a unidimensional a-priori factor structure. Of the variables with multiple dimensions, the subdimensions were treated as separate unidimensional measures as that is how they were modeled in the regression analyses. Additionally, each variable was fit to a unidimensional CFA in order to identify potentially problematic items such as those with poor factor loadings. Across the confirmatory factor analyses, residual covariances were specified to address local dependencies that were not fully explained by the latent constructs alone (see table 8). These covariances were theoretically and empirically justified, often reflecting shared content, similar phrasing, or method effects such as reverse coding. For example, the math and science self-efficacy scales likely had correlated errors for items that tapped into either affective experiences (e.g., stress or anxiety), shared feedback sources, or differential responding due to reverse-coding. In the perceived barriers to STEM and STEM career barriers scales, residual covariances reflected themes such as identity-based discrimination, financial strain, limited support, and structural disadvantages. Finally, in the coping efficacy scale, covariances were modeled for items involving identity-related resilience, external stressors, and motivational challenges, each of which likely requires unique self-regulatory strategies. Collectively, these residual correlations improved model fit while preserving the conceptual integrity of the unidimensional factor structures, allowing the models to more accurately reflect the nature of students' experiences in STEM contexts.

Measurement Invariance Across Ethnic Groups

Measurement invariance was evaluated across three ethnic groups (Native American, Asian American, and White students) for 47 latent constructs using a hierarchical approach that tested configural invariance followed by metric invariance. All models were estimated using robust maximum likelihood (MLR) with full information maximum likelihood (FIML) to handle missing data. Configural invariance was evaluated using established fit criteria (CFI $\geq$ 0.90 and

RMSEA ≤ 0.08, or CFI ≥ 0.95 and RMSEA ≤ 0.06), and metric invariance was assessed using Chen's (2007) practical guidelines (ΔCFI < 0.01 and ΔRMSEA < 0.015).

Configural Invariance

Of the 47 models tested, 41 (87.2%) demonstrated adequate configural invariance, indicating that the same factor structure held across ethnic groups. Six models failed to meet configural invariance criteria: Avoid Negatives Goal Orientation (CFI = 0.995, RMSEA = 0.090), Investigative Verbal Persuasion (CFI = 0.974, RMSEA = 0.082), Investigative Physiological Arousal (CFI = 0.977, RMSEA = 0.097), Artistic Verbal Persuasion (CFI = 0.929, RMSEA = 0.082), Artistic Physiological Arousal (CFI = 0.956, RMSEA = 0.095), Social Verbal Persuasion (CFI = 0.968, RMSEA = 0.088), and Enterprising Performance Accomplishments (CFI = 0.960, RMSEA = 0.084). These models showed acceptable CFI values but exceeded the RMSEA threshold, suggesting potential model misspecification or differential item functioning across groups.

Metric Invariance

Among the 41 models that achieved configural invariance, 40 (97.6%) demonstrated full metric invariance, indicating that factor loadings were equivalent across ethnic groups. The Perceived Likelihood of Barriers model showed borderline metric invariance (ΔCFI = 0.001, p = 0.039), but met practical significance criteria and was retained. Only one model, Artistic Vicarious Learning, failed to achieve metric invariance (ΔCFI = 0.028, p = 0.050), indicating that while the factor structure was equivalent across groups, the item loadings differed significantly.

Domain-Specific Results

Goal Orientation and Implicit Theories. Of the basic psychological constructs tested, seven achieved full measurement invariance. The Avoid Negatives Goal Orientation scale failed configural invariance, while Fixed Science (ΔCFI = 0.002, ΔRMSEA = 0.001) and Math (ΔCFI = 0.000, ΔRMSEA = -0.007) Skills Beliefs both demonstrated excellent metric invariance.

Learning Experiences Questionnaire (LEQ). Among the 24 LEQ subscales, 18 (75.0%) achieved full measurement invariance, while 5 (20.8%) failed configural invariance and 1 (4.2%) achieved only partial invariance. The Realistic domain showed the strongest invariance properties, with all four subscales achieving full invariance. The Artistic domain showed the most problems, with three of four subscales failing to achieve adequate model fit.

Self-Efficacy and Identity Measures. All five constructs in this domain achieved full measurement invariance, including Math Self-Efficacy (ΔCFI = 0.000, ΔRMSEA = -0.003), Science Self-Efficacy (ΔCFI = 0.001, ΔRMSEA = -0.001), Interaction with Faculty (ΔCFI = 0.000, ΔRMSEA = -0.006), Research Experiences (ΔCFI = -0.001, ΔRMSEA = -0.005), and Science Identity (ΔCFI = -0.001, ΔRMSEA = -0.018).

Interests, Expectations, and Barriers. All nine constructs in this domain demonstrated full measurement invariance, including complex models such as Perceived Barriers in STEM (21 items; ΔCFI = 0.006, ΔRMSEA = 0.001) and Perceived Likelihood of Barriers (35 items; ΔCFI = 0.001, ΔRMSEA = -0.001). These results provide strong evidence for the cross-ethnic equivalence of expectancy and barrier constructs.

Summary

Overall, 35 of 47 constructs (74.5%) achieved full measurement invariance (both configural and metric), one construct (2.1%) achieved partial invariance (configural only), and six constructs (12.8%) failed to achieve configural invariance. These results indicate that the majority of psychological constructs can be meaningfully compared across Native American, Asian American, and White students. The constructs that failed configural invariance testing were excluded from specific group comparison analyses; however, these measures were included in machine learning models as the dimensions of the learning experiences questionnaire are not as important to consider as latent constructs, but rather a report of individuals' early life experiences. Any of these variables that are meaningful for all students or Native American samples were discussed alongside the potential for differential functioning of these measures.

Diagnostic analyses were conducted to identify specific items contributing to measurement invariance failures across Native American, Asian American, and White student groups. Seven items across three constructs demonstrated problematic factor loading differences exceeding 0.10 between ethnic groups, suggesting differential item functioning. The Avoid Negatives Goal Orientation scale failed configural invariance primarily due to item "I prefer to avoid situations at school where I might perform poorly", which showed standardized factor loadings ranging from 0.675 in Asian American students to 0.838 in Native American students (difference = 0.163). This suggests that avoidance of academic challenge may be conceptualized or experienced differently across these cultural groups, with potential implications for how academic risk-taking behaviors are understood and measured.

The Artistic Vicarious Learning scale failed metric invariance due to systematic non-invariance across four of its five items, with the most severe problems observed in "I remember watching members of my family create art (loading difference = 0.287 between Asian American and White groups, with loadings of 0.407 and 0.694 respectively), "I watched my friends as they participated in school plays" (difference = 0.236 between Asian American and White groups, with loadings of 0.389 and 0.153 respectively), "During school, I admired teachers whom I saw create art" (difference = 0.213 between Asian American and White groups, with loadings of 0.641 and 0.428 respectively), and "While growing up, I listened to family members play musical instruments" (difference = 0.227 between Asian American and White groups, with loadings of 0.302 and 0.529 respectively). These differences suggest that vicarious artistic learning experiences vary in their psychological meaning and salience across ethnic groups, likely reflecting cultural differences in family artistic practices, peer engagement in creative activities, and the perceived role of teachers as artistic models.

The Investigative Verbal Persuasion scale failed configural invariance due to items "People whom I respect have encouraged me to work hard in math courses" (difference = 0.145 between Asian American and White groups, with loadings of 0.326 and 0.471 respectively) and "I remember my family telling me that it is important to be able to solve science problems" (difference = 0.106 between Native American and White groups, with loadings of 0.675 and 0.569 respectively), indicating that verbal encouragement for STEM engagement functions differently across groups.

The Avoid Negatives Goal Orientation scale failed configural invariance primarily due to item “I prefer to avoid situations at school where I might perform poorly” (loading difference = 0.163 between Native American and Asian American groups, with loadings of 0.838 and 0.675, respectively), indicating that avoidance of academic challenge is conceptualized differently across ethnic groups. This suggests that the psychological meaning of academic risk-taking behaviors varies culturally, potentially reflecting different cultural values regarding perseverance versus face-saving in challenging academic situations.

The Artistic Verbal Persuasion scale failed configural invariance due to systematic non-invariance across four of its five items, with problems observed in “People whom I respect have encouraged me to play a musical instrument” (loading difference = 0.159 between Native American and White groups, with loadings of 0.434 and 0.275 respectively), “Teachers whom I respect have encouraged me to take an art class” (difference = 0.202 between Native American and Asian American groups, with loadings of 0.285 and 0.486 respectively), “Family members have urged me to learn how to sing” (difference = 0.209 between Asian American and White groups, with loadings of 0.759 and 0.550 respectively), and “While growing up, adults whom I admired told me that it is important to be a good writer” (difference = 0.146 between Native American and Asian American groups, with loadings of 0.266 and 0.412 respectively). These differences suggest that verbal encouragement about artistic pursuits is not a consistent domain of experience across ethnic groups. This may reflect cultural variations in how artistic engagement is discussed and valued within families and educational contexts.

The Artistic Physiological Arousal scale failed configural invariance with widespread non-invariance across four of its five items, including “I have felt anxious when I had to act in a play” (loading difference = 0.311 between Native American and White groups, with loadings of 0.237 and 0.547 respectively), “I have felt uptight while writing a short story for school” (difference = 0.221 between Asian American and White groups, with loadings of 0.381 and 0.603 respectively), “I have felt uneasy while drawing something” (difference = 0.177 between Native American and White groups, with loadings of 0.662 and 0.485 respectively), and “I have felt uncomfortable while playing a musical instrument for other people” (difference = 0.124 between Asian American and White groups, with loadings of 0.616 and 0.491 respectively). These measurement differences may indicate that physiological reactions to artistic experiences are conceptualized and experienced differently across ethnic groups, leading to a lack of a unified construct reflecting this domain.

The Social Verbal Persuasion scale failed configural invariance with the most severe non-invariance patterns, affecting all five items such as “My teachers have encouraged me to explore jobs in the helping professions (e.g., counseling)” (loading difference = 0.193 between Native American and White groups, with loadings of 0.489 and 0.297 respectively), “My family encouraged me to take social science courses (e.g., psychology)” (difference = 0.268 between Native American and White groups, with loadings of 0.501 and 0.233 respectively), “My family taught me that it is important to develop my interpersonal communication skills” (difference = 0.323 between Native American and White groups, with loadings of 0.506 and 0.183 respectively), “People whom I respect have encouraged me to perform volunteer work” (difference = 0.353 between Asian American and White groups, with loadings of 0.611 and 0.259 respectively), and most severely “My friends have urged me to help others resolve their personal difficulties” (difference = 0.800 between Asian American and White groups, with loadings of 0.535 and 1.33 respectively). These dramatic differences suggest that verbal encouragement to perform communication- and social-engagement-related activities does not reflect a unified construct across ethnic groups using these items. This may reflect distinct cultural frameworks around interpersonal learning activities and communication skills among the groups included in this study.

The Enterprising Performance Accomplishments scale failed configural invariance due to item “I have successfully persuaded people to do things my way” (loading difference = 0.156 between Native American and Asian American groups, with loadings of 0.398 and 0.530, respectively), indicating that performance in entrepreneurial activities does not reflect a unified construct across ethnic groups. This may suggest cultural variations in how achievement-oriented business and leadership activities are perceived and valued, potentially reflecting different cultural orientations toward individual versus collective success and risk-taking in entrepreneurial contexts.

Missing Data

To assess whether patterns of missingness were systematically associated with participant demographics, I conducted a series of chi-square tests of independence (see Table 5). For each variable used in the study, participants were classified as responders (provided data) or non-responders (missing data). Chi-square tests were then used to evaluate whether responder status was associated with participants' self-identified gender and racial/ethnic background. Cramér's V was used to estimate the effect size for each test. Results revealed several statistically significant associations between missingness and race/ethnicity. For example, responder status significantly differed by race/ethnicity for Educational Supports ($\chi^2(2) = 26.23$, $p < .001$, Cramér's $V = .17$), and for Perceived Supports in STEM ($\chi^2(2) = 11.73$, $p = .003$, Cramér's $V = .11$). Fewer variables showed significant associations with gender; however, responder status differed significantly by gender for Subtle Discrimination ($\chi^2(1) = 5.71$, $p = .017$, Cramér's $V = .08$). These results suggest that missing data may not be completely random, particularly with respect to racial/ethnic group membership, however the effect sizes were either negligible (<0.1) or weak (0.10 – 0.20; Lee, 2016).

Given these differential missingness patterns by ethnicity, group-stratified multiple imputation was employed using the MICE algorithm rather than pooled imputation to prevent bias that could occur if imputation models were dominated by response patterns from groups with more complete data. Imputation was conducted separately within each ethnic group using a single imputation per group (m = 1, maximum iterations = 50). Sensitivity analyses comparing group-stratified imputation with complete case analysis revealed that complete case analysis would have resulted in differential attrition by ethnicity, with 43.5% of Native American participants excluded compared to 32.6% of Asian American participants. Furthermore, complete cases showed systematically different outcome distributions compared to the full sample, confirming that missing data were not random and that listwise deletion would introduce selection bias. If listwise deletion were used, the analysis would have proceeded with 572 participants (61.6% of the original sample) rather than the full 928 participants that were retained through the imputation approach. This substantial loss of data (38.4% of cases) would have reduced statistical power and potentially introduced bias, particularly given that missingness patterns differed across ethnic groups, with Native American participants having the lowest complete case rate.

Analyses

Following imputation, the dataset was randomly divided into three parts using stratified sampling (ensuring equal representation of outcomes across groups): 60% for model training, 20% for model validation during development, and 20% for final testing. All predictor variables were standardized (converted to have a mean of 0 and standard deviation of 1) to ensure fair comparison across different measurement scales. Model performances for both validation and hold-out predictions are reported in Table 9. Confusion matrices for predictions on the hold-out dataset are reported in Tables 10-15. Statistics such as sensitivity, specificity, and balanced accuracy for optimal models predicting hold-out data are reported in Table 16. The results of feature selection and coefficients of predictors for each class are reported in Tables 17-22.

For the all-students sample ($N = 928$), the multinomial model and binary model 2 (no degree versus any degree) analyses included 593 participants in the training set (63.9%), 148 in the validation set (15.9%), and 187 in the hold-out set (20.2%). Binary model 1 (non-STEM versus STEM degree), which excluded participants without degrees, comprised 445 training participants, 111 validation participants, and 140 hold-out participants. The Native American subsample ($N = 352$) followed identical proportional splits, with 226 training participants (64.2%), 55 validation participants (15.6%), and 71 hold-out participants (20.2%) for the multinomial model and binary model 2 analyses. Binary Model 1 included 152 training participants (64.1%), 37 validation participants (15.6%), and 48 hold-out participants (20.3%).

Outcome distributions remained consistent across all dataset splits. In the all-students multinomial model, 25.0% of participants obtained no degree, 21.0% obtained a non-STEM degree, and 54.0% obtained a STEM degree. The Native American subsample showed different outcome patterns with 32.4% obtaining no degree, 24.6% obtaining a non-STEM degree, and 42.9% obtaining a STEM degree. Binary Model 1 exhibited class imbalance favoring STEM degrees at approximately 3:1 ratios across both populations (71.4% vs. 28.6% for all students; 63.2% vs. 36.8% for Native Americans). Similarly, Binary Model 2 demonstrated class imbalance favoring degree attainment, with ratios of 3:1 for all students (75.0% any degree vs. 25.0% no degree) and 2:1 for Native Americans (67.3% any degree vs. 32.7% no degree). The stratified sampling approach successfully maintained proportional outcome distributions across training, validation, and hold-out sets within each model, ensuring representative samples for model development and evaluation.

All Participants Model

Ridge ($\alpha = 0$), Lasso ($\alpha = 1$), and Elastic Net ($\alpha = 0.5$) models were trained to the data and evaluated using metrics such as accuracy, macro-averaged F1, multiclass log loss, and confusion matrices. These metrics are complementary and capture different aspects of predictive quality. Accuracy represents the proportion of correct predictions across all classes and provides an intuitive overall performance measure, though it can be misleading when class distributions are imbalanced (Sokolova & Lapalme, 2009). Macro-averaged F1 scores address this limitation by calculating precision and recall for each class separately, then averaging the resulting F1 scores across all classes, giving equal weight to performance on minority and majority classes regardless of their frequency in the dataset. This metric is particularly valuable in educational contexts where correctly identifying students in smaller outcome categories (e.g., those at risk for departure) may be as important as overall accuracy. Multiclass log loss (also called cross-entropy loss) measures the uncertainty in predictions by penalizing confident incorrect predictions more heavily than uncertain ones, with lower values indicating better calibrated probability estimates (Bishop & Nasrabadi, 2006; Hastie et al., 2009). Confusion matrices provide detailed diagnostic information by displaying the frequency of actual versus predicted classifications for each class, enabling researchers to identify specific patterns of misclassification and understand whether errors are systematic or random (Fawcett, 2006; Provost & Fawcett, 2013). Together, these metrics provide a comprehensive assessment framework that captures both overall performance and class-specific prediction quality, essential for developing reliable educational prediction systems where different types of errors may have varying practical consequences.

Of the models tested on the validation splits, Elastic Net ($\alpha = 0.5$) regression demonstrated the highest overall classification accuracy (56.08%, F1 = 48.80%), followed by

Ridge regression (56.08%, F1 = 47.15%) and Lasso (54.05%, F1 = 47.12%). When evaluated using macro-averaged F1 scores to account for class imbalance, Elastic Net regression maintained superior performance (F1 = 48.80%), while Ridge (F1 = 47.15%) and Lasso (F1 = 47.12%) showed comparable but lower balanced classification performance. Multiclass log-loss values indicated that Lasso (0.933) provided the best probability calibration, followed by Elastic Net (0.964) and Ridge regression (1.030).

Examination of confusion matrices revealed differential performance across outcome classes, with all models exhibiting bias toward predicting STEM degree completion (Class 2) due to the outcome distribution (54.1% of validation cases). Ridge regression showed sensitivity values of 21.6% for no degree completion, 45.2% for non-STEM degree completion, and 70.0% for STEM degree completion. Lasso regression demonstrated improved sensitivity for no degree identification (27.0%) and non-STEM degree completion (51.6%) while maintaining similar performance for STEM degree completion (71.3%). Elastic Net showed sensitivity values of 24.3% for no degree completion, 54.8% for non-STEM degree completion, and 71.3% for STEM degree completion. The models' tendency to over-predict STEM outcomes and under-predict both non-STEM completion and non-completion highlighted the challenge of accurately identifying students in minority outcome categories, particularly those at risk for departure from higher education.

Fine-grained hyperparameter tuning across alpha values from 0.00 to 1.00 (in increments of 0.05) revealed that $\alpha = 0.85$ achieved optimal performance (macro-F1 = 53.00%, accuracy = 56.76%), indicating that near-pure Lasso regularization was most effective. The relationship between regularization strength and model performance showed a complex pattern, with the highest performing models clustering in the $\alpha = 0.55$-0.95 range. A secondary performance cluster emerged around $\alpha = 0.80$ (macro-F1 = 49.54%), while intermediate alpha values (α = 0.30-0.40) showed moderate performance (macro-F1 ≈ 49.00%). Pure Ridge regression (α = 0.00) resulted in the poorest balanced performance (macro-F1 = 44.27%, accuracy = 53.38%), while pure Lasso regularization ($\alpha = 1.00$) achieved reasonable performance (macro-F1 = 47.09%, accuracy = 54.05%). This pattern suggests that aggressive feature selection through Lasso-dominated regularization was more effective than Ridge's approach of retaining all features, indicating that many of the predictors may contain redundant or less informative signals for degree completion prediction. The superior performance of high-alpha models supports the value of automatic feature selection in this educational prediction context, where a subset of carefully selected variables may provide more robust predictions than using all available measures.

Feature Importance and Interpretation

Analysis of Lasso regression coefficients identified 22 significant predictors from the original 63-variable set. The strongest predictor was intention to major in STEM ($\beta = 0.208$ for STEM completion, $\beta = -0.159$ for non-STEM completion), which showed the largest effect sizes and clearly distinguished between educational pathways. Artistic verbal persuasion ($\beta = 0.194$) emerged as the primary predictor of non-STEM degree completion, followed by social verbal persuasion ($\beta = 0.117$ for non-STEM).

Several demographic and background factors showed substantial effects. Asian American group membership demonstrated notable coefficients ($\beta = 0.131$ for STEM, $\beta = -0.102$ for no degree completion), while STEM interest showed a strong positive association with STEM degree attainment ($\beta = 0.146$). Academic preparation variables were influential, with the number of high school mathematics courses positively predicting STEM completion ($\beta = 0.083$) while negatively associated with non-completion (β = -0.067). Gender effects (i.e., Female group membership) were evident (β = -0.024 for STEM, β = 0.018 for non-STEM), reflecting documented participation disparities.

Self-efficacy constructs showed domain-specific patterns, with science self-efficacy facilitating STEM completion (β = 0.112) while deterring non-STEM pathways (β = -0.075). Additional significant predictors included various learning experience factors, science identity (β = -0.043 for non-STEM), and motivational variables like STEM activity interest (β = 0.032 for STEM), though with smaller effect sizes.

Based on the Ridge regression coefficients, several key predictors emerged as most influential in distinguishing between degree completion outcomes. Intention to major in STEM demonstrated the strongest overall effect (β = 0.024 for STEM, β = -0.024 for non-STEM), indicating that declared academic goals substantially influence persistence. STEM interest showed the second-largest effect (β = 0.022 for STEM), with students expressing interest in STEM fields and activities being significantly more likely to complete STEM degrees.

Academic background variables showed expected patterns, with number of high school mathematics courses serving as both a predictor of STEM degree attainment (β = 0.021) and a protective factor against non-completion (β = -0.018). STEM activity interest (β = 0.020 for STEM) and science self-efficacy (β = 0.019 for STEM, β = -0.018 for non-STEM) demonstrated domain-specific influences. Asian American group membership showed a notable negative association with no degree completion (β = -0.019) and a positive association with STEM completion (β = 0.019).

Learning experiences revealed domain-specific influences, with artistic verbal persuasion predicting non-STEM degree completion (β = 0.019), as well as social verbal persuasion (β =

0.018). Science identity followed expected patterns ($\beta = 0.018$ for STEM, $\beta = -0.019$ for non-STEM). Mathematics self-efficacy showed positive associations with STEM completion ($\beta = 0.018$), while female group membership reflected documented disparities ($\beta = -0.017$ for STEM, $\beta = 0.017$ for non-STEM).

The pattern of coefficients suggests that degree completion outcomes may be influenced by multiple interconnected factors, rather than a single dominant factor. Academic background, motivational clarity, domain-specific self-efficacy, and learning experiences likely operate as integrated systems that channel students into different educational pathways.

Based on the Elastic Net regression coefficients, feature selection identified 36 significant predictors from the original 63-variable set, representing a 43% reduction in model complexity while maintaining predictive performance. Intention to major in STEM emerged as the dominant predictor ($\beta = 0.220$ for STEM, $\beta = -0.166$ for non-STEM), demonstrating the strongest coefficient sizes and supporting the notion that declared academic goals serve as the primary determinant of educational pathway selection.

Artistic verbal persuasion learning experiences showed the second-largest effect ($\beta = 0.218$ for non-STEM), suggesting that students who received more verbal support to pursue artistic endeavors are strongly oriented toward non-technical academic fields. Social physiological arousal (e.g., “During school, I have felt uptight while working as a part of a small group.”) demonstrated a substantial effect on no degree completion ($\beta = 0.158$), while avoidance goal orientation showed a strong negative association with no degree completion ($\beta = -0.137$).

Academic and demographic factors played important roles, with Asian American group membership showing substantial effects ($\beta = 0.141$ for STEM, $\beta = -0.135$ for no degree), and number of high school mathematics courses predicting STEM completion ($\beta = 0.084$) as well as negatively predicting non-completion (β = -0.083). Self-efficacy constructs displayed domain-specific relationships, with science self-efficacy simultaneously promoting STEM completion (β = 0.127) and deterring non-STEM pathways (β = -0.101).

Additional significant predictors included past verbal encouragement for social activities (β = 0.129 for non-STEM), perceptions of individual mobility (β = 0.125 for STEM), and STEM interest (β = 0.111 for STEM). The effects of female group membership were moderate (β = -0.033 for STEM, β = 0.049 for non-STEM), while various learning experiences showed smaller but meaningful associations with different outcomes.

The results of the Elastic Net model's balanced approach between feature selection and coefficient shrinkage suggested that educational pathways are determined by a comprehensive set of motivational, experiential, demographic, and academic factors, with the model retaining more predictors than pure Lasso while still achieving substantial dimensionality reduction.

Binary Classification Models

To address the inherent complexity and interpretational challenges associated with three-class prediction, binary classification models were developed to examine specific educational transitions that may be more amenable to accurate prediction and practical intervention. Two distinct binary reformulations were created to capture different aspects of the educational pathway process: (1) non-STEM degree versus STEM degree completion among students who successfully completed any degree, focusing on field choice among degree completers, and (2) no degree completion versus any degree completion, directly addressing educational persistence and retention.

The first binary model examined STEM versus non-STEM degree completion using a subset of 445 training observations and 111 validation observations, excluding students who did not complete degrees. This reformulation addresses the question of academic field selection among students who persist in college, potentially offering insights into factors that differentiate STEM from non-STEM pathway selection. The second binary model utilized the full sample (593 training, 148 validation observations) to predict any degree completion versus departure, directly addressing educational retention and persistence concerns that are central to institutional effectiveness and student success initiatives.

STEM versus Non-STEM Degree Completion. The first binary classification model demonstrated substantially superior performance compared to multinomial approaches, achieving 77.48% accuracy and an F1 of 84.08% on validation data using class-weighted Elastic Net regularization ($\alpha = 0.20$). The training sample distribution showed 125 non-STEM degree completers versus 320 STEM degree completers. Class weighting was implemented to address this imbalance and ensure balanced sensitivity across both outcome categories.

Performance analysis revealed strong discriminative capability, with the model correctly identifying 66 of 80 STEM completers (sensitivity = 0.83) and 20 of 31 non-STEM completers (specificity = 0.65) in the validation sample. The confusion matrix demonstrated reasonable balanced accuracy (0.78), though with slightly higher sensitivity (0.83) than specificity (0.65), indicating some bias toward predicting STEM outcomes consistent with the training distribution.

Feature importance analysis revealed intention to major in STEM as the dominant predictor ($\beta = 0.431$), with coefficients indicating that higher STEM completion intentions were associated with STEM degree completion. Science self-efficacy emerged as the second most important predictor ($\beta = 0.298$), followed by perceived individual mobility ($\beta = 0.268$), demonstrating the importance of domain-specific confidence and personal agency in STEM pathway selection. Learning experience factors showed domain-specific patterns, with verbal social persuasion (β = -0.216) and past performance in entrepreneurial experiences (β = -0.195) predicting non-STEM completion, while vicarious investigative learning experiences (β = 0.089) were associated with STEM completion.

Additional significant predictors for STEM degree attainment included science identity (β = 0.212), verbal support for artistic learning experiences (β = -0.131), and beliefs that math abilities are fixed (β = -0.108). Academic preparation variables showed similar expected patterns, with the number of high school science (β = 0.075) and mathematics (β = 0.046) courses positively predicting STEM degree attainment. The effects of female group membership were modest (β = -0.071), while ethnicity group membership showed mixed patterns across different ethnic classifications.

Any Degree versus No Degree Completion. The second binary model, predicting any degree completion versus departure, achieved moderate performance with 71.62% accuracy and an F1 of 51.16% on validation data using pure Ridge regression. The training distribution showed 148 students with no degree completion versus 445 with any degree completion, representing a substantial class imbalance that was addressed through class weighting approaches. Despite these adjustments, the model showed more limited predictive capability compared to the STEM versus non-STEM classification.

Performance analysis revealed challenges in achieving balanced classification, with the model correctly identifying 22 of 37 non-completers (sensitivity = 0.60) and 84 of 111 degree completers (specificity = 0.76) in the validation sample. The moderate F1 score reflected difficulties in optimizing both precision and recall simultaneously, suggesting that degree completion versus departure involves more complex, multifaceted processes that may not be fully captured by the available predictor set.

Feature importance analysis identified a substantially smaller set of significant predictors compared to the STEM versus non-STEM model, with only five variables surviving Ridge regularization. Minority Asian American group membership emerged as the strongest predictor ($\beta = 0.158$), indicating positive associations with degree completion for this demographic group. The number of high school mathematics courses showed substantial positive effects ($\beta = 0.146$), supporting the importance of a mathematical foundation for college persistence regardless of degree field.

STEM interest demonstrated moderate positive associations with degree completion ($\beta = 0.068$), while number of siblings ($\beta = -0.047$) and physiological unease during social learning experiences ($\beta = -0.026$) showed negative associations with degree completion. The limited number of significant predictors suggests that educational departure may involve factors not adequately captured in the current measurement framework, or that departure processes operate through more complex, non-linear relationships requiring different analytical approaches.

Native American Only Model

Ridge regression ($\alpha = 0$), Lasso regression ($\alpha = 1$), and Elastic Net ($\alpha = 0.5$) models were trained on the Native American subsample and evaluated using comprehensive metrics including accuracy, macro-averaged F1 scores, and confusion matrices. These metrics provide complementary perspectives on model performance, with accuracy representing overall correct predictions and macro-averaged F1 scores addressing class imbalance by giving equal weight to performance across all outcome categories regardless of their frequency in the dataset.

Ridge regression demonstrated the highest overall classification accuracy (43.64%), followed by Elastic Net (40.00%) and Lasso regression (36.36%). The reduced performance of Native American models compared to the full sample reflects the inherent challenges of modeling educational outcomes within a smaller, more homogeneous population where predictor-outcome relationships may be attenuated or different from the broader population. When evaluated using macro-averaged F1 scores through alpha parameter optimization, Ridge regression maintained superior balanced performance (F1 = 42.50%), while models with higher alpha values showed progressively lower F1 scores, with Elastic Net ($\alpha = 0.5$) achieving an F1 of 32.70% and pure Lasso ($\alpha = 1.0$) achieving an F1 of 27.70%. Examination of class distributions revealed the challenges inherent in the Native American subsample, with training data containing 74 students with no degree completion, 56 with non-STEM degrees, and 96 with STEM degrees. This distribution pattern, combined with the smaller overall sample size, contributed to the reduced predictive accuracy compared to the full sample models.

Fine-grained hyperparameter tuning across alpha values from 0.0 to 1.0 revealed that $\alpha = 0.0$ (pure Ridge regression) achieved optimal performance for the Native American sample (macro-F1 = 0.4251, accuracy = 43.64%), contrasting with the full sample where near-pure Lasso regularization was most effective. The relationship between regularization strength and model performance showed a clear pattern favoring Ridge-dominated approaches, with $\alpha = 0.30$ providing secondary optimal performance (macro-F1 = 41.70%, accuracy = 45.45%). Performance declined systematically with increasing alpha values, with pure Lasso regularization ($\alpha = 1.0$) resulting in the poorest balanced performance (F1 = 27.70, accuracy = 36.36%).

This pattern suggests that for the Native American subsample, retaining all features through Ridge regularization was more effective than aggressive feature selection through Lasso regularization. The preference for lower alpha values indicates that the smaller sample size may require the retention of more predictors to capture the complex relationships governing educational outcomes, as aggressive feature selection may eliminate important but subtle signals that are crucial for accurate prediction in this population.

Binary Models

To address the challenges of multinomial classification in the smaller Native American sample, binary classification models were developed to examine specific educational outcome dichotomies. A binary model distinguishing STEM versus non-STEM completion among degree earners achieved substantially higher accuracy (81.80%, F1 = 86.80%) than the multinomial models, suggesting that this population exhibits clearer differentiation patterns when considering field choice among students who successfully complete degrees.

A second binary model predicting any degree completion versus no degree completion showed moderate performance (54.55%, F1 = 41.90%), indicating that factors distinguishing degree completion from non-completion may be more subtle or require different predictive approaches in this population. The superior performance of the STEM versus non-STEM binary model suggests that once Native American students successfully navigate initial college persistence challenges, their choice of academic field follows more predictable patterns based on the measured constructs.

Feature Importance. Analysis of Ridge regression coefficients ($\alpha = 0.0$) for the Native American sample revealed a complex pattern of predictors influencing educational outcomes. Intention to major in STEM emerged as the strongest predictor ($\beta = 0.025$ for STEM completion, $\beta = -0.028$ for non-STEM completion). Physiological arousal when performing investigative activities (e.g., "I have felt anxious while taking a science course in school.") showed substantial effects ($\beta = 0.023$ for non-STEM, $\beta = -0.014$ for no degree), suggesting that the extent to which individuals feel uneasy when engaging in scientific learning experiences is particularly influential for Native American students' educational pathways.

Perceived individual mobility demonstrated notable predictive power ($\beta = 0.022$ for STEM completion, $\beta = -0.018$ for no degree completion), potentially reflecting the importance of social mobility considerations that may be especially relevant for Native American students navigating educational systems. Science self-efficacy showed domain-specific patterns ($\beta = 0.022$ for STEM, $\beta = -0.022$ for non-STEM), while past performance in investigative learning experiences influenced persistence ($\beta = 0.016$ for STEM, $\beta = -0.021$ for non-STEM).

Verbal encouragement to engage in artistic pursuits in one's past predicted non-STEM completion ($\beta = 0.020$), and effects of female group membership were evident ($\beta = -0.018$ for STEM, $\beta = 0.019$ for non-STEM), reflecting broader participation patterns. Tribal engagement showed interesting effects ($\beta = -0.015$ for STEM), suggesting complex relationships between cultural connection and educational pathway selection that warrant further investigation.

The pattern of coefficients for the Native American sample indicates that educational outcomes are influenced by a complex interplay of academic preparation, cultural factors, learning experiences, and individual characteristics, with some predictors showing different patterns of influence compared to the broader population. The retention of numerous predictors in the optimal Ridge model suggests that educational pathway prediction in this population requires consideration of multiple, potentially subtle factors rather than relying on a small set of dominant predictors.

Comprehensive Model Comparison and Final Evaluation

Cross-Sample Performance Analysis

Comparative analysis between the full sample and Native American subsample revealed important differences in model performance and optimal regularization approaches. The full sample models demonstrated superior overall performance, with the best multinomial model achieving 56.08% accuracy and an F1 of 48.80%, compared to the Native American subsample's best multinomial performance of 43.64% accuracy and an F1 of 42.50%. This performance differential of approximately 13.5 percentage points reflects the inherent challenges of modeling educational outcomes within smaller, more homogeneous populations where predictor-outcome relationships may be attenuated or exhibit different patterns compared to the broader population.

Binary classification models showed more consistent performance across samples, with both populations demonstrating strong capability for distinguishing STEM versus non-STEM pathways among degree completers. The full sample achieved 73.87% accuracy (F1 = 81.50%) for STEM versus non-STEM classification, while the Native American subsample achieved 81.08% accuracy (F1 = 86.80%), representing a more modest 7.2 percentage point difference. This pattern suggests that field choice decisions among successful degree completers follow more universal patterns that transcend population-specific factors, while overall degree completion involves more complex, population-sensitive dynamics.

Degree completion prediction (any degree versus no degree) showed more extreme performance differences, with the full sample achieving 71.62% accuracy (F1 = 51.16%) compared to 54.55% accuracy (F1 = 41.90%) for the Native American subsample. The 17.1 percentage point difference indicates that persistence factors may operate differently across populations, potentially reflecting different support systems, institutional experiences, or cultural considerations that influence educational persistence patterns.

Feature Selection Convergence and Divergence

Analysis of predictor selection patterns across models revealed substantial overlap between full sample and Native American models, with 43 variables (74.1%) appearing as significant predictors in both models. This convergence suggests that core educational outcome determinants may operate consistently across populations. Variables showing consistent importance included intention to major in STEM, science self-efficacy, gender, various learning experience factors, number of high school math and science courses, and motivational constructs (i.e., interest in STEM).

Independent Hold-Out Evaluation

Final model validation using an independent hold-out dataset (n = 187) provided a definitive performance assessment across multiple modeling approaches. The hold-out sample maintained similar distributional characteristics to the training data, with 47 students (25.1%) completing no degree, 40 students (21.4%) completing non-STEM degrees, and 100 students (53.5%) completing STEM degrees, ensuring robust evaluation conditions.

The 3-class optimal multinomial model for all students achieved 56.15% accuracy with an F1 of 53.00% and log-loss of 0.975 on the hold-out data, demonstrating reasonable overall performance but with limitations in balanced classification across outcome categories. The 3-class optimal multinomial model for Native American students achieved 46.79% accuracy with an F1 of 41.58% and log-loss of 1.055 on the hold-out data, demonstrating poor overall performance and limitations in balanced classification across outcome categories. Performance for each model was concentrated in predicting the majority STEM completion class, with reduced sensitivity for minority outcome categories, particularly students who did not complete degrees.

Binary classification approaches demonstrated superior performance on the hold-out data, with the STEM versus non-STEM model for all students achieving the highest overall performance (72.14% accuracy, F1 = 79.80). This model showed strong discriminative capability, correctly identifying 78 of 100 non-STEM completers (sensitivity = 0.78) and 24 of 40 STEM completers (sensitivity = 0.600). The binary STEM versus non-STEM model also achieved the best performance among models for Native American students (68.75% accuracy, F1 = 79.80%). The balanced performance across both outcome categories for these models supports the practical utility of a more narrow educational path perspective for obtaining educational insights. The any degree versus no degree binary model achieved moderate performance (60.43% accuracy, F1 = 41.30%), with 29of 47 non-completers correctly identified (sensitivity = 0.553) and 87 of 140 degree completers correctly identified (specificity = 0.621). While performance was adequate, the moderate F1 score indicates challenges in achieving optimal balance between sensitivity and specificity for this outcome distinction.

Feature Importance in Optimal Models

The models in the present study used standardized predictors, thus each coefficient represents, for each increase in standard deviation of the predictor, the change in log-odds of that outcome category relative to the reference category ("No Degree" category in multinomial models, "Non-STEM degree" for binary model 1 and "No Degree" for binary model 2). The log-odds in this context are the natural logarithm of the odds ratio predicting that outcome. Therefore, a coefficient of 0.5 indicates the log-odds of that outcome increase by 0.5 when the predictor increases by one standard deviation. To convert this to odds, you exponentiate the coefficient (raise the mathematical constant e to the power of the coefficient) which "undoes" taking the natural logarithm. This results in $e^{0.5}$ and is equal to approximately 1.65, which means the odds are multiplied by 1.65, making the outcome approximately 65% more likely. However, a direct comparison of coefficient magnitudes across models, as one may compare traditional beta coefficients in standard regression models, is inappropriate because each elastic net model determines its optimal penalty strength through cross-validation. Different penalty strengths result in different amounts of shrinkage applied to coefficients, even when underlying relationships are identical. Thus, coefficients reflect both the true underlying relationship and the model-specific regularization process. Instead of comparing absolute coefficient values, one should focus on the rank-order of predictor importance within each model, as consistent rankings across different samples suggest robust effects that provide more meaningful insights into which factors are most important for predicting outcomes.

Coefficient analysis of the best-performing models on hold-out data revealed consistent patterns of predictor importance across different modeling approaches. In the 3-class original model for all students, intention to major in STEM emerged as the dominant predictor ($\beta = 0.220$ for STEM completion, $\beta = -0.159$ for non-STEM completion), reinforcing the central role of academic goal clarity in educational pathway determination. STEM interests showed the second-largest effect ($\beta = 0.144$ for STEM completion), followed by verbal encouragement to engage in artistic pursuits ($\beta = 0.209$ for non-STEM completion), indicating the importance of both students' interests in STEM topics for technical field attraction, and prior encouragement to engage in artistic pursuits for non-technical field attraction. STEM major intention remained the dominant predictor in the Native American multinomial model ($\beta = 0.025$ for STEM completion, $\beta = -0.028$ for STEM completion). Unique predictors for STEM degree attainment emerged for this population including perceived individual mobility ($\beta = 0.022$ for STEM completion), science self-efficacy ($\beta = 0.022$ for STEM completion), and tribal engagement ($\beta = -0.015$ for STEM completion). Predictors of non-STEM degree attainment for this population included prior discomfort with investigative learning experiences ($\beta = 0.023$ for non-STEM completion), and prior encouragement to engage in artistic pursuits ($\beta = 0.020$ for non-STEM completion). Additionally, an important predictor for obtaining no degree in this population was desire to find a local job ($\beta = 0.017$ for no degree completion).

The binary STEM versus non-STEM model revealed more focused predictor patterns. For all students models and Native American models, intention to major in STEM showed the strongest effect (all students $\beta = 0.152$, Native American students $\beta = 0.450$), followed by science self-efficacy (all students $\beta = 0.098$, Native American students $\beta = 0.199$). All students models also suggested science identity ($\beta = 0.090$), STEM interests ($\beta = 0.063$), and gender ($\beta = -0.055$) were key predictors of STEM degree attainment over non-STEM degree attainment. The second binary model predicting degree attainment versus non-completion suggested that for all students, ethnicity ($\beta = 0.028$ for Asian American identity, $\beta = -0.021$ for Native American identity), number of high school math classes ($\beta = 0.026$), STEM interests ($\beta = 0.019$), and number of siblings ($\beta = -0.017$) were most important. The second binary model for Native American students specifically revealed that perceived individual mobility ($\beta = 0.085$), desire to find a local job ($\beta = -0.075$), being in a relationship ($\beta = -0.070$), having had discomfort with investigative learning experiences ($\beta = 0.054$), and tribal engagement ($\beta = -0.035$) were most informative for predicting attainment of any degree versus non-completion. The positive relationship between discomfort experienced in investigative pursuits was notable. It may reflect a generally stronger engagement with learning, as opposed to apathy, which, while linked in other models to deciding to complete a non-STEM major, may relate overall to an underlying factor that contributes to persistence in college.

Discussion

Using a sample of Native American, Asian American, and White undergraduate STEM majors, the present study applied machine learning approaches to predict degree outcomes using predictors from the Social Cognitive Career Theory (SCCT). The findings of the present study address critical gaps in understanding STEM degree attainment disparities, particularly for Native American students who consistently show the lowest levels of college enrollment and completion in STEM disciplines (De Brey et al., 2019). The results demonstrate the promise and limitations of regularized regression techniques for degree outcome prediction, reveal important insights regarding the SCCT framework, and offer novel information about potential population-specific factors influencing student success in STEM. These findings present a significant advancement in using SCCT to address the national priority of cultivating a skilled STEM workforce (Trapani & Hale, 2022).

As mentioned previously, it is essential to note that the outcome category of obtaining no degree is more accurately described as not obtaining a degree at this particular university. Participants who departed the university before obtaining a degree may have completed a STEM or non-STEM degree at a community college, regional college, or a different university. The results, therefore, regarding predictors of departure from the university should not be interpreted as directly predicting failure to obtain a degree. Instead, these results should be considered as predictors of departing from the university from which the data in the present study were collected and could reflect transferring to a different school to complete a degree, a temporary pause in education that extended beyond six years from their time of initial enrollment, or a decision to not continue pursuing a degree in general.

Regularization Performance and Educational Prediction

The systematic comparison of regularization approaches revealed nuanced patterns in predictive performance that offer important insights for educational data modeling and institutional resource allocation. The performance of machine learning models in terms of accuracy does not have standard thresholds defined in the literature. Some educational studies achieve remarkable accuracy (i.e., 100%) when using artificial neural nets to predict GPA terciles, academic retention, and degree completion via predictors such as coping and learning strategies, cognitive factors, and social support (Musso et al., 2020). However, using accuracy as a way of evaluating models is considered to be misleading, as this metric is highly swayed by the proportion of cases in each outcome category (Varoquaux & Colliot, 2023). Balanced accuracy is better when there is class imbalance; however, a high balanced accuracy does not directly suggest that a model will be informative about the general population, especially when the prevalence of the case that it is detecting is low. Thus, researchers agree that the performance of models must be judged based on their intended uses (Varoquaux & Colliot, 2023). Considering the lack of clarity regarding performance metrics in a vacuum, some educational researchers have used a baseline as a metric by which to evaluate the performance of their models (Zohair & Mahmoud, 2019). That is, one can judge the performance of a machine learning model based on whether the accuracy for predicting a given outcome is better than if one were to simply randomly categorize participants according to the base-rate of each outcome's occurrence in the sample. For the present study, the accuracies for predicting each outcome may seem modest or poor for predicting a given outcome, however the class accuracies of each model were indeed better than if one were to randomly categorize students according to the base-rate of the outcome categories.

The multinomial models achieved moderate accuracy (58.29% on holdout data for all students), representing a meaningful but modest improvement over baseline predictions (4.8 percentage points above the 53.5% accuracy one would achieve if always predicting the most frequent class). The macro-F1 score of 0.53 suggested reasonably balanced performance across outcome classes. The model showed limited sensitivity for minority classes (44.68% for no degree and 45% for non-STEM degree outcomes) and performed better for STEM degree identification (70.0% sensitivity). This level of performance, while statistically meaningful, aligns with the multifaceted nature of educational decision-making during undergraduate years, where numerous unmeasured factors, including family circumstances, economic changes, and life events, can substantially influence student pathways (Foltz et al., 2014). The 58-60% accuracy range is understandable for complex behavioral outcomes in educational prediction research, where potential changes over six years add substantial complexity. These findings support previous research emphasizing that earning a STEM degree represents success over multiple obstacles that STEM majors encounter during college, making prediction challenging but critical for institutional investment decisions.

The Native American multinomial analysis revealed substantially greater challenges in educational outcome prediction, with the optimal multinomial model (Ridge regression, $\alpha = 0.0$) achieving 46.48% accuracy on holdout data compared to a 42.25% modal baseline for STEM degree completion. This modest 4.23 percentage point improvement, while representing a relative improvement over baseline, likely reflects the complex intersection of cultural, academic, and personal factors influencing Native American students' educational pathways that may not be adequately captured by traditional SCCT measures. The macro-F1 score of 0.42 indicated challenges in achieving balanced classification across outcome categories, with particularly poor sensitivity for no degree completion (8.7%) and moderate performance for non-STEM degree identification (61.1%), while achieving reasonable sensitivity for STEM degree completion (66.7%). The substantially lower predictive accuracy compared to the full sample (46.48% vs. 58.29%) suggests that educational outcomes in this population involve factors beyond those measured in conventional frameworks, supporting research indicating that tribal identity, community obligations, and cultural values play critical roles in educational decision-making that may conflict with western or individualistic academic models (Windchief & Brown, 2017). The preference for Ridge regularization, which retained all predictors rather than selecting a subset, suggests that comprehensive, multifaceted perspectives that consider cultural, academic, and personal factors simultaneously may be more effective than those focused on a more narrow set of predictors for supporting Native American student success.

Binary Versus Multinomial Classification

The superior performance of binary classification models, particularly the STEM versus non-STEM distinction for all students (72.14% accuracy, F1 = 0.80) and Native American students (68.75% accuracy, F1 = 0.76), represents a fundamental insight about educational prediction that has potential implications for university support systems. These models' improvement over multinomial approaches indicates that specific pathway choices among degree completers follow patterns more fully captured by the SCCT framework than do broader questions that include university persistence. The finding supports the SCCT model's original purpose, such that students' academic interests, goals, and actions operate through the more proximal and measurable mechanisms of the framework. While the model may be a useful guide for understanding the factors influencing students during college, it was not constructed to fully capture the complex array of factors influencing educational departure.

This pattern of results aligns with research emphasizing that persistence in STEM is not solely a matter of academic or financial resources but also relates to students' sense of belonging, self-efficacy, and availability of support systems (Lent et al., 2013). The superior performance of binary models may suggest that universities implementing targeted interventions such as mentoring programs, research opportunities, and inclusive curricula should focus on field choice guidance for students who have successfully navigated initial persistence challenges, while developing separate intervention strategies for retention issues.

Population-Specific Regularization Strategies and Cultural Responsiveness

The differential effectiveness of regularization approaches across populations represents a key methodological finding with important implications for culturally responsive educational support. The full sample's optimal performance with near-pure Lasso regularization ($\alpha = 0.85$) indicates that more aggressive feature selection was more effective than retaining all predictors, suggesting substantial redundancy among the SCCT variables for diverse populations. Conversely, the Native American subsample's optimal performance with pure Ridge regression ($\alpha = 0.0$) reveals a fundamental difference in how educational outcomes are structured within more homogeneous populations.

The findings for the Native American population support prior research indicating that tribal identity and community values play critical roles in educational choices, such that many Native students express desires to pursue careers allowing them to give back to their communities (Windchief & Brown, 2017). The preference for Ridge regularization in the Native American sample likely reflects the complex intersection of cultural, academic, and personal factors influencing educational choices for this population. Cumulative information across multiple domains provides essential predictive value that would be lost through aggressive feature selection, or focusing on only the most important predictors. This finding supports calls for multifaceted approaches that include improving educational access, creating inclusive learning environments, and fostering cultural competence among educators (Byars-Winston & Rogers, 2019).

SCCT Framework Validation and Theoretical Implications

The machine learning analysis provides empirical support for core SCCT constructs while revealing important nuances about their predictive utility in educational contexts, particularly addressing the limited research on SCCT applications to Native American populations.

Intention and Goal Clarity as Central Mechanisms

Intention to major in STEM emerged as the strongest predictor across all models, with particularly pronounced effects in binary STEM versus non-STEM classification in the all students model ($\beta = 0.152$) and the Native American only model ($\beta = 0.450$). These findings provide robust empirical support for SCCT's emphasis on goal crystallization and intention formation as proximal determinants of career behavior (Lent et al., 1994). The large coefficients reflect the importance of early academic and career planning in shaping educational trajectories. This supports findings of previous research on the positive relationships between self-efficacy and interests, intentions, and persistence in STEM (Byars-Winston & Fouad, 2008).

However, the prominence of major intention also highlights important limitations in current applications of SCCT to educational persistence, as well as the present study. Students' intentions may not remain stable during their academic career. Challenges of rigorous coursework, cultural barriers, or institutional obstacles may lead to fluctuations in their intention to pursue a STEM degree or their belief in the attainability of that goal for themselves. The present study does address the limitation in existing research, whereby focusing on pre-college experiences does not fully capture how STEM education trajectories develop into STEM careers or STEM degrees (Fouad et al., 2002). The results of this study suggest that intentions remain most important for STEM achievement for all STEM majors, even when considered alongside many other SCCT constructs, but additional research is needed to fully understand the complex processes leading to educational departure for STEM majors.

Self-Efficacy and Learning Experiences

The consistent importance of domain-specific self-efficacy variables across models validates SCCT's emphasis on confidence beliefs as mediating mechanisms. Science self-efficacy demonstrated substantial effects in STEM completion prediction for all students (β = 0.019 in multinomial models, β = 0.098 in binary models) and Native American models (β = 0.022 in multinomial models, β = 0.199 in binary models), supporting social cognitive theories about the role of domain-specific confidence in academic achievement. The domain specificity of these effects, with science self-efficacy predicting STEM outcomes and math self-efficacy showing similar (albeit weaker) effects, supports SCCT's theoretical emphasis on construct specificity rather than generalized academic confidence.

Learning experience variables showed interesting patterns, with prior verbal encouragement for artistic pursuits strongly predicting STEM degree completion in the multinomial model for all students (β = .022) but predicting non-STEM degree completion in the multinomial Native American model (β = .020). This finding must be interpreted in the context of the differential measure functioning revealed in the measurement invariance analyses, as the measure may reflect unique constructs for Native American students as opposed to White or Asian American students. Several items showed markedly different factor loadings, namely "People whom I respect have encouraged me to play a musical instrument" (Native American = 0.434, Asian American = 0.375, White = 0.275), "Teachers whom I respect have encouraged me to take an art class" (Native American = 0.285, Asian American = 0.486, White = 0.438), "Family members have urged me to learn how to sing" (Native American = 0.667, Asian American = 0.759, White = 0.550), and "While growing up, adults whom I admired told me that it is important to be a good writer" (Native American = 0.266, Asian American = 0.412, White = 0.271). It may be that White, Asian American, and Native American individuals grow up with very distinct cultural relationships to art or verbal encouragement to engage in learning experiences in general, making the broad concept of "being verbally encouraged to pursue art" not consistent across groups. Thus, the findings related to this predictor can be interpreted such that increases in potential unmeasured constructs that relate to more frequent experiences of prior encouragement to engage in artistic pursuits (e.g., involvement of parents in decisions of students' extracurriculars, importance of artistic pursuits in general within one's school or family, engagement in artistic activities in general, etc.) are important for predicting the outcome in question.

Investigative learning experiences influenced STEM pathways for Native American students such that prior experiences of distress during investigative learning experiences predicted non-STEM degree attainment for Native American students ($\beta = .023$) and prior experiences of success in the same experiences predicted STEM degree attainment ($\beta = .016$). These findings provide empirical support for SCCT's emphasis on experiential learning as a foundation for interest and efficacy development (Lent et al., 2018). However, the interpretation of Investigative Physiological Arousal requires important qualification based on measurement invariance findings as well. Investigative Physiological Arousal failed configural invariance testing (CFI = 0.977, RMSEA = 0.097) due to poor overall model fit across all ethnic groups, rather than differential functioning. Diagnostic analysis revealed that no items showed factor loading differences exceeding 0.10, indicating fundamental structural problems with the five-item scale rather than group-specific measurement bias. While this measure and verbal encouragement to engage in artistic pursuits emerged as predictors in the models, their inclusion remains justified because the machine learning analyses focused on individual-level prediction rather than direct mean comparisons across ethnic groups. These variables should be interpreted as reflecting individual differences in reported experiences rather than coherent latent constructs, with coefficients capturing meaningful variation in self-reported learning experiences while acknowledging that the psychological meaning of these experiences may differ substantially across ethnic groups and that the measures do not represent well-defined unidimensional constructs.

Academic Preparation as Foundation

The consistent importance of academic preparation variables, particularly high school mathematics courses, validates decades of research on academic readiness while demonstrating how SCCT constructs interact with structural factors. The positive association between mathematics participation and STEM completion for all students in the binary model ($\beta = 0.023$) likely reflects both the gatekeeping function of mathematical preparation and its role in building foundation skills necessary for STEM success.

This finding may also address documented barriers faced by Native American students, who often have less access to advanced coursework, particularly in rural or reservation schools

(Betz, 2007). These results suggest that addressing structural inequalities in educational access represents a critical intervention point for improving Native American STEM participation, supporting research indicating that students who take more advanced math and science courses in high school are more likely to pursue and persist in STEM degrees (Shoffner & Dockery, 2015; Tyson et al., 2007).

Framework Limitations for Persistence Prediction

The moderate performance of degree completion prediction models (F1 = 0.41) suggests important limitations in applying SCCT constructs to educational persistence. The framework, originally developed for understanding career decision-making, may not adequately capture the complex array of factors influencing student departure, including financial pressures, family obligations, health issues, and institutional fit. This finding addresses the noted gap in identifying specific predictors of graduation with a STEM degree and suggests that persistence prediction may require integration of SCCT constructs with retention-focused theoretical frameworks that emphasize institutional factors, social integration, and academic engagement.

Native American Cultural Considerations and Universal Factors

The population-specific analysis revealed both universal and culturally distinct factors influencing Native American students' educational pathways, directly addressing the largest disparities in STEM degree attainment and the limited research on this population.

Reduced Predictive Accuracy and Complex Determination

The substantially lower predictive accuracy for Native American students compared to the full sample (46.48% versus 58.29% for multinomial models, 68.75% and 59.15% versus 72.14% and 60.43% for binary models) suggests that educational outcomes in this population may be influenced by factors not adequately captured by traditional SCCT measures. This finding aligns with research emphasizing cultural disconnects, limited access to resources, and the absence of representation in STEM fields that contribute to lower participation rates among Native American students (Reyes & Shotton, 2018). The results support the need for further research that explores factors contributing to STEM disparities for Native American students, addressing the limitation of low sample sizes that often result in exclusion from analyses or aggregation into broader racial groups (Shotton et al., 2013).

The preference for Ridge regularization, which retained all predictors rather than selecting a subset, indicates that Native American students' educational decisions involve complex interactions among multiple factors rather than being driven by a few dominant influences. This pattern supports research suggesting that strong tribal identity may create both opportunities and challenges as students navigate the often individualistic and competitive culture of higher education institutions, particularly in STEM fields (Waterman, 2012).

Universal Versus Culture-Specific Predictors

The substantial overlap in predictors between the all-students and Native American models provides evidence for universal factors in educational success while demonstrating the value of culturally informed approaches. Core SCCT constructs, such as STEM intention, science self-efficacy, and academic preparation, operated consistently across populations, supporting the cross-cultural validity of fundamental social cognitive principles.

However, the influence of culture-specific predictors provides empirical support for theories emphasizing the importance of cultural connection in Indigenous student success. Tribal engagement, which showed a slight negative effect on earning a degree, represents a culturally specific factor that models with only constructs for all students would miss. The particular influence of physiological arousal during investigative activities for Native American students suggests that comfort and anxiety in scientific learning environments may be especially important considerations for this population, potentially reflecting experiences with culturally incongruent educational environments and the culture shock often experienced in predominantly White universities (Gloria & Robinson Kurpius, 2001; Waterman, 2012).

Individual Mobility and Cultural Values

The prominence of perceived individual mobility as a predictor in the Native American model highlights the intersection of educational choices with broader social mobility considerations and community responsibilities. This finding aligns with research indicating that Native American students' desire to "give back" to their communities can conflict with the individualistic focus of STEM disciplines, which often emphasize personal achievement over communal benefits (Khupe, 2014). The complexity of these relationships underscores the need for culturally informed support approaches that acknowledge the intersection of individual aspirations with community responsibilities.

The results suggest that addressing the cultural disconnect between more communal values of Native American communities and the values espoused in many STEM programs continues to represent a potential area in need of positive tools and resources for institutions. Programs designed to foster a sense of belonging and respect for tribal identity, as well as those offering mentorship and community support, have been shown to improve retention rates for Native American students in higher education (Khupe, 2014; Windchief & Brown, 2017). The findings of the present study suggest the same factors may be influential for STEM majors specifically.

Implications for STEM Participation and Workforce Development

The results of this study suggest that efforts to increase Native American STEM participation, critical for addressing disparities that may impede progress toward economic equity (Chen, 2013; US Department of Commerce, 2011), should consider both universal factors (academic preparation, self-efficacy development, interest cultivation) and culturally specific influences (community connection, cultural identity, learning environment comfort). The superior performance of binary field choice models compared to persistence models suggests that Native American students who have the resources to successfully navigate the challenges that may lead to departure will persist in STEM according to more predictable patterns based on SCCT constructs.

These results have implications for maximizing the quality of STEM graduates and addressing concerns that potential talent in underrepresented groups is underutilized (Olszewski et al., 2024). The findings support the development of positive tools and resources for universities that promote the acknowledgment of Native American STEM students' experiences. Such resources may include specialized support for new STEM students from this population. These resources should focus on providing Native American STEM students with information and resources to promote their beliefs in their ability to achieve a STEM degree at the university, as well as promote their beliefs in their ability to perform science. There could also be a benefit to having discussions of the potential influence of past investigative learning experiences and the potential for a more communal or collective motivation to pursue STEM fields.

Methodological Contributions and Future Directions

This study demonstrates several methodological advances with implications for educational research and practice. First, the present study addresses the gap in data linking SCCT variables to graduation outcomes. Additionally, the present study incorporates many SCCT predictors simultaneously without the typical threats to validity and generalizability that come with including the same number of predictors in more typically used analyses, such as standard regression. The systematic comparison of regularization approaches revealed that optimal prediction strategies vary across populations, suggesting that variable selection methods should be tailored to population characteristics and research contexts. The substantial performance improvements achieved through binary classification suggest that more focused models provide more actionable and accurate prediction systems, potentially because they align better with the psychological processes underlying specific educational transitions that the SCCT was designed to capture.

Limitations

The moderate predictive accuracy achieved across models suggests that additional variables beyond SCCT constructs—such as detailed financial circumstances, family dynamics, institutional characteristics, and cultural factors—could improve model performance and practical utility. The framework's stronger performance for field choice prediction compared to persistence prediction indicates the need for theoretical integration with retention-focused models that emphasize institutional and environmental factors. Additionally, the present study only captured cross-sectional data due to limited overlap in when participants completed each measure. A larger study that focuses not only on STEM majors may be able to incorporate the longitudinal effects of the predictors used in this study. The present study also employed a single imputation method for missing data due to computational limitations, which is not as robust as creating multiple imputed datasets, running the same models for each dataset, then pooling the results to obtain standard errors. While efforts were made to ensure the single imputation considered the nuances of the dataset and was sufficiently stable, a proper multiple imputation approach would strengthen the estimates obtained in this study. Lastly, some predictors were found not to be invariant across ethnic groups, which presents concerns for group comparisons of these variables. While no direct mean comparisons were made in the present study, and the variables at issue were not traditional latent constructs, these measures could be improved in future studies to ensure invariance across groups.

Despite these limitations, the findings demonstrate that machine learning approaches can effectively identify systematic patterns in educational outcomes, revealing both universal and population-specific factors that influence student success. The results provide the first empirical evidence linking SCCT variables to graduation outcomes for Native American college students, addressing a critical gap in the literature. The study provides valuable insights for developing institutional tools and resources to support the success of Native American students in STEM, ultimately contributing to educational policies and practices that may enhance outcomes for other underrepresented groups.

The results support the continued development of data-informed support systems while emphasizing the importance of culturally responsive approaches that acknowledge the complex intersection of individual, academic, and cultural factors in educational achievement. For universities investing significantly in admitting undergraduates, these findings provide guidance on where to direct resources for maximum effectiveness in promoting student achievement and addressing the national priority of cultivating a skilled STEM workforce capable of addressing complex global challenges.

Conclusion

The results of these analyses provide novel contributions to the SCCT literature. Primarily, these results are the first to simultaneously analyze the influence of SCCT factors on students’ career and degree pathways. The results support that students’ intention to earn a degree in STEM is the most influential factor in their STEM degree attainment. Even when considering many other SCCT components, students who strongly endorsed the items “I intend to major in a STEM field,” “I think that earning a bachelor’s degree in STEM is a realistic goal for me,” and “I am fully committed to getting my college degree in STEM” were much more likely to go on to obtain a STEM degree. Moreover, the lackluster performance of models that incorporate students who earned no degree support the notion that the decision to exit college is nuanced and not fully captured by components of the SCCT. Thus, these results support the utility of the SCCT framework for understanding persistence in a given academic domain, but less so for persistence in college in general. The reasons why students exit their university before obtaining a degree are likely nuanced and include many economic, social, and personal factors not captured in the present study or SCCT framework in general.

The role of Science Self-Efficacy also emerged as a meaningful predictor of STEM degree obtainment for all students and Native American students. This supports prior SCCT literature on the influence of self-efficacy on STEM persistence, however the present study provides novel insight into the direct influence of this construct on domain achievements. In the SCCT framework, self-efficacy influences performance and achievement via its effects on interests, goals, and actions. The results of the present study suggest that science self-efficacy is an important factor on its own in predicting domain performance and attainment for STEM. Science self-efficacy may have an effect on STEM major intentions which are the largest contributor to STEM degree attainment, however their co-occurrence in the regression models suggest that both factors contribute in uniquely meaningful ways to the final outcome.

While the results of the best model for all students (binary non-STEM vs STEM) suggest that 18 SCCT factors contribute meaningfully to STEM degree attainment, the Native American only model revealed only two meaningful predictors. These results may be due to the smaller sample size of the Native American subsample, however they also support the dominance of STEM major intentions and science self-efficacy even for this unique, understudied population. These findings have implications for researchers and practitioners seeking to develop positive tools and resources for Native American STEM majors. Specifically, the most meaningful determinants of persistence and success in STEM degree fields are students' intentions and commitment to earning the degree, as well as their beliefs in their own science ability. While these have been known to be important factors for predicting STEM success, the present study highlights these factors as especially influential above and beyond any potential antecedents or consequences of these constructs. Thus, the focus for future research should be the determinants of STEM major intention and science self-efficacy in order to understand how to best support Native American student achievement in STEM.

Overall, while this study provides essential information regarding degree path persistence for Native American undergraduate STEM majors, the findings related to this population suggest a few critical considerations before conclusions can be drawn. First, university is where students learn the most information about their chosen degree path which allows them to make informed decisions about the degree they want to pursue. Therefore, students who choose to major in STEM fields by their second year of college but ultimately depart from that degree path are not failing to obtain some universally desirable outcome. Rather, these decisions likely reflect a growth in students' knowledge and awareness of the careers that follow certain degrees and the fit those individuals perceive they have with certain fields. This fact provides critical context to the findings regarding tribal engagement negatively predicting STEM degree attainment and desire to find a local job predicting departure from the university for Native American undergraduates.

It may be that the central role that Native American students' tribal communities play relates to an increased desire to obtain a degree that will benefit their communities. During college, these students may learn up-to-date and crucial information that informs them about the jobs needed in their communities and the degree paths that lead to those jobs. Native American undergraduates may learn that STEM pathways are not ideal for serving themselves or their communities in some cases. Students who are deeply engaged with their tribal communities may, in turn, shift out of STEM degree fields to pursue pathways that are more beneficial for them or their communities. Additionally, Native American students' desire to find a local job may drive departure from the university, not because of family demands that impact college persistence, but rather because they transfer to other universities that are closer to their home. The results of these two variables should not be interpreted as information about obstacles to STEM achievement, but rather as important areas for future research into how STEM degree pathways in college may not satisfy the needs of Native American students or their communities. Studies should seek to identify the relationships between tribal engagement as well as desire to find a local job and the perceptions of STEM fields. Information about how the centrality of Native American students' cultural roots and their physical homes influences the importance that students place on STEM degree paths can provide crucial insights into how STEM fields are positioned in Native American communities. It must be known whether there is truly a potential for STEM degree pathways to benefit Native American communities, and if so, what knowledge, tools, or resources must institutions provide for Native American students to allow them to make the best decisions possible for their education and the well being of their communities.

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Table 1.

Measures of SCCT components and surveys in which measures occur

SCCT Component	Measure	Pre-A	B	A
Person Inputs	Socioeconomic Status and Parental Education	X		
	Goal Orientation	X		
	Implicit Theories of Math and Science Ability	X		X
Background Contextual Affordances	Previous Math and Science Courses	X		
	Tribal Engagement	X	X	X
	Concern with Finding Job Locally		X	
	Family Structure and Dependency	X		
	Family and Community Attitudes Toward Education		X	
	Subtle Discrimination		X	X
	Explicit Discrimination Towards Native Americans		X	
	Non-Discriminatory Campus Climate			X
	Incivility			
	Perceived Individual Mobility			X
	Hours of Employment per Week		X	
Learning Experiences	Learning Experiences		X	
	Experiences with Faculty		X	
	Undergraduate Research Experience		X	
	Quality of Mentoring Relationship		X	X
Self-Efficacy	Math Self-Efficacy	X		X
	Science Self-Efficacy			X
	Leadership Efficacy Scale			X
	Identity as a Scientist	X		X
Outcome Expectations	Outcome Expectations	X		X
Interests	Research Interests	X	X	
	STEM Interests	X		X
Choice Goals	Intention to Major in STEM	X		X
Contextual Influences Proximal to Choice Behavior	Perceived Supports			X
	Perceived Barriers			X
	Coping Efficacy for Barriers		X	
	Educational Supports		X	
	Career Barriers		X	

Table 2.

All STEM Major Participants Survey Completion by Year

Year Since Enrollment	Pre-A	Survey B	Survey A
1	1,360	519	8
2	203	713	603
3	8	504	507
4	-	345	349
5	-	108	102
6	-	8	12

Table 3.

Sample Descriptives

Ethnicity	Gender		Total
	Women	**Men**	
Native American	230 (24.8%)	122 (13.2%)	**352 (37.9%)**
Asian American	205 (22.1%)	142 (15.3%)	**347 (37.4%)**
White	137 (14.8%)	92 (9.9%)	**229 (24.7%)**
Total	**572 (61.6%)**	**356 (38.4%)**	**928**

Note. Percentages in parentheses represent the proportion of the total.

Table 4.

Educational Outcomes by Gender and Ethnicity

Characteristic	No Degree	Non-STEM Degree	STEM Degree	Total
Total	**232 (25.0%)**	**196 (21.1%)**	**500 (53.9%)**	**928**
Gender				
Men	72 (31.0%)	40 (20.4%)	244 (48.8%)	356
Women	160 (69.0%)	156 (79.6%)	256 (51.2%)	572
Ethnicity				
Native American	**115 (32.7%)**	**87 (24.7%)**	**150 (42.6%)**	**352**
Men	38 (16.4%)	16 (8.2%)	68 (13.6%)	122
Women	77 (33.2%)	71 (36.2%)	82 (16.4%)	230
Asian American	**56 (16.1%)**	**69 (19.9%)**	**222 (64%)**	**347**
Men	16 (6.9%)	14 (7.1%)	112 (22.4%)	142
Women	40 (17.2%)	55 (28.1%)	110 (22.0%)	205
White	**61 (26.6%)**	**40 (17.5%)**	**128 (55.9%)**	**229**
Men	18 (7.8%)	10 (5.1%)	64 (12.8%)	92
Women	43 (18.5%)	30 (15.3%)	64 (12.8%)	137

Note. Bolded percentages in parentheses represent the proportion of total ethnic group within each educational outcome category; non-bolded parentheses represent proportion of the outcome category within each demographic group. STEM = Science, Technology, Engineering, and Mathematics.

Table 5.

Chi-Square Tests Comparing Responder Status Across Demographic Groups

Variable	Grouping	χ^2	df	*p*	CramersV
Knowledge of Educational Supports	Ethnicity	26.448	3	0.00	0.168
Subtle Discrimination	Ethnicity	20.664	3	0.00	0.148
Interaction With Faculty	Ethnicity	20.377	3	0.00	0.147
Perceived Individual Mobility	Ethnicity	13.36	3	0.00	0.119
Perceived Support in STEM	Ethnicity	11.757	3	0.01	0.112
Perceived Barriers in STEM	Ethnicity	11.757	3	0.01	0.112
Perceived Hinderance of STEM Barriers	Ethnicity	11.68	3	0.01	0.112
Science Self Efficacy	Ethnicity	11.297	3	0.01	0.11
Perceived Individual Mobility	Gender	5.806	1	0.02	0.082
Subtle Discrimination	Gender	5.69	1	0.02	0.082
Interaction With Faculty	Gender	4.779	1	0.03	0.075
Undergraduate Research Experience	Ethnicity	9.031	3	0.03	0.098
Enterprising Verbal Persuasion	Ethnicity	8.817	3	0.03	0.097

Note. Only tests where $p < 0.05$ are shown. N =928. χ^2 = chi-square test statistic; df = degrees of freedom; *p* = significance level; Cramer's V = effect size measure.

Table 6.

Variables Removed Due to Low Completion

Variable	% Completed
All Students	
Hours Worked per Week	36.78%
Parents' Combined Salary	36.78%
Perceived Discrimination on Campus	14.07%
Experiences of Incivility	32.62%
Family and Community Attitudes Towards Education	29.85%
Quality of Mentoring Experiences	32.94%
Leadership Self Efficacy	52.24%
Native American Students	
Hours Worked per Week	36.65%
Parents' Combined Salary	36.65%
Perceived Discrimination on Campus	37.50%
Experiences of Incivility	34.09%
Family and Community Attitudes Towards Education	34.09%
Quality of Mentoring Experiences	34.66%
Leadership Self Efficacy	52.56%

Note. % Completed = the percentage of participants who had provided data for the variable.

Table 7.

Measure Reliabilities

Scale	*N* Items	α	ω Total
Learning Goal Orientation	5	.86	.86
Prove-Self Goal Orientation	4	.75	.76
Avoid Negatives Goal Orientation	4	.85	.85
Fixed Mindset Science	8	.91	.91
Fixed Mindset Math	8	.92	.92
Tribal Engagement	5	.90	.90
Desire to Find Local Job	3	.79	.80
Subtle Discrimination	8	.83	.84
Explicit Discrimination Towards Native Americans	10	.87	.89
Perceived Individual Mobility	4	.78	.78
Realistic Performance Accomplishments	5	.82	.83
Realistic Vicarious Learning	5	.79	.80
Realistic Verbal Persuasion	5	.75	.75
Realistic Physiological Arousal	5	.75	.76
Investigative Performance Accomplishments	5	.65	.65
Investigative Vicarious Learning	5	.73	.74
Investigative Verbal Persuasion	5	.74	.74
Investigative Physiological Arousal	5	.75	.76
Artistic Performance Accomplishments	5	.61	.65
Artistic Vicarious Learning	5	.58	.59
Artistic Verbal Persuasion	5	.60	.61
Artistic Physiological Arousal	5	.68	.69
Social Performance Accomplishments	5	.68	.69
Social Vicarious Learning	5	.67	.71
Social Verbal Persuasion	5	.67	.67
Social Physiological Arousal	5	.75	.75
Enterprising Performance Accomplishments	5	.71	.73
Enterprising Vicarious Learning	5	.65	.65
Enterprising Verbal Persuasion	5	.68	.70
Enterprising Physiological Arousal	5	.77	.77
Conventional Performance Accomplishments	5	.53	.54
Conventional Vicarious Learning	5	.65	.67
Conventional Verbal Persuasion	5	.60	.60
Conventional Physiological Arousal	5	.72	.72
Interaction With Faculty	10	.87	.87
Undergraduate Research Experience	14	.91	.91
Math Self Efficacy	18	.95	.95
Science Self Efficacy	18	.94	.94

Science Identity	5	.93	.93
Outcome Expectations	14	.91	.92
Research Interests	10	.90	.90
STEM Interests	8	.69	.73
STEM Activities Interests	7	.82	.83
Intention to Major in STEM	3	.95	.95
Perceived Support in STEM	15	.92	.92
Perceived Barriers in STEM	21	.92	.92
Perceived Likelihood of STEM Barriers	35	.95	.95
Perceived Hinderance of STEM Barriers	6	.84	.84
Coping Efficacy for Barriers	18	.94	.94

Note. α = Cronbach's alpha; ω = McDonald's omega (unidimensional).

Table 8.

Measurement Model Fit Indices

Variable	Model	χ^2	*df*	CFI	TLI	RMSEA	SRMR
Learning Goal Orientation	Initial	27.838	5	0.989	0.978	0.070	0.022
	Debugged	27.838	5	0.989	0.978	0.070	0.022
Prove-Self Goal Orientation	Initial	12.381	2	0.99	0.969	0.074	0.023
	Debugged	12.381	2	0.99	0.969	0.074	0.023
Avoid Negatives Goal Orientation	Initial	23.239	2	0.987	0.961	0.106	0.021
	Debugged	8.089	1	0.996	0.974	0.087	0.012
Fixed Mindset Science	Initial	1146.336	20	0.772	0.68	0.245	0.095
	Debugged	38.402	13	0.995	0.989	0.046	0.019
Fixed Mindset Math	Initial	1060.24	20	0.805	0.728	0.235	0.084
	Debugged	35.08	13	0.996	0.991	0.043	0.013
Tribal Engagement	Initial	69.571	5	0.948	0.897	0.192	0.033
	Debugged	9.793	4	0.995	0.988	0.064	0.015
Desire to Find Local Job	Initial	0.000	0	1.000	1.000	0.000	0.000
	Debugged	0.000	0	1.000	1.000	0.000	0.000
Subtle Discrimination	Initial	315.829	20	0.878	0.829	0.126	0.06
	Debugged	70.806	14	0.977	0.953	0.066	0.026
Explicit Discrimination	Initial	248.76	35	0.876	0.840	0.132	0.073
	Debugged	67.657	25	0.975	0.955	0.070	0.036
Perceived Individual Mobility	Initial	315.923	2	0.773	0.318	0.409	0.127
	Debugged	7.096	1	0.996	0.973	0.081	0.01
Realistic Performance Accomplishments	Initial	49.804	5	0.971	0.943	0.098	0.03
	Debugged	15.594	4	0.993	0.982	0.056	0.017
Realistic Vicarious Learning	Initial	49.006	5	0.966	0.932	0.097	0.034
	Debugged	17.087	4	0.990	0.975	0.059	0.02
Realistic Verbal Persuasion	Initial	27.358	5	0.977	0.954	0.069	0.028
	Debugged	27.358	5	0.977	0.954	0.069	0.028
Realistic Physiological Arousal	Initial	10.152	5	0.995	0.990	0.033	0.017
	Debugged	10.152	5	0.995	0.990	0.033	0.017
Investigative Performance Accomplishments	Initial	238.029	5	0.688	0.377	0.223	0.100
	Debugged	9.893	4	0.992	0.980	0.040	0.020
Investigative Vicarious Learning	Initial	207.122	5	0.833	0.666	0.208	0.099
	Debugged	17.268	4	0.989	0.973	0.059	0.032
Investigative Verbal Persuasion	Initial	73.808	5	0.931	0.862	0.121	0.049
	Debugged	30.054	4	0.974	0.935	0.083	0.032
Investigative Physiological Arousal	Initial	191.586	5	0.842	0.684	0.199	0.077
	Debugged	16.104	3	0.989	0.963	0.068	0.02
	Initial	25.348	5	0.971	0.941	0.066	0.036

Artistic Performance Accomplishments	Debugged	25.348	5	0.971	0.941	0.066	0.036
Artistic Vicarious Learning	Initial	18.24	5	0.965	0.929	0.053	0.027
	Debugged	18.24	5	0.965	0.929	0.053	0.027
Artistic Verbal Persuasion	Initial	32.468	5	0.938	0.876	0.077	0.038
	Debugged	32.468	5	0.938	0.876	0.077	0.038
Artistic Physiological Arousal	Initial	61.829	5	0.927	0.854	0.110	0.050
	Debugged	33.639	4	0.962	0.905	0.089	0.032
Social Performance Accomplishments	Initial	23.911	5	0.971	0.942	0.063	0.030
	Debugged	23.911	5	0.971	0.942	0.063	0.030
Social Vicarious Learning	Initial	10.045	5	0.994	0.987	0.033	0.019
	Debugged	10.045	5	0.994	0.987	0.033	0.019
Social Verbal Persuasion	Initial	105.439	5	0.852	0.705	0.146	0.062
	Debugged	33.335	3	0.955	0.851	0.104	0.033
Social Physiological Arousal	Initial	63.547	5	0.943	0.886	0.112	0.047
	Debugged	4.963	4	0.999	0.998	0.016	0.013
Enterprising Performance Accomplishments	Initial	35.911	5	0.964	0.928	0.081	0.033
	Debugged	35.911	5	0.964	0.928	0.081	0.033
Enterprising Vicarious Learning	Initial	8.728	5	0.993	0.985	0.028	0.019
	Debugged	8.728	5	0.993	0.985	0.028	0.019
Enterprising Verbal Persuasion	Initial	48.779	5	0.945	0.889	0.097	0.043
	Debugged	14.94	3	0.985	0.95	0.065	0.022
Enterprising Physiological Arousal	Initial	65.969	5	0.944	0.888	0.114	0.042
	Debugged	29.851	4	0.976	0.941	0.083	0.027
Conventional Performance Accomplishments	Initial	56.519	5	0.838	0.675	0.105	0.052
	Debugged	4.743	4	0.998	0.994	0.014	0.014
Conventional Vicarious Learning	Initial	41.038	5	0.941	0.882	0.088	0.042
	Debugged	21.754	4	0.971	0.927	0.069	0.03
Conventional Verbal Persuasion	Initial	211.296	5	0.647	0.295	0.210	0.104
	Debugged	11.724	3	0.985	0.950	0.056	0.026
Conventional Physiological Arousal	Initial	53.554	5	0.941	0.883	0.102	0.044
	Debugged	18.684	4	0.982	0.956	0.063	0.024
Interaction With Faculty	Initial	465.226	35	0.876	0.841	0.114	0.066
	Debugged	134.865	30	0.97	0.955	0.061	0.034
Undergraduate Research Experience	Initial	2131.829	77	0.746	0.700	0.169	0.105
	Debugged	354.769	65	0.964	0.950	0.069	0.044
Math Self Efficacy	Initial	5041.941	135	0.681	0.639	0.197	0.123
	Debugged	446.687	101	0.978	0.966	0.060	0.049
Science Self Efficacy	Initial	5739.601	135	0.618	0.568	0.210	0.158
	Debugged	224.308	88	0.991	0.984	0.041	0.037
Science Identity	Initial	19.801	5	0.996	0.992	0.056	0.010
	Debugged	19.801	5	0.996	0.992	0.056	0.010

Outcome Expectations	Initial	1765.363	77	0.764	0.722	0.153	0.086
	Debugged	281.362	57	0.969	0.950	0.065	0.034
Research Interests	Initial	814.741	35	0.84	0.795	0.154	0.079
	Debugged	158.503	27	0.973	0.955	0.072	0.033
STEM Interests	Initial	335.189	20	0.812	0.736	0.13	0.072
	Debugged	73.029	17	0.967	0.945	0.059	0.039
STEM Activities Interests	Initial	1142.192	14	0.669	0.504	0.293	0.142
	Debugged	59.66	12	0.986	0.976	0.065	0.032
Intention to Major in STEM	Initial	0.000	0	1.000	1.000	0.000	0.000
	Debugged	0.000	0	1.000	1.000	0.000	0.000
Perceived Support in STEM	Initial	2252.085	90	0.722	0.675	0.16	0.093
	Debugged	343.872	73	0.965	0.95	0.063	0.04
Perceived Barriers in STEM	Initial	3217.256	189	0.676	0.641	0.131	0.094
	Debugged	460.47	133	0.965	0.945	0.051	0.047
Perceived Likelihood of Barriers	Initial	10490.93	560	0.577	0.551	0.137	0.11
	Debugged	1364.763	455	0.961	0.949	0.046	0.049
Perceived Hinderance of Barriers	Initial	253.7	9	0.888	0.814	0.17	0.068
	Debugged	37.708	7	0.986	0.97	0.068	0.023
Coping Efficacy for Barriers	Initial	1747.261	135	0.84	0.819	0.113	0.062
	Debugged	496.531	109	0.962	0.946	0.062	0.035

Note. N = 928. χ^2 = chi-square test statistic; df = degrees of freedom; CFI = comparative fit index; TLI = Tucker-Lewis index; RMSEA = root mean square error of approximation; SRMR = standardized root mean square residual.

Table 9.

Model Performance Comparison

Model	Accuracy	95% CI	Macro F1	Log Loss	λ (1se)
All Students Multinomial					
Ridge	56.08%	[47.96, 64.19]	47.15%	1.030	3.608
Lasso	54.05%	[45.27, 62.16]	47.12%	0.933	0.023
Elastic Net	56.08%	[47.97, 64.19]	48.80%	0.964	0.074
Optimal EN (α = .85)	56.15%	[49.20, 63.10]	53.00%	0.975	0.035
Native American Multinomial					
Ridge	43.64%	[30.30, 57.68]	42.50%	1.073	4.400
Lasso	36.36%	[23.81, 50.44]	27.70%	1.07	0.086
Elastic Net	40.00%	[27.02, 54.09]	32.70%	1.072	0.173
Optimal EN (α = .00)	46.79%	[35.11, 58.48]	41.58%	1.055	4.369
All Students Binary Model 1					
Ridge	73.87%	[64.68, 81.75]	81.50%	0.607	1.930
Lasso	72.97%	[63.72, 80.96]	80.00%	0.517	0.031
Elastic Net	72.07%	[62.76, 80.17]	79.50%	0.526	0.063
Optimal EN (α = .20)	72.14%	[63.94, 79.38]	79.80%	0.59	0.250
Native American Binary Model 1					
Ridge	67.57%	[50.21, 81.99]	73.90%	0.675	8.180
Lasso	81.08%	[64.84, 92.04]	86.80%	0.597	0.111
Elastic Net	78.38%	[61.79, 90.17]	85.20%	0.638	0.267
Optimal EN (α = 1.0)	68.75%	[53.75, 81.34]	76.20%	0.62	0.111
All Students Binary Model 2					
Ridge	71.62%	[63.64, 78.72]	51.16%	0.673	4.370
Lasso	59.46%	[51.09, 67.44]	43.40%	0.661	0.054
Elastic Net	60.81%	[52.46, 68.72]	45.30%	0.663	0.108
Optimal EN (α = .00)	60.43%	[53.03, 67.49]	41.30%	0.682	4.370
Native American Binary Model 2					
Ridge	54.55%	[40.55, 68.03]	41.90%	0.69	0.914
Lasso	45.45%	[31.97, 59.45]	37.50%	0.704	0.060
Elastic Net	45.45%	[31.97, 59.45]	40.00%	0.703	0.110
Optimal EN (α = .00)	59.15%	[46.84, 70.68]	35.60%	0.654	0.914

Note. Optimal models are tested on the hold-out dataset, other models are tested on the validation split of the training data; CI = Accuracy bootstrap confidence interval; λ 1se = largest regularization parameter within one standard error of the minimum cross-validation error; EN = Elastic Net. All models used class weights to address imbalance. Optimal Elastic Net selected based on macro F1 score.

Table 10.

Confusion Matrix for Optimal All Students Multinomial Model

Predicted Category	Outcome Category		
	No Degree	Non-STEM Degree	STEM Degree
No Degree	19	13	17
Non-STEM Degree	11	17	14
STEM Degree	17	10	69

Table 11.

Confusion Matrix for Optimal Native American Multinomial Model

Predicted Category	**Outcome Category**		
	No Degree	**Non-STEM Degree**	**STEM Degree**
No Degree	2	4	5
Non-STEM Degree	8	11	5
STEM Degree	13	3	20

Table 12.

Confusion Matrix for Optimal All Students Binary Model 1

Predicted Category	Outcome Category	
	Non-STEM Degree	STEM Degree
Non-STEM Degree	24	16
STEM Degree	23	77

Table 13.

Confusion Matrix for Optimal Native American Binary Model 1

Predicted Category	Outcome Category	
	Non-STEM Degree	STEM Degree
Non-STEM Degree	9	9
STEM Degree	6	24

Table 14.

Confusion Matrix for Optimal All Students Binary Model 2

Predicted Category	Outcome Category	
	No Degree	**Any Degree**
No Degree	26	21
Any Degree	53	87

Table 15.

Confusion Matrix for Optimal Native American Binary Model 2

Predicted Category	Outcome Category	
	No Degree	**Any Degree**
No Degree	8	15
Any Degree	14	34

Table 16.

Model Statistics for Optimal Models Predicting Hold-Out Dataset

Model	Class 0	Class 1	Class 2
Multinomial All Students			
Sensitivity	44.68%	45.00%	70.00%
Specificity	80.00%	82.99%	71.26%
Balanced Accuracy	62.34%	63.99%	70.63%
Multinomial Native American			
Sensitivity	8.70%	61.11%	66.67%
Specificity	81.25%	75.47%	60.98%
Balanced Accuracy	44.97%	68.29%	63.82%
Binary Non-STEM/STEM All Students			
Sensitivity	60.00%	77.00%	--
Specificity	77.00%	60.00%	--
Balanced Accuracy	68.50%	68.50%	--
Binary Non-STEM/STEM Native American			
Sensitivity	50.00%	80.00%	--
Specificity	80.00%	50.00%	--
Balanced Accuracy	65.00%	65.00%	--
Binary No Degree/Any Degree All Students			
Sensitivity	55.32%	62.14%	--
Specificity	62.14%	55.32%	--
Balanced Accuracy	58.73%	58.73%	--
Binary No Degree/Any Degree Native American			
Sensitivity	34.78%	70.83%	--
Specificity	70.83%	34.78%	--
Balanced Accuracy	52.81%	52.81%	--

Table 17.

Coefficients for Optimal All Students Multinomial Model

Predictor	No Degree	Non-STEM Degree	STEM Degree
STEM Major Intention	0.001	-0.024	0.024
Artistic Verbal Persuasion	-0.010	-0.013	0.022
STEM Interests	-0.018	-0.003	0.021
Asian American Identifier	-0.008	-0.012	0.020
Social Verbal Persuasion	-0.001	-0.018	0.019
Science Self Efficacy	-0.019	0.000	0.019
Social Physiological Arousal	0.001	-0.019	0.018
Number of Siblings	-0.009	0.019	-0.009
Realistic Verbal Persuasion	-0.003	0.018	-0.015
Perceived Individual Mobility	-0.008	-0.010	0.018
Avoid Negatives Goal Orientation	0.000	0.017	-0.017
Enterprising Performance Accomplishments	0.014	0.003	-0.017
High School Math Classes Taken	0.016	-0.007	-0.009
Fixed Science Skills Beliefs	-0.008	0.015	-0.007
Social Performance Accomplishments	-0.011	0.015	-0.004
Science Identity	-0.002	-0.012	0.015
Artistic Physiological Arousal	0.002	-0.014	0.012
STEM Activities Interests	0.006	-0.014	0.008
Native American Identifier	-0.013	0.008	0.005
Math Self Efficacy	-0.007	-0.007	0.013
Woman Identifier	-0.005	0.013	-0.008
Fixed Math Skills Beliefs	0.005	0.008	-0.013
Intention to Remain in Major	0.013	-0.009	-0.003
Outcome Expectations	-0.007	-0.005	0.012

Table 18.

Coefficients for Optimal Native American Multinomial Model

Predictor	No Degree	Non-STEM Degree	STEM Degree
STEM Major Intention	0.003	-0.028	0.025
Investigative Physiological Arousal	-0.014	0.023	-0.009
Perceived Individual Mobility	-0.018	-0.005	0.022
Science Self Efficacy	0.000	-0.022	0.022
Investigative Performance Accomplishments	0.004	-0.021	0.016
Artistic Verbal Persuasion	-0.013	0.020	-0.007
Woman Identifier	-0.001	0.019	-0.018
In Relationship	0.018	-0.018	0.000
Science Identity	0.000	-0.017	0.017
Desire to Find Local Job	0.017	-0.011	-0.006
Enterprising Vicarious Learning	-0.012	0.016	-0.003
STEM Interests	-0.002	-0.013	0.016
Investigative Vicarious Learning	-0.013	-0.002	0.015
Knowledge of Educational Supports	-0.003	0.015	-0.012
Tribal Engagement	0.006	0.009	-0.015
Undergraduate Research Experience	-0.007	-0.007	0.014
Outcome Expectations	0.000	-0.014	0.014
Social Vicarious Learning	-0.009	0.014	-0.004
Investigative Verbal Persuasion	-0.007	-0.007	0.013
Interaction With Faculty	-0.012	0.013	-0.002

Table 19.

Coefficients for Optimal All Students Non-STEM Degree vs STEM Degree Binary Model

Predictor	STEM Degree
STEM Major Intention	0.152
Science Self Efficacy	0.098
Science Identity	0.090
Social Verbal Persuasion	-0.074
STEM Activities Interests	0.067
STEM Interests	0.063
Woman Identifier	-0.055
Perceived Individual Mobility	0.051
Artistic Verbal Persuasion	-0.040
Coping Efficacy for Barriers	0.026
High School Math Classes Taken	0.023
Enterprising Performance Accomplishments	-0.020
Math Self Efficacy	0.016
Fixed Math Skills Beliefs	-0.016
Social Vicarious Learning	-0.013
Social Performance Accomplishments	-0.011
High School Science Classes Taken	0.011
Native American Identifier	-0.006

Table 20.

Coefficients for Optimal Native American Non-STEM Degree vs STEM Degree Binary Model

Predictor	STEM Degree
STEM Major Intention	0.450
Science Self Efficacy	0.199

Table 21.

Coefficients for Optimal All Students No Degree vs Any Degree Binary Model

Predictor	Any Degree
Asian American Identifier	0.028
High School Math Classes Taken	0.026
Native American Identifier	-0.021
STEM Interests	0.019
Number of Siblings	-0.017
Avoid Negatives Goal Orientation	0.017
Math Self Efficacy	0.016
STEM Activities Interests	0.015
Social Physiological Arousal	-0.015
Research Interests	0.013
Investigative Vicarious Learning	0.013
In Relationship	-0.011
High School Science Classes Taken	0.011
Fixed Science Skills Beliefs	0.011
Intention to Remain in Major	-0.010
Investigative Physiological Arousal	-0.010
Perceived Support in STEM	0.010
STEM Major Intention	0.009
Realistic Verbal Persuasion	-0.009
Science Self Efficacy	0.008
Enterprising Physiological Arousal	-0.008
Realistic Vicarious Learning	-0.008
Perceived Individual Mobility	0.007
Artistic Verbal Persuasion	0.007
Fixed Math Skills Beliefs	0.007
Woman Identifier	-0.007
Investigative Performance Accomplishments	0.007
Science Identity	0.006
Enterprising Verbal Persuasion	0.006
Social Performance Accomplishments	-0.006
Investigative Verbal Persuasion	0.006
Conventional Vicarious Learning	0.006
Non-Responder: In Relationship	0.006
Undergraduate Research Experience	0.005
Conventional Verbal Persuasion	0.005
White Identifier	-0.005
Enterprising Vicarious Learning	0.005
Realistic Performance Accomplishments	-0.004

Interaction With Faculty	0.004
Knowledge of Educational Supports	0.004
Artistic Physiological Arousal	-0.004
Outcome Expectations	-0.004
Realistic Physiological Arousal	-0.004
Desire to Find Local Job	-0.004
Conventional Physiological Arousal	-0.003
Perceived Hinderance of Barriers	0.003
Perceived Likelihood of Barriers	0.003
Children	-0.003
Highest Parent Education	0.003
Prove-Self Goal Orientation	-0.003
Coping Efficacy for Barriers	0.002
Enterprising Performance Accomplishments	0.002
Subtle Discrimination	-0.002
Social Verbal Persuasion	-0.002
Conventional Performance Accomplishments	-0.002
Artistic Vicarious Learning	0.002
Learning Goal Orientation	0.001
Non-Responder: Number of Siblings	0.001
Married	0.001
Perceived Barriers in STEM	0.001
Social Vicarious Learning	-0.001
Artistic Performance Accomplishments	0.000
Non-Responder: Highest Parent Education	0.000

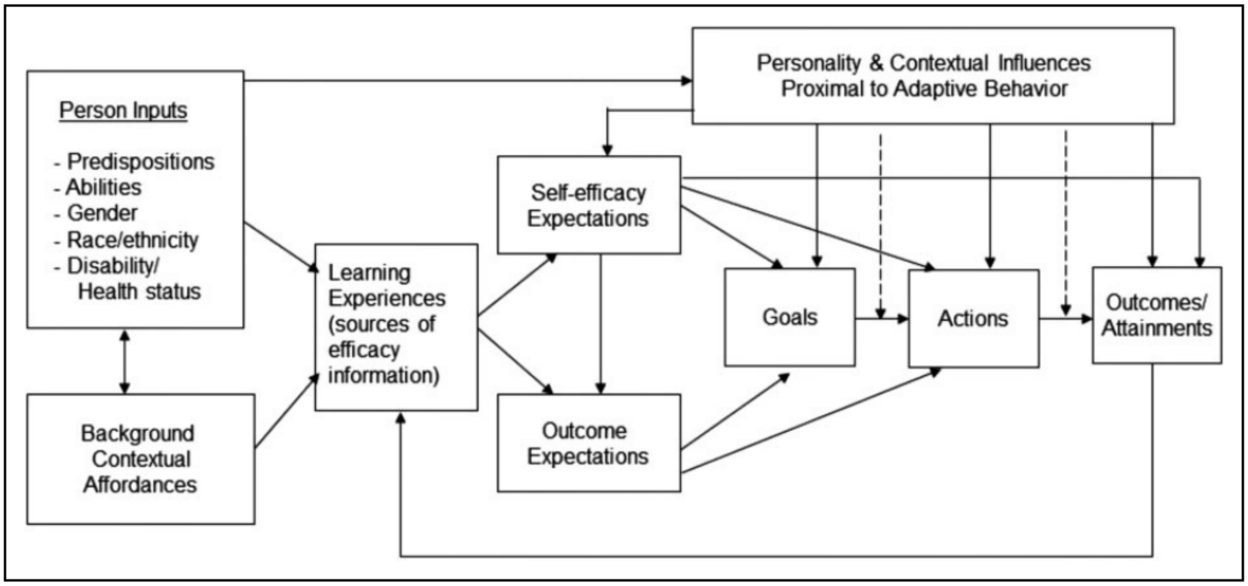
Table 22.

Coefficients for Optimal Native American No Degree vs Any Degree Binary Model

Predictor	Any Degree
Perceived Individual Mobility	0.085
Desire to Find Local Job	-0.075
In Relationship	-0.070
Investigative Vicarious Learning	0.054
Realistic Vicarious Learning	-0.053
Investigative Physiological Arousal	0.053
Intention to Remain in Major	0.047
Interaction With Faculty	0.044
Artistic Verbal Persuasion	0.040
Highest Parent Education	0.040
Enterprising Vicarious Learning	0.040
High School Math Classes Taken	0.037
Tribal Engagement	-0.035
High School Science Classes Taken	0.034
Realistic Physiological Arousal	0.033
Coping Efficacy for Barriers	0.033
Social Vicarious Learning	0.032
Number of Siblings	-0.032
Math Self Efficacy	0.032
Perceived Support in STEM	0.030

Figure 1.

Social Cognitive Career Theory Framework



Appendix A
Measure Information

Socioeconomic Status and Parental Education

Number of Items	11
Rating Scale	Open-ended/sectioned questions to gauge the participant’s socioeconomic status
Items	SES.FatherEducation: What is the highest level of education that your father / male guardian (Parent 1) has achieved? 1. Less than High School Diploma or GED 2. GED 3. High School Diploma 4. Some college, no degree 5. Vocational Tech diploma or Certification 6. Associate’s Degree 7. Bachelor’s Degree 8. Master’s Degree 9. Doctoral or Professional Degree SES.MotherEducation: What is the highest level of education that your mother / female guardian (Parent 2) has achieved? 1. Less than High School Diploma or GED 2. GED 3. High School Diploma 4. Some college, no degree 5. Vocational Tech diploma or Certification 6. Associate’s Degree 7. Bachelor’s Degree 8. Master’s Degree 9. Doctoral or Professional Degree SES.ParentSalary: What is your parents’ combined yearly income? For divorced parents, list the income of the parent who was granted with your custody (combined with his or her current spouse’s income, if applicable). 1. Less than $20,000 2. Greater than $20,000 but less than $30,000 3. Greater than $30,000 but less than $45,000 4. Greater than $45,000 but less than $60,000 5. Greater than $60,000 but less than $80,000 6. Greater than $80,000 but less than $100,000 7. Greater than $100,000 but less than $150,0000 8. Greater than $150,000 but less than $200,000 9. Greater than $200,000 10. Don’t know/Decline to Answer (999)

SES.Employed: Are you currently employed?

0. No
1. Yes

SES.HoursWorked: How many hours do you work per week?

1. 5 or less
2. 5-10
3. 10-20
4. 20-30
5. 30-40
6. 40-more

SES.INJ What are your weekly earnings from this job?

1. $50 or less
2. $50-$100
3. $100-$300
4. $300-$500
5. $500-$800
6. $800-$1100
7. $1100-$1500
8. $1500 or more

SES.INM What is your current monthly income from the sources that you listed in the previous question?

1. Less than $1,000
2. Greater than $1,000 but less than $1,500
3. Greater than $1,500 but less than $2,000
4. Greater than $2,000 but less than $2,500
5. Greater than $2,500 but less than $3,000
6. Greater than $3,000 but less than $3,500
7. Greater than $3,500 but less than $4,000
8. Greater than $4,000

TribalSchool Did you ever go to school on a reservation or other tribal land?

0. No
1. Yes

TOWN Please indicate the size of town in which you spent the majority of your time growing up

1. Rural (outside of a town)
2. Small Town
3. Medium Sized Town (< 10,000 people)
4. Small City
5. Medium Sized City (> 100,000 people)
6. Big City (> 200,000)

Goal Orientation

Number of Items	13
Assessment	Learning – “A desire to develop the self by acquiring new skills, mastering new situations, and improving one’s competence.” Prove – “The desire to prove one’s competence and to gain favorable judgments about it.” Avoid – “The desire to avoid the disproving of one’s competence and to avoid negative judgments about it.”
Rating Scale	Please use the scale below to indicate your agreement with the following statements. 1 (Strongly Disagree) – 7 (Strongly Agree) Higher score indicates more agreement/identify with that subscale
Items	**Learning Goal Orientation** 1. I am willing to select a challenging assignment that I can learn a lot from 2. I often look for opportunities to develop new skills and knowledge 3. I enjoy challenging and difficult tasks at school where I’ll learn new skills 4. For me, development of my academic ability is important enough to take risks 5. I prefer situations at school that require a high level of ability and talent **Prove Self Goal Orientation** 6. I would rather prove my ability on a task that I can do well at than to try a new task 7. I try to figure out what it takes to prove my ability to others at school 8. I enjoy it when others at school are aware of how well I am doing 9. I prefer to work on projects where I can prove my ability to others **Avoid Negatives Goal Orientation** 10. I would avoid taking on a new task if there was a chance that I would appear rather incompetent to others 11. Avoiding a show of low ability is more important to me than learning a new skill 12. I’m concerned about taking on a task at school if my performance would reveal that I had low ability 13. I prefer to avoid situations at school where I might perform poorly

Implicit Theories of Math and Science Ability

Number of Items	16

Rating Scale	This questionnaire has been designed to investigate ideas about math and science ability. There are no right or wrong answers. We are interested in your ideas. Using the scale below, please indicate the extent to which you agree or disagree with each of the following statements. 1 (Strongly Disagree) – 5 (Strongly Agree) Higher scores indicate increased agreement with idea that math/science ability can't be changed
	Fixed Mindset Science 1. You have a certain amount of science ability, and you can't really do much to change it. 3. Your science ability is something about you that you can't change very much. 5. (R) No matter who you are, you can significantly change your science ability level. 7. To be honest, you can't really change how intelligent you are at science. 9. (R) You can always substantially change how intelligent you are at science. 11. You can learn new things, but you can't really change your basic science ability. 13. (R) No matter how much science ability you have, you can always change it quite a bit. 15. (R) You can change even your basic science ability level considerably **Fixed Mindset Math** 2. You have a certain amount of math ability, and you can't really do much to change it. 4. Your math ability is something about you that you can't change very much. 6. (R) No matter who you are, you can significantly change your math ability level. 8. To be honest, you can't really change how intelligent you are at math. 10. (R) You can always substantially change how intelligent you are at math. 12. You can learn new things, but you can't really change your basic math ability. 14. (R) No matter how much math ability you have, you can always change it quite a bit. 16. (R) You can change even your basic math ability level considerably

Previous Math and Science Training

Number of Items	15
Rating Scale	Multiple selection questions asking the participant the number of math/science courses completed in high school

<table>
<tr><td>Items</td><td>High School Math Courses: Please select the math courses you have completed during high school
1. Pre-Algebra
2. Algebra
3. Geometry
4. Trigonometry/Algebra II
5. Pre-Calculus
6. Calculus I
7. Calculus II
8. Statistics

High School Science Courses: Please select the science courses you have completed during high school
1. Biology
2. Chemistry
3. Physics
4. Environmental Science
5. Economics
6. Psychology
7. Computer Science</td></tr>
</table>

Tribal Engagement

<table>
<tr><td>Number of Items</td><td>5</td></tr>
<tr><td>Rating Scale</td><td>Questions regarding one’s connection to their tribe/tribal community
Higher scores indicate greater involvement/connection to tribe</td></tr>
<tr><td>Items</td><td>1. How would you rate your involvement in your Native American culture?
1. Not at all Involved
2. Not Involved
3. Involved
4. Very Involved

2. How would you rate your connection to Native American culture?
1. Not at all Strong
2. Not Strong
3. Strong
4. Very Strong

3. How would you rate your involvement in your tribal community?
1. Not at all Involved
2. Not Involved
3. Involved
4. Very Involved

4. How you would rate your connection to your tribal community?
1. Not at all Strong</td></tr>
</table>

	2. Not Strong 3. Strong 4. Very Strong 9. How connected are you to a Native American community on campus? 1. Not at all Connected 2. Not Very Connected 3. Quite Connected 4. Very Connected

Concern with Finding Job Locally

Number of Items	3
Rating Scale	How important are the following factors in choosing where you would like to live after college? 1(Not at all important) – 5 (Extremely important) Higher scores indicate more agreement/identify with that subscale
Items	1. To live close to your relatives 2. To live near your parent(s) 3. To live in the community where you were raised

Family Structure and Dependency

Items	Married: Are you currently married? 0. No 1. Yes Relationship: Are you currently involved in a romantic relationship? 0. No 1. Yes

Family and Community Attitudes Toward Education

Number of Items	24 4 repeated for Parents, Siblings, Relatives, Community, Spouse, Boyfriend/Girlfriend
Rating Scale	To your ________, how important is it that you do each of the following statements? 1 (Not Important) – 5 (Very Important) Higher score indicates higher academic support from that party
Items	1. Doing well in school 2. Getting good grades 3. Staying close to home after high school 4. Making college education a top priority in my life

Subtle Discrimination

Number of Items	8
Rating Scale	Since you've been a student at OU, how many times have you felt…? 0 times (1) – 10 or more times (11) Higher scores indicate higher frequency of instances of subtle discrimination
Items	1. That your contribution during a discussion was discounted 2. Like you had to prove yourself more than other students in your classes 3. That faculty members didn't take you seriously, when you talked to them 4. Like you had to prove yourself to other students before they would listen to your ideas 5. That other students in a group ignored you 6. That students didn't want you to sit by them in class 7. Pressured/singled out by faculty 8. Like you had to represent your entire group

Explicit Discrimination Towards Native Americans

Number of Items	10
Rating Scale	Since you've been a student at OU, how many times have you been asked…? 1 (0 times) – 11 (10 or more times) Higher ratings indicate higher frequency of explicitly discriminatory instances
Items	1. To talk about being Native 2. If you live in a teepee? 3. If you can talk "Indian"? 4. If you dance at powwows? 5. If you wear "Indian" clothes? 6. "What are you?" 7. Witnessed students at OU dressing up as "Indians" in an offensive manner? 8. Heard or seen racial slurs toward Native Americans on campus? 9. Been called "Native" names, like Pocahontas or Chief. 10. Heard someone say they thought "Indians were all dead"

Non-Discriminatory Campus Climate

Number of Items	5
Rating Scale	Please rate the extent to which you agree with having observed or experienced the following: *Strongly disagree – Strongly agree* (*5-point scale*) Higher ratings indicate more discrimination on campus

Items	1. I have observed discriminatory words, behaviors, or gestures directed at people like me. 2. I have encountered discrimination while attending this institution. 3. I feel there is a general atmosphere of prejudice among students. 4. Faculty have discriminated against people like me. 5. Staff members have discriminated against people me.

Incivility

Number of Items	7
Rating Scale	During your time at OU, how often have you been in a situation where someone at the university… *Never – Most of the time (4-point scale)* Higher scores indicate more incivility
Items	1. Put you down or was condescending to you? 2. Paid little attention to your statement or showed little interest in your opinion? 3. Made demeaning or derogatory comments about you? 4. Addressed you in inappropriate terms, either publicly or privately? 5. Ignored or excluded you from social interactions? 6. Doubted your knowledge and opinions? 7. Asked you inappropriately personal questions?

Perceived Individual Mobility

Number of Items	4
Rating Scale	Please indicate the extent you which you agree with the following statements 1 (Strongly disagree) – 7 (Strongly Agree) Higher ratings indicate a higher perception of mobility through socioeconomic classes
Items	1. America is an open society where individuals of any ethnicity can achieve higher status 2. Advancement in American society is possible for individuals of all ethnic groups 3. (R) Individual members of a low status ethnic group have difficulty achieving higher status 4. (R) Individual members of certain ethnic groups are often unable to advance in American society

Hours of Employment per Week

Number of Items	2

Rating Scale	0 = No, 1 = Yes; 1 = 1 hour, 2 = 2 hours, …, 41 = 40+ hours
Items	Employed: Are you currently employed? 0. No 1. Yes Hours Worked per Week: On average, how many hours do you work per week? 1. 1 hour 2. 2 hours … 41. 40+ hours

Learning Experiences

Number of Items	120
Rating Scale	Please indicate the extent to which you agree that you experienced each event. 1 (Strongly Disagree) – 6 (Strongly Agree) Higher ratings indicate a higher frequency of learning experiences had
Items	**Realistic Performance Accomplishments** 1. I have made simple car repairs. 2. I have made repairs around the house. 3. I have been successful when I used tools to work on things. 4. I have done a good job at things that involved physical labor (e.g., landscaping). 5. I have done well in building things. **Realistic Vicarious Learning** 6. I have observed members of my family build things. 7. I watched people whom I respect work in the outdoors. 8. I observed people whom I respect repair mechanical things. 9. While growing up, I watched adults whom I respect fix things. 10. I observed people whom I admire work in a garden. **Realistic Verbal Persuasion** 11. People I respect have urged me to learn how to fix things that are broken. 12. Teachers I admired encouraged me to take classes in which I can use my mechanical abilities. 13. While growing up, adults I respected encouraged me to work with tools. 14. People whom I look up to have urged me to pursue activities that require manual dexterity. 15. Family members have encouraged me to pursue activities that involve working outdoors. **Realistic Physiological Arousal**

	16. I have become uptight while trying to repair something that was broken. 17. I have become nervous when working on mechanical things (e.g., appliances). 18. I have felt uneasy while using tools to build something. 19. I have felt anxious while performing basic repairs on a car. 20. I remember feeling anxious while working on something that required manual labor. **Investigative Performance Accomplishments** 21. I performed well in biology courses in school. 22. I was successful performing science experiments in school. 23. I received high scores on the math section of my college entrance exam (e.g., SAT). 24. I have easily understood new math concepts after learning about them in class. 25. I have demonstrated skill at conducting research for my term papers. **Investigative Vicarious Learning** 26. In school, I saw teachers whom I admired work on science projects. 27. While growing up, I saw people I respected using math to solve problems. 28. I have seen people whom I respect participating in activities that require math abilities. 29. I recall seeing adults whom I admire working in a research laboratory. 30. While growing up, I recall seeing people I respected reading scientific articles. **Investigative Verbal Persuasion** 31. People whom I respect have encouraged me to work hard in math courses. 32. I remember my family telling me that it is important to be able to solve science problems. 33. People whom I looked up to told me that it is important to read scholarly articles. 34. My friends have encouraged me to use my research abilities. 35. Teachers whom I admire have encouraged me to take science courses. **Investigative Physiological Arousal** 36. I have become nervous while solving math problems. 37. I have felt anxious while taking a science course in school. 38. I have felt uneasy while learning new topics in biology courses. 39. Reading scientific articles has made me feel uneasy. 40. I have felt dread while using math in a job. **Artistic Performance Accomplishments** 41. The artwork I have created usually turned out well. 42. I received good grades in my art courses in school. 43. I have done a good job at writing poetry. 44. I have been successful at creating a sculpture with clay. 45. I have been successful at playing a musical instrument.

	Artistic Vicarious Learning 46. I remember watching members of my family create art. 47. I watched my friends as they participated in school plays. 48. I have seen people whom I admire write fiction stories. 49. During school, I admired teachers whom I saw create art. 50. While growing up, I listened to family members play musical instruments. **Artistic Verbal Persuasion** 51. People whom I respect have encouraged me to play a musical instrument. 52. Teachers whom I respect have encouraged me to take an art class. 53. Family members have urged me to learn how to sing. 54. While growing up, adults whom I admired told me that it is important to be a good writer. 55. Friends have urged me to act in a play. **Artistic Physiological Arousal** 56. I have felt anxious when I had to act in a play. 57. I have felt anxious about creating artwork. 58. I have felt uptight while writing a short story for school. 59. I have felt uneasy while drawing something. 60. I have felt uncomfortable while playing a musical instrument for other people. **Social Performance Accomplishments** 61. I have been successful at caring for children. 62. I have been successful at teaching people. 63. I have been able to hold a conversation with all types of people. 64. I have listened well to people who are having personal difficulties. 65. I earned good grades in social science courses. **Social Vicarious Learning** 66. While growing up, I saw people whom I admire work in youth ministry. 67. I have seen people whom I respect enter the teaching profession. 68. I have seen people whom I admire dedicate their lives to helping others. 69. I have observed people whom I admire perform volunteer work. 70. I have seen people I know enter work in the helping professions (e.g., social work). **Social Verbal Persuasion** 71. My teachers have encouraged me to explore jobs in the helping professions (e.g., counseling). 72. My family encouraged me to take social science courses (e.g., psychology). 73. My family taught me that it is important to develop my interpersonal communication skills. 74. People whom I respect have encouraged me to perform volunteer work.

	75. My friends have urged me to help others resolve their personal difficulties. **Social Physiological Arousal** 76. I have felt uneasy when people would come to me with their problems. 77. I have become nervous while teaching something new to a classmate. 78. During school, I have felt uptight while working as a part of a small group. 79. I have become anxious initiating conversations with people I do not know. 80. I have become nervous while developing new friendships. **Enterprising Performance Accomplishments** 81. I have been able to sell a product effectively. 82. I have successfully persuaded people to do things my way. 83. I have been a successful leader in school. 84. I have done well at public speaking. 85. I have successfully supervised the work of others. **Enterprising Vicarious Learning** 86. I have seen people whom I respect read business magazines. 87. I have seen people whom I trust successfully manage a business. 88. I have listened to members of my family speak in public. 89. I have seen people whom I respect enter politics. 90. Adults whom I admire have urged me to enter a profession in which I manage others. **Enterprising Verbal Persuasion** 91. Teachers whom I respect have encouraged me to take a business management course. 92. Adults whom I admire have urged me to enter a profession in which I manage others. 93. People whom I respect have encouraged me to develop my leadership skills. 94. People whom I trust have told me that it is important to be able to persuade others to do things. 95. People whom I admire have encouraged me to be a salesperson. **Enterprising Physiological Arousal** 96. I have felt nervous when I had to sell something. 97. I have felt nervous while debating a topic. 98. I have felt uneasy about taking a leadership role in a group. 99. I have felt uneasy while supervising the work of others. 100. I have felt anxious when I attempted to persuade someone to do things my way. **Conventional Performance Accomplishments** 101. I have kept accurate records of my financial documents. 102. I have done a good job at proofreading my papers for mistakes. 103. I have accurately balanced a checkbook.

	104. I have done a good job at operating new computer programs (e.g., word processing). 105. I have done a good job at performing basic office work (e.g., filing). **Conventional Vicarious Learning** 106. I remember seeing my family plan out the details of vacations. 107. I have seen family members perform work which involved organizing information. 108. I have seen my parents keep organized records of their important financial documents. 109. I have watched people whom I respect perform detail-oriented work. 110. I have seen people whom I respect hold jobs which involved performing routine office work. **Conventional Verbal Persuasion** 111. People whom I admire have told me that it is important to learn new computer software. 112. My parents have encouraged me to pursue jobs that involve keeping track of records. 113. Teachers whom I respect have told me that it is important to have good organizational skills. 114. My family has encouraged me to find a job which involves performing basic office tasks. 115. People whom I respect have encouraged me to be a detail-oriented person. **Conventional Physiological Arousal** 116. I have become anxious while learning new computer software. 117. I have felt anxious while organizing resources for a term paper. 118. I have felt nervous learning how to operate office machines. 119. I have felt uptight while entering data at a computer terminal. 120. I remember feeling uptight when I had to keep clear, precise records.

Interaction with Faculty

Number of Items	10
Rating Scale	In your experience at this institution, how often have you done each of the following? 1 (Never) – 4 (Very Often) Higher ratings indicate higher amount of interaction with faculty
Items	1. Worked harder than you thought you could to meet an instructor's expectations and standards 2. Worked with a faculty member on a research project 3. Talked with your instructor about information related to a course you were taking (grades, make-up work, assignments, etc.) 4. Discussed your academic program or course section with a faculty member 5. Discussed ideas from a term paper or other class project with a faculty member

	6. Discussed your career plans and ambitions with a faculty member 7. Worked harder as a result of feedback from an instructor 8. Socialized with a faculty member outside of class (had a snack or soft drink, etc.) 9. Participated with other students in a discussion with one or more faculty members outside of class 10. Ask your instructor for comments and criticisms about your academic performance

Undergraduate Research Experience

Number of Items	14
Rating Scale	Please respond to the following statements using the scale provided 1 (Not at all) – 5 (A lot) Higher scores indicate a higher amount of research experience gained
Items	1. I learned technical science skills (e.g., use of tools, instruments and/or techniques). 2. I learned scientific language and terminology. 3. I had the opportunity to generate my own research question to answer. 4. I worked on a research project in which I figured out what data/observations to collect and how to collect them. 5. I worked on a research project in which I interpreted the meaning of my data/observations. 6. I created my own explanation for the results of a study/research project. 7. I used scientific literature and/or reports to guide my project. 8. I related my research results and explanation to the work of others. 9. I reported my research results in an oral presentation or in a written report. 10. I played a leadership role in a scientific research team on science-related tasks. 11. I worked on assignments with other students outside of class. 12. I networked with fellow students. 13. I was a peer mentor for other science students. 14. I participated in social events with faculty or staff members, and/or fellow students.

Quality of Mentoring Relationship

Number of Items	18
Rating Scale	Describe the extent to which your mentor(s) provided you with the following opportunities 1 (Not at all) – 5 (to a very large extent)

	Higher ratings indicate a higher quality of relationship with mentor
Items	1. My mentor gave me the sense that s/he cared about me and respected me as an individual, not just a student or worker. 2. My mentor gave me the sense that s/he understood my background. 3. My mentor gave me the sense that s/he and I shared similarities of background, personality, or other important personal characteristics. 4. My mentor gave me the impression that s/he believed in me. 5. My mentor told me that I could do something I thought was too hard for me. 6. My mentor earned my trust. 7. My mentor helped me overcome insecurities about my abilities. 8. My mentor encouraged me to try new ways of behaving in school. 9. I tried to imitate my mentor's behavior in school. 10. I agreed with my mentor's attitudes and values regarding education. 11. I respected and admired my mentor. 12. I will try to be like my mentor when I reach a similar position in my academic career. 13. My mentor demonstrated good listening skills in conversations with me. 14. My mentor discussed my questions or concerns regarding feelings of competence, commitment to academic advancement, relationships with peers or faculty, or work/family conflicts. 15. My mentor shared personal experiences as an alternative perspective to my problems. 16. My mentor encouraged me to talk openly about anxiety and fears that detract from my schoolwork. 17. My mentor conveyed empathy for the concerns and feelings I discussed with him/her. 18. My mentor kept the feelings and doubts I shared with him/her in strict confidence.

Math Self-Efficacy

Number of Items	18
Rating Scale	Please indicate how true or false each statement below is for you. In the statements below, "mathematics" refers to subjects like algebra, geometry, calculus, and trigonometry. 1 (Definitely false) – 5 (Definitely true) Higher scores indicate higher math-related self-efficacy
Items	1. I make excellent grades on math tests 2. I have always been successful with math 3. (R) Even when I study very hard, I do poorly in math 4. I got good grades in math on my last report card 5. I do well on math assignments 6. I do well on even the most difficult math assignments

	7. My math teachers have told me that I am good at learning math 8. People have told me that I have a talent for math 9. Adults in my family have told me what a good math student I am 10. I have been praised for my ability in math 11. Other students have told me that I am good at learning math 12. My classmates like to work with me in math because they think I am good at it 13. (R) Just being in math class makes me feel stressed and nervous 14. (R) Doing math work takes all of my energy 15. (R) I start to feel stressed-out as soon as I begin my math work 16. (R) My mind goes blank and I am unable to think clearly when doing math work 17. (R) I get depressed when I think about learning math 18. (R) My whole body becomes tense when I have to do math work

Science Self-Efficacy

Number of Items	18
Rating Scale	Please indicate how true or false each statement below is for you. In the statements below, "science" refers to subjects such as biology, geology, chemistry, physics, and computer science. 1 (Definitely False) – 6 (Definitely True) Higher ratings indicate a higher ability in science areas
Items	1. I make excellent grades on science tests 2. I have always been successful with science 3. (R) Even when I study very hard, I do poorly in science 4. I got good grades in science on my last report card 5. I do well on science assignments 6. I do well on even the most difficult science assignments 7. My science teachers have told me that I am good at learning science 8. People have told me that I have a talent for science 9. Adults in my family have told me what a good science student I am 10. I have been praised for my ability in science 11. Other students have told me that I am good at learning science 12. My classmates like to work with me in science because they think I am good at it 13. (R) Just being in science class makes me feel stressed and nervous 14. (R) Doing science work takes all of my energy 15. (R) I start to feel stressed-out as soon as I begin my science work 16. (R) My mind goes blank and I am unable to think clearly when doing science work 17. (R) I get depressed when I think about learning science 18. (R) My whole body becomes tense when I have to do science work

Leadership Efficacy Scale

Number of Items	4
Rating Scale	How confident are you that you can be successful at the following: Not confident at all (1) – Very confident (5) Higher ratings indicate a higher leadership self-efficacy
Items	1. Leading others 2. Organizing group tasks to accomplish goals 3. Taking initiative to improve something 4. Working with a team on a group project

Identity as a Scientist

Number of Items	6
Rating Scale	The following questions ask how you think about yourself and your personal identity. We want to understand how much you think that being a scientist is part of who you are. Please indicate the extent that you agree or disagree with the following statements Strongly Disagree (1) – Strongly Agree (5) Higher scores indicate higher identity as scientist
Items	1. In general, being a scientist is an important part of my self-image. 2. I have a strong sense of belonging to the community of scientists. 3. Being a scientist is an important reflection of who I am. 4. I have come to think of myself as a "scientist." 5. I feel like I belong in the field of science. 6. I am a scientist.

Outcome Expectations

Number of Items	14
Rating Scale	Graduating with a bachelor's degree with a major **in a science, technology, engineering or mathematics field** would likely allow me to... 1 (Strongly Disagree) – 5 (Strongly Agree) Higher scores indicate more agreement/identify with subscale
Items	1. ...receive a good job offer 2. ...earn an attractive salary 3. ...get respect from other people 4. ...do work that I would find satisfying 5. ...increase my sense of self-worth 6. ...have a career that is valued by my family 7. ...do work that can "make a difference" in people's lives 8. ...go into a field with high employment demand 9. ...do exciting work

	10. ...have the right type and amount of contact with other people (i.e., "right" for me) 11. ...get the job I want most 12. ...feel good about myself 13. ...help the community that I grew up in 14. ...help the community where I will be living in the future

Research Interests

Number of Items	10
Rating Scale	Using the scale provided, please indicate the degree of interest you have in the activities listed below. Please remember that the term "research" encompasses both quantitative and qualitative approaches, for the purpose of this instrument. 1 (Very Uninterested) – 5 (Very interested Higher scores indicate more agreement/identify with that subscale
Coding	Average across all items
Items	1. Reading a research journal article 2. Being a member of a research team 3. Conducting a literature review 4. Having research activities as part of every work week 5. Taking a research design course 6. Analyzing data 7. Discussing research findings with other students 8. Writing for publication/presentation 9. Designing a study 10. Collecting data

STEM Interests, Interest in STEM Activities

Number of Items	15
Rating Scale	Please indicate your degree of interest in studying each of the following topics. Use the scale below to show how interested you are in each topic 1 (Strongly Dislike) – 5 (Strongly Like) Higher scores indicate a higher interest in STEM fields/STEM activities
Items	**STEM Interests** 1. Statistics 2. Chemistry 3. Physics 4. Basic Math 5. Computer Science 6. Biology 7. Advanced Math 8. Engineering **Interest in STEM Activities**

	1. Solving practical math or science problems 2. Reading articles or books about scientific issues 3. Solving computer software problems 4. Working on a project involving lots of math or science 5. Solving complicated math or science problems 6. Learning new computer programs 7. Working on a project involving scientific concepts

Intention to Major in STEM

Number of Items	3
Rating Scale	Please indicate how strongly you agree or disagree with the following statements 1 (Strongly Disagree) – 5 (Strongly Agree) Higher scores indicate a stronger intention to Major in STEM
Items	1. I intend to major in a science/technology/engineering/math field. 2. I think that earning a bachelor's degree in science/technology/engineering/math is a realistic goal for me. 3. I am fully committed to getting my college degree in science/technology/engineering/math.

Perceived Supports

Number of Items	15
Rating Scale	People face a variety of factors that may support or hinder their college and career plans. We are interested in knowing about the situations, either helpful or unhelpful, you believe you might experience in relation to one particular choice option: the decision to pursue an academic major involving a heavy concentration of math or science**.** We realize that you may not have declared a major or are not intending to pursue a degree in a math or science-related area, but for the purposes of the questions in this part: **Assume that you want to select a math or science-related college major (e.g., Mathematics, Engineering, Physics, Computer Science). How likely would you be to experience each of the following situations?** 1 (Not at all likely) – 5 (Extremely likely) Higher ratings indicate a higher amount of support with academics
Coding	Average across all items
Items	1. Feel accepted by your classmates 2. Have access to a "role model" in this field (i.e., someone you can look up to and learn from by observing) 3. Be able to afford the extra cost of advanced training in this field 4. Feel support for this decision from important people in your life (e.g., teachers)

	5. Feel that there are people "like you" in this field 6. Get helpful assistance from a tutor, if you felt you needed such help 7. Get encouragement from your friends for pursuing this major 8. Get helpful assistance from your advisor 9. Be able to receive enough money through financial aid or other sources to allow you to pursue this major 10. Feel that your family members support this decision 11. Have friends or family members who would help you with math or science problems 12. Have enough money saved up to be able to complete your education in this field 13. Feel that close friends or relatives would be proud of you for making this decision 14. Have access to a "mentor" who could offer you advice and encouragement 15. Have enough financial support from your family to pursue this academic major

Perceived Barriers

Number of Items	21
Rating Scale	People face a variety of factors that may support or hinder their college and career plans. We are interested in knowing about the situations, either helpful or unhelpful, you believe you might experience in relation to one particular choice option: the decision to pursue an academic major involving a heavy concentration of math or science. We realize that you may not have declared a major or are not intending to pursue a degree in a math or science-related area, but for the purposes of the questions in this part: **Assume that you want to select a math or science-related college major (e.g., Mathematics, Engineering, Physics, Computer Science). How likely would you be to experience each of the following situations?** 1 (Not at all likely) – 5 (Extremely likely) Higher ratings indicate a higher amount of support with academics
Coding	Average across all items
Items	1. Receive negative comments or discouragement about your major from family members 2. Worry that such a career path would require too much time or schooling 3. Feel that you don't fit in socially with other students in this major 4. Receive unfair treatment because of your racial or ethnic group 5. Have professors or teaching assistants who are difficult to understand 6. Not have enough time for social or leisure activities 7. Feel pressure from your family to get out of college and begin making money 8. Receive unfair treatment because of your gender

	9. Have trouble getting assistance from teachers and teaching assistants 10. Feel that the demands of pursuing such a field would get in the way of family responsibilities 11. Experience financial strain, especially if this career path required additional training 12. Receive negative comments or discouragement about your major from friends 13. Feel a lack of support from professors or your advisor 14. Feel that you are different from others in this major because of your racial or ethnic group 15. Have too many other demands on your time to allow the study time required for this field 16. Have poor-quality teachers in your math and science-related courses 17. Feel that you are different from others in this major because of your gender 18. Have too little money to afford things (like computer software or tutoring) that you might need to do well in your coursework 19. Be concerned about the amount of competition among students in this field 20. Feel that your educational/career options are limited by financial concerns 21. Feel pressure from parents or other important people to change your major to some other field

Career Barriers

Number of Items	35
Rating Scale	**Likelihood** Please think about each of the common barriers listed below in terms of your own career progress, and please indicate how likely you think it is that you may experience each one **if you were majoring in a Science, Technology, Engineering or Math (STEM) field.** We recognize that you may have no intention of majoring in a STEM field, but for the purpose of this question, please indicate the likelihood of encountering the following barriers **if you had decided to major in a STEM field.** 1 (Very Unlikely) – 7 (Very Likely) **Hinderance** b) how much each barrier would hinder or interfere with your career progress. In other words, how much would each barrier make your progress difficult **if you were majoring in a science, technology, engineering or math (STEM) field?** 1 (Not At All) – 7 (Completely) Higher ratings indicate higher perceived likelihood and hinderance of barriers to STEM appearing in life

Items	**Perceived Likelihood of STEM Barriers** 1. Lacking information about possible jobs/careers 2. Being undecided about what job/career I would like 3. Being limited to certain career choices because of my gender 4. Being limited to certain career choices because of my race/ethnicity 5. Being discouraged from pursuing math/science fields (e.g. Engineering) 6. Being discouraged from pursuing non-math/science fields (e.g. Journalism) 7. Other people's beliefs that certain careers are not appropriate for men/women 8. Lacking the necessary experience for a job 9. Not being able to find a job after graduation 10. Not wanting to move away from my friends and/or family 11. Unsure of how to actually find a job 12. Tight economy 13. Not knowing the "right people" to get a job 14. Racial discrimination in hiring for a job 15. Sex discrimination in hiring for a job 16. Not being able to perform my job well 17. Lacking the required skills for my job 18. Being dissatisfied with my job/career 19. Not receiving support from my coworkers/supervisors 20. Fear of being considered unattractive to the opposite sex because of my job/career 21. Difficulty dealing with "politics" at work 22. Racial discrimination in promotions in job/career 23. Not being taken seriously at work because I'm a man/woman 24. Sexual harassment on the job 25. Sex discrimination in promotions in job/career 26. Lack of respect from coworkers/supervisor because of my gender 27. Lack of respect from coworkers/supervisor because of my race/ethnicity 28. Being the "token" in a job because of my gender 29. Being the "token" in a job because of my race/ethnicity 30. Getting married 31. Having children 32. Not feeling supported by my family 33. Conflict between my marriage/family plans and my career plans 34. Not being able to find good day-care services for my children 35. Feeling guilty about working while my children are young **Hinderance** 1. Getting married 2. Having children 3. Not feeling supported by my family

	4. Conflict between my marriage/family plans and my career plans 5. Not being able to find good day-care services for my children 6. Feeling guilty about working while my children are young

Coping Efficacy for Barriers

Number of Items	18
Rating Scale	Here we are interested in knowing how well you believe you could cope with each of the following barriers, or problems, that students could possibly face in pursuing a math or science-related college major. Although you might have declared your major in a different field, for this question, assume you want to pursue a math or science-related major. Please respond to the following items by indicating your confidence in your ability to cope with, or solve, each of the situations if you were to experience such a situation at the university. How confident are you that you could... 1 (No confidence at all) – 9 (Complete confidence) Higher ratings indicate a higher perceived ability to overcome barriers to succeed in math/science areas
Items	1. Succeed in a math or science course despite having a poor instructor 2. Balance family responsibilities with the demands of pursuing a major in a math or science field 3. Find ways to get to know math/science instructors even if they are busy 4. Find ways to afford things, like software or tutoring, that you might need to do well in your coursework, even if your budget is tight 5. Deal with unfair treatment you might receive because of your gender 6. Cope with lack of support from professors or your advisor 7. Persist with these courses even if you did not see many other people of your culture or racial/ethnic group in them 8. Deal successfully with competition among students in this field 9. Stick with the decision to take a math/science major even if someone close to you tried to discourage this decision 10. Complete a degree in math or science despite financial pressures 11. Find adequate tutoring help in math or science, if you felt you needed such help 12. Continue taking these courses even if you did not feel well-liked by your classmates or professors 13. Find ways to overcome communication problems with professors or teaching assistants in this field 14. Find ways to study effectively for math/science courses despite having competing demands for your time

	15. Continue on in math or science even if you felt that, socially, the environment in these classes was not very welcoming for persons of your gender 16. Overcome pressure from your family to get out of school and begin earning money 17. Cope with unfair treatment you might receive because of your race or ethnicity 18. Balance the pressures of studying for math/science courses with the desire to have free time for fun and other activities

Educational Supports

Number of Items	9
Subdimensions	Educational Support Received While an Undergraduate, Educational Support from American Indian Student Life, Educational Support from Student Organizations, Educational Support from Campus Resources, Educational Support from Scholarships, Educational Support from Gateway Courses
Rating Scale	The following statements describe how you might feel about the availability of financial opportunities for your education. Please rate the extent that you agree or disagree with the statements. 1 (Strongly Disagree) – 5 (Strongly Agree) Higher scores indicate higher awareness of educational support opportunities
Items	1. There are a lot of scholarships and financial aid available for me 2. I know where to search for scholarships 3. I am successful at getting scholarships 4. I know how to find and apply for financial aid from my tribe (leave blank if you are not a member of a Native American tribe) 5. I know how to find and apply for scholarships from local private organizations 6. I did not apply for scholarships and financial aid, because the process takes too much time 7. I try to apply for every scholarship opportunity that I am eligible for 8. I understand money and finance well enough to understand the sources of funding available to me 9. I know how to apply for financial aid from the Federal Government (e.g., Pell Grants)