EXPECTANCY-VALUE MODEL: INVESTIGATING ACADEMIC SUCCESS AND RETENTION PREDICTORS OF FIRST-YEAR STEM MAJORS

by

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ABSTRACT

NICKCOY FINDLATER. Expectancy-Value Model: Investigating Academic Success and Retention Predictors of First-Year STEM Majors
(Under the direction of DR. XIAOXIA NEWTON & DR. STELLA KIM)

The gap in supply (i.e., shortage) and demand of the STEM workforce have prompted extensive research on identifying factors that predict STEM outcomes and retention of students. Few studies, however, have examined the relationships between STEM outcomes and predictors in an integrated model, taking into account measurement errors in the predictors. Drawing upon the Expectancy-Value Model of Achievement Related Performance and Choice, I conducted a structural equation modeling (SEM) analysis to examine the relationships between *academic support*, *academic engagement*, *mathematics readiness,* student *hours worked*, and first-year STEM students' academic success and retention. The SEM allowed me to investigate the relationships between predictors and outcomes simultaneously while accounting for the measurement errors. The sample consisted of 798 first-year STEM majors who took the National Survey of Student Engagement during the 2016, 2018, and 2020 academic years in a large urban university. Results indicated that *academic support* was a statistically significant predictor of first-year STEM students' academic success and retention.
Additionally, *mathematics readiness* was found to be a statistically significant predictor of first-year retention. Lastly, results suggested that female students on average were more likely than their male counterparts to engage in *academic support* and *academic engagement* activities even though females worked more hours than males. The results have implications for policies and practices aimed at improving STEM retention. Areas of further research are also identified.

Keywords: expectancy-value model, structural equation modeling, STEM retention, academic success predictors, mathematics readiness

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CHAPTER 1: INTRODUCTION

Problem Statement

Annually, institutions of higher education, within the United States, allocate and invest significant amounts of money, time, and resources (e.g., web services and digital advertising, student search lists, recruitment events) in recruiting students to attend their institutions (Jaquette & Han, 2020; McClure, 2019; RNL, 2020). Specifically, a national higher education survey, assessing the financial cost institutions incurred by recruiting students, reported an increase of 21% (private institutions) and 30% (public institutions) between the 2019-2020 calendar years; this is approximately $3,000 spent per student for recruitment purposes (RNL, 2020). Even globally, there has been a significant increase in students deciding to attend higher education institutions year after year through higher education institution recruitment initiatives (UNESCO Institute for Statistics [UIS], 2018). By focusing recruitment efforts to increase student enrollment, universities aim to achieve their academic and economic goals, through high student retention and graduation rates (Berger & Lyon, 2005; Larsen et al., 2013). However, many higher education institutions struggle with student retention and persistence. Retention and persistence are, respectively, defined as the percent of students returning to the same institution (i.e., retention) or a different institution (i.e., persistence) for their sophomore year (National Student Clearing House [NSCH], 2017).

Retention Gaps in STEM Education

The gap between higher education institutional investments (i.e., students' recruitment, retention, and persistence) and the returns on their investments, is further heightened when it comes to science, technology, engineering, and mathematics (STEM) fields of study (RNL, 2020). STEM fields of study have been noted as preparing students for occupations "…with the highest paying, fastest-growing, and most influential in driving economic growth and innovation in the U. S." (Thomasian, 2011, p. 29). Moreover, researchers have noted that the United States' economic dominance throughout the 20th and 21st centuries was closely tied to its advances in science and technology (Goldin & Katz, 2008; Xie & Killewald, 2012). However, there are documented concerns that the U.S. is losing its dominance in science and technology as institutions of higher education, throughout the nation, struggle with recruitment and retention in STEM fields of study (National Academy of Science, 2007, 2011).

Furthermore, interests in supporting the growth of science, technology, engineering, and mathematics majors in higher education, from government and private agencies, has increased substantially in the past decade – aided by well-documented shortages of the government sector and private industry STEM workers; as well as, an increase in first-year college students declaring STEM majors (Xue & Larson, 2015). Not only are White and Asian first-year college students showing an increase in declaring STEM majors, but African American, Hispanic, and Native American students are also declaring STEM majors at a higher rate than in past decades (Eagan et al., 2013). Even with this increased interest in STEM majors, bachelor's degree retention and completion rates in STEM remain persistently low, especially among women (Nix & Perez-Felkner, 2019) and historically minoritized students in the STEM fields (i.e., African American, Hispanic, and Native American) (Schnettler et al., 2020).

Additionally, at the higher education level, financial incentive packages, and special government funding are offered to encourage students to study in the science, technology, engineering, and mathematics fields. Despite continued investments in STEM education, the U.S.-based dropout rate of students participating in a STEM major is estimated to be 40 to 50 percent higher, relative to non-STEM-focused majors (Schnettler et al., 2020). Though the U.S.

federal government has mandated policies to prioritize STEM education, the task ultimately falls to higher education institutions to produce STEM graduates ready to enter STEM fields of practice (Romash, 2019).

First-Year STEM Majors

Griffith's (2010) longitudinal study found that most students dropping out of their STEM majors take place during the first year of their undergraduate study. During this time, students are completing their introductory gateway courses relative to their disciplines (Griffith, 2010). Regarding STEM majors, or more specifically, Physical, Engineering, Mathematics, and Computer Science (PEMC) majors, these introductory gateway courses tend to be mathematics-based in their content (e.g., Calculus, Physics, Chemistry, etc.), and earning a grade below a "C" in a course can result in removal from the STEM major or even extended degree completion by more than one year (Griffith, 2010; Maltese & Tai, 2011). From this finding, we can assume research, policies, and practices to increase retention for STEM majors may best be served by focusing on the first year of participation in the major.

As previously outlined, students pursuing STEM majors will take mathematics-based introductory coursework during their first year of study. The sequencing of these courses is deliberate in their content progression, as it requires, since being adopted in 1905, for students to complete chemistry or physics and calculus in the first year, followed by biology and physics in the second year (mainly for PEMC majors) (Barr et al., 2010; Romash, 2019; Zhang et al, 2004). The progression of these content areas (i.e., Calculus, Chemistry, Physics) is prerequisite intensive, as proficiency in the introductory content is required to understand more advanced content in later courses (Griffith, 2010; Maltese & Tai, 2011). Considering the first-year mathematics intensive curriculum, many first-year STEM majors report having significant struggles and difficulties with what they consider to be "...too heavy a course load in their first year" (Noel-Levitz, 2006, p. 4). Additionally, previous research has found STEM students, in need of completing remedial mathematics coursework during their first year, were approximately 50% more likely to leave the STEM fields of study after their first year (Adelman, 2006; Cabrera, et al., 2005; Herzog, 2005). Given these points, it is advantageous for future research on first-year STEM major retention to account for student math readiness. As such, this current study included the element of STEM students' mathematics readiness by investigating their possible enrollment in a developmental mathematics course during the first year of study.

PEMC-STEM Majors

Furthermore, this study also explored student majors from physical, engineering, mathematics, and computer science (PEMC) and other-STEM majors, regarding if varying STEM major subsets influenced first-year and minoritized students' retention and academic achievement. Researchers have reported that first-year STEM major students are tasked with intensive and time-consuming mathematics-based courses for their first year of study (Barr et al., 2010; Romash, 2019; Zhang et al, 2004); however, this is not generally the case for all STEM majors (Griffith, 2010; Maltese & Tai, 2011). Previous research has highlighted this point as findings showed differing relationships regarding female student outcomes in other-STEM majors and non-STEM majors, relative to mathematic-intensive STEM majors, or physical sciences, engineering, mathematics, and computer sciences majors (Dika & D'Amico, 2015; Nix & Perez-Felkner, 2019; Perez-Felkner et al., 2012).

Nix and Perez-Felkner (2019) define PEMC majors as a subset of STEM majors considered to be the most mathematics-intensive in their coursework (e.g., Chemistry, Computer Science, Engineering, Mathematics, Physics). The authors note that previous publications may have erroneously reported STEM major participation and retention without adequately delineating the areas in which gender and minoritized students may be struggling (Lubinski et al., 2001; McPherson, 2017; Meyer et al., 2015; Snow, 1961). A quantitative study by Dika and D’Amico (2015) explored the relationship between PEMC-STEM majors, other-STEM majors, and non-STEM majors of first-generation college students when considering the significance of academic and pre-college factors. Of the findings reported, Dika and D’Amico (2015) stated “…[we] should not paint STEM with a broad brush.…findings from the present study is that the preparation leading to PEMC-STEM majors and then transitions for PEMC-STEM students may, in fact, be different than those for other-STEM majors” (p. 380). The authors go on to recommend that future research explore the varying STEM subsets and the potential differing relationships that may be present.

Marginalized Students

The obstacles in STEM major retention noted previously are not equally distributed across social groups, and have been found to, more so, adversely affect women and racial minorities, when compared to White and Asian male students (Xie et al., 2015). For instance, the U. S. Census Bureau (2016) reported that women represent more than half of the U.S. population, and attained approximately 57% of bachelor’s degrees, 59% of master’s degrees, and 51% of doctorate degrees between 2013 and 2014. However, during the same years, and in years previous, women were found to be underrepresented in PEMC fields of study and practice (Charles & Bradley, 2002, 2006, 2009; DiPrete & Buchmann, 2013; Xie & Shauman 2003; Xie & Killewald, 2012). In 2018, The National Science Foundation (NSF) reported that female students achieved less than 20% of bachelor’s degrees in the physical sciences, and less than 40% in mathematics and statistics during the 2013-2014 academic year.

Regarding race and ethnicity, the U.S. population was and continues to be in the coming decades, ever more racially and ethnically diverse (NSF, 2018a). The National Science Foundation (2018a) predicts by 2060, 56% of the U.S. population will be minorities (i.e., non-White/European descent). However, data highlights that minoritized students in STEM majors continue to lag their population representation in educational attainment (NSF, 2018a). The National Science Board (2016) reports, that in 2014, minoritized students earned 20% of bachelor's, less than 15% of master's, and less than 8% of doctorate degrees in STEM fields of study. Given the reported underrepresentation of women and minoritized students in STEM majors, it is crucial for research focused on first-year STEM major retention to include gender and race as measures of assessment.

Regarding minoritized students in STEM, it is important to note that though Asians are considered racial minorities within the United States, the Pew Research Center classifies Asians as being overrepresented in STEM majors and the STEM workforce (PRC, 2018). When compared to the overall workforce population, especially considering college-educated workers, Asians are 10% of the overall workforce, yet account for 17% of the college-educated STEM workforce (PRC, 2018). As such, this paper referred to ethnic/racial minoritized students relative to STEM fields of study (e.g., African American, Hispanic, and Native American). Nevertheless, given that Asians are racial minorities within the U.S., this study included Asian STEM students when examining this study's proposed research questions across racial groups.

Challenges of Working While Studying

Alongside the aforementioned struggles of first-year STEM majors, the necessity of paying for college is an ever-increasing challenge for higher education students in the 21st century. The National Center for Education Statistics reports that, between 2008-09 and 2017-18, the average tuition and fees of four-year public institutions rose by 36 percent, while two-year public institutions rose by 34 percent (NCES, 2018). All the while, the maximum federal Pell Grant available per student has decreased by more than 92 percent since 1999 (Perna & Odle, 2020). As such, if a student does not have sufficient savings, wealth, or access to other financial resources to cover the costs of enrollment, they are usually left with taking on loans, working while studying, or both (Perna & Odle, 2020). In 2017, the U.S. Department of Education reported that 43 percent of all full-time undergraduate students were working while studying, and 81 percent of part-time students were working while studying; in all, 11.4 million students throughout the nation were working while enrolled in an institution of higher education (NCES, 2018).

Though it is not uncommon for students to be employed while studying, there, however, may be negative implications for students working while studying. There are growing bodies of literature highlighting the negative implications of hours spent working and academic achievement (Bozick, 2007; Douglas & Attewell, 2019; Stinebrickner & Stinebrickner, 2003, 2004). Research has shown that students allocating time to work, tend to reduce the necessary time needed to allocate for educational activities which may lead to increased attrition in a bachelor’s degree program or continuing full-time enrollment (Douglas & Attewell, 2019). As noted previously, STEM major students are more likely to experience demanding and challenging curriculums than non-STEM majors, coupled with increased time being spent working, which may lead to increased attrition in STEM retention. Given these points, this paper included this phenomenon (i.e., hours worked) when evaluating STEM students' first-year retention and performance.

Academic Success and Retention Predictors

The previously presented challenges to STEM student retention and academic success have been examined; as such, scholars have identified various predictor and motivational variables considered to contribute to the phenomenons of STEM retention and academic success (Adelman, 2006; Cabrera, et al., 2005; Herzog; Perez et al., 2014; Robinson et al., 2018; Trautwein et al., 2012). However, previous works have excluded possible contextual interrelationships with persisting and possible emerging predictors of STEM retention. Of the previous empirical studies examining this topic, the research designs did not account for predictor contributions to STEM first-year retention and academic success, while controlling for additional predictors in a single model (Adelman, 2006; Chen, 2013; Ost, 2010; Sklar, 2015; Watkins & Mazur, 2013). This has resulted in gaps in current literature. Given that the aforementioned challenges presented continue to persist, this dissertation aims to evaluate and enlarge the scope of this topic. This dissertation aimed to explore previously researched and possible emerging predictors of STEM first-year retention and academic success, by utilizing a single theoretical model to control for potential interrelationships and assess their influence on predicting STEM students' academic success and retention after their first year of study. As such, this section will introduce the three primary predictors of academic success and retention driving this study.

Academic Support

Aiming to address the multitude of challenges obstructing student persistence and retention, as well as, overall academic achievement, previous empirical research studies have been conducted to identify key predictors related to student retention and success (DiPrete & Buchmann, 2013; Eagan, et al., 2013; Lubinski et al., 2001; McPherson, 2017; Meyer et al., 2015; Snow, 1961). One such extensively researched predictor of academic success and retention in higher education is *academic support*. Though academic support initiatives in higher education can be accounted for in various methods (e.g., co-curricular support, faculty-student interactions, peer support) (DeFreitas & Bravo, 2012; Ferguson, 2021; Gnebola, 2015; Martinez, 2016); Gnebola's (2015) extensive empirical study identified faculty-student interactions to be especially of note, as faculty-student interactions positively correlated in predicting student achievement outcome measures, such as GPA.

Furthermore, additional research studies have supported Gnebola's (2015) findings, by noting student interactiveness with faculty and peers, in and outside of the instructional space, to be especially crucial in increasing their chances of academic success (Aikens, et al., 2017; Ferguson, 2021; Pajares, 1996; Thiry & Laursen, 2011). Specifically from a STEM major perspective, Micari and Pazos's (2012) study confirmed faculty-student interactions as a predictor of academic retention and success, as they reported confirmed correlations between students' course grades and the feelings of how connected the student felt to their professors. Allen et al. (2018) confirmed these findings, as their study reported increased student performance with increased student-faculty interaction. Though the aforementioned research studies support the notion of *academic support* metrics being a key predictor of academic success, the research studies did not specifically account for the STEM first-year student experience, regarding retention to the second year of study and academic success. As such, this dissertation aimed to contribute to this gap in current literature regarding STEM first-year success and retention.

Academic Engagement

Another extensively researched, and considered to be a key predictor of academic retention and success, is *academic engagement* (Bryson & Hand, 2007; Glanville & Wildhagen, 2007; Horstmanshof & Zimitat, 2007; Krause & Coates, 2008). Though there are extensive academic debates regarding a primary definition of *academic engagement* (Bryson & Hand, 2007; Glanville & Wildhagen, 2007; Horstmanshof & Zimitat, 2007; Krause & Coates, 2008); a general interpretation of *academic engagement* can be summarized by stating, the amount of time a student devotes to their academic activities, both in and outside of the classroom, are reliable predictors of student retention and academic success (Fredericks et al., 2004). These academic activities, or engagement, can be further grouped into three categories of *academic engagement* (i.e., behavioral engagement, emotional engagement, and cognitive engagement) (Lester, 2013).

The three categories of *academic engagement* are further investigated in Chapter 2, however, Fredericks et al.'s (2004) study found that there may be varying levels of overlap regarding the three categories of academic engagement. Fredericks et al. (2004) further argued that the three *academic engagement* categories are "dynamically interrelated within the [participant]; they are not isolated processes" (p. 61). As such, research designs that encompass overlapping elements of the three categories ought to assess the *academic engagement* construct from a "meta" perspective (i.e., as a single construct). Nevertheless, previous research investigating *academic engagement* has yet to investigate STEM first-yeat retention and academic success, while accounting for the *academic support* and *hours worked* (to be presented in the following subsection) predictors (Fredericks et al., 2004; Lester, 2013; Martinex, 2016). The current study aimed to close the gap in research by assessing first-year STEM student retention and academic success, with the predictor's *academic engagement*, *academic support*, and *hours worked*.

Hours Worked

Though research gaps exist regarding *academic support* and *academic engagement* for STEM first-year students, these latent constructs are, nevertheless, extensively researched and documented predictors of higher education student retention and academic success (Martinez, 2016). In addition to these predictors, this study aimed to include the less researched, yet impacting phenomenon of higher education students working while studying (Perna & Odle, 2020). With the increase in higher education students working while studying, research studies have noted that students devoting more time to work, rather than studying, has demonstrated to have negative effects on overall student academic performance and retention (Scott-Clayton & Minaya, 2016; Stinebrickner & Stinebrickner, 2003, 2004).

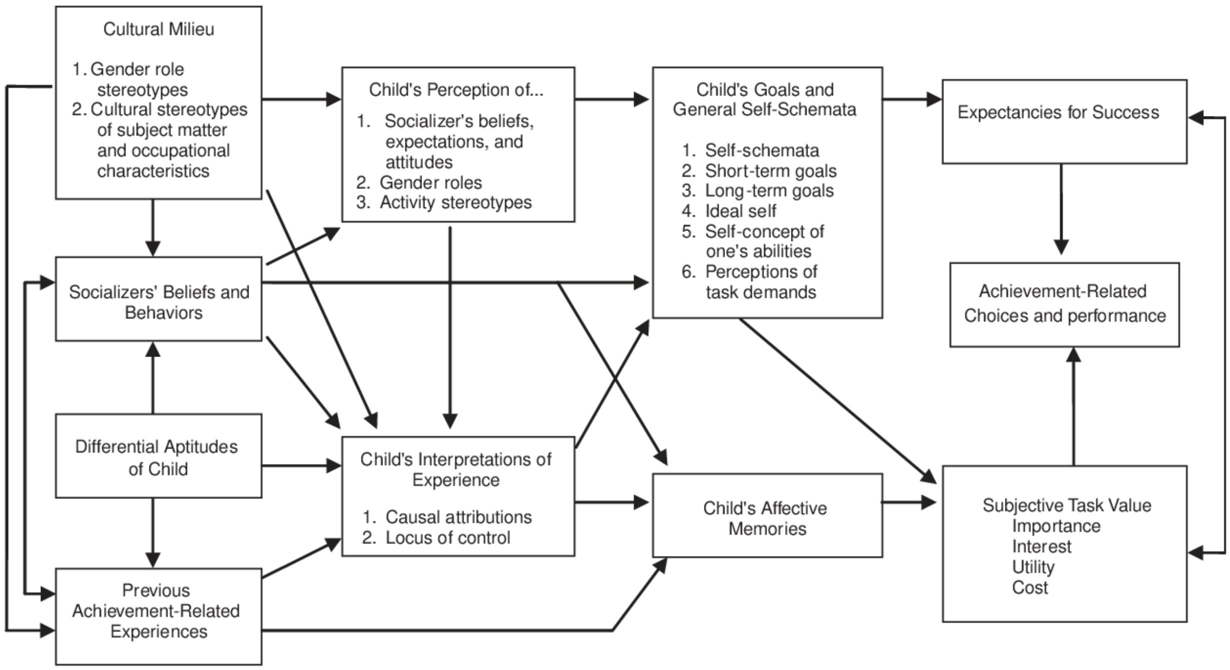
Research on the subject matter has documented that more than half of higher education students within the United States are working while enrolled in a degree-seeking program (National Center for Education Statistics, 2015). This level of work commitment has been founded to be directly related to financial need and not an optional endeavor, as researchers have investigated and found an increase in financial hardships for undergraduate degree-seeking students (Broton & Goldrick-Rab, 2016). Though this subject matter of research is emerging (Scott-Clayton & Minaya, 2016), there is currently a research gap investigating the impacts of first-year STEM students working while studying as a predictor of student academic success and retention beyond the first year. Similar to predictors, *academic support,* and *academic engagement,* student *hours worked* have not been investigated holistically, within a single model, to assess first-year STEM students' retention and overall academic success. This current research study aimed to explore this proposed phenomenon and contribute to the literature gap in improving first-year STEM major success and retention through a single model accounting for correlational relationships that may exist between the aforementioned predictors of academic success and retention. To execute the vision of this research study, a singular model grounded in theoretical evidence was imperative to account for the predictors of academic success and retention presented in this section. The following section highlights the Expectancy-Value Model, which the researcher aimed to use in aligning the aforementioned predictors, to address the key concerns presented in the *Problem Statement* section.

Expectancy-Value Model

As presented earlier, the concerns regarding attrition in STEM education, especially among first-year, women, and minoritized students in STEM majors, continue to be a key concern for researchers and policies-makers to address. The multiplicity of varying issues and predictors presented in the previous sections illustrates the need for continued research utilizing theoretical frameworks with multidimensional factors, which may better account for the numerous obstacles contributing to the attrition of STEM major first-year retention and academic success (Perez et al., 2014; Robinson et al., 2018; Trautwein et al., 2012). Martinez (2016) notes that one such theoretical model, which is well-grounded in accounting for student persistence and academic success in primary and secondary education, is the *Expectancy-Value Model* (see Figure 1).

Figure 1

Framework of Expectancy-Value Model (Wigfield & Eccles, 2000)



According to Andersen and Ward (2014), more than a decade of research utilizing the *expectancy-value model* of achievement-related choices has been employed to demonstrate unique relationships between student *beliefs* and *task values*, concerning outcomes related to middle and high school STEM persistence and future degree completion intentions (Maltese & Tai, 2011; Mau, 2003; Syed et al., 2011; Tai et al., 2006; Simpkins et al., 2006). More generally, Xie and Andrews (2012) noted that the Expectancy-Value Model has a well-documented foundation for understanding how student attitudes and behaviors can influence achievement-related choices and performance. As such, this present study aimed to be the first in applying this theoretical framework, which was conceptualized as a model by Eccles and colleagues (Eccles et al., 1983; Wigfield & Eccles, 2000) (see Figure 1.1), to specifically investigate the retention and academic success of first-year students in STEM majors, while accounting for the predictor variables presented in the previous section (i.e., *academic support*, *academic engagement*, and *hours worked*). The following paragraphs will briefly outline the major components of the Expectancy-Value Model, and how they relate to investigating students' choices to persist in an academic domain. Moreover, the alignment of the previously identified predictor variables and the Expectancy-Value Model will be briefly presented in this section and further stated, in-depth, in Chapter 2.

Eccles and colleagues' (Eccles et al., 1983; Wigfield & Eccles, 2000) Expectancy-Value Model emphasizes two essential "…motivational questions that individuals [i.e., students] ask themselves before engaging in a particular task: *Can I do this?* and *Why do I want to do this?"* (Perez et al., 2019, p. 3). Given this theoretical framework, individuals will be most motivated when they express feelings of competence and success in a domain (i.e., Expectancies for Success; e.g., I can be successful in mathematics) and how highly they value the domain (Subjective Task Value; e.g., I want to study this because it's interesting) (Andersen & Chen, 2016). Regarding expectancies for success, previous research has aligned this construct to latent factors related to faculty-student interactions in way of *academic support* measures (Ferguson, 2021; Gnebola, 2015; Martinez, 2016; Pajares, 1996).

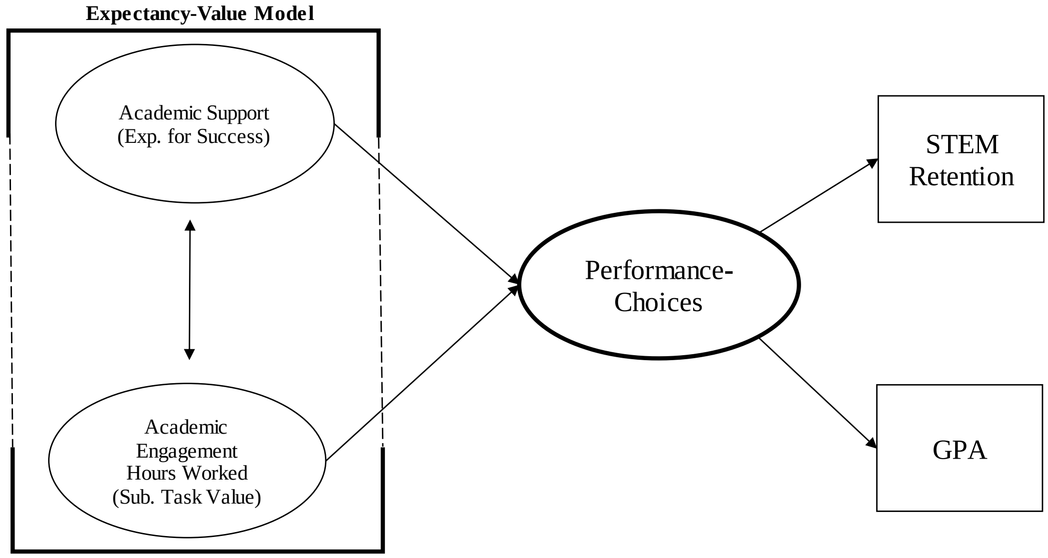
In terms of subjective task values, Eccles and colleagues' (Eccles & Wigfield, 2002; Wigfield & Eccles, 2000) noted three unique sub-components contributing to an individuals' positive task values: "(1) *intrinsic interest value,* the anticipated enjoyment of a task or interest in a domain; (2) *attainment value*, the perceived importance of a task to one's identity; and (3) *utility value*, the subjective value of a task for attaining an extrinsic goal such as a career goal" (Perez et al. 2019, p. 4). All three sub-components can be summarised as indicators that assess an individual's likelihood to engage in a task or behavior, given that their self-interests align with the engaging task or behavior (Wigfield & Eccles, 2000). As a result, previous researchers have identified the latent factor, *academic engagement*, to be theoretically associated with Eccles's first three sub-components of subjective task value (Chow et al., 2012; Fan & Dempsey, 2017; Martinez, 2016; Plante et al., 2013; Wang & Liou, 2018; Wu et al., 2019).

Lastly, a fourth sub-component (i.e., negative task value), *perceived cost (i.e., cost)*, which has been traditionally included under the subjective task value, is thought of like the question, “why don’t I want to do this?” (Perez et al., 2019). Eccles et al., (1983) represent perceived *cost* as any apparent drawbacks of an individual choosing to engage in a task. For example, as noted previously, the need for undergraduate higher education students to work more than 15 to 20 hours a week (i.e., *hours worked*) while enrolled in a STEM program (Douglas & Attewell, 2019), may contribute to a student’s *perceived cost* of remaining enrolled and completing their program. Currently, there is limited research utilizing the Expectancy-Value Model while including the fourth sub-component of subjective task value (i.e., *cost*), and its contribution to first-year STEM retention and academic outcomes (Barron & Hulleman, 2015; Wigfield & Cambria, 2010).

With the aforementioned theoretical alignment of the predictors driving this study, the researcher was able to utilize a revised version of Eccles and colleagues (Eccles et al., 1983; Wigfield & Eccles, 2000) Expectancy-Value Model of Achievement-Related Performance and Choices (see Figure 2). As such, this study utilized the expectancy-value model to assess higher education STEM first-year retention and academic success with the following factors: (1) Expectancies for Success (i.e., *academic support*); (2) Subjective Task Values (i.e., *academic engagement* and *hours worked*); and (3) Achievement Related Performance (i.e., academic success through GPA) and Choices (i.e., persistence to the second year in STEM major).

Figure 2

Proposed Revised Framework of Expectancy-Value Model



Research Purpose

Though the expectancy-value model has been utilized extensively in research for primary and secondary education, research designs specifically in postsecondary education are limited (Martinez, 2016); even more so when considering expectancy-value model research designs focusing on STEM fields of study (Schnettler et al., 2020). Specifically, there is limited research utilizing this well-grounded theoretical model of student choice and academic success (Andersen & Ward, 2014; Martinez, 2016), while connecting STEM-focused students' expectations and performance during the first year of college while accounting for the academic and success predictors: *academic support*, *academic engagement*, and *hours worked* (Andersen & Ward, 2014; Martinez, 2016; Perez, 2019). More so, this gap in the literature is more apparent regarding the following demographic groups: women and minoritized students in STEM majors (DiPrete & Buchmann, 2013; Eagan et al., 2013; Schnettler et al., 2020; Xie & Shauman 2003; Xie & Killewald, 2012).

The purpose of this study was to utilize a revised version of the Expectancy-Value Model of Achievement Related Performance and Choice: (1) Expectancies for Success; (2) Subjective Task Values; and (3) Achievement Related Performance and Choice (see Figure 2). The aim was to assess if first-year and marginalized college students in the STEM major's *academic support* and *academic engagement* are predictors of overall student success and retention after their first year of study. In addition to these two predictors, the researcher assessed if *hours worked* while studying was a predictor as a subjective task value. The researcher used the National Survey of Student Engagement (NSSE), an assessment instrument completed during approximately the first and senior years of college. The use of analyzing secondary data from the NSSE survey was especially deliberate, as the survey instrument has more than two decades of participation at more than 601 colleges and universities throughout the United States; as well as, well-documented psychometrics validating its reliability in assessing student *academic support* and *academic engagement* predictors (Ewell & McCormick, 2020; NSSE Psychometric Portfolio, 2019). Using secondary data from the NSSE survey assessment tool, along with institutional data (i.e., student demographics, second-year cumulative GPA, mathematics remedial course completion, and enrollment intention) the following research questions guided the study:

1. To what extent does the Expectancy-Value Model of Achievement Motivation explain:
    - First-year STEM major students' academic success and retention?
    - First-year STEM major students' academic success and retention by *gender*?
    - First-year STEM major students' academic success and retention by *race*?
2. Given the Expectancy-Value Model of Achievement Motivation, are *hours worked (perceived cost)* a predictor of academic success and retention for:

- First-year STEM majors?
- First-year STEM major students across *gender*?
- First-year STEM major students across *race*?

3. Is the relationship between the Expectancy-Value Model of Achievement Motivation and first-year STEM major students' academic success and retention mediated by math coursework readiness?
4. To what extent does the Expectancy-Value Model of achievement motivation explain first-year students' declared PEMC or Other-STEM majors' academic success and retention?

Significance of the Study

Previous research studies have explored the three predictive latent constructs (i.e., *academic support*, *academic engagement*, and *hours worked*), and how they influence higher education student retention and academic success. However, these research studies have yet to explore these predictors collectively (i.e., in a single model controlling for possible interrelationships) relative to first-year STEM major students (Adelman, 2006; Cabrera et al., 2005; Herzog, 2005); as well as, the growing number of women and minoritized STEM students unable to persist in a STEM field of study (Bozick, 2007; Douglas & Attewell, 2019; Stinebrickner & Stinebrickner, 2003, 2004). Moreover, this study aimed to explore this current literature gap, by including the predictors in a single model while assessing STEM first-year retention and academic success relationships. As such, future researchers may account for factors most influential in predicting first-year STEM retention and academic success.

To elaborate further on the current literature gap, Gnebola's (2015) study found that faculty-student interaction (i.e., *academic support*) and academic self-efficacy positively correlated in predicting student achievement outcome measures, such as GPA. Pajares (1996) also found that *academic support*, through students' ability to interact with their environment (i.e., faculty, advisor, administrators), increased their chances of academic success. However, these studies did not control for correlational relationships between other possible predictive constructs (e.g., *academic engagement*, *hours worked*) concerning student achievement outcome measures.

Moreover, Lester (2013) notes that higher education research initiatives have found *academic engagement* to be especially effective in predicting student engagement behavior and academic achievement outcomes of students in post-secondary education. Lastly, the growing number of higher education students working while studying is contributing to the broader discussion of academic success and retention, as such, should be a primary predictor for future educational research focus (Douglas & Attewell, 2019). For example, Stinebrickner & Stinebrickner's (2003, 2004) study found that the number of student *hours worked* has negative effects on academic performance and student retention. The authors highlighted that student *hours worked* contributed to a phenomenon known as "time bind"; this occurs when higher education students are unable to contribute the time and effort needed to complete their coursework. Tinto (1993), earlier, supports this view "…full-time employment limits time for interaction with other students and faculty, leading to poor social integration and higher rates of student drop-out" (p. 64).

All three predictors (which will be expanded on in Chapter 2), *academic support*, *academic engagement*, and *hours worked*, which have been researched independently, were found to be especially important in assessing the retention and/or achievement of higher education students in varying institutional settings (DiPrete & Buchmann, 2013; Eagan et al., 2013; Martinez, 2016; Schnettler et al., 2020; Xie & Killewald, 2012; Xie & Shauman 2003). By utilizing a well-grounded theoretical multi-construct model (i.e., expectancy-value model), the study will be able to assess the predictive relationship of the three predictor constructs (i.e., *academic support*, *academic engagement*, and *hours worked*) relative to first-year STEM and marginalized students in a single theoretical model. This particular study is important as its findings will contribute to current educational research aiming to aid in stemming the growing attrition rate of domestic STEM students in institutions of higher education throughout the United States (Griffith, 2010; Maltese & Tai, 2011; Romash, 2019). Moreover, this study's findings may aid higher education leaders and policymakers allocate resources toward STEM retention and academic success predictors most relevant to their institution's needs and strategic goals.

Definitions of Relevant Terms

Definitions for terms relevant to this study are provided below:

- *Academic Engagement*: constitutes the level of effort and time a student devotes to educational activities, both in and outside of the instructional space (NSSE, 2011).
- *Academic Success*: A higher value grade point average (GPA) on a scale of 0.00 to 4.00 will indicate better grades and higher academic success (Meyer et al., 2019).
- *Academic Support*: In this study, academic support is defined by the quality of faculty and academic advisor interactions with students both within and beyond the classroom (Lee & Matusovich, 2016).
- *Marginalized Students*: Marginalized students, relative to STEM fields of study, are defined as identity groups encompassing: Blacks/African Americans, Native Americans, Latinx, Pacific Islanders, women, English language learners, newcomers or immigrants to

the U.S., LGBTQ people, first-generation college students, individuals from low-income backgrounds, and people with disabilities (Gushue & Whitson, 2006). For this study, marginalized students will include the following identity groups: Blacks/African Americans, Native Americans, Latinx, Pacific Islanders, and women (Lee & Matusovich, 2016).

- *Other-STEM*: Other-STEM is defined as STEM majors comprising the study of human and animal behaviors, interactions, thoughts, and feelings (e.g., biology, psychology, sociology, anthropology) (Nix & Perez-Felkner, 2019)
- *PEMC*: Defined as physical sciences, engineering, mathematics, and computer sciences, and are considered mathematics-intensive science fields of study (Perez-Felkner et al., 2012).
- *Retention*: This study utilizes retention relative to a student's acquisition to an institution of higher education and remains enrolled in the following academic year (Bean & Eaton, 2002).
- *STEM Retention*: STEM retention, for this study, is defined as students' enrollment in a STEM major until the following academic year (Khan, 2012).
- *Hours Worked*: The amount of time a student has worked either on-campus or off-campus while enrolled in a degree-seeking program (NCES, 2018).

CHAPTER 2: LITERATURE REVIEW

Introduction

This chapter will first review the current demand, and excessive shortages, for STEM majors in fields of practice. Next, an examination of past and current literature that investigates the *challenges in first-year STEM major retention* will be presented. Lastly, the chapter will examine past and current literature regarding the *expectancy-value model* and the three core predictors found to contribute to academic success and retention in post-secondary education (Martinez, 2016). To adequately collect relevant scholarly literature related to the research focus of this study, the researcher systematically collected and synthesized previous research publications related to STEM education and higher education first-year student retention and persistence (Baumeister & Leary, 1997; Tranfield et al., 2003) from Springer International Publisher, Sage Journals, and ERIC Education databases.

Furthermore, the review of the literature was aligned with the research conducted in the theoretical framework of Eccles and colleagues' (Eccles et al., 1983; Wigfield & Eccles, 2000) Expectancy-Value Model, to focus the review method to address the proposed research focus in Chapter 1. By aligning these focus areas in the review of the literature, the researcher was able to illustrate research evidence of findings at a meta-level and present potential research gaps warranting further investigation (Tranfield et al., 2003); these potential research gaps are highlighted in the following sections.

Demand for STEM Majors

Xue and Larson (2015) note that there are labor shortages in the STEM fields and these shortages vary across the STEM fields of practice, degree levels of workers, and geographic locations. Belser (2017) posited that the argument of there being a shortage, and simultaneously a surplus in STEM jobs for industry and academia is possible given the focus area being investigated. For example, STEM fields such as computer science and technology fields, as well as, petroleum engineers are some areas in STEM fields of practice that are in major shortage concerns given increased retirements and creation of new jobs through the 21st-century technological evolution (NSB, 2015).

The demand for STEM degree seekers and *qualified* workers is at an all-time high as the industrial automation of developed nations continues to dominate the industry and societal needs (NSB, 2015). However, students with declared STEM major's attrition continues to show a downward trend after their first year in college (Sithole et al., 2017). Chen (2013) highlights that less than 30 percent of students awarded a bachelor's degree had chosen their major in the STEM fields. Of the students that declared a STEM major, almost half had changed their major to a non-STEM major before graduation (Chen, 2013). To aid in combating this growing concern in attrition rates of STEM majors, higher education institutions across the county devoted time and resources (e.g., targeted STEM recruitment initiatives and STEM learning communities) to develop programs to increase student retention and persistence in the STEM fields-of-study (Bouwma-Gearhart et al., 2014; Defraine et al., 2014; Schneider et al., 2015).

These efforts saw increased spikes in the number of STEM graduates; however, the increase related primarily to the number of international students studying in the United States and pursuing STEM degrees (NSB, 2016b). As such, the STEM retention and persistence downfall are still apparent for non-international students, especially among female and underrepresented minoritized students (Sithole et al., 2017). Hossain and Robinson (2012), emphasize that a nation's success, security, and leadership will depend on the usage of technology; as well as, the number of *native* (i.e., domestic) workers in the STEM fields.

Friedman (2005) and Reid (2009) summarize that American leaders across the STEM fields believe the nation to be in a steady erosion of domestic talent within the scientific and engineering fields. Reid (2009) goes on to describe this downward trend in domestic talent as a "quiet crisis" (p. 5) which primarily resides in the inadequate quality and quantity of STEM education throughout the nation. Given these concerns in domestic STEM major retention and academic success, it is imperative educational researchers, practitioners, and policy-makers, continue to investigate methodologies, relationships, and potential predictors linked to inadequate STEM retention and persistence in STEM fields of practice within the United States.

First-Year STEM Retention Challenges

The National Center for Education Statistics found that the withdrawal rate for first-year students at four-year institutions in the U.S. was 24 percent from 2004 to 2009; with only 64 percent of students having obtained a degree or certificate by 2014 (U.S. Dept. of Education, 2011). Colleges and universities throughout the nation struggle with first-year student retention, especially among the "hard sciences" in STEM fields, as large amounts of recourses, are devoted to these students that leave with an incomplete education and are tasked with having to find employment to repay an educational debt that may have accrued (Vedder et al., 2010). Tinto (1993) described, even years earlier, that the first-year retention issue is a "…tremendous loss of resources (i.e., talent and revenue) and a principal concern for students, parents, and administrators" (p. 309). Though increased attention has been given to student retention and persistence, the graduation rates for U.S. colleges and universities have remained consistent over the past 30 years (AASCU, 2005).

Unprepared for First-Year Mathematics Coursework

To better understand the first-year retention gap and its underlying student characteristics, several research studies (Adelman, 2006; Chen, 2013; Ost, 2010; Sklar, 2015; Watkins & Mazur, 2013) has attempted to centralize key factors to consider when assessing first-year student retention intentions, especially those from STEM majors. Unfortunately, research has indicated that the first-year student retention gap begins well before the higher education experience begins. Wirt et al. (2004) found that 76% of postsecondary institutions offered some variation of remedial basic skills courses in the areas of reading, writing, or mathematics; mathematics being foundational for many STEM fields of study. Their finding suggests that many first-year students entering higher education are underprepared in the required course content (e.g., mathematics preparedness for STEM major coursework) for their college anticipated major field of study.

The National Math Panel of the American College Testing published their research report in 2006 revealing a 14% reduction in students' progress toward college readiness in mathematics (ACT, 2007; McCormick & Lucas, 2011). The report goes on to note that the reduction can be attributed to a lack of general direction, on the part of state education boards, regarding specific course content and expectations needed for the achievement of high school and college readiness in STEM majors (ACT, 2007). The report also highlighted a clear misalignment between K-12 and higher education institutions on the readiness level of student's mathematics education, "…more than two-thirds of high school teachers surveyed believe they are meeting state standards for preparing students for college-level mathematics, [while] approximately the same ratio of post-secondary educators believe students are coming to college unprepared" (McCormick & Lucas, 2011, p. 12). This reported finding indicates that mathematics under-preparedness may contribute critically to first-year STEM major retention and academic success.

Challenges for Women and Minortized STEM Majors

In addition to mathematics under-preparedness, Malcolm and Feder (2016) note from their study's findings, that gateway STEM courses are also contributors to the challenges of retaining STEM majors after the first year of study. The authors emphasize that gateway STEM courses, which are typically experienced during the first year of study and are mathematics intensive, often serve as barriers to career aspirations and retention. Gateway courses are found to be sequential in their focus and tend to rely on mastery of previous content to be successful moving forward in the program. As such, students who fail to master the content tend to leave the major and are often derailed of any hopes in a STEM field of study.

Moreover, Weston et al. (2019) found that first-year gateway courses can be especially "unwelcoming" to minoritized STEM students (i.e., female, Native American, Black, and Hispanic students). As stated earlier, STEM faculty members have considered the withdrawal of students from their courses as a sign of successfully weeding out those incapables of navigating the rigors of scientific inquiry (Christe, 2013). Weston and colleagues note that "weed out" classes are especially detrimental to female and minoritized student STEM persisters, as their findings stated that 25% of the student participants reported negative consequences arising from their participation. These negative experiences were attributed to 43% of STEM degree changers, of which, 35% reported that their decision came as a direct consequence of their negative experience in the gateway courses.

Furthermore, Kudish et al.'s (2016) study of first-year STEM gateway courses found that many of these courses are considered traditional in their delivery format. Traditional courses are lecture-based which, "…relay decontextualized scientific minutiae [and] presuppose a familiarity with implicit premises and values that are culturally narrow" (Kudish et al., 2016, p. 10). Their findings also found that minority students tend to not seek help when feeling overwhelmed or falling behind in these early gateway courses as "…they perceive [questioning] reveals a deficit in their knowledge base and exposes them as an outsider" (Kudish et al., 2016, p. 6). Ballen et al. (2017) echo these findings by noting that minoritized students tend to struggle in traditional lecture formats as "…the lecture format undermines their abilities due to the burden of social isolation, low confidence, and stereotype threat these students feel" (p. 1). First-year gateway courses are not holistically designed to encourage all students to weather the challenges of early college experiences, especially for minoritized students.

Summary of Challenges

As presented in Chapter 1, students declaring STEM majors experience intensive mathematics-based curriculums in their very first year of study, which students have found to be "...too heavy a course load in their first year" (Noel-Levitz, 2006, p. 4); which may lead to increased attrition in STEM majors. Researchers have also found concerns regarding STEM students being under-prepared for their mathematics intensive first year of study (Adelman, 2006; Chen, 2013; Ost, 2010; Sklar, 2015; Watkins & Mazur, 2013). Additionally, researchers have reported that STEM major students of marginalized groups (i.e., women and racial minorities in STEM majors) are especially susceptible to enrollment attrition and eventual lack of degree completion beginning in their first-year courses (Lubinski et al., 2001; McPherson, 2017; Meyer et al., 2015; Snow, 1961). Lastly, higher education students are spending more time working, while enrolled in a degree-seeking program, than in years past (NCES, 2018; Perna & Odle, 2020). For varying reasons (Perna & Odle, 2020), this increase in time working may lead to less time devoted to academic coursework, which is already considered demanding for first-year STEM majors (Bozick, 2007; Douglas & Attewell, 2019; Stinebrickner & Stinebrickner, 2003, 2004). Given the multitude of challenges presented facing first-year STEM majors, further research utilizing measures of theoretical assessment that accounts for multiple predictors is needed (DiPrete & Buchmann, 2013; Eagan et al., 2013; Schnettler et al., 2020; Xie & Killewald, 2012). As such, the subsequent sections will present a theoretical model that accounts for this dissertation's three guiding predictors, and the past and present literature expanding on the theoretical model's validity and efficacy in predicting student retention and academic success.

Expectancy Value Model of Achievement Related Performance and Choice

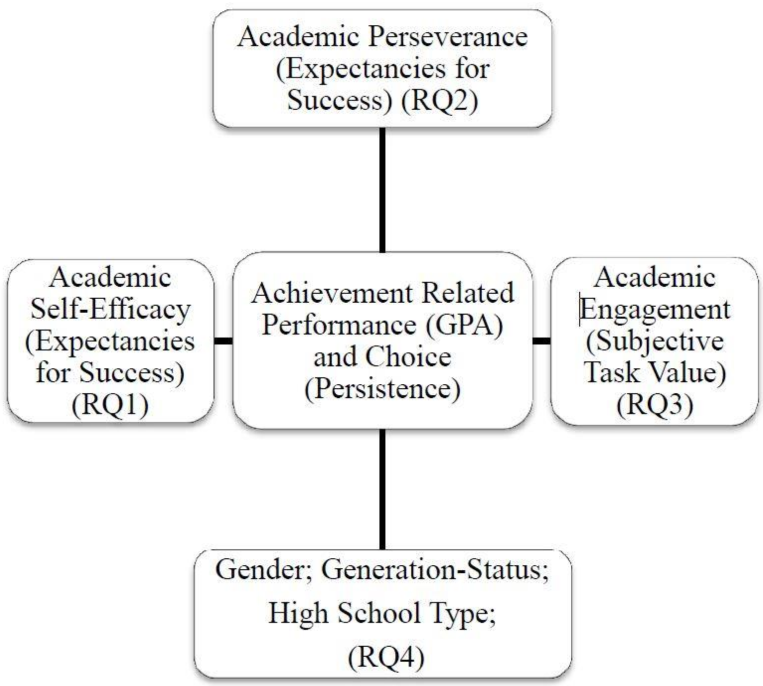
Though not designed specifically to measure STEM majors, Martinez’s (2016) study utilized three factors of the expectancy-value model, (1) Expectancies for Success; (2) Subjective Task Values; and (3) Achievement Related Performance and Choice, to examine if they’re predictors for higher education academic success and educational attainment of Hispanic students. Kuh et al. (2006) and Martinez (2016) emphasized that higher levels of educational attainment are not only directly linked to an enhanced quality of life through improved economic and social benefits, “…but also benefit communities and society as a whole since educated citizens tend to be more involved in national and community initiatives” (Martinez, 2016, p. 16). As such, Tinto (1997) argued that it is the responsibility of postsecondary institutions to provide sufficient opportunities to participate in college academic and social constructs while providing access to education. Research conducted by Upcraft and Gardner (1989) and Upcraft et al. (2005) concluded that the most important academic year in predicting student retention in higher education achievement was the first year of study.

Furthermore, Wigfield and Eccles (2000) note that educational achievement is predicated on a students’ motivation to engage with an educational task, persistence, performance, and self-efficacy. Martinez (2016) highlights that these constructs align with

Vroom's (1964) Expectancy-Value Theory, "…which proposes that expectations of success, ability beliefs, and values associated with certain tasks directly influence achievement and persistence" (p. 15). In an extension of the expectancy-value theory, Eccles, Wigfield, and their colleagues proposed an expectancy-value model of achievement-related performance and choice (see Figure 1), which aims to measure expectancies and values which are assumed to directly influence educational achievement (Eccles, 1984; Eccles et al., 1983; Wigfield, 1994; Wigfield & Eccles, 1992).

Figure 3

Martinez's (2016) Revised Expectancy-Value Model



Given the focus of Eccles et al.'s (1983) expectancy-value model, Martinez (2016) proposed a quantitative study that utilized an abbreviated expectancy-value model to investigate probable associations between pre-college experiences and expectations of first-year Hispanic students at a predominantly Hispanic serving institution of higher education in the southwest.

The abbreviated model focused primarily on the following three factors from the expectancy-value model in Figure 3: (1) Expectancies for Success, (2) Subjective Task Values, and (3) Achievement Related Performance and Choice. Martinez's (2016) model aligned, through an extensive review of literature, with the following three areas of Wigfield and Eccles's (2000) expectancy-value model: (1) Academic Self-Efficacy (Expectancies for Success); (2) Academic Perseverance (Expectancies for Success); and (3) Academic Engagement (Subjective Task Value).

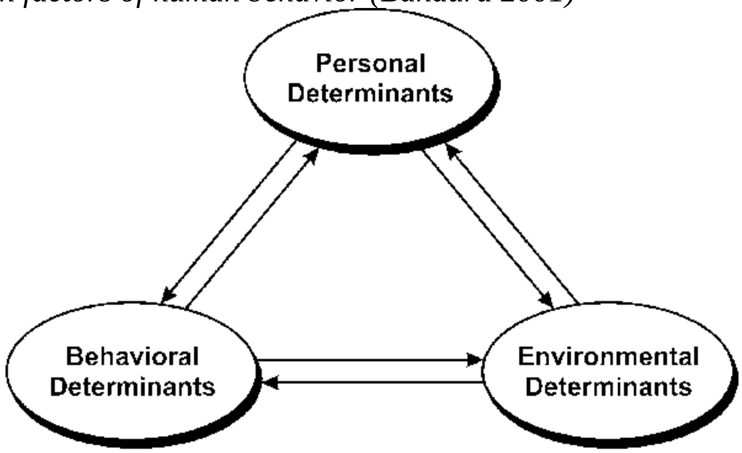
Though Martinez's (2016) study did not specifically account for STEM majors or other racial and/or ethnic groups in higher education, her study was able to assess known higher education achievement-related predictors in a single theoretical model, as such, the currently proposed study will utilize an abbreviated version of Martinez's revised Expectancy-Value Model with the following factors to assess first-year STEM student's academic success and choice to retain: (1) *Academic Support* (Expectancies for Success); (2) *Academic Engagement* (Subjective Task Value); and (3) *Hours Worked* (Subjective Task Value).

Academic Support (Expectancies for Success)

Academic support initiatives, more specifically, concerning the currently proposed research study, *faculty-student interactions*, and academic self-efficacy in higher education have limited research consideration when attempting to investigate the impact of first-year student STEM retention and academic achievement using the *expectancy-value model* (DeFreitas & Bravo, 2012; Ferguson, 2021; Gnebola, 2015; Martinez, 2016). Gnebola (2015) notes this is especially true in how these two factors correlate with student race and ethnicity and student first-year retention and persistence to careers in their chosen major. Gnebola's study found that faculty-student interaction is positively correlated in predicting student achievement outcome measures, such as GPA; however, this study did not account specifically for STEM students and first-year retention.

Figure 4

Bandura's model of Social Cognitive Theory represents the triangular relationship between the three main factors of human behavior (Bandura 2001)



Moreover, Pajares (1996) found that a student's ability to interact and manage their environment increases their chances of academic success (see Figure 4). Pajares goes on to note that it is in the student's best interest to create and maintain a cordial relationship with their campus faculty and staff to increase their overall chances of academic success. Lastly, Pajares notes that this interactive relationship between students with faculty and staff must be especially mindful of the student's demographics. Ferguson (2021) echoes this point as student interactions with faculty and staff have been found to have differing conclusions regarding White and non-White students' academic achievement. Studies have identified minoritized students, more so than White students, to be especially sensitive to faculty-student interaction experiences, particularly concerning academic performance (Aikens et al., 2017; Thiry & Laursen, 2011).

As noted previously, the expectancy-value model has solid foundational literature in understanding how attitudes and behaviors can lead to student achievement-related choices and performance (Martinez, 2016). Of the two main factors contributing to student achievement-related choices and performance, *expectancies for success* are considered crucial in Eccles et al.'s (1983) model when attempting to understand an individual's belief in how well they can accomplish a task (Schunk, 1991). As such, this study will include academic support variables related to students' interaction experiences with university faculty and staff. The three following sub-sections will cover literature regarding STEM academic support factors germane to the purpose of this study.

STEM Student-Faculty Interactions

Seymour and Hewitt (1997) earlier characterized the climate in STEM education as "chilly and unwelcoming" (p. 22) to current and prospective students. Literature has also documented that science and engineering faculty tend to view their status in higher education as educators aimed at producing top-quality graduates while encouraging attrition of weaker STEM students (Kokkelenberg & Sinha, 2010; Seymour & Hewitt, 1997). As such, STEM faculty members have considered the withdrawal of students from their courses as a sign of successfully weeding out those incapables of navigating the rigors of scientific inquiry (Christe, 2013). Still, Seymour and Hewitt's publication in 1997, with others that followed later (Eris et al., 2010; Marra et al., 2012; Wagner et al., 2012), found that not only were underprepared or low performing students leaving STEM disciplines, but high performing students were leaving at similar frequencies.

Tinto's (1993) stance on student persistence and causes of withdrawal from college is from a sociological approach. He supports the perspective that educators should focus on relationships between students and faculty members, as the social experiences between the two are vital to promoting degree completion. Though Tinto's encouragement was made years earlier, literature continues to show that faculty member interactions play a crucial role in student decisions to retain in the STEM disciplines (Chrise, 2013; Jamieson & Lohmann, 2012; Mastascusa et al., 2011; Rodgers & Marra, 2012; Vogt, 2008); nevertheless, "…despite all of the literature-based evidence pointing to the importance of student-faculty interactions in college, many faculty overlook, or underestimate, the impact they have on their students" (Micari & Pazos, 2012, p. 45).

Micari and Pazos (2012) conducted a quantitative study around student-faculty interaction in an organic chemistry course. Their study found correlations between students' course grades and the feelings of how connected the student felt to their professors. The findings also documented three qualities of positive relationships between student and instructor: approachability, respect for students, and the faculty as a role model. Lastly, the authors also reported that students with a strong-perceived relationship with their instructor exhibited increased student confidence in course success. Similarly, Allen et al. (2018) conducted a quantitative study examining student questionnaire data from a sample (n = 272) of engineering student persisters (i.e., juniors and seniors) regarding the association of student-faculty interaction and the perceived quality of such interactions. Their findings reported that frequent interactions with faculty in class, along with lesser negative experiences from faculty resulted in greater levels of engineering self-efficacy.

These findings are not isolated to quantitative research methods alone, as Hong and Shull (2010) qualitative study explored the role of faculty in retaining STEM students. The researchers reported from students interviewed, the following common negative themes were identified in describing their experiences with their STEM faculty interactions: the absence of "any positive relationships with faculty members" (Hong & Shull, 2010, p. 274); also, "learners described their professors as, insensitive to their learning and personal needs" (Hong & Shull, 2010, p. 274). Moreover, students described feeling humiliated and insulted by their faculty members (Christe, 2013). Lastly, Hong and Shull (2010) noted that there were contrasting responses as some learners identified that they received caring and engaging interactions with their faculty members.

As noted previously by the presented literature, not only are student-faculty interactions crucial to promoting higher levels of student academic achievement but are especially important for STEM major retention. As such, institutions of higher education have focused on initiatives that can be utilized to improve STEM retention, at the institutional level, to encourage better faculty-student relationships. One such initiative is the implementation of undergraduate research programs readily supported financially by the National Science Foundation and several other agencies (Erbes, 2008). Through undergraduate research programs, STEM undergraduate students have the chance to make meaningful connections with faculty which have been shown to increase STEM retention and persistence in STEM careers and fields of study; especially that of minoritized students in STEM education (Badger, 2008; Groccia, 2012; Johnson, 1995; Miller, 1997; Sadler & McKinney, 2010; Thiry & Laursen, 2011) Given this point, the following two sub-sections will cover literature related to undergraduate research programs and their relationship with minoritized student STEM retention.

STEM Minoritzed Students and Faculty Interactions

Among all the STEM degrees granted in 2015, including nonresident aliens, Black students received 8% of STEM Bachelor's degrees, 10% of STEM Master's degrees, and only 5% of STEM doctoral degrees; these figures highlight that Blacks (15%) remain underrepresented in every degree level when considering their proportion of the U.S. college-age population (National Science Foundation, 2018). Despite these alarming figures, many institutions of higher education continued to implement “one-size fit all” undergraduate research programs to mentor STEM majors; however, it is negligent to assume that what is recommended for the general STEM student body, will work effectively for minoritized students (Domingo & Carrillo, 2011)

Previous researchers have sought to identify significant links between undergraduate research programs’ mentoring structures and the likelihood of student retention, graduation rate, and aspirations to professional practice in STEM fields – accounting specifically for minoritized students. One such study, by Thiry and Laursen (2011), developed an empirical research design to investigate key approaches to promoting successful student-advisor mentoring practices in undergraduate research (UR) programs; specifically, to assimilate students to the norms, values, and specialized practice in the science fields.

The authors implemented a qualitative comparative study, using a phenomenological research approach, which explored the outcomes associated with varying types of guidance and support factors from the point of view of novice and experienced UR students. 73 UR students were interviewed; divided according to the students’ prior research experience: *novice* (first-year researchers) and *experienced* (three or more semesters and one summer of UR). Women made up 48% of the sample, while minoritized groups represented 36%. Specifically, 23% were African American, 12% were Hispanic, and 1% were multi-racial; the remaining students were White (47%) and Asian or Asian-American (17%) (Thiry & Laursen, 2011).

The authors concluded that three main support frames are crucial in successful faculty mentoring of UR students in STEM majors: (a) *Professional socialization,* which transmits the values and norms of the profession; (b) *Intellectual support, which* helps with problem-solving or progression through experiments; and (c) *Personal/emotional support,* be supportive, accessible, friendly, et cetera (Thiry & Laursen, 2011). Their findings also highlighted that minoritized students reported interactions with senior-level scientists, not student scientists and/or adjuncts, as being extremely beneficial to their scientific confidence and development. These interactions and mentoring relationships led to Black and Hispanic students showing greater socialization in their STEM programs and planning to continue their coursework in STEM at the graduate school level (Thiry & Laursen, 2011). As noted by the authors, minoritized students in STEM education tend to be less prepared for college-level scientific coursework and have fewer faculty role models within the STEM fields. As such, those minoritized students that are members of STEM programs will require strong socialization benefits with research mentors within their field of study, to overcome having little research knowledge and confidence from their K-12 educational experience (Thiry & Laursen, 2011).

Academic Engagement (Subjective Task Value)

As stated earlier, the expectancy-value model has proven to provide a solid foundation for understanding attitudes and behaviors that can lead to achievement-related choices and performances. Given the expectancy-value model's extensive usage in primary and secondary education and continuous emergence in higher education research, expectancies for success and subjective task value are considered to be the most crucial areas of the model that link individuals' academic goals with achievements (Martinez, 2016). Given this point, the next two sections will cover subjective task value and the constructs (i.e., *academic engagement* and *hours worked*) which align with the aims of this study.

Wigfield and Eccles' (2000) model, see Figure 1, theorizes that individuals are more likely to engage in activities, behaviors, and tasks if they consider the activities to be aligned with their self-interests and goals. Eccles's expectancy-value model encompasses this theoretical perspective in the construct called subjective task value. As presented in Chapter I, subjective task value includes four factors: attainment, intrinsic interest, utility, and cost (Wigfield & Eccles, 2000). First, the *attainment* value constructs measure the degree of importance an individual considers to be performing well on a task, given a person's self-concept and identity (Wigfield & Eccles, 2000; Wu et al., 2020). The *intrinsic interest* (or *intrinsic*) value construct aims to predict an individual's interest and contentment in engaging in a given task or activity (Wigfield & Eccles, 2000). The *utility* value refers to the usefulness of a task or goal relative to an individual's short- and long-term goals (Wigfield & Eccles, 2000; Wu et al., 2020). Finally, the last construct, *cost (or perceived cost),* and arguably the least researched construct of the four constructs (Barron et al., 2015; Wigfield & Cambria, 2010), refers to the perceived drawbacks or burden of engaging in a task (Wigfield & Eccles, 2000). This study will aim to include the *cost* construct concerning *student hours worked* for STEM first-year majors; literature will be presented on this topic in the next section (i.e., Student Hours Worked -Subjective Task Value).

Given the first three subjective task values (i.e., attainment, intrinsic interest, and utility), researchers have empirically found that student engagement or academic engagement is theoretically associated with Eccles's first three subjective task values (Chow et al., 2012; Fan & Dempsey, 2017; Martinez, 2016; Plante et al., 2013; Wang & Liou, 2018; Wu et al., 2019). Student engagement, or academic engagement, is defined as, "…the investment of time, effort and other relevant resources by both students and their institutions intended to optimize the student experience and enhance the learning outcomes and development of students and the performance, and reputation of the institution" (Astin, 1984, p. 2). This broad definition has taken on systematic review and categorization over the past decades, as researchers aimed to gain clarity around the construct of academic engagement (Lester, 2013).

Moreover, the definition of academic engagement has been debated extensively regarding the theoretical approach of engagement being singular or multi-faceted (Bryson & Hand, 2007; Glanville & Wildhagen, 2007; Horstmanshof & Zimitat, 2007; Krause & Coates, 2008); however, Fredericks et al.'s (2004) paper proposed a unique multi-faceted definition of academic engagement which includes the following categories: behavioral, emotional, and cognitive. These categories constitute what Lester (2013) refers to as "meta constructs" of engagement; Lester goes on to note that these three categories have shown to have a wide range of applicability in K-12 and higher education settings.

The first category, *behavioral engagement*, is defined to consist of students' participation in both social and academic endeavors. Fredericks et al. (2004) elaborate that there are three main constructs of behavioral engagement, which include, (1) positive conduct, (2) involvement in learning, and (3) participation in school-related activities. Positive conduct assumes indicators that include students adhering to defined class rules. Involvement in learning posits that students' behaviors are "…related to concentration, attention, persistence, effort, asking questions, and contributing to [class] discussion" (Fredericks et al., 2004, p. 32). Participation in school-related activities incorporates students' involvement in school extra-curricular activities (e.g., school government, athletics, non-academic clubs, etc.) (Fredericks et al., 2004).

The second category, *emotional engagement*, consists of students' attitudes, interests, and values as they are related to positive and negative interactions with faculty, staff, students, academics, and/or other institutional factors (Fredericks et al., 2004). This category has three main constructs which delineate into the following components: affective reactions, emotional reactions, and school identification. Affective reactions measures student interest, boredom, anxiety, sadness, and happiness in the classroom (Fredericks et al., 2004). Emotional reactions constitute a student's feelings, positive or negative, toward their instructor or institution. Lastly, school identification relates to students' sense of belongingness and significance within their institutional environment (Fredericks et al., 2004).

The third category, *cognitive engagement*, consists of two main components: psychological and cognitive. According to Fredericks et al. (2004), the component of psychological engagement includes motivational goals and self-regulated learning. Both components are related to students' thoughtfulness, willingness, and effort to engage in an academic task, to gain an understanding of complex ideas (Fredericks et al., 2004). Lastly, the cognitive engagement component includes the student's effort to "…self-regulated learning, metacognition, application of learning strategies, and [being strategic] in thinking and studying" (Fredericks et al., 2004, p. 608).

In aiming to capture the academic engagement predictor, this study utilized survey items that overlapped *behavioral engagement* and *cognitive engagement* categories. This is not a surprise, as Fredericks et al. (2004) argued that three engagement categories are "dynamically interrelated within the [participant]; they are not isolated processes" (p. 61). Moreover, Fredericks et al. (2004) note that the term academic engagement should be used in a "meta" construct, which is reserved for when multiple categories of academic engagement are present in the study's design (Guthrie & Anderson, 1999; Guthrie & Wigfield, 2000). As such, this study included questions aimed at ascertaining higher education students' level of effort in gaining an understanding of course content and mastering complex academic content, through the singular use of the term academic engagement.

Hours Worked (Subjective Task Value)

The fourth and final sub-component of subjective task value is *perceived cost* or *cost*. Eccles and Wigfield (1995) stated, "the first three [sub] components [attainment, intrinsic interest, utility] are best thought of as attracting characteristics that affect the positive valence of the task…cost, in contrast, is best thought of as those [sub-components]…that affect the negative valence of the activity" (p. 216). For example, if a student perceives the effort and time (i.e., cost) needed to achieve a STEM degree is too much, they may be less likely to persist in the STEM major (Perez et al., 2014). As such, students' perceived costs in a STEM major may be especially important when attempting to understand first-year students' intentions to persist beyond their first year (Barron & Hulleman, 2015; Flake et al., 2011; Perez et al., 2014). While a sub-component of subjective task value, researchers have noted that the cost component has received comparatively less research focus related to STEM achievement and persistence than the first three sub-components (Barron & Hulleman, 2015; Wigfield & Cambria, 2010). This section will elaborate on past and current research on the cost sub-component, and how the factor (i.e., student hours worked) this study aims to assess, relates to this sub-component.

In its earliest form, Eccles et al. (1983) presented cost as an important mediator of value in their theoretical model (i.e., Expectancy-Value Model). In later writings, Eccles and her team promoted the cost value as one of the four sub-components aligned with the subjective task value component. Eccles and colleagues noted that the need to make this change was paramount as their early writings found "…the overall effect of value on promoting motivation depends on knowing whether or not someone experiences high or low cost" (Barron & Hulleman, 2015, p. 10). As such, including cost into the expectancy-value model is crucial to adequately measure the motivational dynamics or factors that encourage or discourage individuals from engaging in a task. Unlike the first three sub-components, researchers noted that Eccles and colleagues' previous works fail to illustrate a clear picture or recommended direction of how to measure, sufficiently, the cost sub-component (Chen & Liu, 2009; Chiang et al., 2011; Luttrell et al., 2010; Watkinson et al., 2005).

Eccles et al. (1983) first conceptualized the cost sub-component along three theoretical dimensions: "(1) *effort cost*, perceptions of whether the time and effort needed to be successful on a task [are] worthwhile; (2) *opportunity cost*, perceptions of lost opportunities to engage in other valued activities; and (3) *psychological costs*, perceptions related to fear of failure and anxiety associated with engaging in the task" (Perez et al., 2019, p. 12). Though theoretically separable, some researchers have noted that the cost sub-types should be measured as a single, or general, construct given that there is limited empirical evidence to separate them as distinct sub-types (Trautwein et al., 2012). For example, Chiang et al. (2011) conducted a quantitative study that surveyed elementary school students' beliefs regarding their expectancy, value, and cost attitudes and willingness to engage in physical activities. The researchers accounted for the three sub-types of cost theorized by Eccles and colleagues (1983). Their factor analysis revealed that all three cost sub-components loaded onto a single factor when combined with both the expectancy and value factors. Their findings reported that, when predicting students' level of physical activity, students reporting higher levels of costs (all three sub-components) were less likely to be active, as opposed to students reporting higher levels of expectancy/values, who were more likely to be active.

Another example of the generalizable assumption in using cost as a single sub-component of subjective task value was confirmed in a large-scale study by Trautwein et al. (2012). Their study deployed items aimed at assessing the expectancy, intrinsic value, utility value, attainment value, and cost of mathematics and English students. Their study measured cost as the following items: (1) the amount of effort required to be successful in their class; and (2) the loss of engaging in a valued alternative task. For both Math and English students, the researchers reported that their factor analysis revealed a singular cost sub-type, along with the three value factors to be supported by a four-factor structure (i.e., subjective-task value). Moreover, their findings showed that cost was negatively correlated with the other three value sub-components, as well as, being negatively correlated with the expectancy factor. This study also supports previous findings that analysis of students using the expectancy-value model will yield differing beliefs by the academic domain (i.e., reading, writing, mathematics) (Barron & Hulleman, 2015).

Though the above research was presented noting findings to support a singular use of cost, this assumption is not shared by all researchers utilizing the expectancy-value model. For example, a study by Robinson et al. (2018) investigated engineering students during their first two years of college given their development in the first three sub-components of subjective task values (utility, interest, attainment) and the three types of cost (effort cost, opportunity cost, psychological cost). The authors modeled their analysis to account for the separate motivation components and found that students with slower declines in the first three sub-components of value and slower increases in *effort cost* were more likely to remain in an engineering major. As such, Robinson et al. (2018) empirically identified a singular sub-type (i.e., effort cost) of cost to be predictive of student retention in an engineering major. Nevertheless, given the scope of this study, a singular design of cost was employed given previous empirical findings on this topic (Chiang et al., 2011; Li et al., 2008; Mamaril et al., 2016; Trautwein et al., 2012;).

As stated earlier by Eccles and her colleagues, cost, or perceived cost can be theorized as any perceived shortcomings of participating in a task (Eccles et al., 1983). For example, an individual's perceived cost of participating in a task, given the time and effort needed to be successful, is directly related to Eccles and her colleagues' theoretical assumptions related to subjective task values. In Chapter I, literature was presented emphasizing that STEM students, when compared to non-STEM students, and even more so for PEMC majors, are tasked with increased course content and study time required to successfully persist beyond the first year of study (Griffith, 2010; Maltese & Tai, 2011). However, statistical trends from the past decade continue to show that higher education students are engaging in working on and off-campus at a much higher rate than in previous years (National Center for Education Statistics, 2015). This phenomenon of increased student hours worked may reduce the available time needed to engage in STEM course content and negatively influence STEM students' retention in their majors. The following sub-section will present literature on the growing trend of higher education students devoting more time to work while studying.

The Cost of Working While Studying

Years of previous research summarize undergraduate students that work, regardless of year or term of enrollment, are less likely to graduate than their non-working peers (Douglas & Attewell, 2019). The National Postsecondary Student Aid Study (NPSAS) documented that 62.3% of undergraduate students were employed during the 2015 and 2016 academic years. The distribution of students working while studying was evenly distributed among demographic variables such as student gender, race/ethnicity, first-generation status, et cetera (National Center for Education Statistics, 2015). Employment while studying was more common at community colleges and less-selective colleges and universities – the student demographic at these institutions tends to be part-time enrollees and are from disproportionality lower-income families (National Center for Education Statistics, 2015). However, Perna et al. (2007) note that approximately half of the students attending highly selective 4-year institutions work while studying.

Furthermore, NPSAS has documented that 54% of students felt that they must work to afford to attend college. Previous research findings have documented those numerous undergraduate students face financial hardships while attending colleges and universities; some of these hardships include food and housing insecurities (Broton & Goldrick-Rab, 2016). Other researchers have debated that current financial aid packages are insufficient for many undergraduate students, as the Federal financial aid, calculations include estimates of “Expected Family Contribution” which many families cannot afford (Goldrick-Rab, 2016; King, 2002; Stringer et al., 1998; St. John, 2003).

Considering the other half of undergraduates saying they *must work* to attend school, are those students choosing to work for less dire reasons. Clydesdale's (2007) ethnography study of freshman students working found that the academic side of college took secondary priority overworking to pay for practical life skills, such as “…paying for dating, entertainment, and consumerism, and earning $1,000 a month. These activities and reasons took on a symbolic meaning, as a measure of adulthood” (p. 111). When considering these factors, it is not a simple factor to consider whether students are working because *they must* or because they choose to for *non-financial requirements* or *social factors*.

A major consideration related to working while studying is what researchers call a “time bind”, which has been demonstrated to have negative effects on academic performance and student retention (Stinebrickner & Stinebrickner, 2003, 2004). Tinto (1993) has stated that “…full-time employment limits time for interaction with other students and faculty, leading to poor social integration and to higher rates of student drop-out” (p. 64). However, not all researchers support the notion that working while studying is a solely negative effect. For example, Bozick (2007) found that working, in moderation, does not negatively affect student academic progression; however, notes that "working more than 20 [hours] a week during the first year of college…limits students' ability to sustain enrollment" (p. 271-273).

Moreover, labor economists have contributed to this field of study by assessing the effects of student employment on academic progression and outcomes. Darolia (2014) found that students working while studying did not have any significant impact on students' academic performance but did note that the work demand itself did result in students completing fewer credit hours than full-time students. This study's findings may provide insight into why working students take longer to complete their degree requirements within five years. Additionally, where the students worked, on or off-campus, plays a factor in their academic performance while working. A study by Scott-Clayton and Minaya (2016) found that working students that engaged in on-campus work-study programs performed better, academically, than students working off-campus. Given the points outlined above, this study aims to assess the working commitments and locations (on or off-campus) of first-year STEM majors.

Summary of Literature

Higher education first-year retention is a major concern, especially for those in STEM fields of study (Vedder et al., 2010). Tinto (1993) found that the first-year retention issue is an especially troubling loss of talent and resources from fields of study and practice. To better understand the first-year STEM retention gap, researchers have found the troubles begin well before students enter postsecondary institutions (ACT, 2007; McCormick & Lucas, 2011; Wirt et al., 2004). More specially, researchers expressed concerns related to student math readiness and STEM retention (Conley, 2007; Chait & Venezia, 2009; McCormick & Lucas, 2011; Wirt et al., 2004). Given these challenges, this study aimed to assess student math readiness at college entry, conceptualized by developmental mathematics course attendance during the first year, concerning STEM major retention and academic success.

Eccles and colleagues' (1983) Expectancy-Value Model of Achievement-Related Choices has been shown to demonstrate unique relationships between student beliefs and task values, concerning student education attainments. Kuh et al. (2006) and Martinez (2016) emphasized that higher levels of educational attainment are not only directly linked to an enhanced quality of life through improved economic and social benefits, but also improved community and societies as a whole. Current literature suggests that the first year of college is the most important academic year in predicting student retention in higher education attainment (Upcraft & Gardner,1989; Upcraft et al., 2005).

Wigfield and Eccles (2000) note that educational attainment is predicated on a students' motivation to engage with an educational task, persistence, performance, and self-efficacy. Building on Wigfield and Eccles's (2000) work, Martinez's (2016) study aligned the following factors in predicting student retention and academic success at a Hispanic-serving institution of higher education (1) Expectancies for Success, (2) Subjective Task Values, and (3) Achievement Related Performance and Choice. Eccles et al.'s (1983) Expectancy-Value Model of Achievement-Related Performance and Choices are also aligned with the following predictors of retention and academic success: (1) *Academic Support* (Expectancies for Success); (2) *Academic Engagement* (Subjective Task Value); and (3) *Hours Worked* (Subjective Task Value).

Regarding the first factor, *academic support*, Pajares (1996) found that a student's ability to interact and manage their environment increases their chances of academic success. Ferguson (2021) supported this notion as their study upheld Pajares' (1996) findings, but also noted that academic support varied across racial groups. The second factor of the model address the theoretical construct of *academic engagement*. Wigfield and Eccles' (2000) study found that individuals are more likely to engage in activities, behaviors, and tasks if they consider the activities to be aligned with their self-interests and goals. Researchers continue to debate if *academic engagement* should be singular or multi-faceted (Bryson & Hand, 2007; Glanville & Wildhagen, 2007; Horstmanshof & Zimitat, 2007; Krause & Coates, 2008). Fredericks et al. (2004) recommend the singular (i.e., meta-level) use of academic engagement when assessing engagement categories that overlap in their assessment purposes.

Lastly, *hours worked*, which has yet to be assessed by Eccles et al.'s (1983) expectancy-value model, aims to include a growing trend of student behavior in higher education. NPSAS documented that 62.3% of undergraduate students were employed during the 2015 and 2016 academic years. Stinebrickner and Stinebrickner (2003, 2004) noted that students working while a student can be influenced by a "time bind", where they lack the time to contribute to their academic tasks. Tinto (1993) echoed a similar finding by stating that higher education students working while studying can limit their interaction with their campus, and may have negative consequences for their retention and increase dropout rates (Tinto, 1993). Given the challenges presented regarding first-year STEM major retention, this study aimed to assess student math readiness concerning first-year STEM major retention and academic success. Based upon the review of various existing literature influencing first-year STEM student retention, this study attempted to connect theory to practice by operationalizing Eccles and colleagues (1983) expectancy-value model to explore possible relationships between *academic support* (i.e., Expectancies for Success), *academic engagement* (i.e., Subjective Task Value), and *hours* *worked* (i.e., Subjective Task Value), as predictors of academic success (i.e., Achievement Related Performance) and retention (i.e, Choices) of STEM first-year and marginalized students.

CHAPTER 3: METHODOLOGY

Introduction

The purpose of this study investigated if *academic support*, *academic engagement,* and *hours worked* are predictors of overall student success and retention of first-year and marginalized college students in STEM majors. Independently, existing research confirms that the aforementioned predictors contribute (on various levels) to student retention and/or academic success (please review Chapters 1 and 2); however, there is a lack of existing research accounting for these predictors in a sole model while focusing exclusively on first-year students in STEM majors (Andersen & Ward, 2014; Martinez, 2016; Perez, 2019). Martinez's (2016) study confirmed that a revised version of the well-grounded theoretical model, Expectancy-Value Model of Achievement Motivation, sufficiently accounts for the stated predictors through the following theoretical components: (1) Expectancies for Success; (2) Subjective Task Values; and (3) Achievement Related Performance and Choices.

The results of this study aimed to provide new perspectives on understanding first-year STEM major retention and academic success. Moreover, the results will potentially aid higher education administrators, researchers, and policymakers increase STEM degree completers, especially among marginalized students (i.e., women and STEM racial minorities). To outline the focus of this chapter, the researcher first introduced the research questions driving the study. After this point, the researcher presented the following research methodological components: (a) research questions; (b) data source; (c) data sample; (d) instrumentation; (e) definition of variables; and (f) assumptions and limitations.

Research Questions

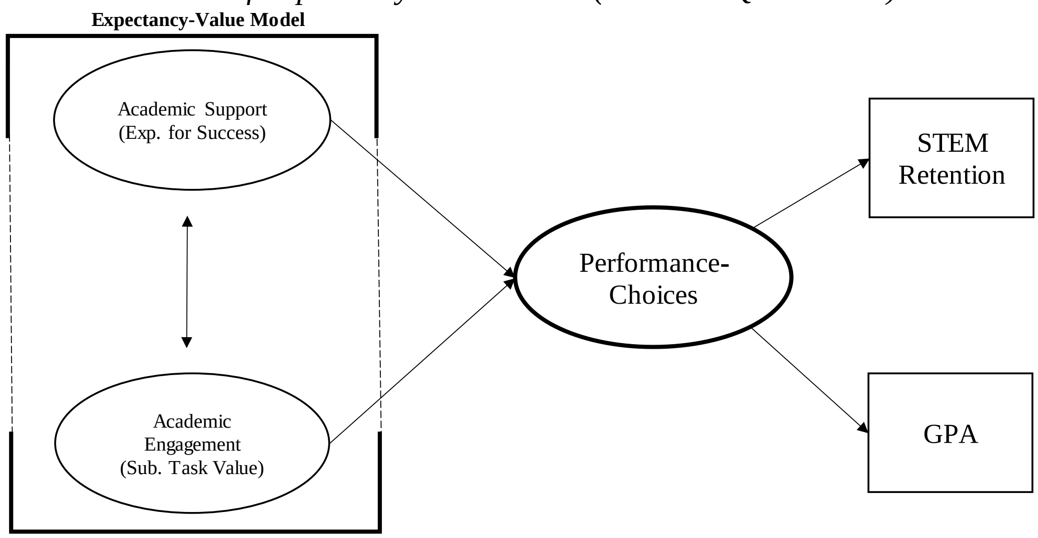
As stated previously, Eccles and colleagues' (1983) Expectancy-Value Model of Achievement-Related Performance and Choices has a well-documented foundation for understanding how student attitudes and behaviors can influence achievement-related choices and performance (Anderson & Ward, 2014; Martinez, 2016; Perez, 2019; Xie & Andrews, 2012). Given that STEM majors' retention continues to show a downward trend after their first year in college (Sithole et al., 2017), it is advantageous for research questions investigating this phenomenon to focus on first-year STEM students to better understand STEM retention. Moreover, STEM major attrition is a phenomenon that is not equally distributed across social groups and has been found to, more so, adversely affect women and racial/ethnic minorities students, when compared to White and Asian male students in STEM fields of study (DiPrete & Buchmann, 2013; Xie & Killewald, 2012; Xie et al., 2015). As such, the *first* research questions aimed to utilize this model in exploring possible relationships between STEM first-year and marginalized students' academic success and retention beyond their first year (the model became more advanced as additional research questions were explored):

- (RQ1)To what extent does the Expectancy-Value Model of Achievement Motivation explain:
  - First-year STEM major students' academic success and retention?
  - First-year STEM major students' academic success and retention by *gender*?
  - First-year STEM major students' academic success and retention by *race*?

Figure 5 illustrates a theoretical model addressing the first research question. This model assumed correlations for the study's first two predictor variables (i.e., *academic support*, *academic engagement*) through the theoretical components presented by Eccles et al.'s (1983) expectancy-value model and its theoretical constructs: Expectancies for Success and Subjective-Task Values. Research subquestions related to *gender* and *race* illustrate the same revised expectancy-value model in Figure 5 and follow the same structure.

Figure 5

Revised Framework of Expectancy-Value Model (Research Question 1a)



Note. Not all observed indicators of latent variables are listed (see Table 3).

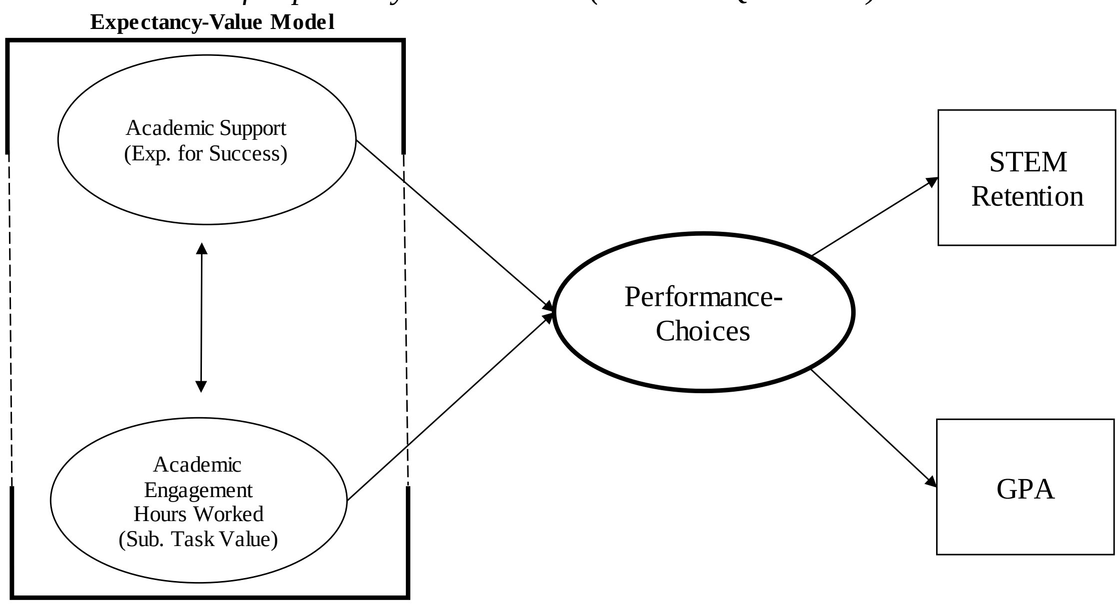
Given the growing phenomenon of higher education students working while studying, and the growing bodies of literature highlighting the negative implications of hours spent working and academic achievement (Bozick, 2007; Douglas & Attewell, 2019; Stinebrickner & Stinebrickner, 2003, 2004), this study was the first to include student's self-reported hours worked as a subjective-task value to investigate the relationships between STEM first-year student academic success and retention. As such, the *second* research question included student *hours worked* as a predictor variable to the expectancy-value model from the first research question (see Figure 6; *gender* and *race* models follow the same structure):

- (RQ2) Given the Expectancy-Value Model of Achievement Motivation, are *hours worked (perceived cost)* a predictor of academic success and retention for:

- First-year STEM majors?
- First-year STEM major students across *gender*?
- First-year STEM major students across *race*?

Figure 6

Revised Framework of Expectancy-Value Model (Research Question 2)



Note. Not all observed indicators of latent variables are listed (see Table 3).

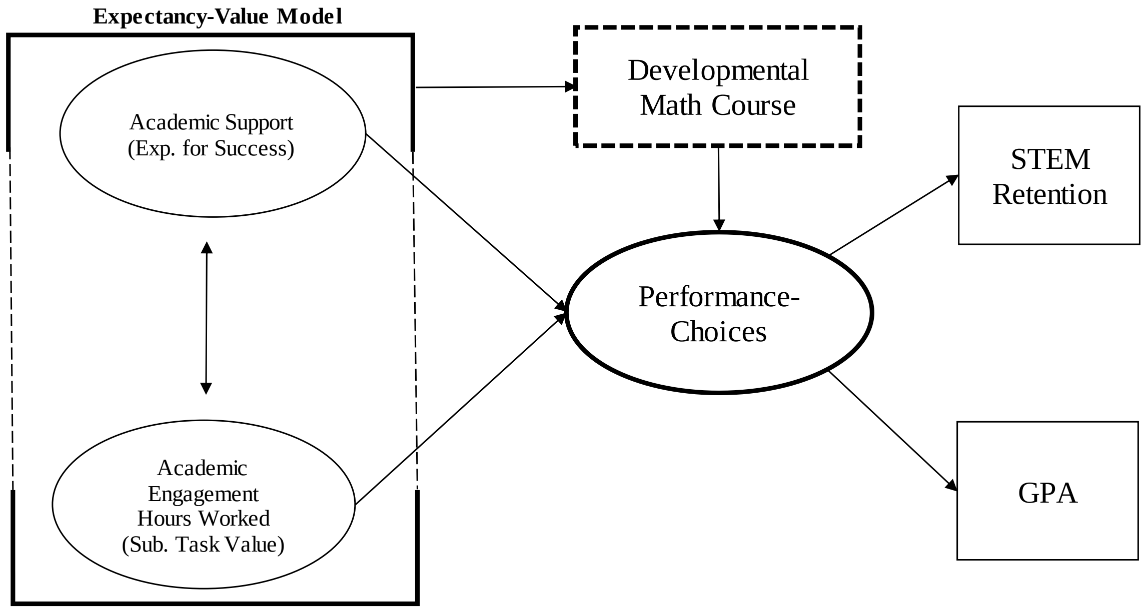
Previous research has highlighted that STEM major first-year students tend to be exposed to mathematics intensive curriculums during their first-year introductory coursework. Former research has also found STEM students, in need of completing developmental math coursework during their freshmen year, were approximately 50% more likely to leave the STEM fields of study after their first year (Adelman, 2006; Cabrera et al., 2005; Herzog, 2005). As such, the *third* research question included, in the revised expectancy-value model, if the STEM first-year student completed a developmental math course during their first year of study:

- (RQ3) Is the relationship between the Expectancy-Value Model of achievement motivation and first-year STEM major students' academic success and retention mediated by math coursework readiness?

By including this predictor variable as a mediator (see Figure 7), the researcher was able to analyze the direct and indirect effects of students completing a developmental math course during their first year and the relationship between STEM first-year students' academic success and retention beyond the first year.

Figure 7

Revised Framework of Expectancy-Value Model (Research Question 3)



Note. Not all observed indicators of latent variables are listed (see Table 3).

Lastly, though STEM students' first-year retention and academic success are the focus of this proposed study, previous researchers have noted that not all STEM majors are considered to be equally affected by the obstacles presented in Chapter 1 (Dika & D'Amico, 2015; Meyer et al., 2015; Snow, 1961). As such, by posing the *fourth* research question, this study was able to explore student majors from PEMC and Other-STEM majors to investigate if the varying STEM subsets influence first-year students' retention (see Figure 6; *PEMC* and *Other-STEM* models follow the same structure):

- (RQ4) To what extent does the Expectancy-Value Model of achievement motivation explain first-year students’ declared PEMC or Other-STEM majors' academic success and retention?

Research Design

The proposed study employed a quantitative research design. This study was designed to be non-experimental, as the data collection and analysis of the study did not require the researcher to manipulate variables, and relied on relationships given measurements of variables as they naturally occur. McMillan and Schumacher (2010) note that educational research, specifically, should rely on establishing relationships among variables, as they “…make a preliminary identification of possible causes of important educational outcomes… identify variables that need further investigation…predict one variable from another” (p. 222). By investigating variables through relationships, a deeper understanding of phenomena through educational research can be attained (McMillan & Schumacher, 2010).

This study was conducted utilizing a correlational design. Creswell (2012) notes that a correlational design is appropriate given a researcher’s goal is to relate more than one variable and account for their influences. Creswell (2012) identified two main categories of correlational design: *prediction* and *explanatory*. Creswell notes that research designs aimed at predicting outcomes, follow the *prediction* category, while designs aimed at explaining relationships among variables, follow the *explanatory* design. Given that this study aimed to explore possible relationships between aca*demic support*, *academic engagement*, and *hours worked* through an abbreviated expectancy-value framework, this study utilized a correlational, explanatory design.

Furthermore, Creswell (2012) states that there are two main types of survey designs: cross-sectional and longitudinal. Creswell (2012) defines cross-sectional survey designs as being especially relevant for studies that aim to collect data from a population at a specific point in time. While a longitudinal survey design aims to collect data from the same population at different points in time (Creswell, 2012). This study utilized data collected from different populations at three different points in time (i.e., Spring 2016, Spring 2018, and Spring 2020 academic terms). All survey items utilized in this study were administered across the three academic terms previously noted. Given this distinction and this study's data sample, a cross-sectional research design was utilized for this study.

Instrumentation

The National Survey of Student Engagement (NSSE, pronounced "nessie") is a student survey aimed at measuring undergraduate students' academic experiences, co-curricular experiences, and potential for partaking in educational events during their first year and senior year of college (Ewell & Jones, 1993). To quote from the NSSE project's lead designer and current director (Ewell & McCormick, 2020):

> NSSE annually collects information at hundreds of four-year colleges and universities about first-year and senior students' participation in programs and activities that institutions provide for their learning and personal development.… Survey items represent empirically confirmed 'good practices' in undergraduate education. That is, they reflect behaviors by students and institutions that are associated with desired outcomes of college. NSSE doesn't assess student learning directly, but survey results point to areas where colleges and universities are performing well and to aspects of the undergraduate experience that could be improved (p. 2).

The NSSE assessment survey evaluates student behaviors respective to decades of research that align these behaviors with constructs related to learning and development (Ewell & McCormick, 2020). Table 1 shows the Cronbach's alpha coefficient and inter-item correlation for the NSSE scales which highlight a medium to a high degree of internal consistency and reliability for most of the ten NSSE scales (NSSE Psychometric Portfolio, 2019). Moreover, the NSSE assessment survey consists of 39 questions (varies by year), consisting of various Likert scale ranges for each question posed. This study aims to explore the relationships between multiple predictor variables relative to student academic success and retention, as such, the NSSE survey incorporates many of these multiple variables; therefore, not all 39 survey questions will be utilized for this study (see Table 3).

Table 1

Scale Cronbach's Alphas

NSSE scales	Cronbach's α	Inter-Item Correlation	Average Inter-Item Correlation
Higher-Order Learning	0.83	.46-.63	0.48
Reflective & Integrative Learning	0.85	.35-.57	0.45
Learning Strategies	0.76	.42-.64	0.5
Quantitative Reasoning	0.82	.55-.69	0.59
Collaborative Learning	0.83	.49-.62	0.55
Discussions with Diverse Others	0.87	.47-.58	0.51
Student-Faculty Interaction	0.81	.47-.58	0.52
Effective Teaching Practices	0.84	.43-.62	0.51
Quality of Interactions	0.85	.40-.70	0.54
Supportive Environment	0.88	.33-.64	0.47

Note. NSSE 2019 questionnaire sample included 129,108 first-year students and 152,028 seniors from 491 higher education institutions throughout the U.S. (NSSE Psychometric Portfolio, 2019).

Structural Equation Modeling (SEM)

This study employed the use of Structural Equation Modeling (SEM), using the Lavaan package in *R* Project for Statistical Computing (Rosseel, 2012), to quantitatively analyze the collected data to answer the previously posed research questions. As this study aimed to explore possible relationships between theoretical latent variables (i.e., Expectancies for Success and Subjective-Task Values) relative to predicted outcome variables, SEM is considered especially useful in this matter. Meyers et al. (2013) note that SEM can analyze two types of models: *measurement* and *structural*. The *measurement* model aims to assess the extent to which a predicted relationship among variables can be found to relate to observed variables (Kline, 2011; Meyers et al., 2013; Proitsi et al., 2009). While the *structural* model aims to measure possible relationships among latent constructs, as well as, the possible relationships among other measured variables (Kline, 2016; Meyers et al., 2013; Proitsi et al., 2009). Moreover, Meyers et al. (2013) note that, if a hypothesized model and observed model match, SEM can be used to further explain the hypothesized model. Given the proposed study's research question and theoretical models previously presented, this study used SEM as a data analysis technique.

As stated earlier, structural equation modeling analysis can be utilized in both measurement and structural models. Though this study focused on the findings generated by testing the structural component of the model, the measurement model is crucial in assessing model fit statistics (i.e., reliability and validity), before testing the structural model (Meyers et al., 2013). Meyers et al. (2013) note that the following model fit indices of the measurement model should precede any analysis of a structural model: The chi-square (χ^2) likelihood ratio statistic, the goodness-of-fit index (GFI), the comparative fit index (CFI), and the root mean square error of estimation (RMSEA).

The chi-square (χ^2) likelihood ratio statistic is considered to be crucial in evaluating a model's absolute fit index. Meyers et al. (2013) notes that the chi-square (χ^2) statistic tests the differences between both theoretical and the proposed empirical model. Moreover, Meyers et al. (2013) states that a significant χ^2 statistic indicates that the proposed theoretical model does not fit the empirical data being utilized. In contrast, a non-significant χ^2 statistic indicates an acceptable model fit between theoretical and empirical models.

Moreover, the goodness-of-fit index measures the number of variances and covariances measured by the model. GFI estimates that are equal to or greater than .90 are considered to have a good model fit (Khine et al., 2013). CFI analyzes the level of difference between the theoretical model and the empirical data being utilized (Meyers et al., 2013). As such, values at or greater than .95 indicate a good model fit. The RMSEA statistic measures estimate the amount of error between the observed model's covariance and the covariance of the theoretical model; as such, an RMSEA statistic of .08 or less is considered to have a good model fit (Meyers et al., 2013).

Lastly, because the instrumentation for data collection utilized Likert-type scale items (see Table 3), the use of maximum likelihood (ML) in estimating parameters in SEM is not appropriate. ML is not appropriate for Likert-type scale items, as the model's estimation presumes that the observed indicators in the model follow a multivariate normal distribution (Bollen, 1989; Jöreskog, 1969; Satorra, 1990). However, a diagonally weighted least squares (WLSMV) estimate is specifically designed to estimate non-continuous and abnormal distributions, or ordinal data (Li, 2015). As such, this study utilized WLSMV for model estimation.

Recommended Sample Size for Structural Equation Modeling

There have been varying positions taken regarding a minimum sample size to sufficiently assess and interpret analysis from structural equation modeling (Khine et al., 2013; Schumacker & Lomax, 2010). Khine et al. (2013) note that while the sample size is crucial when considering the utilization of SEM in research designs, “no consensus has been reached among researchers at present” (p. 10). Khine et al. (2013) go on to note that there seems to be a forming consensus that SEM is well suitable for analyzing larger sample sizes (Loehlin, 2004; Schumacker & Lomax, 2004). Schumacker and Lomax (2010) found that sample sizes of 400 or more were required to maintain statistical power and increase the chance of obtaining accurate results. Nevertheless, Kline (2011) notes that SEM is acceptable for use in simpler models with fewer parameters. Moreover, researchers have found sample sizes as small as 100 to 150 respondents to be minimally recommended size in preserving statistical precision and yielding accurate results (Kline et al., 2013; Schumacker & Lomax, 2010). More specifically, Hair et al. (2009) note that a minimum sample size of 100 respondents was recommended for empirical research investigating SEM models containing fewer than five latent variables.

Sample

This proposed study utilized secondary data analysis from a large public university in the Southeast. The university is a co-educational, urban research institution with approximately 30,000 students enrolled as of Fall 2021. The institution's student demographics can be considered generally diverse: 60% Caucasian, 17% African-American, 7% Hispanic, 5% Asian/Pacific Islander, 6% other/unknown, and 5% international students. The proposed study focused on first-year students from STEM majors. The university enrolled approximately 5,000 first-year students for the Fall 2016, 2018, and 2020 terms.

This study used secondary data collected by way of a student survey questionnaire, The National Survey of Student Engagement (NSSE). The survey is administered by the university in-practice and Indiana University’s Center for Survey Research. This process is adhered to by upholding standard administration protocols and ensuring comparability across all administering institutions. The NSSE survey is marketed and encouraged to student participation (on a biennial basis by the institution), regardless of admitted major, college, program, et cetera; however, this study, specifically, focused on first-year STEM students that completed the survey. The NSSE survey is administered through computerized self-administered questionnaires. All first-year students from the undergraduate entering class from 2016, 2018, and 2020 academic years were invited (approximately 5,000 students per entering class year), via email recruitment, to complete the survey. The email recruitment contained a survey invitation link, and the invitations were sent up to four times to remind students of their invitation to complete the NSSE survey.

Additional student data points (i.e., declared major, gender, GPA, race, developmental math attendance) were provided to the researcher by the universities Office of Institutional Research (IR). Because the IR office collected these student data points outside of the NSSE survey’s administration, the means of collecting the data by the IR office was not shared with the researcher.

Definition of Variables

This study’s conceptual and operational definitions of all variables used in this study are presented below and in Table 3. The variables consist of three predictor variables, consistent with Eccles and colleagues' (1983) Expectancy-Value Model of Achievement Motivation, six independent variables, and two outcome variables.

Academic Support (Expectancies for Success)

Previous literature has noted the importance of academic support as related to student success measures. Gnebola’s (2015) study found that faculty-student interaction and academic support positively correlated in predicting student achievement outcome measures, such as GPA. Pajares (1996) found that students' ability to interact and manage their environment increased their chances of academic success. To connect theory to practice, this latent variable includes items aiming to gauge varying levels of perceived student support through faculty-student interactions. Ten items were used to represent the *academic support* latent factor.

Academic Engagement (Subjective-Task Value)

Lester (2013) identified higher education research initiatives that have found the *cognitive engagement* category to be especially effective in predicting student engagement behavior and academic achievement outcomes of students in post-secondary education. Martinez (2016) echoes this statement as she states, "[m]ultiple researchers have found that the amount of time and the level of energy that students devote to educational activities, inside and outside of the classroom, are effective predictors of student development and success" (p. 27). Moreover, researchers have found that higher education students that collectively (i.e., with peers) interacted with course material, both in and outside of the classroom setting, were more academically engaged, as well as, exhibited higher levels of critical thinking (Mcormick, 2010; Pascarella & Terenzini, 2005). Given these points, the Academic Engagement latent construct included questions aimed at ascertaining higher education students' level of effort (in and outside of the classroom), including curricular interactions with classmates, in gaining an understanding of course content and mastering complex academic content. Seven items were used to represent the *academic engagement* latent factor.

Hours Worked (Subjective-Task Value)

Hours Worked is a novel indicator variable to assess student success and retention utilizing the expectancy-value model. Eccles and Wigfield (1995) stated the sub-component of subjective-task value, *perceived cost* or *cost*, is the negative valence of predicting an individual completing a task. For example, if a student believes the time and effort (i.e., cost) needed to achieve a STEM degree is too much, they may be less likely to persist in the STEM major (Perez et al., 2014). As such, students' perceived costs in a STEM major may be especially important when attempting to understand first-year students' intentions to persist beyond their first year (Barron & Hulleman, 2015; Flake et al., 2011; Perez et al., 2014). To measure this phenomenon within the context of the expectancy-value framework, this variable assessed self-declared student hours worked in on- and off-campus work environments. Two items were used to represent the *hours worked* indicator variables.

Gender

The variable Gender is conceptually defined as a students' institutionally reported gender, male or female. This variable was provided by the higher education institutions Office of Institutional Research (IR). The variable was operationally recorded (i.e., dummy coded) with values of "0" and "1" (i.e., male = 0; female = 1).

Developmental Math Course

Previous research has found STEM students, in need of completing remedial mathematics coursework during their freshmen, were approximately 50% more likely to leave the STEM fields of study after their first year (Adelman, 2006; Cabrera et al., 2005; Herzog, 2005). To assess previous literature findings, and the importance of mathematics readiness for first-year STEM majors, this variable was included and provided by the higher education institution's IR office. The variable measured if a student attended a developmental math course during their first year of study. The institution defines its developmental mathematics course as covering the following content areas: elementary algebra, inequalities, exponents, and equations.

The variable was operationally recorded (i.e., dummy coded) with values of “0” and “1” to indicate if the student attended a developmental math course (i.e., No = 0; Yes = 1).

Major During First Year of Study

These variables indicate if the student was a PEMC, Other-STEM, or non-STEM student during their first year of study (see Table 2). Given that previous research has reported differing relationships among PEMC and Other-STEM majors (Dika & D’Amico, 2015; Nix & Perez-Felkner, 2019; Perez-Felkner et al., 2012), this study aimed to assess the relationship of the varying STEM subgroups and non-STEM majors in the revised expectancy-value model. There were three distinct variables, operationally recorded (i.e., dummy coded) with values of “0” and “1” to directionally compare these subgroups within the model. STEM First-Year variable will be coded as 0 = non-STEM major and 1 = STEM major; PEMC First-Year variable will be coded as 0 = non-PEMC major and 1 = PEMC major; and Other-STEM First-Year variable will be coded as 0 = non-Other-STEM major and 1 = Other-STEM major.

Table 2

Major Variables

STEM and non-STEM majors
PEMC Majors
Civil and Environmental Engineering
Chemistry
Computer Science
Electrical and Computer Engineering
Engineering Technology and Construction Management
Mathematics and Statistics
Mechanical Engineering and Engineering Science
Physics and Optical Science
Systems Engineering and Engineering Management
Other-STEM Majors
Biological Sciences
Exercise Science
Geography & Earth Sciences
Health Systems Management

Health Informatics and Analytics
Health Services Research
Interdisciplinary Biology
Kinesiology
Neurodiagnostics & Sleep Science
Operations and Supply Management
Psychology
Sociology

Non-STEM Majors
Accounting
Architecture
Art history
Business Administration
Communications
Criminology
Economics
Education
English (language and literature)
French (language and literature)
Gender Studies
History
Humanities (general)
Music
Philosophy
Political science
Theater and Drama
Spanish (language and literature)
Undecided

Race

The race variable allowed the researcher to assess if group differences exist relative to the study's proposed model. Student race variables were included and provided by the higher education institutions' IR offices. The category was dummy coded to account for lower levels of participation from applicable racial/ethnic groups (i.e., Other) (see Table 3 for items).

Academic Achievement

This variable was provided by the higher education institutions' IR offices. The variable included the student's end of first-year GPA, which is on an interval scale ranging from

0.00 to 4.00. This study utilized Meyer et al.'s (2019) definition of Academic Success, or Achievement, as related to the Expectancy-Value Model of Achievement Motivation. As such, a higher value GPA on a scale of 0.00 to 4.00 indicated better grades and higher academic achievement (Meyer et al., 2019).

Persistence in STEM

Lastly, the Persistence_STEM variable was provided by the higher education institutions' IR offices. The variable assessed if the first-year STEM student persisted to the start of the second year (following fall term) as a STEM major. The variable was dummy coded "0" or "1" when assessing if the student retained at the institution and remain with a STEM major, 0 = No and 1 = Yes. Allowing for this variable to be dummy coded in the model accounted for student predictor and independent variables and showed directional relationships as an outcome variable.

Table 3

Predictor Variables

Academic Support (Expectancies for Success)	
Q: During the current school year, about how often have you done the following?	1. Discussed course topics, ideas, or concepts with a faculty member outside of class (*SFdiscuss*) 2. Discussed your academic performance with a faculty member (*SFperform*) Scale: 1=Never; 2=Sometimes; 3=Often; 4=Very often.
Q: During the current school year, to what extent have your instructors done the following?	3. Clearly explained course goals and requirements (*ETgoals*) 4. Taught course sessions in an organized way (*ETorganize*) 5. Used examples or illustrations to explain difficult points (*ETexample*) 6. Provided feedback on a draft or work in progress (*ETfeedback*) 7. Provided prompt and detailed feedback on tests or completed assignments (*ETdraftfb*)

	Scale: 1=Very little; 2=Some; 3=Quite a bit; 4=Very much.
Q: During the current school year, to what extent have your courses challenged you to do your best work?	8. During the current school year, to what extent have your courses challenged you to do your best work? (*challenge*)
	Scale: 1=Not at all to 7=Very much
Q: Indicate the quality of your interactions with the following people at your institution.	9. Academic Advisor (*QIadvisor*) 10. Faculty (*QIfaculty*)
	Scale: 1=Poor to 7=Excellent
Academic Engagement (Subjective Task Value)	
Q: During the current school year, about how often have you done the following?	1. Asked questions or contributed to course discussions in other ways (*askquest*) 2. Come to class without completing readings or assignments (*unprepared*) 3. Asked another student to help you understand course material (*CLaskhelp*) 4. Explained course material to one or more students (*CLexplain*) 5. Prepared for exams by discussing or working through course material with other students (*CLstudy*) 6. Worked with other students on course projects or assignments (*CLproject*) 7. Given a course presentation (*present*) Scale: 1=Never; 2=Sometimes; 3=Often; 4=Very often.
Hours Worked (Subjective Task Value)	
Q: About how many hours do you spend in a typical 7-day week doing the following?	Hours per week: Working for pay ON CAMPUS (*tmworkon*) Hours per week: Working for pay OFF CAMPUS (*tmworkoff*)
	Scale: 1=0 Hours per week; 2=1-5 Hours; 3=6-10 Hours; 4= 11-15 Hours; 5=16-20 Hours; 6=21-25 Hours; 7=26-30 Hours; 8=More than 30.
Independent Variables	
Gender	Male = 0; Female = 1
Develop. Math Attended	No = 0; Yes = 1

MajorFirstYear_STEM	Non_STEM_Major = 0; STEM_Major = 1
MajorFirstYear_PEMC	Non_PEMC_Major = 0; PEMC_Major = 1
MajorFirstYear_Other-STEM	Non_Other-STEM_Major = 0; Other-STEM_Major = 1
Race (Dummy Coded)	White = 0 (reference group); Asian = 1; Black or African American = 1; Hispanic or Latino = 1.
Outcome Variables	
Academic Achievement	End of first-year GPA
	Interval Scale: 0 to 4
Persistence_STEM	Continuation to the second year in STEM
	No = 0; Yes = 1

Note. Other race variable includes the following groups: American Indian or Alaska Native; Foreign or Nonresident alien; Native Hawaiian or Other Pacific Islander; Unknown.

Assumptions and Limitations

It should be noted that this study made assumptions and was beholden to general limitations. The following assumptions were presumed for this study: (a) students were willing to complete the NSSE survey and were truthful with their responses; (b) the researcher is allowed access to relevant institutional data, and (c) the sample size of the data will be sufficient to recognize associations. Also, the statistical methodology utilized in this study (i.e., SEM), the following assumptions were presumed to be acceptable: sufficient sample size (n > 100); (b) no missing data; (c) normality; (d) absence of outliers; (e) collinearity; and (f) factor correlations. Regarding limitations to this study's research design the following were identified: (a) dependence on self-reported opinions about a student's level of academic engagement, academic support, and hours worked; (b) the NSSE surveys were completed voluntarily; therefore, respondents were not selected at random; lastly, (c) the data collected were particular to only one institution; thus, generalizability is difficult to infer.

CHAPTER 4: RESULTS

Introduction

The primary purpose of this study was to utilize a revised version of the Expectancy-Value Model of Achievement Motivation: (1) Expectancies for Success; (2) Subjective Task Values; and (3) Achievement Related Performance and Choices, to assess if first-year and marginalized college students in the STEM major's *academic support*, *academic engagement*, and *hours worked* are predictors of overall student success and retention after their first year of study. By utilizing secondary data from the NSSE survey assessment tool and institutional data, over three academic years, this chapter reports on the descriptive statistics relevant to the study; as well as, presents inferential statistics of the research questions guiding the study:

1. To what extent does the Expectancy-Value Model of Achievement Motivation explain:
    - First-year STEM major students' academic success and retention?
    - First-year STEM major students' academic success and retention by *gender*?
    - First-year STEM major students' academic success and retention by *race*?
2. Given the Expectancy-Value Model of Achievement Motivation, are *hours worked (perceived cost)* a predictor of academic success and retention for:
    - First-year STEM majors?
    - First-year STEM major students across *gender*?
    - First-year STEM major students across *race*?
3. Is the relationship between the Expectancy-Value Model of Achievement Motivation and first-year STEM major students' academic success and retention mediated by math coursework readiness?
4. To what extent does the Expectancy-Value Model of achievement motivation explain

first-year students' declared PEMC or Other-STEM majors' academic success and retention?

Description of the Sample

The sample consisted of first-year STEM undergraduate students from a large, urban, university in the southeast with an overall student population of approximately 30,000. The first-year STEM major sample was taken across three academic years, 2016-2017 (N = 3,453), 2018-2019 (N = 3,708), and 2020-2021 (N = 3,999). Table 4 shows a breakdown of demographic information for first-year STEM majors by academic year of survey administration.

Table 4

Demographic Characteristics by Academic Year

	2016-2017		2018-2019		2020-2021	
Variable	N	Percent (%)	N	Percent (%)	N	Percent (%)
Gender						
Male	120	42.7	72	52.9	183	49.2
Female	161	57.3	64	47.1	189	50.8
Ethnicity						
White	165	58.7	88	64.7	217	58.3
Asian	--	--	10	7.4	36	9.7
Black/African American	33	11.7	16	11.8	46	12.4
Hispanic/Latino	31	11	9	6.6	40	10.8
Two or More Races	16	5.7	6	4.4	16	4.3
Other	36	12.8	7	5.1	17	4.6

Descriptive Statistics

The overall sample for the study consisted of 798 first-year students across the three academic years previously noted. Descriptive statistics were used to attain an accurate description of the sample (see Table 5). Participants in the study were predominantly White (59.3%), with Black/African American (12.2%) and Hispanic/Latinx (10.2%), accounting for the second and third largest racial and ethnic groups respectively. Female students (52.4%) consisted of a larger group of participants than male students (47.6%). Of the reported first-year STEM majors, PEMC majors accounted for the majority (56.5%), when compared to Other-STEM majors (43.5%). Lastly, of the sample, the majority of participants reported attending a developmental math course (64.2%) during their first year of study.

Table 5

Total Demographic Characteristics (N = 798)

Variable	*N*	Percent (%)
Gender		
Male	380	47.6
Female	418	52.4
Race/Ethnicity		
White	473	59.3
Asian	47	5.9
Black/African American	97	12.2
Hispanic/Latinx	81	10.2
Two or More Races	39	4.9
Other	61	7.5
STEM Major		
PEMC	451	56.5
Other STEM	347	43.5
Attended Developmental Math Course		
Yes	512	64.2
No	286	35.8

Note. *N* = 798, % = 100

Missing Data

Data elements were screened for missing values during an initial review of the data. As noted by Little and Rubin (1987), missing data, especially in large frequencies, can be generally troubling when considering research data analysis. Becker and Walstad (1990), support this notion as their meta-analysis of the effects of varying levels of missing data in research designs found that missing data can introduce varying levels of bias into concluding estimates from various statistical models. This loss in information can render a data sample no longer random and/or representative of the sample's intended population (Schafer, 1997). Furthermore, Rubin

(1987), reaffirmed the seriousness of missing data in quantitative data analysis as many multivariate statistical methods rely on and assume a complete dataset with there being no missing data present.

Though Rubin (1987) highlights the importance of quantitative research having complete datasets, free of missing data, the issue of *how much, is too much* missing data has very little to no clear set of assumptions (Kline, 1998). Cohen (1983) notes that the missingness of data on a variable between 5% to 10% can be considered *small*, while 40% or higher may be considered to be high (Kline, 1998). Regardless of the level of missing data, a meta-analysis research study found missing data on a variable of 5% or higher should be remedied before further data analysis (Xu, 2004). Given the importance of screening data for missingness of variables, a Missing Value Analysis (MVA) was conducted (see Table 6). The MVA concluded that there were missing data from participant responses on 19 of the survey items utilized from the NSSE survey. The scale of missingness in the data ranged from 1.1% to 26.30% (see Table 6).

Before identifying a method to remedy the missing data in this study, an effort was made to detect the reason for the "missingness" of the data. Little and Rubin (2002) note that there are three main categories of missing data, as related to randomness: Missing completely at random (MCAR); missing at random (MAR); and not missing at random (NMAR) or non-ignorable missing data. Firstly, to assess if the data were missing completely at random, *Little's* MCAR test was conducted. The results of *Little's* MCAR test were statistically significant (χ^2 = 1945.465, df =1705, p =.005). These results indicate that the data were not missing completely at random, as such, the missing data cannot be ignored, and further analysis of the missing data must be assessed. To evaluate if the data were missing at random or not missing at random, Allison (2002) recommends analyzing the structural patterns of the missing data. Figure 8 illustrates the pattern of missing data and non-missing data. Figure 8 is interpreted by first observing the x-axis; where the x-axis is aligned from variables with the least missingness patterns detected (left side), to variables with the most patterns of missingness (right side) (Von Hippel, 2004). This illustrates both missing data in random and non-random pattern effects. As such, neither MAR nor NMAR can be concluded. Given this finding, Allison (2002) recommends data remediation through the replacement of each missing value.

One such remediation technique to replace missing data, multiple imputations, was first developed by Rubin (1987). A study by Ping Xu's (2004) found, that of the various remedies utilized for missing data in quantitative survey research, "…multiple imputation procedures provided more reliable parameter estimates than did listwise deletion…producing parameter estimates with smaller standard errors" (p. 5). As such, the multiple imputation techniques, utilizing the Markov Chain Monte Carlo (MCMC) simulation method, were applied to replace the missing values through five imputations of pooling estimates from the imputed datasets.

Table 6

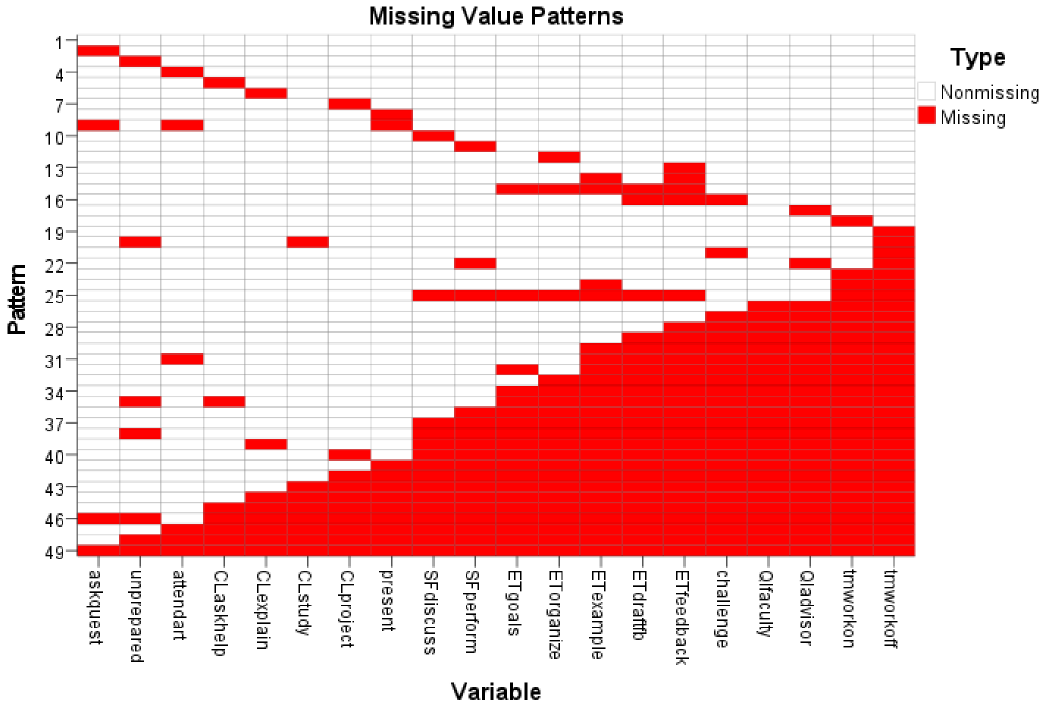
Missing Value Analysis (N = 798)

Var. Name	Variable Summary	Missing	Percent	Valid N
tmworkoff	Hours per week: Working for pay OFF CAMPUS	210	26.30%	588
tmworkon	Hours per week: Working for pay ON CAMPUS	206	25.80%	592
QIadvisor	Quality of interactions with academic advisors	177	22.20%	621
QIfaculty	Quality of interactions with faculty	175	21.90%	623
challenge	To what extent have your courses challenged you to do your best work?	168	21.10%	630

ETfeedback	Instructors: Provided prompt and detailed feedback on tests or completed assignments	134	16.80%	664
ETdraftfb	Instructors: Provided feedback on a draft or work in progress	128	16.00%	670
ETexample	Instructors: Used examples or illustrations to explain difficult points	128	16.00%	670
ETorganize	Instructors: Taught course sessions in an organized way	124	15.50%	674
ETgoals	Instructors: Clearly explained course goals and requirements	122	15.30%	676
SFperform	Discussed your academic performance with a faculty member	102	12.80%	696
SFdiscuss	Discussed course topics, ideas, or concepts with a faculty member outside of class	99	12.40%	699
present	Given a course presentation	23	2.90%	775
CLproject	Worked with other students on course projects or assignments	21	2.60%	777
CLstudy	Prepared for exams by discussing or working through course material with other students	15	1.90%	783
CLexplain	Explained course material to one or more students	14	1.80%	784
CLaskhelp	Asked another student to help you understand course material	13	1.60%	785
unprepared	Come to class without completing readings or assignments	9	1.10%	789
askquest	Asked questions or contributed to course discussions in other ways	4	0.50%	794

Figure 8

Missing Value Patterns (N = 798)



Note. Each pattern (along the y-axis) represents grouped variables with the same pattern of missing values. The variables on the x-axis are organized by the frequency of missing values identified; from left to right, smallest to largest (Von Hippel, 2004).

Assumptions

Outliers. As for univariate outliers, an examination of all nineteen predictor variables utilizing boxplots indicated that there were univariate outliers present in three of the variables: *unprepared* (*n* = 10); *challenge* (*n* = 17); *tmworkon* (*n* = 27). However, closer inspection of the univariate outliers detected in the aforementioned variables did not respond outside of the established survey item response range (see Figures 9, 10, 11. correspondingly). The responses were within the provided range of possible choices, and no data entry error was identified; as such, the outlier responses are assumed to be present given the skewness of the responses from the variables mean, see Table 7 (Hyndman & Shangsee, 2010). Given these observations, the univariate outliers were retained in the dataset for further analysis.

Moving on to assessing for multivariate outliers within the dataset, the *Mahalanobis* distance test was used to assess if there are multivariate anomalies in the distribution of variables (Brereton, 2014). Analysis of the Chi-square distribution of the Mahalanobis distance reported 8 *p* - values less than .01, therefore, 8 participants reported for the variables are problematic for multivariate analysis. Because SEM relies heavily on the assumption of multivariate normality (Yuan & Bentler, 2001; Yuan & Zhong, 2013), the 8 participants were removed from the study.

Collinearity. The collinearity of the nineteen variables was not problematic. The following *Tolerance* and *Variance Inflation Factor* (VIF) was reported for all nineteen predictor variables (see Table 8). Based on supported guidelines (Kline, 2011), a Tolerance of less than 1.0 and VIF greater than 10 is indicative of multicollinearity. Given the reported collinearity statistics (see Table 8), all nineteen predictor variables did not appear to be problematic.

Factor Correlations. To assess the correlation among the predictor variables, and the appropriateness of using the predictor variables in factor analysis (i.e., SEM), a Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy and Bartlett’s Test of Sphericity were conducted (Schriesheim et al, 1999; Williams et al., 2010). Table 9 shows the KMO measure of sample adequacy as (.824), which is close to 1.00. Furthermore, Bartlett’s Test of Sphericity analysis (Dziuban et al. 1974; Williams et al., 2010) resulted in a significance value ($p<.001$) that was less than .05. As such, the sample and predictor variables are appropriate for use in factor analysis.

Figure 9

Boxplot of Univariate Outliers (Var. unprepared; N = 798)

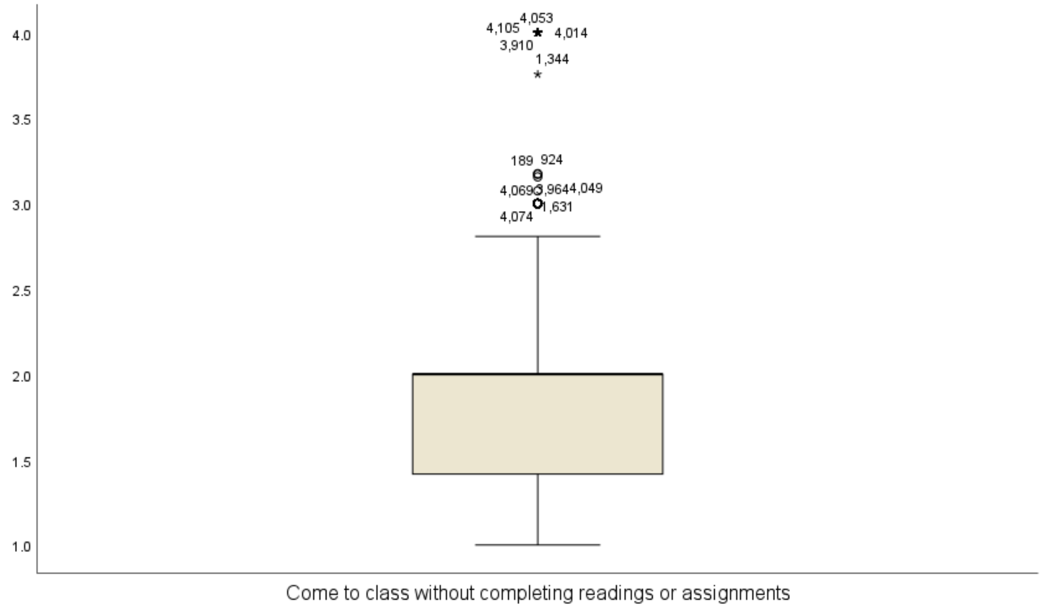


Figure 10

Boxplot of Univariate Outliers (Var. challenge; N = 798)

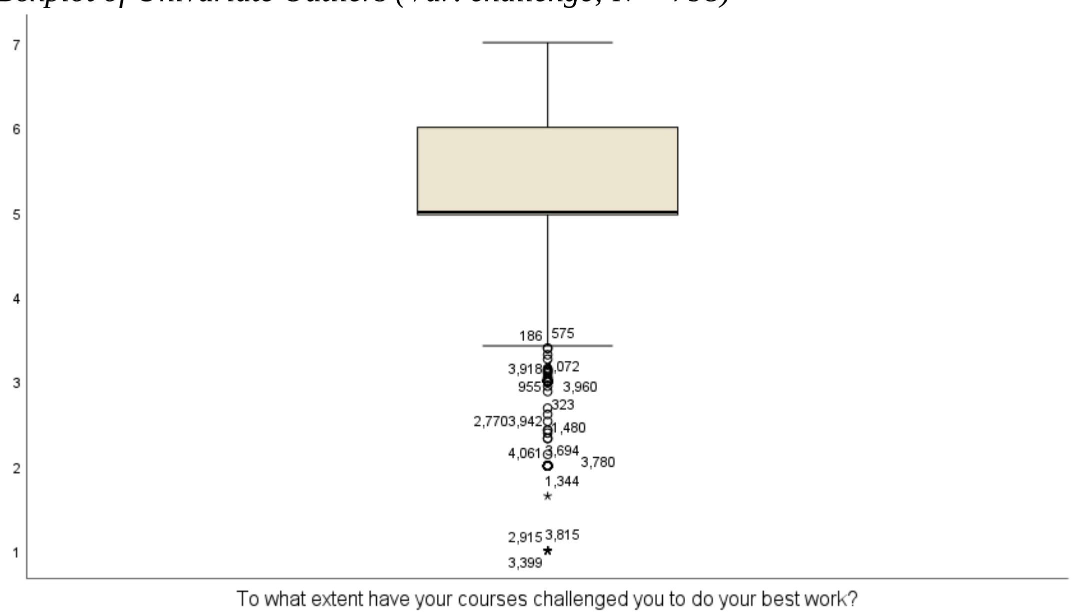


Figure 11

Boxplot of Univariate Outliers (Var. tmworkon; N = 798)

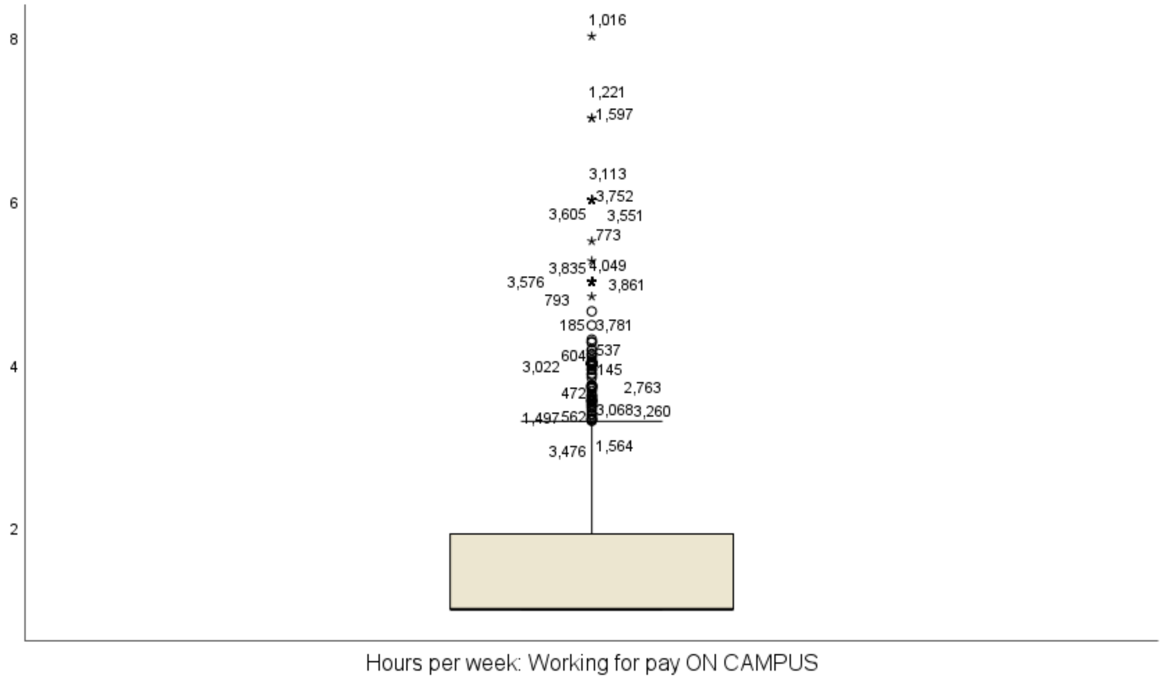


Table 7

Variable Descriptive Statistics

						Skewness		Kurtosis	
Variable	*n*	Minimum	Maximum	*M*	*SD*	Statistic	Std. Error	Statistic	Std. Error
ETgoals	797	1.000	4.000	2.930	.724	-.230	.087	-.360	.173
ETorganize	797	1.000	4.000	2.840	.778	-.188	.087	-.525	.173
ETexample	797	1.000	4.000	2.930	.791	-.295	.087	-.523	.173
ETdraftfb	797	1.000	4.000	2.550	.847	.051	.087	-.658	.173
ETfeedback	797	1.000	4.000	2.510	.841	.109	.087	-.629	.173
challenge	797	1.000	7.000	5.380	1.121	-.575	.087	.424	.173
QIadvisor	797	1.000	9.000	5.110	1.684	-.535	.087	-.257	.173
QIfaculty	797	1.000	9.000	5.110	1.366	-.389	.087	.218	.173
SFdiscuss	797	1.000	4.000	1.940	.847	.636	.087	-.255	.173
SFperform	797	1.000	4.000	2.080	.792	.517	.087	-.002	.173
askquest	797	1.000	4.000	2.650	.819	.248	.087	-.772	.173
unprepared	797	1.000	4.000	1.950	.773	.749	.087	.579	.173
CLaskhelp	797	1.000	4.000	2.690	.845	.030	.087	-.760	.173

CLexplain	797	1.000	4.000	2.850	.800	-.037	.087	-.843	.173
CLstudy	797	1.000	4.000	2.670	.940	-.104	.087	-.914	.173
CLproject	797	1.000	4.000	2.790	.808	-.078	.087	-.667	.173
present	797	1.000	4.000	2.240	.827	.422	.087	-.261	.173
tmworkon	797	1.000	7.000	1.560	1.022	2.077	.087	3.976	.173
tmworkoff	797	1.000	8.000	2.400	1.913	1.240	.087	.443	.173
GPA	798	.500	4.000	3.305	.588	-1.322	.087	2.271	.173
Persist	798	.000	1.000	.840	.366	-1.867	.087	1.490	.173

Table 8

Intercorrelations Statistics

Model		Collinearity Statistics	
Var. Name	Variable Summary	Tolerance	VIF
unprepared	Come to class without completing readings or assignments	.936	1.069
CLaskhelp	Asked another student to help you understand course material	.598	1.673
CLexplain	Explained course material to one or more students	.599	1.669
CLstudy	Prepared for exams by discussing or working through course material with other students	.538	1.858
CLproject	Worked with other students on course projects or assignments	.595	1.680
present	Given a course presentation	.728	1.373
SFdiscuss	Discussed course topics, ideas, or concepts with a faculty member outside of class	.604	1.655
SFperform	Discussed your academic performance with a faculty member	.630	1.587
ETgoals	Instructors: Clearly explained course goals and requirements	.579	1.726
ETorganize	Instructors: Taught course sessions in an organized way	.509	1.963
ETexample	Instructors: Used examples or illustrations to explain difficult points	.535	1.870
ETfeedback	Instructors: Provided feedback on a draft or work in progress	.551	1.814

ETdraftfb	Instructors: Provided prompt and detailed feedback on tests or completed assignments	.518	1.929
challenge	To what extent have your courses challenged you to do your best work?	.815	1.227
QIadvisor	Quality of interactions with academic advisors	.726	1.377
QIfaculty	Quality of interactions with faculty	.627	1.594
tmworkon	Hours per week: Working for pay ON CAMPUS	.940	1.063
tmworkoff	Hours per week: Working for pay OFF CAMPUS	.952	1.050
askquest	Asked questions or contributed to course discussions in other ways	.785	1.273

Table 9

KMO and Bartlett's Test

Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy		.824
Bartlett's Test of Sphericity	χ^2	20848.976
	df	190
	Sig.	.000

Note. Significance is less than .001.

Variable Description

This section presents descriptive statistics of the three latent factors, along with their corresponding indicator variables, that were utilized in this study. Indicator variables aimed at assessing first-year STEM students' motivation, willingness, and competence to interact and manage their environment to increase their chances of academic success (Pajares, 1996), were grouped under the Expectancies for Success (*esuccess*) latent factor. Indicator variables that assessed first-year STEM students' likeness to engage in activities, behaviors, and tasks that align with their self-interest (Andersen & Chen, 2016; Guo et al., 2016; Nagengast et al., 2011), were grouped under the Subjective Task Values (*subjective_hoursworked*) latent factor. Lastly, the two indicator variables that assessed first-year STEM students' willingness to persist in a

STEM field of study and their academic performance during their first year, were grouped under the Achievement Related Performance and Choices (perfchoice) latent factor.

Expectancies for Success

Descriptive statistics for each indicator variable for the *esuccess* latent factor are presented in Table 10. Overall descriptive analysis of the *esuccess* latent factor yielded an average mean of 3.34 and an average standard deviation of .979. Mean scores ranged from 1.940 to 5.380. It's important to note that not all survey items for the *esuccess* latent factor were assessed on the same response scale (see Table 3). The lowest mean score (*M* = 1.940, *SD* = .847; Scale: 1=Never; 2=Sometimes; 3=Often; 4=Very often.), was assessed from the indicator item, *SFdiscuss* (Discussed course topics, ideas, or concepts with a faculty member outside of class). While the highest mean score (*M* = 5.380, *SD* = 1.121; Scale: 1=Not at all to 7=Very much), was assessed from the indicator variable, *challenge* (To what extent have your courses challenged you to do your best work). Of note, indicator items, QIadvisor (*M* = 5.110, *SD* = 1.684; Scale: 1=Poor to 7=Excellent), "Quality of interactions with academic advisors", and QIfaculty (*M* = 5.110, *SD* = 1.366; Scale: 1=Poor to 7=Excellent), "Quality of interactions with faculty", also assessed high mean scores.

The general results infer that first-year STEM students were likely to have low levels of engagement to discuss course topics, ideas, or concepts with a faculty member outside of class. The results also suggest that first-year STEM students were likely to feel challenged by their courses to do their best, as well as, felt their quality of interaction with their academic advisor and faculty was of higher quality.

Table 10

Mean and Standard Deviation for Expectancies for Success (N = 797)

Variable	Variable Summary	*M*	*SD*
ETgoals	Instructors: Clearly explained course goals and requirements	2.930	.724
ETorganize	Instructors: Taught course sessions in an organized way	2.840	.778
ETexample	Instructors: Used examples or illustrations to explain difficult points	2.930	.791
ETdraftfb	Instructors: Provided feedback on a draft or work in progress	2.550	.847
ETfeedback	Instructors: Provided prompt and detailed feedback on tests or completed assignments	2.510	.841
challenge	To what extent have your courses challenged you to do your best work?	5.380	1.121
QIadvisor	Quality of interactions with academic advisors	5.110	1.684
QIfaculty	Quality of interactions with faculty	5.110	1.366
SFdiscuss	Discussed course topics, ideas, or concepts with a faculty member outside of class	1.940	.847
SFperform	Discussed your academic performance with a faculty member	2.080	.792

Subjective Task Value

Descriptive statistics for each indicator variable for the *subjective_hoursworked* latent factor are presented in Table 11. Overall descriptive analysis of the *subjective_hoursworked* latent factor yielded an average mean of 2.42 and an average standard deviation of .972. Similar to the *esuccess* latent factor, *subjective_hoursworked* latent factor indicator variables were assessed on the same response scale (see Table 3). Mean scores ranged from 1.560 to 2.850. The lowest mean score (*M* = 1.560, *SD* = 1.088; Scale: 1=0 Hours per week; 2=1-5 Hours; 3=6-10 Hours; 4= 11-15 Hours; 5=16-20 Hours; 6=21-25 Hours; 7=26-30 Hours; 8=More than 30.), was assessed from indicator item, *tmworkon* (Hours per week: Working for pay ON CAMPUS). While the highest mean score (*M* = 2.850, *SD* = .800; Scale: 1=Never; 2=Sometimes; 3=Often;

4=Very often.), was assessed from the indicator variable, *CLexplain* (Explained course material to one or more students). Worth mentioning, indicator items, *tmworkoff* (*M* = 2.400, *SD* = 1.913; Scale: 1=0 Hours per week; 2=1-5 Hours; 3=6-10 Hours; 4= 11-15 Hours; 5=16-20 Hours; 6=21-25 Hours; 7=26-30 Hours; 8=More than 30.), "Hours per week: Working for pay OFF CAMPUS", and *tmworkon* (Hours per week: Working for pay ON CAMPUS), assessed high standard deviations relative to their mean.

The general results infer that STEM students were likely to engage in working less than 5 hours per week on-campus during their first year of study. The results also suggest that first-year STEM students are more likely to engage in explaining course materials with their peers than not engaging with their peers regarding course materials.

Table 11

Mean and Standard Deviation for Subjective Task Value (N = 797)

Variable	Variable Summary	*M*	*SD*
askquest	Asked questions or contributed to course discussions in other ways	2.650	.819
unprepared	Come to class without completing readings or assignments	1.950	.773
CLaskhelp	Asked another student to help you understand course material	2.690	.845
CLexplain	Explained course material to one or more students	2.850	.800
CLstudy	Prepared for exams by discussing or working through course material with other students	2.670	.940
CLproject	Worked with other students on course projects or assignments	2.790	.808
present	Given a course presentation	2.240	.827
tmworkon	Hours per week: Working for pay ON CAMPUS	1.560	1.022
tmworkoff	Hours per week: Working for pay OFF CAMPUS	2.400	1.913

Descriptive statistics for each indicator variable for the *perfchoice* latent factor are presented in Table 12. The *Persist* (Retained in STEM major) had a mean score of .840 (*SD* = .366; Scale: No = 0, Yes = 1). While *GPA* (GPA in all coursework after the first year) reported a mean score of 3.305 (*SD* = .588; Interval Scale: 0 to 4). The general results infer that first-year STEM students were more likely to persist in their STEM major after their first year than to change to a non-STEM major. The results also suggest that first-year STEM students were likely to have a GPA higher than 2.50 after their first year of study.

Table 12

Mean and Standard Deviation for Achievement Related Performance and Choices (N = 797)

Variable	Variable Summary	*M*	*SD*
GPA	GPA in all coursework after the first year	3.305	.588
Persist	Retained in STEM major	.840	.366

Measurement Model

Before assessing the full structural models to answer the research questions proposed for this exploratory study, a measurement model was conducted to test whether the data fit the latent variables with covariances among the latent variables (Mueller & Hancock, 2001). The measurement model was evaluated against five model fit estimates. The criteria included: chi-square (χ^2) likelihood ratio statistic, the goodness-of-fit index (GFI), the standardized root mean square residual (SRMR), the comparative fit index (CFI), and the root mean square error of estimation (RMSEA). The overall model fit indices suggested an approximate poor fit (χ^2= 890.074, *df* =149, *p*<.001; RMSEA=.079, CFI=.841; SRMR=.084; GFI=.937). The chi-square test is statistically significant which indicates a poor fit; however, this test is sensitive to large sample sizes; as such, the chi-square statistic will not be considered a core indicator of model fit.

The RMSEA is less than .08 (Hu & Bentler, 1999) and the GFI is greater than .90 which all indicate a good model fit. The SRMR is greater than the recommended .08, which is an indicator of a poor global model fit (Hu & Bentler, 1999). Moreover, the CFI statistic was less than the recommended level of greater than .95 (Myers et al., 2013), which is an indicator of poor model fit. Overall, the fit indices indicate a poor global model fit with the data (Hair et al., 2013; Myers et al., 2013).

The standardized regression weight (or pattern coefficients) are reported in Table 4.13 (also see Appendix A). A closer examination of the standardized regression weights shows that there are several variable loadings ≤ .40. Hair et al. (2013, p. 736) note that model fit modifications can be initiated by first examining the local model fit indices (see Table 13), specifically the standardized regression weights, and recommending the removal of indicator loadings that are less than .40 for exploratory studies. The authors also noted that the removal of indicators should be backed by theory; more specifically, the potential contribution the indictor is making to the latent construct being assessed (Hair et al., 2013).

Given these guidelines for an exploratory research study, and to improve the local and global model fit, the following indicators were removed from the study: *challenge* ($\beta = .21$, $p < .001$), *SFdiscuss* ($\beta = .31$, $p < .001$), *SFperform* ($\beta = .33$, $p < .001$), *unprepared* ($\beta = .03$, $p = .496$). Theoretical grounds for removing these indicator variables are found in Martinez (2016), as the researcher's findings, utilizing multiple regression models, did not yield statistical significance, given First-Year Academic Engagement, relative to predicting academic success and persistence to the second year of college. Moreover, indicators *QIadvisor* ($\beta = .360$, $p < .001$) and *askquest* ($\beta = .400$, $p < .001$) were not removed as they're aligned with this study's need to assess levels and engagement with faculty and staff. Lastly, *Persistnc_STEM* ($\beta = .372$, *p*

= .137) indicator was not removed as it relates directly to the outcome measure within the theoretical model. The remaining indicator variables were retained and were used in the structural models. After the aforementioned modifications were made to the measurement model, the overall model fit indices suggested an approximate good fit (χ^2= 357.589, *df* =87, *p*<.001; RMSEA=.063, CFI=.929; SRMR=.066; GFI=.969).

Table 13

Standardized Regression Weights for the Measurement Model (N = 797)

Latent Factor		Variable	Estimate	Std.Err	P(>|z|)	Std.lv	Std.all
esuccess	⇒	ETgoals	1.000			.421	.587
esuccess	⇒	ETorganize	1.093	.075	.000*	.460	.599
esuccess	⇒	ETexample	1.293	.087	.000*	.545	.694
esuccess	⇒	ETdraftfb	1.223	.093	.000*	.515	.613
esuccess	⇒	ETfeedback	1.333	.097	.000*	.562	.670
esuccess	⇒	challenge	.554	.110	.000*	.233	.212
esuccess	⇒	QIadvisor	1.426	.163	.000*	.600	.360
esuccess	⇒	QIfaculty	1.498	.147	.000*	.631	.466
esuccess	⇒	SFdiscuss	.624	.095	.000*	.263	.314
esuccess	⇒	Sfperform	.615	.089	.000*	.259	.330
subjective	⇒	askquest	1.000			.326	.400
subjective	⇒	unprepared	.078	.115	.496	.026	.033
subjective	⇒	CLaskhelp	1.613	.181	.000*	.526	.627
subjective	⇒	CLexplain	1.674	.180	.000*	.546	.684
subjective	⇒	CLstudy	2.119	.219	.000*	.691	.739
subjective	⇒	CLproject	1.640	.177	.000*	.535	.669
subjective	⇒	present	1.046	.134	.000*	.341	.415
perfchoice	⇒	Persistnc_STEM	1.000			.137	.372
perfchoice	⇒	GPAONEYEAROUT	2.618	1.341	.051	.358	.608
esuccess	⇔	subjective	.042	.009	.000*	.307	.307
esuccess	⇔	perfchoice	.011	.006	.059	.183	.183
subjective	⇔	perfchoice	.006	.004	.068	.145	.145

Note. *Std.lv* = illustrates standardized results when the latent variable has a variance of one; *Std.all* = illustrates standardized results when the latent variable and observed variables have a variance of one (Hu & Bentler, 1999).

Research Question 1: Expectancy-Value Model and First-Year STEM Majors

The primary purpose of this study was to utilize a revised version of the Expectancy-Value Model of Achievement Motivation: (1) Expectancies for Success; (2) Subjective Task Values; and (3) Achievement Related Performance and Choices, to assess if first-year and marginalized college students in the STEM major's *academic support*, *academic engagement*, and *hours worked* are predictors of overall student success and retention after their first year of study. The first revised hypothesized theoretical model tested if the Expectancy-Value Model of Achievement Motivation can explain: (a) First-year STEM major students' academic success and retention; (b) First-year STEM major students' academic success and retention by gender; and (c) First-year STEM major students' academic success and retention by race.

Research Question 1A (First-Year STEM)

Regarding research subquestion 1A (i.e., First-year STEM major students' academic success and retention, the structural model was evaluated against five model fit estimates. The overall model fit indices suggested an approximate good fit (χ^2 = 357.589, *df* =87, *p*<.001; RMSEA=.063, CFI=.929; SRMR=.066; GFI=.969). The standardized regression weight (or pattern coefficients) are reported in Table 14 and Figure 12. All the weights were statistically significant, at an alpha level of .05, except for the path between the latent variable *perfchoice* and indicator variable GPAONEYEAROUT. This suggests that GPA after the first year does not have a direct effect on a student's performance and choice to retain in a STEM major. Moreover, path coefficients for the structural model show that latent factor Expectancies for Success are not a statistically significant predictor of Achievement Related Performance and Choices (β = .155, *p* = .093). Additionally, the Subjective Task Value latent factor is not a statistically significant predictor of Achievement Related Performance and Choice (β = .108, *p* = .148).

Table 14

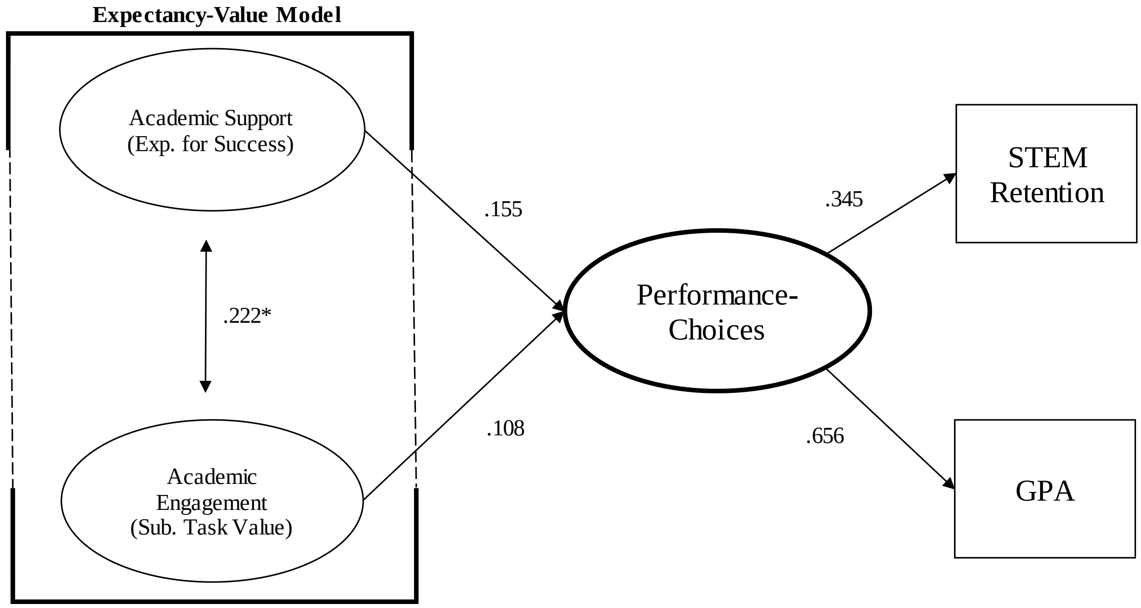
Standardized Regression Weights for RQ1A-First-Year STEM (N = 789)

Latent Factor		Variable	Estimate	Std.Err	P(>|z|)	Std.lv	Std.all
esuccess	⇒	ETgoals	1.000			.447	.623
esuccess	⇒	ETorganize	1.106	.071	.000*	.494	.643
esuccess	⇒	ETexample	1.271	.079	.000*	.568	.724
esuccess	⇒	ETdraftfb	1.135	.086	.000*	.507	.604
esuccess	⇒	ETfeedback	1.258	.087	.000*	.563	.672
esuccess	⇒	QIadvisor	1.383	.151	.000*	.618	.371
esuccess	⇒	QIfaculty	1.445	.133	.000*	.646	.478
subjective	⇒	askquest	1.000			.297	.364
subjective	⇒	CLaskhelp	1.811	.217	.000*	.537	.640
subjective	⇒	CLexplain	1.860	.215	.000*	.552	.691
subjective	⇒	CLstudy	2.376	.267	.000*	.705	.754
subjective	⇒	CLproject	1.811	.212	.000*	.537	.672
subjective	⇒	present	1.111	.151	.000*	.330	.401
perfchoice	⇒	Persistnc_STEM	1.000			.127	.345
perfchoice	⇒	GPAONEYEAROUT	3.047	1.604	.057	.387	.656
esuccess	⇔	subjective	.029	.008	.000*	.222	.222
esuccess	⇒	perfchoice	.044	.026	.093	.155	.155
subjective	⇒	perfchoice	.046	.032	.148	.108	.108

Note. (*) the *p*-value is less than .001

Figure 12

Structural Model (Standardized Path Coefficients) of First-Year STEM Major (RQ1A; N = 789)



Note. (*) the *p*-value is less than .001. A revised theoretical model of the Expectancy-Value Model of Achievement Motivation. Latent constructs are shown in ellipses. Lines with arrows represent the path or direction of influence. Curved arrows represent correlations among latent variables. An observed variable is represented by a rectangle.

Research Question 1B (First-Year STEM: Gender)

Research subquestion 1B utilized the same structural model presented in research subquestion 1A, with the added independent exogenous variable of *gender* (i.e., dummy coded) included. The overall model fit indices suggested an approximate good fit (χ^2 = 564.784, *df* =101, *p*<.001; RMSEA=.076, CFI=.880; SRMR=.076; GFI=.994). The path coefficients for *gender* (Male = 0; Female = 1) show that there is a statistically significant relationship between STEM first-year students' gender (β = .164, *p* < .001) and the latent factor Expectancies for Success. The structural model shows that there is a statistically significant relationship between STEM first-year students' gender (β = .172, *p* = .001) and the latent factor

Subjective Task Value. Lastly, path coefficients for the structural model show that latent factors Expectancies for Success (β = .169, p = .111) and Subjective Task Value (β = .130, p = .133) are not statistically significant predictors of Achievement Related Performance and Choices given student *gender* (see Table 15).

Table 15

Standardized Regression Weights for RQ1B-Gender (N = 789)

Latent Factor		Variable	Estimate	Std.Err	P(>|z|)	Std.lv	Std.all
esuccess	⇒	ETgoals	1.000			.458	.639
esuccess	⇒	ETorganize	1.107	.067	.000*	.507	.659
esuccess	⇒	ETexample	1.214	.073	.000*	.556	.709
esuccess	⇒	ETdraftfb	1.080	.083	.000*	.494	.588
esuccess	⇒	ETfeedback	1.201	.082	.000*	.550	.657
esuccess	⇒	QIadvisor	1.397	.146	.000*	.640	.384
esuccess	⇒	QIfaculty	1.435	.128	.000*	.657	.486
subjective	⇒	askquest	1.000			.254	.312
subjective	⇒	CLaskhelp	2.282	.305	.000*	.579	.691
subjective	⇒	CLexplain	2.156	.281	.000*	.547	.686
subjective	⇒	CLstudy	2.833	.367	.000*	.719	.769
subjective	⇒	CLproject	2.073	.278	.000*	.526	.658
subjective	⇒	present	1.240	.187	.000*	.315	.383
perfchoice	⇒	Persistnc_STEM	1.000			.113	.307
perfchoice	⇒	GPAONEYEAROUT	3.841	2.273	.091	.434	.736
Gender_Recoded	⇒	esuccess	.151	.039	.000*	.329	.164
Gender_Recoded	⇒	subjective	.087	.026	.001	.343	.172
esuccess	⇒	perfchoice	.042	.026	.111	.169	.169
subjective	⇒	perfchoice	.058	.038	.133	.130	.130

Note. (*) the p-value is less than .001

Research Question 1C (First-Year STEM: Asian Students)

Research subquestion 1C utilizes the structural model from 1A and includes the race independent exogenous independent variable, *race* (i.e., dummy coded). Subquestion 1C was focused on Asian students with White students as the reference group (White = 0; Asian = 1). The overall model fit indices suggested an approximate good fit (χ^2 = 426.280, df =101, p<.001; RMSEA=.079, CFI=.858; SRMR=.081; GFI=.942). The path coefficients for the structural model show that latent factor Expectancies for Success (β = .263, p = .047), is a statistically significant predictor of Achievement Related Performance and Choices, as related to Asian first-year STEM majors. However, the path coefficients for subquestion 1C show that there are no statistically significant relationships between Asian first-year STEM students and the latent factor Expectancies for Success (β = .063, p = .165); this also holds for the latent factor Subjective Task Value (β = -.027, p = .629) which is not significantly associated with STEM Asian first-year STEM students (see Table 16).

Table 16

Standardized Regression Weights for RQ1C-Asian Students (N = 516)

Latent Factor		Variable	Estimate	Std.Err	P(>|z|)	Std.lv	Std.all
esuccess	⇒	ETgoals	1.000			.444	.631
esuccess	⇒	ETorganize	1.005	.087	.000*	.447	.604
esuccess	⇒	ETexample	1.162	.100	.000*	.516	.670
esuccess	⇒	ETdraftfb	1.032	.107	.000*	.459	.560
esuccess	⇒	ETfeedback	1.052	.106	.000*	.467	.581
esuccess	⇒	QIadvisor	1.497	.175	.000*	.665	.406
esuccess	⇒	QIfaculty	1.457	.165	.000*	.647	.484
subjective	⇒	askquest	1.000			.226	.276
subjective	⇒	CLaskhelp	2.438	.460	.000*	.550	.659
subjective	⇒	CLexplain	2.439	.439	.000*	.550	.683
subjective	⇒	CLstudy	3.180	.567	.000*	.717	.777
subjective	⇒	CLproject	2.432	.443	.000*	.549	.674
subjective	⇒	present	1.387	.275	.000*	.313	.390
perfchoice	⇒	Persistnc_STEM	1.000			.141	.376
perfchoice	⇒	GPAONEYEAROUT	2.902	1.477	.049	.409	.687
Asian_Recoded	⇒	esuccess	.098	.070	.165	.220	.063
Asian_Recoded	⇒	subjective	-.022	.045	.629	-.096	-.027
esuccess	⇒	perfchoice	.083	.042	.047	.263	.263
subjective	⇒	perfchoice	.066	.050	.188	.105	.105

Note. (*) the *p*-value is less than .001

Research Question 1D (First-Year STEM: Black Students)

For subquestion 1D (i.e., First-year STEM major students' academic success and retention by *race*), the model focuses on the exogenous independent variable *Black_recoded.* The structural model uses that of subquestion 1A, with the added exogenous variable dummy coded to assess Black first-year STEM majors (White = 0; Black = 1). The overall model fit indices suggested an approximate good fit (χ^2 = 429.987, *df* =101, p<.001; RMSEA=.076, CFI=.868; SRMR=.078; GFI=.948). The findings of the path coefficients for the structural model show that latent factor Expectancies for Success (β = .217, *p* = .073) and Subjective Task Value (β = .159, *p* = .107) are not statistically significant predictors of Achievement Related Performance and Choices. Furthermore, the path coefficients for *Black_recoded* show that there are no statistically significant relationships given Black first-year STEM students and the latent factors Expectancies for Success (β = .008, *p* = .877) and Subjective Task Value (β = -.023, *p* = .601) (see Table 17).

Table 17

Standardized Regression Weights for RQ1D-Black Students (N = 565)

Latent Factor		Variable	Estimate	Std.Err	P(>|z|)	Std.lv	Std.all
esuccess	⇒	ETgoals	1.000			.457	.629
esuccess	⇒	ETorganize	1.038	.081	.000*	.475	.622
esuccess	⇒	ETexample	1.195	.092	.000*	.546	.697
esuccess	⇒	ETdraftfb	1.073	.101	.000*	.490	.587
esuccess	⇒	ETfeedback	1.164	.103	.000*	.532	.637
esuccess	⇒	QIadvisor	1.504	.172	.000*	.688	.404
esuccess	⇒	QIfaculty	1.427	.158	.000*	.652	.480
subjective	⇒	askquest	1.000			.232	.283
subjective	⇒	CLaskhelp	2.369	.426	.000*	.549	.664
subjective	⇒	CLexplain	2.211	.381	.000*	.513	.659
subjective	⇒	CLstudy	2.982	.505	.000*	.692	.761
subjective	⇒	CLproject	2.272	.397	.000*	.527	.664
subjective	⇒	present	1.155	.237	.000*	.268	.336
perfchoice	⇒	Persistnc_STEM	1.000			.131	.347
perfchoice	⇒	GPAONEYEAROUT	3.334	1.784	.062	.438	.734
Black_Recoded	⇒	esuccess	.010	.066	.877	.022	.008
Black_Recoded	⇒	subjective	-.014	.027	.601	-.062	-.023
esuccess	⇒	perfchoice	.062	.035	.073	.217	.217
subjective	⇒	perfchoice	.090	.056	.107	.159	.159

Note. (*) the *p*-value is less than .001

Research Question 1E (First-Year STEM: Hispanic Students)

In the final subquestion for the first research question, the structural model included the exogenous independent variable *Hispanic_recoded*. The variable includes Hispanic first-year STEM majors and their White student peers (White = 0; Hispanic = 1). The overall model fit indices suggested an approximate good fit (χ^2 = 410.120, *df* =101, *p*<.001; RMSEA=.075, CFI=.876; SRMR=.077; GFI=.949). The main findings of the model show that there are no statistically significant relationships between predictor latent factors Expectancies for Success (β = .217, *p* = .099) and Subjective Task Value (β = .137, *p* = .155), and the outcome latent factor Achievement Related Performance and Choices. Moreover, the path coefficients for *Hispanic_recoded* show that there are no statistically significant associations given STEM first-year student's race and the latent factors Expectancies for Success (β = .034, *p* = .504) and Subjective Task Value (β = -.047, *p* = .345) (see Table 18).

Table 18

Standardized Regression Weights for RQ1E-Hispanic Students (N = 550)

Latent Factor		Variable	Estimate	Std.Err	P(>|z|)	Std.lv	Std.all
esuccess	⇒	ETgoals	1.000			.440	.628
esuccess	⇒	ETorganize	1.086	.089	.000*	.478	.631
esuccess	⇒	ETexample	1.209	.097	.000*	.531	.680
esuccess	⇒	ETdraftfb	1.036	.105	.000*	.455	.555
esuccess	⇒	ETfeedback	1.107	.106	.000*	.487	.599
esuccess	⇒	QIadvisor	1.563	.178	.000*	.687	.417
esuccess	⇒	QIfaculty	1.466	.161	.000*	.644	.488
subjective	⇒	askquest	1.000			.232	.286
subjective	⇒	CLaskhelp	2.382	.419	.000*	.552	.660
subjective	⇒	CLexplain	2.446	.415	.000*	.567	.696
subjective	⇒	CLstudy	3.169	.523	.000*	.734	.796
subjective	⇒	CLproject	2.277	.396	.000*	.528	.666
subjective	⇒	present	1.203	.239	.000*	.279	.350
perfchoice	⇒	Persistnc_STEM	1.000			.127	.335
perfchoice	⇒	GPAONEYEAROUT	3.719	2.194	.090	.471	.778
Hispanic_Recoded	⇒	esuccess	.042	.063	.504	.095	.034
Hispanic_Recoded	⇒	subjective	-.031	.033	.345	-.134	-.047
esuccess	⇒	perfchoice	.063	.038	.099	.217	.217
subjective	⇒	perfchoice	.075	.053	.155	.137	.137

Note. (*) the *p*-value is less than .001

Research Question 2: Expectancy-Value Model and First-Year STEM Majors

The second revised hypothesized theoretical model tested if hours worked (perceived cost) is a predictor of academic success and retention for (a) First-year STEM major students' academic success and retention; (b) First-year STEM major students' academic success and retention by *gender*; and (c) First-year STEM major students' academic success and retention by *race*. As such, the second structural model mirror the first research questions model, with the added indicator variables of assessing student hours worked, on- and off-campus (*tmworkon* and *tmworkoff*, respectively) with the Subjective Task Value latent factor.

Research Question 2A (First-Year STEM)

As for the model's overall fit, indices suggested an approximate good fit (χ^2 = 407.433, *df* =116, *p*<.001; RMSEA=.056, CFI=.924; SRMR=.062; GFI=.966). The standardized regression weight (path coefficients) are reported in Table 19 and Figure 13. All the weights were statistically significant except for the path between the latent variable *perfchoice* and indicator variables loading onto the latent construct GPAONEYEAROUT; as well as, the path between latent variable *subjective_hoursworked* and indicator variable *tmworkoff*. Regarding the GPAONEYEAROUT indicator, given that the observed indicator variable is not statistically significant, it can be assumed that GPAONEYEAROUT is not reliably inferred given the hypothesized observed latent factor, *perfchoice*.

Similarly, the model hypothesized that student time dedicated to working off-campus (*tmworkoff*) can be inferred by the hypothesized unobserved latent factor, *subjective_hoursworked*. Given that *tmworkoff* was not statistically significant, the observed estimates captured by *tmworkoff* may be due to chance, when being grouped by the *subjective_hoursworked* latent factor. Also, student time dedicated to working off-campus does not have a statistically significant direct effect on a student's subjective task values. Moreover, path coefficients for the structural model show that latent factor Expectancies for Success is not a statistically significant predictor of Achievement Related Performance and Choices (β = .157, *p* = .087). Additionally, the Subjective Task Value (including student hours worked) latent factor is not a statistically significant predictor of Achievement Related Performance and Choice (β = .109, *p* = .141).

Table 19

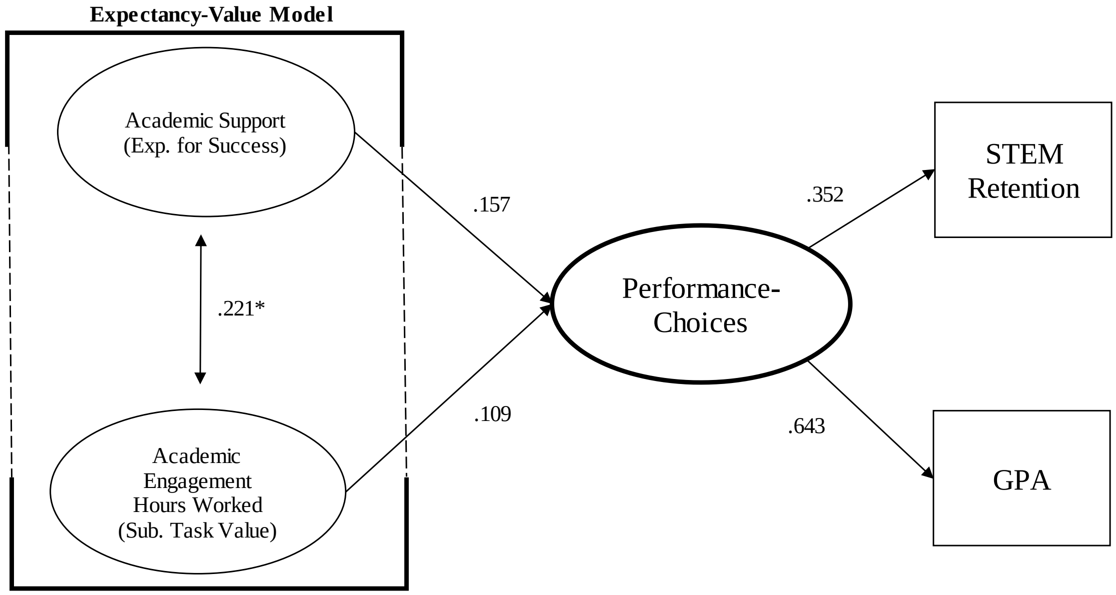
Standardized Regression Weights for RQ2A-First-Year STEM (N = 789)

Latent Factor		Variable	Estimate	Std.Err	P(>|z|)	Std.lv	Std.all
esuccess	⇒	ETgoals	1.000			.447	.623
esuccess	⇒	ETorganize	1.106	.071	.000*	.494	.642
esuccess	⇒	ETexample	1.271	.079	.000*	.567	.723
esuccess	⇒	ETdraftfb	1.139	.087	.000*	.509	.605
esuccess	⇒	ETfeedback	1.262	.087	.000*	.564	.673
esuccess	⇒	QIadvisor	1.382	.151	.000*	.617	.371
esuccess	⇒	QIfaculty	1.447	.134	.000*	.646	.478
subjective_hoursworked	⇒	askquest	1.000			.298	.365
subjective_hoursworked	⇒	CLaskhelp	1.803	.215	.000*	.537	.640
subjective_hoursworked	⇒	CLexplain	1.845	.213	.000*	.550	.689
subjective_hoursworked	⇒	CLstudy	2.361	.265	.000*	.703	.752
subjective_hoursworked	⇒	CLproject	1.810	.211	.000*	.539	.674
subjective_hoursworked	⇒	present	1.111	.150	.000*	.331	.403
subjective_hoursworked	⇒	tmworkon	.292	.134	.029	.087	.085
subjective_hoursworked	⇒	tmworkoff	.393	.270	.146	.117	.061
perfchoice	⇒	Persistnc_STEM	1.000			.129	.352
perfchoice	⇒	GPAONEYEAROUT	2.933	1.513	.053	.379	.643
esuccess	⇔	subjective_hoursworked	.029	.008	.000*	.221	.221
esuccess	⇒	perfchoice	.045	.027	.087	.157	.157
subjective_hoursworked	⇒	perfchoice	.048	.032	.141	.109	.109

Note. (*) the *p*-value is less than .001

Figure 13

Structural Model (Standardized Path Coefficients) of First-Year STEM Major (RQ2A; N = 789)



Note. (*) the *p*-value is less than .001. A revised theoretical model of the Expectancy-Value Model of Achievement Motivation. Latent constructs are shown in ellipses. Lines with arrows represent the path or direction of influence. Curved arrows represent correlations among latent variables. An observed variable is represented by a rectangle.

Research Question 2B (First-Year STEM: Gender)

Research subquestion 2B (i.e., First-year STEM major students' academic success and retention by *gender*), adds student gender (Male = 0; Female = 1) as an exogenous independent variable to the structural model utilized for research subquestion 2A. The model's overall fit indices suggested an approximate good fit (χ^2 = 615.762, *df* =132, *p*<.001; RMSEA=.068, CFI=.876; SRMR=.070; GFI=.993). The main findings show that latent factor Expectancies for Success (β = .171, *p* = .102) and Subjective Task Value_Hoursworked (β = .131, *p* = .125) are not statistically significant predictors of Achievement Related Performance and Choices. However, the path coefficients for *gender* (β = .165, *p* < .001) show that there is a statistically significant association with the latent factor Expectancies for Success. Because the path coefficient is positive, the analysis infers that female students indicated higher levels of academic support during their first year of study in a STEM Major. Similarly, *gender* (β = .173, *p* = .001) has a statistically significant direct effect on the latent factor Subjective Task Value. More specifically, female first-year STEM majors responded as having higher levels of academic engagement and working on-campus (see Table 20). The results, however, do not support the notion of an indirect predictive relationship with academic performance and choice, through both latent factors, Expectancies for Success and Subjective Task Value.

Table 20

Standardized Regression Weights for RQ2B-Gender (N = 789)

Latent Factor		Variable	Estimate	Std.Err	P(>|z|)	Std.lv	Std.all
esuccess	⇒	ETgoals	1.000			.458	.638
esuccess	⇒	ETorganize	1.107	.067	.000*	.507	.659
esuccess	⇒	ETexample	1.214	.073	.000*	.556	.709
esuccess	⇒	ETdraftfb	1.080	.083	.000*	.495	.588
esuccess	⇒	ETfeedback	1.202	.082	.000*	.550	.657
esuccess	⇒	QIadvisor	1.397	.146	.000*	.640	.384
esuccess	⇒	QIfaculty	1.435	.128	.000*	.657	.486
subjective_hoursworked	⇒	askquest	1.000			.256	.314
subjective_hoursworked	⇒	CLaskhelp	2.264	.301	.000*	.579	.690
subjective_hoursworked	⇒	CLexplain	2.131	.276	.000*	.545	.683
subjective_hoursworked	⇒	CLstudy	2.805	.362	.000*	.717	.767
subjective_hoursworked	⇒	CLproject	2.066	.275	.000*	.528	.661
subjective_hoursworked	⇒	present	1.237	.185	.000*	.316	.385
subjective_hoursworked	⇒	tmworkon	.342	.152	.025	.087	.086
subjective_hoursworked	⇒	tmworkoff	.513	.318	.106	.131	.068
perfchoice	⇒	Persistnc_STEM	1.000			.115	.313
perfchoice	⇒	GPAONEYEAROUT	3.692	2.132	.083	.426	.722
Gender_Recoded	⇒	esuccess	.151	.039	.000*	.330	.165
Gender_Recoded	⇒	subjective_hoursworked	.089	.026	.001	.347	.173
esuccess	⇒	perfchoice	.043	.026	.102	.171	.171
subjective_hoursworked	⇒	perfchoice	.059	.038	.125	.131	.131

Note. (*) the *p*-value is less than .001

Research Question 2C (First-Year STEM: Asian Students)

Research subquestion 1C (i.e., First-year STEM major students' academic success and retention by *race*), includes student race exogenous variable assessing Asian and White (White = 0; Asian = 1) first-year STEM majors to the structural model in subquestion 1A. Regarding the model's overall fit, indices suggested an approximate good fit (χ^2 = 477.127, *df* =132, *p*<.001; RMSEA=.071, CFI=.851; SRMR=.076; GFI=.938). The main results show that latent factor Expectancies for Success (β = .263, *p* = .047) is a statistically significant predictor of Achievement Related Performance and Choices, given student first-year STEM student's race. Moreover, Subjective Task Value_Hoursworked (β = .105, *p* = .189) was found to not be a statistically significant predictor of Achievement Related Performance and Choices. Lastly, the path coefficients for *Asian_recoded* show that there are no statistically significant relationships regarding STEM first-year students' race and the latent factors Expectancies for Success (β = .062, *p* = .171) and Subjective Task Value_Hours Worked (β = -.030, *p* = .603) (see Table 21).

Table 21

Standardized Regression Weights for RQ2C-Asian Students (N = 516)

Latent Factor		Variable	Estimate	Std.Err	P(>|z|)	Std.lv	Std.all
esuccess	⇒	ETgoals	1.000			.444	.631
esuccess	⇒	ETorganize	1.005	.087	.000*	.447	.604
esuccess	⇒	ETexample	1.162	.100	.000*	.516	.670
esuccess	⇒	ETdraftfb	1.032	.107	.000*	.459	.560
esuccess	⇒	ETfeedback	1.052	.106	.000*	.467	.581
esuccess	⇒	QIadvisor	1.497	.175	.000*	.665	.406
esuccess	⇒	QIfaculty	1.457	.165	.000*	.647	.484
subjective_hoursworked	⇒	askquest	1.000			.227	.278
subjective_hoursworked	⇒	CLaskhelp	2.426	.456	.000*	.550	.659
subjective_hoursworked	⇒	CLexplain	2.414	.433	.000*	.548	.679
subjective_hoursworked	⇒	CLstudy	3.169	.564	.000*	.719	.779
subjective_hoursworked	⇒	CLproject	2.416	.438	.000*	.548	.673
subjective_hoursworked	⇒	present	1.386	.273	.000*	.314	.392
subjective_hoursworked	⇒	tmworkon	.185	.196	.345	.042	.042
subjective_hoursworked	⇒	tmworkoff	.473	.436	.278	.107	.055
perfchoice	⇒	Persistnc_STEM	1.000			.141	.377
perfchoice	⇒	GPAONEYEAROUT	3.019	1.624	.063	.415	.699
Asian_Recoded	⇒	esuccess	.096	.070	.171	.217	.062
Asian_Recoded	⇒	subjective_hoursworked	-.023	.045	.603	-.103	-.030
esuccess	⇒	perfchoice	.084	.042	.047	.263	.263

subjective_hoursworked	⇒	perfchoice	.065	.050	.189	.105	.105

Note. (*) the *p*-value is less than .001

Research Question 2D (First-Year STEM: Black Students)

The global model fit indices suggested an approximate good fit (χ^2 = 497.565, *df* =132, *p*<.001; RMSEA=.070, CFI=.856; SRMR=.075; GFI=.943). The main findings for research subquestion 2D show that latent factor Expectancies for Success (β = .218, *p* = .071) and Subjective Task Value_Hoursworked (β = .159, *p* = .106) are not statistically significant predictors of Achievement Related Performance and Choices. Furthermore, the path coefficients for *Black_recoded* show that there are no statistically significant relationships between White and Black (White = 0; Black = 1) STEM first-year students (β = .007, *p* = .891) and the latent factor Expectancies for Success. Lastly, the structural model shows that there is not a statistically significant relationship between Black STEM first-year students (β = -.025, *p* = .566) and the latent factor Subjective Task Value including student works worked (see Table 22).

Table 22

Standardized Regression Weights for RQ2D-Black Students (N = 565)

Latent Factor		Variable	Estimate	Std.Err	P(>|z|)	Std.lv	Std.all
esuccess	⇒	ETgoals	1.000			.457	.629
esuccess	⇒	ETorganize	1.038	.081	.000*	.475	.622
esuccess	⇒	ETexample	1.195	.092	.000*	.546	.697
esuccess	⇒	ETdraftfb	1.073	.101	.000*	.490	.587
esuccess	⇒	ETfeedback	1.164	.103	.000*	.532	.637
esuccess	⇒	QIadvisor	1.504	.172	.000*	.688	.404
esuccess	⇒	QIfaculty	1.427	.158	.000*	.652	.480
subjective_hoursworked	⇒	askquest	1.000			.234	.285
subjective_hoursworked	⇒	CLaskhelp	2.352	.421	.000*	.549	.664
subjective_hoursworked	⇒	CLexplain	2.185	.374	.000*	.510	.656
subjective_hoursworked	⇒	CLstudy	2.961	.499	.000*	.692	.761
subjective_hoursworked	⇒	CLproject	2.259	.392	.000*	.528	.665
subjective_hoursworked	⇒	present	1.149	.234	.000*	.268	.337
subjective_hoursworked	⇒	tmworkon	.158	.191	.408	.037	.035
subjective_hoursworked	⇒	tmworkoff	.389	.401	.332	.091	.048
perfchoice	⇒	Persistnc_STEM	1.000			.132	.349
perfchoice	⇒	GPAONEYEAROUT	3.296	1.754	.060	.436	.730
Black_Recoded	⇒	esuccess	.009	.066	.891	.020	.007
Black_Recoded	⇒	subjective_hoursworked	-.016	.028	.566	-.068	-.025

esuccess	⇒	perfchoice	.063	.035	.071	.218	.218
subjective_hoursworked	⇒	perfchoice	.090	.056	.106	.159	.159

Note. (*) the *p*-value is less than .001

Research Question 2E (First-Year STEM: Hispanic Students)

Lastly, regarding Hispanic students (White = 0; Hispanic = 1) and the structural model presented in subquestion 2A, the model's overall fit, indices suggested an approximate good fit (χ^2 = 453.179, *df* =132, *p*<.001; RMSEA=.067, CFI=.872; SRMR=.072; GFI=.946). The structural model show that latent factor Expectancies for Success (β = .218, *p* = .097) and Subjective Task Value_Hoursworked (β = .136, *p* = .154) are not statistically significant predictors of Achievement Related Performance and Choices. Furthermore, the path coefficients for *Hispanic_recoded* show that there are no statistically significant relationships between STEM first-year students' race and the latent factors Expectancies for Success (β = .034, *p* = .501) and Subjective Task Value_Hours Word (β = -.047, *p* = .348) (see Table 23).

Table 23

Standardized Regression Weights for RQ2E-Hispanic Students (N = 550)

Latent Factor		Variable	Estimate	Std.Err	P(>|z|)	Std.lv	Std.all
esuccess	⇒	ETgoals	1.000			.440	.628
esuccess	⇒	ETorganize	1.086	.089	.000*	.478	.631
esuccess	⇒	ETexample	1.209	.097	.000*	.531	.680
esuccess	⇒	ETdraftfb	1.036	.105	.000*	.455	.555
esuccess	⇒	ETfeedback	1.107	.106	.000*	.486	.599
esuccess	⇒	QIadvisor	1.563	.178	.000*	.687	.417
esuccess	⇒	QIfaculty	1.466	.161	.000*	.644	.488
subjective_hoursworked	⇒	askquest	1.000			.232	.286
subjective_hoursworked	⇒	CLaskhelp	2.382	.419	.000*	.552	.661
subjective_hoursworked	⇒	CLexplain	2.437	.414	.000*	.565	.694
subjective_hoursworked	⇒	CLstudy	3.167	.522	.000*	.734	.796
subjective_hoursworked	⇒	CLproject	2.278	.395	.000*	.528	.666
subjective_hoursworked	⇒	present	1.207	.238	.000*	.280	.351
subjective_hoursworked	⇒	tmworkon	.133	.183	.469	.031	.031
subjective_hoursworked	⇒	tmworkoff	.358	.423	.398	.083	.043
perfchoice	⇒	Persistnc_STEM	1.000			.127	.336
perfchoice	⇒	GPAONEYEAROUT	3.691	2.171	.089	.470	.770
Hispanic_Recoded	⇒	esuccess	.042	.063	.501	.096	.034
Hispanic_Recoded	⇒	subjective_hoursworked	-.031	.033	.348	-.133	-.047

esuccess	⇒	perfchoice	.063	.038	.097	.218	.218
subjective_hoursworked	⇒	perfchoice	.075	.053	.154	.136	.136

Note. (*) the *p*-value is less than .001

Research Question 3: Expectancy-Value Model and First-Year STEM Majors

The third revised hypothesized theoretical model tested is the relationship between the Expectancy-Value Model of Achievement Motivation and first-year STEM major students' academic success and retention mediated by math coursework readiness. The hypothesized model's overall fit indices suggested an approximate good fit (χ^2 = 433.052, *df* =130, *p*<.001; RMSEA=.054, CFI=.921; SRMR=.060; GFI=.970). The path coefficients for the structural model show that latent factors Expectancies for Success (β = .163, *p* = .046) and Subjective Task Value_Hours Worked (β = .116, *p* = .099) are not statistically significant predictors of Achievement Related Performance and Choices. Moreover, the path coefficients also indicate that neither Expectancies for Success (β = .003, *p* = .993) nor Subjective Task Value_Hours Worked (β = -.001, *p* = .975) are statistically significant predictors of attending a Developmental Math course during their first year (see Table 24 and Figure 14).

Furthermore, the Developmental Math variable is a statistically significant predictor of Achievement Related Performance and Choices (β = -.146, *p* = .030). Lastly, the *indirect effect* of latent factors Expectancies for Success and Subjective Task Value (including student hours worked) are not statistically significant predictors of Achievement Related Performance and Choice (β < -.001, *p* = .933). The path coefficients *total effect* of latent factors Expectancies for Success and Subjective Task Value_Hours Worked with the outcome latent factor Achievement Related Performance and Choice were statistically significant (β = .162, *p* = .048), with an alpha of .05 (see Table 24 and Figure 14).

Table 24

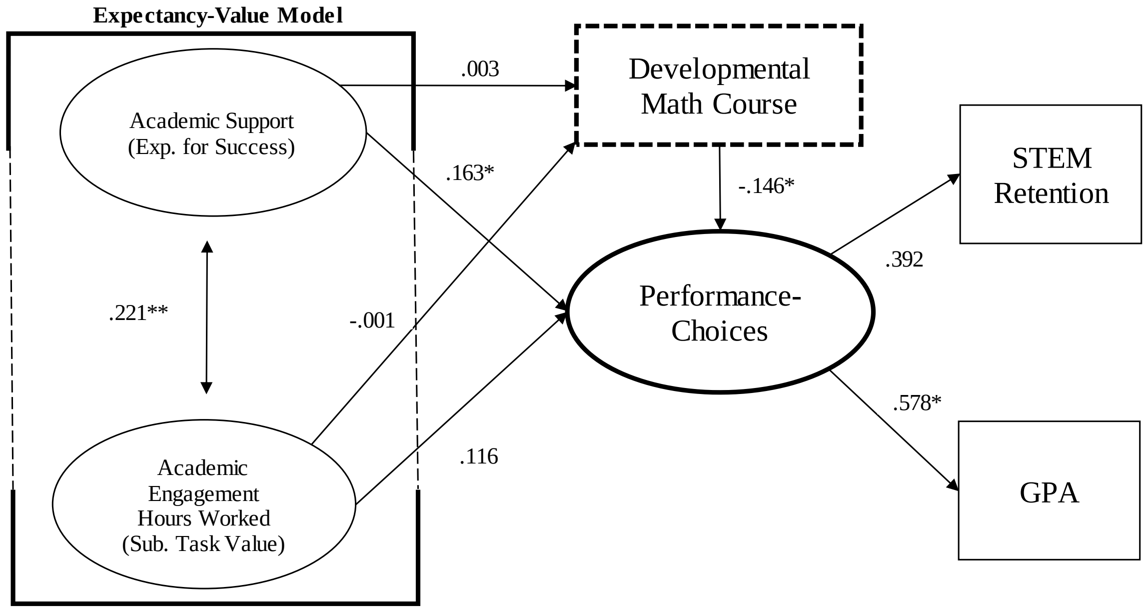
Standardized Regression Weights for RQ3-First-Year STEM (N = 789)

Latent Factor		Variable	Estimate	Std.Err	P(>|z|)	Std.lv	Std.all
esuccess	⇒	ETgoals	1.000			.446	.623
esuccess	⇒	ETorganize	1.106	.071	.000*	.494	.642
esuccess	⇒	ETexample	1.271	.079	.000*	.567	.723
esuccess	⇒	ETdraftfb	1.140	.087	.000*	.509	.605
esuccess	⇒	ETfeedback	1.262	.087	.000*	.564	.673
esuccess	⇒	QIadvisor	1.383	.151	.000*	.617	.371
esuccess	⇒	QIfaculty	1.447	.134	.000*	.646	.478
subjective_hoursworked	⇒	askquest	1.000			.298	.365
subjective_hoursworked	⇒	CLaskhelp	1.804	.215	.000*	.537	.640
subjective_hoursworked	⇒	CLexplain	1.845	.213	.000*	.549	.688
subjective_hoursworked	⇒	CLstudy	2.362	.265	.000*	.703	.752
subjective_hoursworked	⇒	CLproject	1.811	.211	.000*	.539	.674
subjective_hoursworked	⇒	present	1.112	.151	.000*	.331	.403
subjective_hoursworked	⇒	tmworkon	.294	.134	.028	.087	.086
subjective_hoursworked	⇒	tmworkoff	.393	.270	.146	.117	.061
perfchoice	⇒	Persistnc_STEM	1.000			.144	.392
perfchoice	⇒	GPAONEYEAROUT	2.366	.956	.013	.341	.578
esuccess	⇔	subjective	.029	.008	.000*	.221	.221
esuccess	⇒	perfchoice	.052	.026	.046	.163	.163
subjective_hoursworked	⇒	perfchoice	.056	.034	.099	.116	.116
esuccess	⇒	DEV_MATH	.004	.043	.933	.002	.003
subjective_hoursworked	⇒	DEV_MATH	-.002	.066	.975	-.001	-.001
DEV_MATH	⇒	perfchoice	-.044	.020	.030	-.306	-.146

Note. (*) the *p*-value is less than .001

Figure 14

Structural Model (Standardized Path Coefficients) of First-Year STEM Major (RQ3; N = 789)



Note. (*) the *p*-value is less than .05; (**) the *p*-value is less than .001. A revised theoretical model of the Expectancy-Value Model of Achievement Motivation. Latent constructs are shown in ellipses. Lines with arrows represent the path or direction of influence. Curved arrows represent correlations among latent variables. An observed variable is represented by a rectangle.

Research Question 4: Expectancy-Value Model and First-Year STEM Majors

The fourth, and final, revised hypothesized theoretical model tested to what extent the Expectancy-Value Model of achievement motivation explains first-year students' declared PEMC or Other-STEM majors' academic success and retention.

Research Question 4A (PEMC Majors)

Research subquestion 4A (i.e., First-year STEM major students' academic success and retention regarding PEMC majors), utilized the same structural model presented in subquestion 2A and included first-year PEMC majors from this study's sample. Considering the model's overall fit, indices suggested an approximate good fit (χ^2 = 258.784, *df* =116, *p*<.001; RMSEA=.053, CFI=.930; SRMR=.065; GFI=.961). Regarding findings, student time dedicated to working off-campus or on-campus does not have a statistically significant direct effect on a student's subjective task values given that they were declared in a PEMC major (see Table 25). Moreover, path coefficients for the structural model show that latent factor Expectancies for Success (β = .138, *p* = .129) and Subjective Task Value_Hoursworked (β = .078, *p* = .335) are not statistically significant predictors of Achievement Related Performance and Choices when considering declared PEMC majors (see Table 25).

Table 25

Standardized Regression Weights for RQ4-PEMC Majors (N = 444)

Latent Factor		Variable	Estimate	Std.Err	P(>|z|)	Std.lv	Std.all
esuccess	⇒	ETgoals	1.000			.422	.590
esuccess	⇒	ETorganize	1.190	.108	.000*	.502	.657
esuccess	⇒	ETexample	1.328	.124	.000*	.561	.713
esuccess	⇒	ETdraftfb	1.165	.130	.000*	.492	.589
esuccess	⇒	ETfeedback	1.162	.126	.000*	.491	.609
esuccess	⇒	QIadvisor	1.344	.227	.000*	.568	.333
esuccess	⇒	QIfaculty	1.626	.208	.000*	.687	.494
subjective_hoursworked	⇒	askquest	1.000			.313	.386
subjective_hoursworked	⇒	CLaskhelp	1.635	.248	.000*	.512	.613
subjective_hoursworked	⇒	CLexplain	1.733	.247	.000*	.543	.675
subjective_hoursworked	⇒	CLstudy	2.279	.326	.000*	.714	.765
subjective_hoursworked	⇒	CLproject	1.749	.253	.000*	.548	.686
subjective_hoursworked	⇒	present	1.235	.191	.000*	.387	.473
subjective_hoursworked	⇒	tmworkon	.268	.163	.100	.084	.086
subjective_hoursworked	⇒	tmworkoff	.023	.346	.948	.007	.004
perfchoice	⇒	Persistnc_STEM	1.000			.199	.595
perfchoice	⇒	GPAONEYEAROUT	1.590	1.049	.130	.317	.506
esuccess	⇔	subjective	.029	.010	.004	.219	.219
esuccess	⇒	perfchoice	.065	.043	.129	.138	.138
subjective_hoursworked	⇒	perfchoice	.049	.051	.335	.078	.078

Note. (*) the *p*-value is less than .001

Research Question 4B (Other-STEM Majors)

Lastly, research subquestion 4A (i.e., First-year STEM major students' academic success and retention regarding Other-STEM majors), included students from the sample that indicated a declared Other-STEM major during their first year of study. The overall model fit indices suggested an approximate good fit (χ^2 = 238.409, *df* =116, *p*<.001; RMSEA=.055, CFI=.932; SRMR=.071; GFI=.958). An analysis of the standardized regression weight (or path coefficients) indicates that there is a statistically significant direct effect of student time working off-campus and Subjective Task Value given that they are a declared Other-STEM major, see Table 26. Moreover, path coefficients for the structural model show that latent factor Expectancies for Success (β = .192, *p* = .301) and Subjective Task Value_Hoursworked (β = .103, *p* = .360) are not statistically significant predictors of Achievement Related Performance and Choices when considering Other-STEM majors (see Table 26).

Table 26

Standardized Regression Weights for RQ4-Other-STEM Majors (N = 345)

Latent Factor		Variable	Estimate	Std.Err	P(>|z|)	Std.lv	Std.all
esuccess	⇒	ETgoals	1.000			.473	.661
esuccess	⇒	ETorganize	1.030	.093	.000*	.487	.630
esuccess	⇒	ETexample	1.223	.098	.000*	.579	.741
esuccess	⇒	ETdraftfb	1.094	.113	.000*	.518	.615
esuccess	⇒	ETfeedback	1.357	.116	.000*	.643	.737
esuccess	⇒	QIadvisor	1.394	.195	.000*	.660	.408
esuccess	⇒	QIfaculty	1.260	.170	.000*	.596	.456
subjective_hoursworked	⇒	askquest	1.000			.269	.331
subjective_hoursworked	⇒	CLaskhelp	2.140	.421	.000*	.576	.684
subjective_hoursworked	⇒	CLexplain	2.103	.406	.000*	.567	.717
subjective_hoursworked	⇒	CLstudy	2.554	.470	.000*	.688	.734
subjective_hoursworked	⇒	CLproject	1.960	.387	.000*	.528	.660
subjective_hoursworked	⇒	present	.961	.249	.000*	.259	.313
subjective_hoursworked	⇒	tmworkon	.306	.231	.186	.082	.077
subjective_hoursworked	⇒	tmworkoff	.921	.454	.043	.248	.127
perfchoice	⇒	Persistnc_STEM	1.000			.099	.247
perfchoice	⇒	GPAONEYEAROUT	4.152	3.681	.259	.412	.806
esuccess	⇔	subjective	.028	.011	.010	.222	.222
esuccess	⇒	perfchoice	.040	.039	.301	.192	.192
subjective_hoursworked	⇒	perfchoice	.038	.042	.360	.103	.103

Note. (*) the *p*-value is less than .001

Summary of Major Findings

This chapter utilized student responses from three years of the National Survey of Student Engagement survey, at an urban institution of higher education in the Southeast. The primary purpose of this study was to apply a revised version of the Expectancy-Value Model of Achievement Motivation: (1) Expectancies for Success; (2) Subjective Task Values; and (3) Achievement Related Performance and Choices, to assess if first-year and marginalized college students in the STEM major's *academic support*, *academic engagement*, and *hours worked* are predictors of overall student success and retention after their first year of study. Structural equation modeling was deployed to assess the four main research questions presented. The validity of each observed model was tested, and considered to have an overall good model fit, given the theorized model and the data presented. The main findings from Chapter 4 are presented in the following:

- Across both models presented in the first and second research questions, with and without hours worked as an indicator of subjective task value, first-year STEM major students' gender was found to be a statistically significant predictor of Expectancies for Success and Subjective Task Value latent factors; however, Achievement Related Performance and Choices did not have a statistically significant association with the predictor latent factors.
- First-year STEM students' race was not found to be a statistically significant predictor of either of the latent factors presented in this study. Regarding first-year STEM major students attending a developmental math course during their first-year results indicated that there is a direct statistically significant relationship between a first-year STEM student's Achievement Related Performance and

Choices and if they attended a developmental math course.

- The results presented indicated that developmental math course attendance does not mediate first-year STEM students' Expectancies for Success and Subjective Task Value, and their Achievement Related Performance and Choices after their first year of study.
- Lastly, both PEMC and Other-STEM major students are considered to have no statistically significant relationships between Expectancies for Success and Subjective Task Value latent factors and Achievement Related Performance and Choices.

The following, and final chapter, will summarize the primary sections presented throughout this dissertation. The final chapter encompasses a general overview of the purpose of the study and methodology utilized, a general discussion of the major findings; as well as, conclusions inferred from the findings. Lastly, the final chapter will discuss possible recommendations for policy, practice, and future research.

CHAPTER 5: DISCUSSION

Introduction

The purpose of this study was to assess if first-year college students in the STEM major's *academic support* and *academic engagement* are predictors of overall student success and retention after their first year of study. In addition to these two predictors, the researcher assessed if *hours worked* while studying was a predictor as a subjective task value. In this chapter, the researcher provided a review and discussion of the key findings and implications of the study. Following, the research presents limitations of the study, as well as, recommendations for policy, practice, and future research to conclude this chapter.

Key Findings & Implications

Research Question 1

- To what extent does the Expectancy-Value Model of Achievement Motivation explain:
  - First-year STEM major students' academic success and retention?
  - First-year STEM major students' academic success and retention by *gender*?
  - First-year STEM major students' academic success and retention by *race*?

The first research question, and subquestions, employed the use of a revised model grounded in Eccles and colleagues' (1983) theorized model, Expectancy-Value Model of Achievement-Related Performance and Choices. The *first* research question aimed to determine if STEM student experiences related to *academic support* and *academic engagement* are predictors of academic performance and retention after their first year of study. The revised model utilized in the first research question consisted of three parameters; the first is a bivariate correlation, between *academic support*, and *academic engagement* latent factors. The second and third parameters were between the two predictors (i.e., *academic support* and *academic* *engagement*) and the outcome latent factor which included academic performance and choice to remain in a STEM major after the first year (see Figure 5). Of the three parameters observed, only the bivariate correlation estimate between *academic support* and *academic engagement* predictors attained statistical significance (see Appendix A; Figure A2). This finding supports Gnebola's (2015) and Martinez's (2016) findings that *academic support* and *academic engagement* behaviors of higher education students share a relationship regarding their influence on student performance. However, the latent factors (i.e., *academic support* and *academic engagement*) were not significant predictors of STEM first-year students' performance and choice.

The failure of this study's revised expectancy-value model to reach statistical significance may be related to measurement issues; as well as, the observed indicators utilized to assess *academic support* and *academic engagement* latent factors. For example, the observed model for the first research question resulted in standardized regression weights of $\leq .40$. Hair et al. (2013) recommend a minimum factor loading for indicator variables of .40. A possible reason for the low factory loadings may be the result of using secondary data. As the secondary data was collected from the use of survey items that were not designed and collected specifically to address this study's research questions.

For theoretical purposes, however, indicators loading below the .40 threshold (i.e., *Quality of interactions with academic advisors*, *Asked questions or contributed to course discussions in other ways*, and *Persisted in STEM Major After the First Year*) were retained in this study. Furthermore, the outcome latent factor, Achievement-Related Performance and Choices (i.e., *perfchoice*) included two indicators (i.e., *GPA* and *Persist_STEM*) to estimate the latent factor *perfchoice*. Kenny (1979) notes that this may be an issue, as the indicator-per-factor ratio may be too low to adequately estimate a latent variable. Kenny (1979) recommends a minimum of three observed variables per latent variable, and having more "is gravy" (p. 143). Nunnally and Bernstein (1994) supported Kenny's (1979) findings and noted that the more abstract and loosely defined a latent construct is, referencing an exploratory research design, the more observed indicators will be needed to sufficiently measure the proposed latent factor.

By *gender*. The *first* research question also aimed to explore possible relationships regarding STEM students' gender, in addressing the predictability of *academic support* and *academic engagement* latent factors of academic performance and retention after their first year of study. The findings suggest that *gender* is a predictor of both *academic support* ($\beta = .164$, $p < .001$) and *academic engagement* ($\beta = .172$, $p = .001$) latent factors. The positive β coefficient of the analysis indicates that female STEM students were more likely to engage in *academic support* and *academic engagement* activities during their first year of study. This finding supports previous literature that has found, though female students experience increased gender biases in STEM majors, female STEM students are more likely to engage with their faculty and peers, both in and outside of the classroom, than their male counterparts (Bloodhart et al., 2020; Ding et al., 2006; Felder et al., 1995; Lorenzo et al., 2006; Martinez, 2016). However, no statistical significance was identified regarding the latent predictors and STEM students' choice to remain in a STEM major or academic performance. As noted previously, this observation may be due to measurement issues and/or a lack of well-designed observed indicators.

By *race*. The first research question was also explored if first-year STEM students' race provided significant relationships with this revised expectancy-value model proposed in this study. Surprisingly, the results from this study did not identify statistically significant relationships given students' race and the *academic support* and *academic engagement* latent predictors. Previous research findings noted that social integration, peer support, and academic engagement activities play a significant part in STEM student retention and academic success, given their race (Arcidiacono et al., 2012; Fleming, 2002; Martinez, 2016; Severo et al., 2021).

However, with the *Asian_Recoded* independent variable included in the model, the latent factor, *academic support*, was found to be a significant predictor of first-year STEM retention and academic success. This is to say, for Asian students, *academic support* is a significant predictor of STEM first-year performance in courses and retention in the second year. This finding supports the growing body of literature focused on STEM student race and the quality of interactions with their faculty and advisors (Dortch & Patel, 2017; Packard, 2015; Park et al., 2019). More specifically, Park et al. (2019) identified Asian American STEM students to have higher quality levels of interaction with their faculty, and are more likely to remain in their STEM major, when compared to White, Black, and Latinx racial/ethnic groups.

Though first-year STEM Asian students were found to have a significant relationship given their quality level of interaction with faculty and advisor, this was not found to be a significant predictor for Black and Hispanic STEM students. A possible reason for this phenomenon may be due to this study not assessing the frequency of interactions, as well as, capturing perceived negative attitudes from faculty-student and advisor-student interactions. Previous research has noted the benefits (i.e., academic performance) of these interactions for minoritized STEM students may contribute primarily to the frequency of interactions, along with, STEM students' perceived importance given their interactions with faculty and advisors (Allen et al., 2018; Carini et al., 2006). Future research aiming to replicate this study should include survey items seeking to capture further depth in first-year STEM student interactions with faculty and advisors. Moreover, this study's Asian student sample was overrepresented when compared to Black and Hispanic students. As the NSSE survey was collected through voluntary recruitment methods, the lack of representativeness of the sample may have introduced some bias into the data. As such, future research should aim to collect data from racial groups that are proportional to their representation in the population. Doing so will allow for further accuracy and inference in evaluating possible predictor relationships across the different racial groups.

Research Question 2

- Given the Expectancy-Value Model of Achievement Motivation, are *hours worked (perceived cost)* a predictor of academic success and retention for:
    - First-year STEM majors?
    - First-year STEM major students across *gender*?
    - First-year STEM major students across *race*

With regards to the addition of the working, while studying indicators, *tmworkon* (i.e., *Hours per week: Working for pay ON CAMPUS*) was found to have a statistically significant association with the subjective task value latent factor (see Appendix A; Figure 6). This finding from the observed model confirms the theoretical alignment of STEM students reporting their time spent working on-campus, and other indicators significantly aligned with students being more likely to engage in activities, behaviors, and tasks if they consider the activities to be aligned with their self-interests and goals (Wigfield & Eccles, 2000; Wu et al., 2020). With this said, *tmworkoff* (i.e., *Hours per week: Working for pay OFF CAMPUS*) was not a statistically significant indicator of the subjective task value latent factor. This finding may be explained by Bozick’s (2007) study, which noted that first-year students tend to contribute their time working for pay on-campus, as opposed to off-campus work.

Similar to the *first* research question, the *second* research question's proposed predictors (i.e., *academic support*, *academic engagement*, and *hours worked*) were not statistically significant predictors of STEM first-year students' performance and choice to retain after their first year. Even though measurement issues and/or lack of well-designed observed indicators, may play a factor in this finding (similar to the *first* research question), it is important to note that previous findings have found significant relationships between student time allocated to working on-campus and academic performance (Darolia, 2014; Scott-Clayton & Minaya, 2016).

Moreover, given the findings of the second research question, further delineation may be needed, regarding students working for pay while studying in a STEM program. Future research studies should include survey questions to capture potential financial hardship indicators as reasons for working while studying. Broton and Goldrick-Rab (2016) confirmed that students that *must work* while studying (i.e., food, housing, income insecurities) have experienced more challenges in academic performance and retention when compared to students working for pay to fund play and social needs. Additionally, future research should account for the type of work a student is engaging in while enrolled in a STEM major. Students working in an office or laboratory typesetting may be more likely to engage with their coursework on the job or have time to complete their coursework when compared to service-based jobs which may demand longer hours and are not suited for engaging with coursework on the job. This level of delineation may capture potential nuances in STEM student retention and academic success during their first year of study. As such, this study's findings present a need for further research on student hours worked while accounting for other theoretical predictors of academic performance in higher education.

By *gender*. Considering STEM first-year student gender, the observed model's results suggests that *gender* is a statistically significant predictor of *academic support* ($\beta = .165$, $p < .001$) and *academic engagement/hours worked* ($\beta = .173$, $p = .001$). This finding is noteworthy as previous research on the predictability of Eccles et al.'s (1983) expectancy-value model and the growing literature focused on students working while studying (Stinebrickner & Stinebrickner, 2003, 2004), did not investigate possible relationships of student *gender*. Moreover, this finding suggests that female first-year STEM students are more likely to engage in *academic support* and *academic engagement* activities; as well as, spend more time working on-campus while studying. Furthermore, the results indicated that there were no statistically significant relationships between the hypothesized predictors (i.e., *academic support*, *academic engagement,* and *hours worked*) and first-year STEM students' choice to retain in a STEM major or academic performance.

By *race*. The *second* research question was also explored if first-year STEM students' race provided significant relationships with this revised expectancy-value model proposed in this study. Similar to the *first* research question, student *race* was not a significant predictor of latent factors, Expectancies for Success, and Subjective Task Values_Hours Worked. This finding suggests, that even with the inclusion of student hours working on and off-campus, student race is not a factor in predicting a significant relationship to this study's proposed predictors of academic achievement and retention. Moreover, with the *Asian_Recoded* independent variable included in the model, the latent factor *academic support* was found to be a significant predictor of first-year STEM retention and academic success. This finding remains unchanged from the first research question, which omitted the student *hours worked* indicators to the subjective task value latent factor.

Research Question 3

- Is the relationship between the Expectancy-Value Model of Achievement Motivation and first-year STEM major students' academic success and retention mediated by math coursework readiness?

The *third* research question aimed to assess if developmental math course attendance, or math readiness, during the first year of study has a significant influence on first-year STEM students' retention and academic success while accounting for this study's theorized predictors (i.e., *academic support*, *academic engagement,* and *hours worked*). Given the Expectancies for Success and Subjective Task Value latent constructs, the results suggest that developmental math course attendance does not mediate (i.e., indirect effect) first-year STEM students' academic success and choice to remain in a STEM major (see Appendix A; Figure A12). This is to say that first-year STEM students' developmental math course attendance (i.e., math readiness) does not significantly help to explain the theorized predictor's (i.e., *academic support*, *academic engagement,* and *hours worked*) influence on first-year STEM academic success and choice to retain in a STEM major.

However, this study's results did find that developmental math course attendance is a significant predictor (i.e., direct effect) of performance and choice to remain in a STEM major. This finding adds context to the previous research which has found math readiness, more specifically, remedial math course attendance, to be a significant predictor of STEM retention and GPA (Cabrera et al., 2005; Adelman, 2006; Herzog, 2005). The finding also supports the notion that STEM first-year "leavers" tend to do so because of academic underperformance (i.e., GPA) in their first-year STEM courses (Chen, 2013).

Given this study's findings related to developmental math course attendance, it should be theorized that math readiness may be sufficiently captured within the model's Expectancies for Success latent construct, as opposed to mediation. The *expectancies for success* construct posits factors that attempt to understand an individual's belief in how well they can accomplish a task (Eccles et al, 1983; Schunk, 1991). Because first-year developmental math course attendance includes *academic* (e.g., mathematics performance and preparedness in K-12) and *social* (e.g., mathematics self-efficacy) factors that predate their first year of study in higher education (Adelman, 2006; Herzog, 2005), future research should consider aligning the developmental math course attendance variable with the *expectancies for success* latent construct. Another consideration is to assess the final grades of first-year STEM students that completed a developmental math course, to investigate if academic performance in a developmental math course attendance influences student interactions with *academic support*, *academic engagement*, and *hours worked* predictors; and if these interactions are then predictors of their first-year academic performance and choice to remain in their STEM major.

Research Question 4

- To what extent does the Expectancy-Value Model of achievement motivation explain first-year students' declared PEMC or Other-STEM majors' academic success and retention?

This study's results did not identify, for either PEMC or Other-STEM majors, statistically significant relationships between *academic support*, *academic engagement*, and *hours worked* predictors and first-year STEM students' academic success and choice to retain in a STEM major. Though previous research has noted possible differences in experiences of PEMC and Other-STEM majors (Nix & Perez-Felkner, 2019), this study did not support that opinion regarding first-year STEM students' academic success and choice to remain in a STEM major. A possible explanation for this finding may be attributed to the relatively high average first-year grade point average of both PEMC (3.20 GPA) and Other-STEM (3.43 GPA) students (Chen, 2013). Moreover, this study's descriptive results found that first-year STEM students were more likely to persist in their STEM major after their first year (see Table 12). This level of a high academic profile from both groups may have allowed both PEMC and Other-STEM majors a smooth transition to their second year of study. Furthermore, though this study did not find significant relationships within the model for either PEMC or Other-STEM student groups; assessing STEM students by PEMC and Other-STEM student groups alone may be insufficient. Nix and Perez-Felkner (2019) found significant academic performance differences between both groups by examining the gender and race of the PEMC or Other-STEM students. As such, consideration should be made to further delineate PEMC and Other-STEM groups by gender and student race, given the this study's theorized predictors and the student's choice to remain in their STEM major and their academic performance during the first year of study.

Limitations of the Study

This study included fundamental limitations which should be considered when interpreting the findings. Firstly, this study utilized secondary data to investigate and answer the proposed research questions. A disadvantage of utilizing secondary data from the NSSE survey lies in that the survey items were not developed specifically to address this study's research questions. For example, *academic support*, or student-faculty and student-advisor interactions, were found to be significant predictors of first-year stem retention and academic success; however, more information is needed regarding the context of such interactions, frequency of interactions, and the subject (e.g., academic, career, social) of discussions held between student and faculty/advisor. A survey designed to capture explicit information regarding student interactions with faculty and advisors is needed.

Another limitation of this study's design is its dependence on participants' self-reported data. Though self-reported information from research participants is advantageous when aiming to capture their lived experiences, a disadvantage in this approach lies in the potential of receiving less accurate information, due to social desirability (Barker et al., 2002). As noted in the next section, future researchers should aim to create a well-designed survey to capture various points of the predictors being assessed. Moreover, the data collected for this study included participant responses from the spring 2020 academic term; given the start of a global pandemic during this same period, participant responses may have been influenced by factors related to the global COVID-19 pandemic. It should also be noted that this study captured student gender identity as a binary construct (i.e., male or female), provided by the university's department of Institutional Research. As such, student gender identity was not self-reported and should be considered a limitation of this study (Gushue & Whitson, 2006).

Lastly, this study's outcome latent factor, Achievement-Related Performance, and Choices (i.e., *perfchoice*), included first-year STEM students' overall GPA. The overall GPA included STEM and non-STEM courses completed during the first year of study. In observing and including the STEM student's overall GPA, and not solely their GPA in STEM major courses, the outcome latent factor may not have been representative of their actual performance in their first-year STEM courses. Furthermore, the developmental math course attendance variable was not captured to delineate between students *required* to take the course, or if the student *voluntarily* attended the course during their first year of study. That is to say, the developmental math course attendance variable was not able to distinguish if a student was not sufficiently prepared for their first year of mathematics study, or highlight the student's willingness to prepare themselves for subsequent advanced mathematics courses by voluntarily attending a developmental math course. As such, the developmental math course attendance variable used in this study is noted as a limitation.

The limitations listed in this section are not indicative of this study's design for future research. Nevertheless, future research should account for this study's limitations, and attempt to remedy them with future data collection and comparative analysis. As such, the following section will present recommendations for future research, given these limitations.

Recommendations for Future Research

This study's findings differed from previously reported findings regarding *academic support*, *academic engagement*, and *hours worked* as significant predictors of higher education student retention and/or academic success (Andersen & Ward, 2014; Martinez, 2016; Perez, 2019; Scott-Clayton & Minaya, 2016; Stinebrickner & Stinebrickner, 2003, 2004). This study assessed all three predictors in a single model, utilizing structural equation modeling, as well as, first-year STEM students, which were both deviations from previous research designs. This study did not identify all of the aforementioned predictors as statistically significant influencers of student retention and/or academic success. Given this study's observed findings and review of relevant literature, this section will present recommendations for future research.

Recommendation 1. Replicate this study, but remove the *hours worked* predictor from the subjective task value latent construct and include this predictor as two observed variables (i.e., *hours worked on-campus* and *hours worked off-campus*) as potential mediators of first-year STEM retention and academic success (Scott-Clayton & Minaya, 2016; Stinebrickner & Stinebrickner, 2003, 2004). Though theoretically aligned, the *hours worked* predictor was not significantly associated with the subjective task value latent factor. For example, the *hours worked on-campus* indicator loaded significantly to the subjective task value latent factor for all but the *fourth* research question; this was not the case for *hours worked off-campus*, as the indicator did not load significantly to the subjective task value latent factor. As such, the reported findings did not support the theoretical alignment. Nevertheless, previous research confirms that student *hours worked* influences student retention and academic achievement (Scott-Clayton & Minaya, 2016; Stinebrickner & Stinebrickner, 2003, 2004). Given the continued increase in higher education students working while studying (Perna & Odle, 2020), further investigation is needed regarding this predictor's influence on first-year STEM student retention and academic success.

Recommendation 2. Given that the hypothesized outcome latent factor, Achievement-Related Performance and Choices (i.e., *perfchoice*), was minimally supported by its indicator variables: GPA and retention in a STEM major, future research should consider including, at minimum, a third observed indicator to the *perfchoice* latent factor. Though this study’s revised model fit indices reached an approximate good model fit at the local and global levels, previous researchers have noted that latent factors with less than three indicators, may be insufficient to adequately estimate a latent factor (Kenny, 1979; Nunnally & Bernstein, 1994). A third possible indicator may be STEM credit hours attempted. For example, previous research has found that STEM credit hours attempted significantly predicted first-year retention (Bettinger, 2010; Westrick, 2014; Zhang et al., 2004). Romash (2019) found that STEM students taking less demanding (e.g., liberal studies and orientational coursework) during their first year, had an increase in their chances to remain in their STEM major beyond the first year. Furthermore, disaggregating STEM credit hours earned from STEM credits hours attempted may provide further depth in investigating factors contributing to first-year STEM retention and academic success, given STEM credit hours. For example, future research may consider including *STEM credit hours attempted* as an independent variable within the model, while aligning *STEM credit hours earned* with the *perfchoice* latent factor as an outcome predictor, given previous research (Bettinger, 2010; Westrick, 2014; Zhang et al., 2004).

Recommendation 3. This study assessed the theorized revised expectancy-value model across students' racial identity. However, the racial demographic of this study's sample was taken primarily from White students (59.3%). Future research should replicate this study with a more racially diverse (i.e., heterogenous) sample of first-year STEM students.

Recommendation 4. This study's theoretical model can be expanded with the inclusion of other researched predictors of student retention and academic success. For example, previous research has identified *academic self-efficacy* to be significantly aligned with the Expectancies for Success latent construct (Ferguson, 2021; Martinez, 2016). More specifically, previous research has found statistically significant relationships between students' *academic self-efficacy* (i.e., Expectancies for Success) in their writing and mathematics ability, and their choice to persist to the second year of college (Martinez, 2016; Safavian, 2019). However, these studies were not designed to control for other predictors of academic success and retention, as well as, error variances within a single model while assessing first-year STEM major students.

Recommendation 5. This study utilized secondary data from a survey instrument not specifically designed to assess this study's research questions. As such, future researchers can replicate this study's design with survey questions specifically designed to capture this study's hypothesized predictors (i.e., *academic support*, *academic engagement*, and student *hours worked*) of retention and academic success.

Recommendations for Policy & Practice

Following the previous section's recommendations for future research, this section will present recommendations for policy and practice.

Recommendation 1. This study confirmed *academic support* as a significant predictor of first-year STEM students' academic performance and choice to retain. This finding is aligned with previous studies which emphasized how STEM students' sense of connectedness with advisors and level of interaction with their professors was correlated with academic performance (Allen et al., 2018; Hong & Shull, 2010; Micari & Pazos, 2012). As such, higher education institutions should proactively target faculty-student and academic advisor-student interaction training to enhance the experiences of these exchanges in and outside of the classroom. For example, policies should aim to encourage mandatory interaction sessions with faculty and academic advisors at interval points throughout the term. Though areas for training will vary based on institutional setting and culture, past and current research have found faculty-student interaction to be especially engaging when faculty convey areas of support and interest to their students (Allen et al., 2018; Carini et al., 2006; Christe, 2013). This recommended training should be especially encouraged for faculty that teach first-year STEM introductory courses. As previous research has found STEM students feel that their first-year STEM introductory courses are especially unwelcoming, given their interactions with faculty (Kokkelenberg & Sinha, 2010; Seymour & Hewitt, 1997). Lastly, this policy should encourage interactions of STEM students if they are identified to be struggling in their first-year STEM courses; as well as, female and minoritized STEM students.

Recommendation 2. In this study, developmental math course attendance was a direct significant predictor of first-year STEM academic performance and choice to retain. The finding confirmed that students that did not attend a developmental math course during their first year were more likely to have a higher GPA and remain in their STEM major. This supports the extensive literature regarding math readiness and STEM academic success (Adelman, 2006; Cabrera et al., 2005; Herzog, 2005). As such, higher education institutions should encourage their STEM programs to collaborate with regional high schools, and encourage college math readiness. This should be relative to college readiness benchmarks in mathematics required for first-year STEM coursework (e.g., Pre-Calculus, Calculus I, Physics I).

Recommendation 3. Given this study's findings noting the significance of math readiness and predicting first-year STEM academic success and retention, higher education institutions should encourage the creation of summer bridge programs. STEM summer bridge programs have been found to encourage and enhance both student-faculty interactions, as well as, increase first-year STEM students' math readiness before the start of their first academic term (Zuo et al., 2018). Moreover, previous research has reported that STEM summer bridge programs have increased the STEM academic success rate and have been found to aid, especially students coming from academically challenging high school experiences, specifically in the mathematics and physical science subjects (National Academy of Sciences, 2010).

Summary

The United States continues to experience labor shortages in the STEM fields (Belster, 2014; Xue & Larson, 2015). All the while, students with declared STEM majors continue to experience a higher level of attrition, especially during their first year of study, when compared to non-STEM majors (Sithole et al., 2017). This labor market gap in the supply of a *qualified workforce*, and demand for technology and automation throughout developed nations, has encouraged and led to extensive research investigating possible predictors of academic success and retention for STEM majors. Of possible predictors identified in previous literature, *academic support*, *academic engagement*, and student *hours worked* have been found, independently, to significantly influence higher education student retention and academic success (DiPrete & Buchmann, 2013; Eagan et al., 2013; Martinez, 2016; Schnettler et al., 2020; Xie & Killewald, 2012; Xie & Shauman 2003).

Despite previous empirical findings of potential predictors, previous research has not accounted for these predictors in a single model, controlling for possible intercorrelation relationships, to assess their influence on student academic success and retention. Moreover, previous studies have not assessed these predictors solely for first-year STEM majors, which is found to be the most decisive year for STEM retention (Griffith, 2010). To provide evidence and context to this gap in literate, this study utilized Eccles and colleagues' (1983) Expectancy-Value Model of Achievement-Related Performance and Choices to investigate if possible, predictors: *academic support*, *academic engagement*, and student *hours worked.* significantly influence STEM students' academic success and retention after the first year of study.

Results of this study suggest that *academic support* is a predictor of first-year STEM students' academic success and likelihood to remain in their major. Findings also infer that mathematics readiness is a significant predictor of retention and academic success of first-year STEM majors. Future researchers should aim to replicate this study by including *academic self-efficacy* as a possible predictor of the model, as well as, assessing student *hours worked* as a mediating factor, and not directly aligned to the expectancy-value model. Lastly, institutions of higher education should aim to encourage implementing training and professional development initiatives aligned with this study's *academic support* predictor (i.e., faculty-student interactions;

academic advisor-student interactions); as well as, working with pre-college stakeholders to increase first-year STEM student's mathematics readiness.

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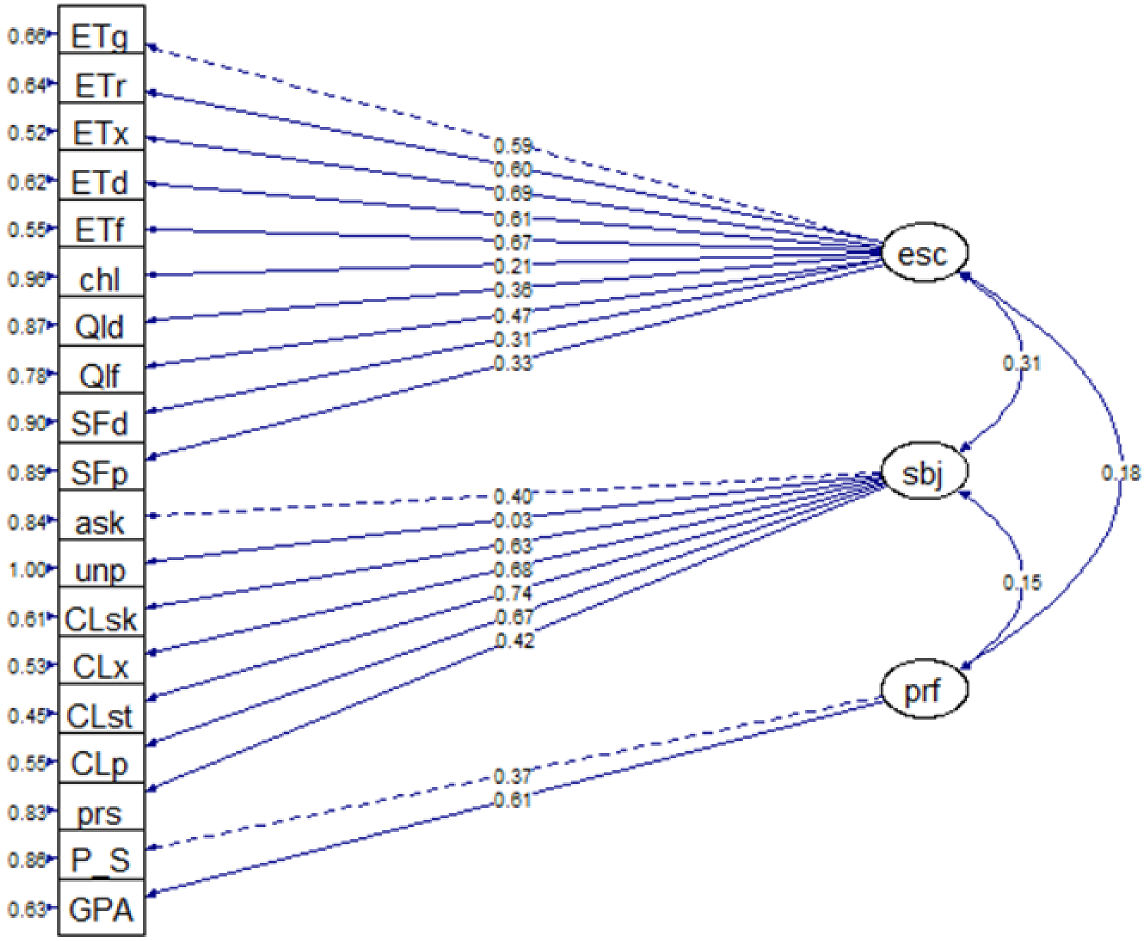
APPENDIX A: Observed Model Data (*R* Project for Statistical Computing)

Figure A1

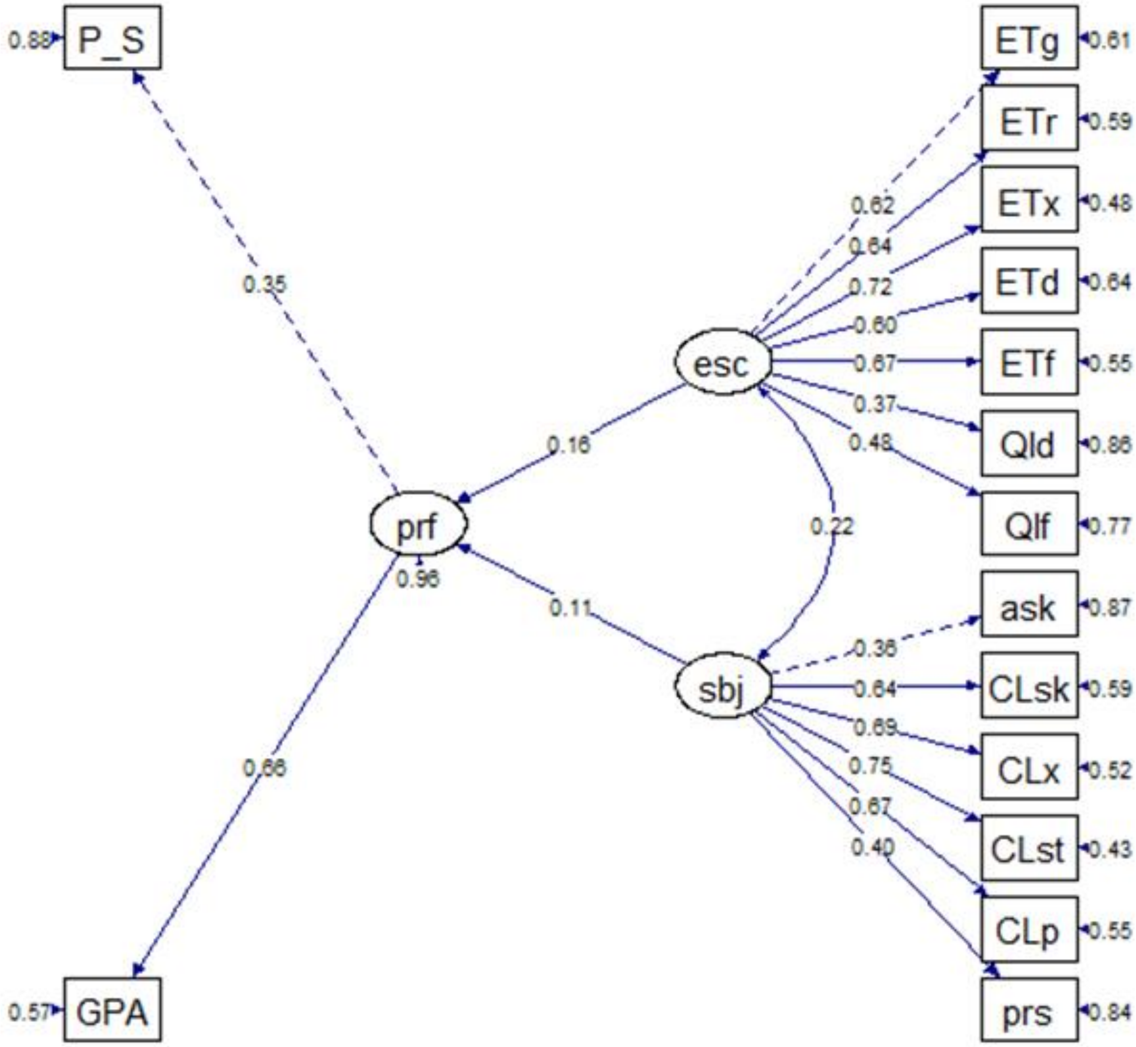
Measurement Model (Standardized Path Coefficients) of First-Year STEM Major (N = 797)



Note. A revised theoretical model of the Expectancy-Value Model of Achievement Motivation. Latent constructs are represented by the ellipses. The arrowed lines signify the path of influence. Curved lines show correlations between latent variables. An observed indicator is characterized by a rectangle.

Figure A2

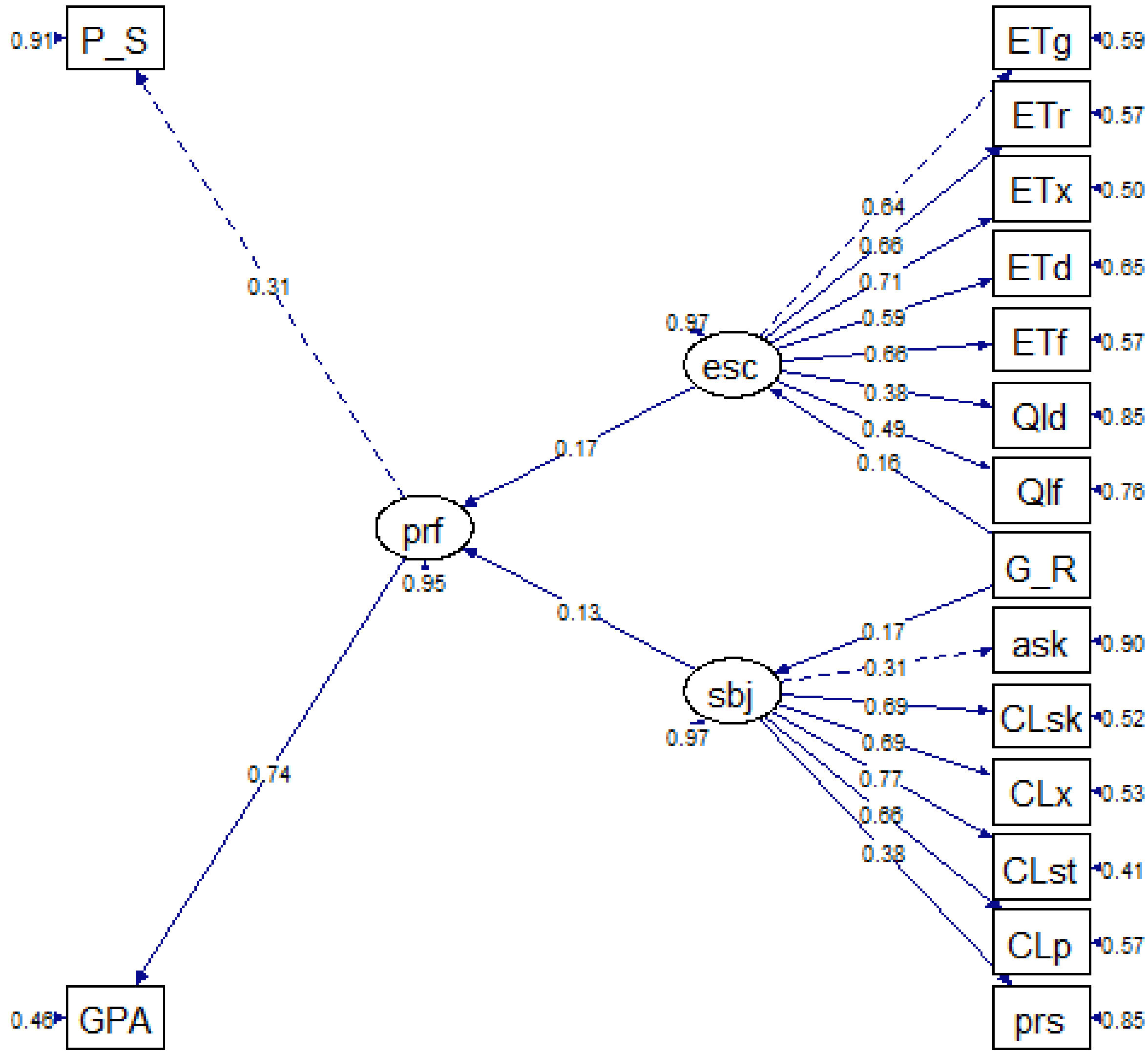
Structural Model (Standardized Path Coefficients) of First-Year STEM Major (RQ1A; N = 789)



Note. A revised theoretical model of the Expectancy-Value Model of Achievement Motivation. Latent constructs are represented by the ellipses. The arrowed lines signify the path of influence. Curved lines show correlations between latent variables. An observed indicator is characterized by a rectangle.

Figure A3

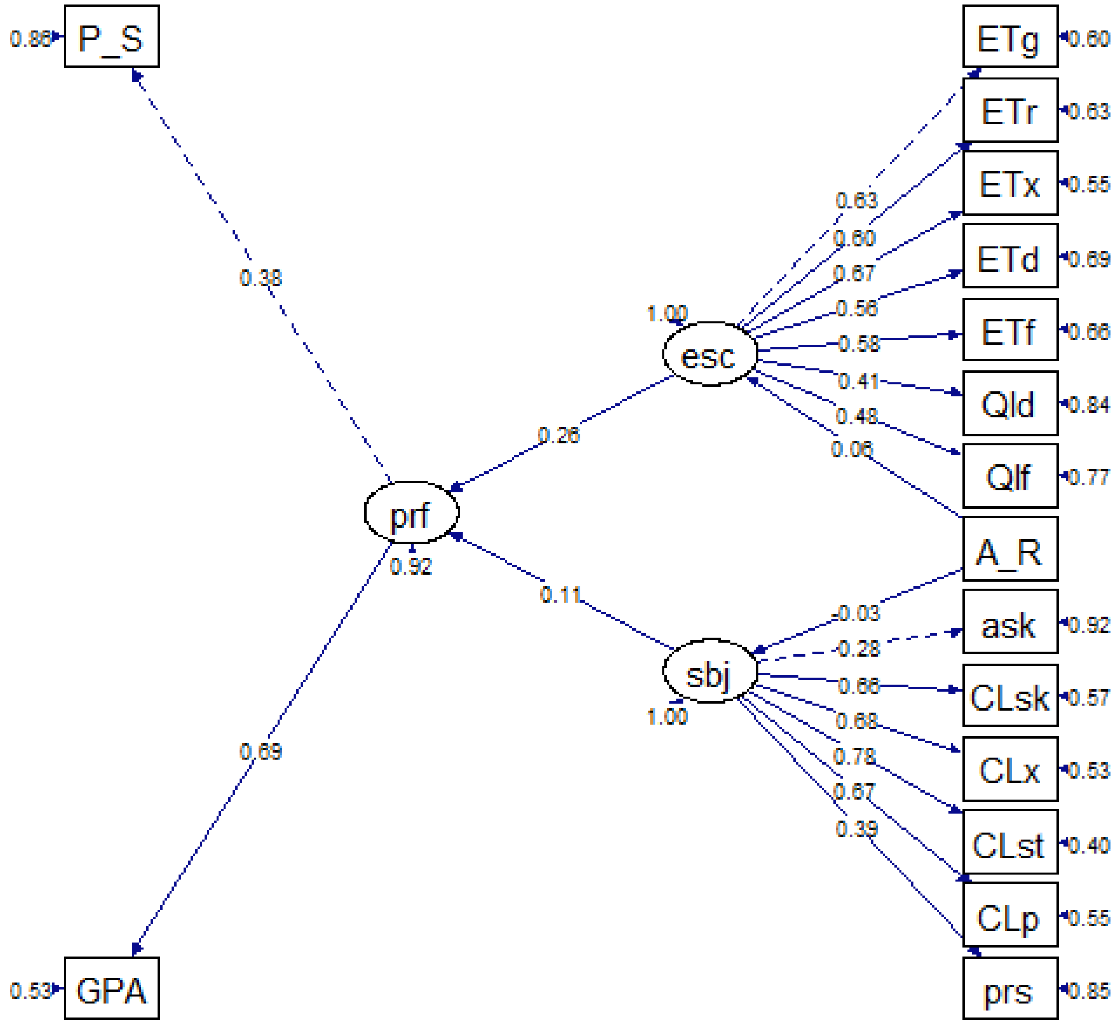
Structural Model (Standardized Path Coefficients) for RQ1B-Gender (N = 789)



Note. A revised theoretical model of the Expectancy-Value Model of Achievement Motivation. Latent constructs are represented by the ellipses. The arrowed lines signify the path of influence. Curved lines show correlations between latent variables. An observed indicator is characterized by a rectangle.

Figure A4

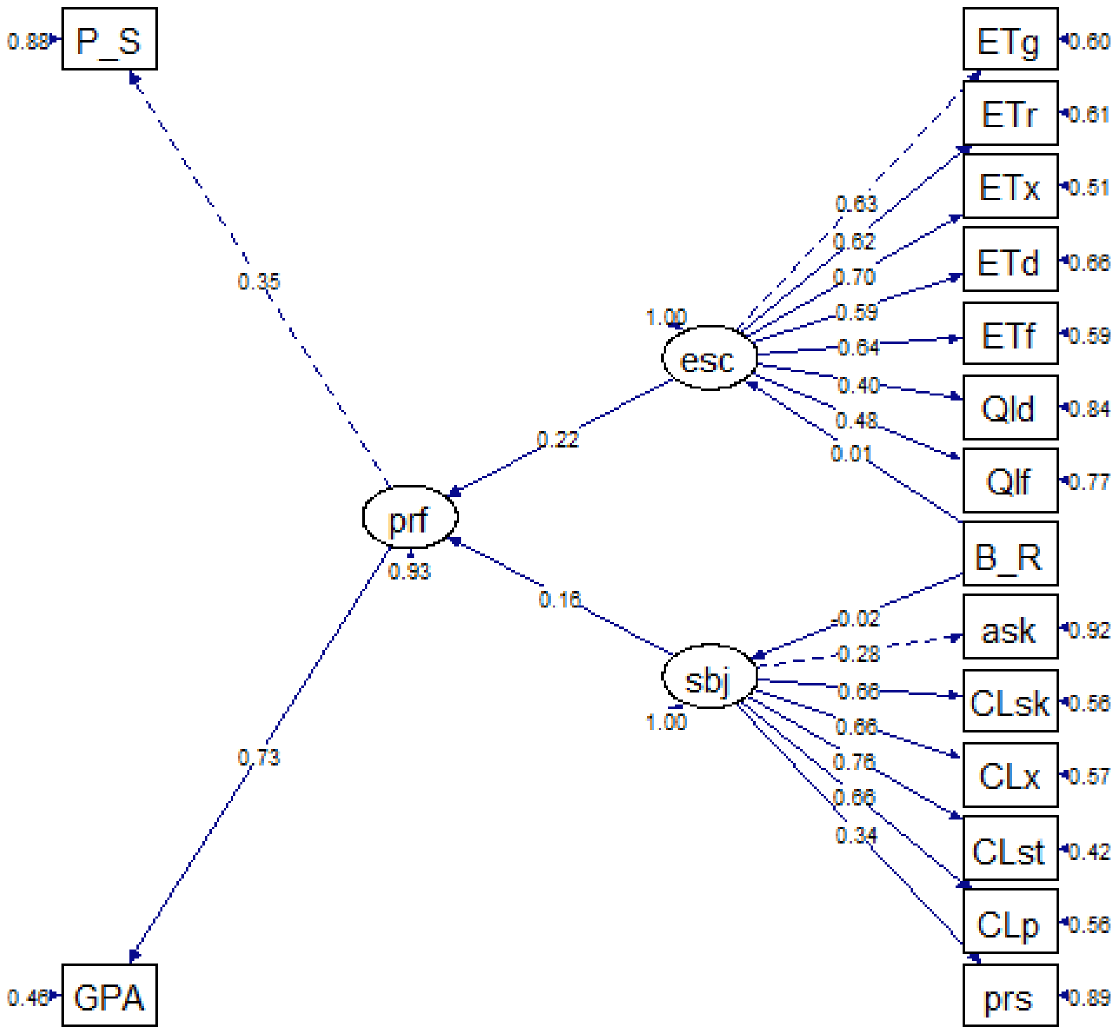
Structural Model (Standardized Path Coefficients) for RQ1C-Asian Students (N = 516)



Note. A revised theoretical model of the Expectancy-Value Model of Achievement Motivation. Latent constructs are represented by the ellipses. The arrowed lines signify the path of influence. Curved lines show correlations between latent variables. An observed indicator is characterized by a rectangle.

Figure A5

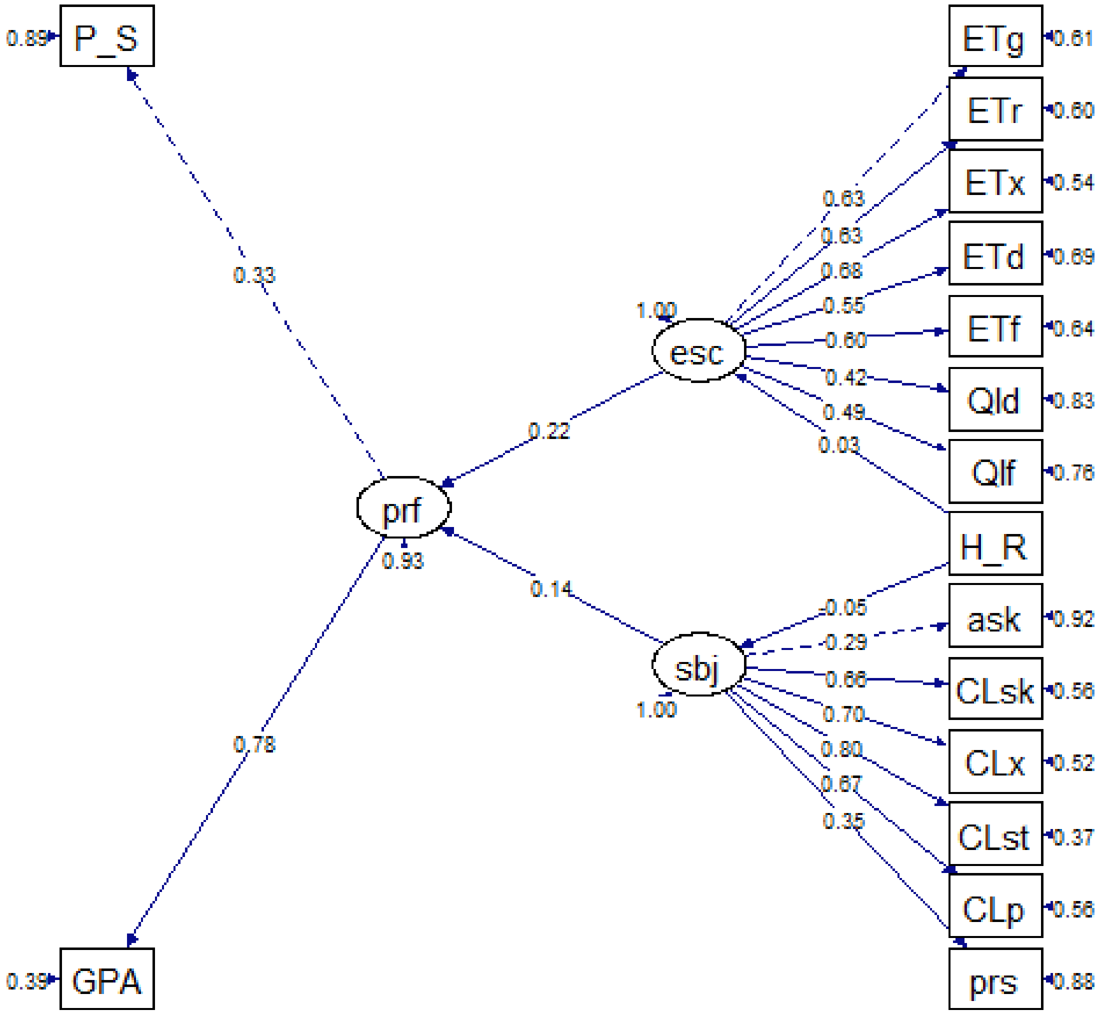
Structural Model (Standardized Path Coefficients) for RQ1D-Black Students (N = 565)



Note. A revised theoretical model of the Expectancy-Value Model of Achievement Motivation. Latent constructs are represented by the ellipses. The arrowed lines signify the path of influence. Curved lines show correlations between latent variables. An observed indicator is characterized by a rectangle.

Figure A6

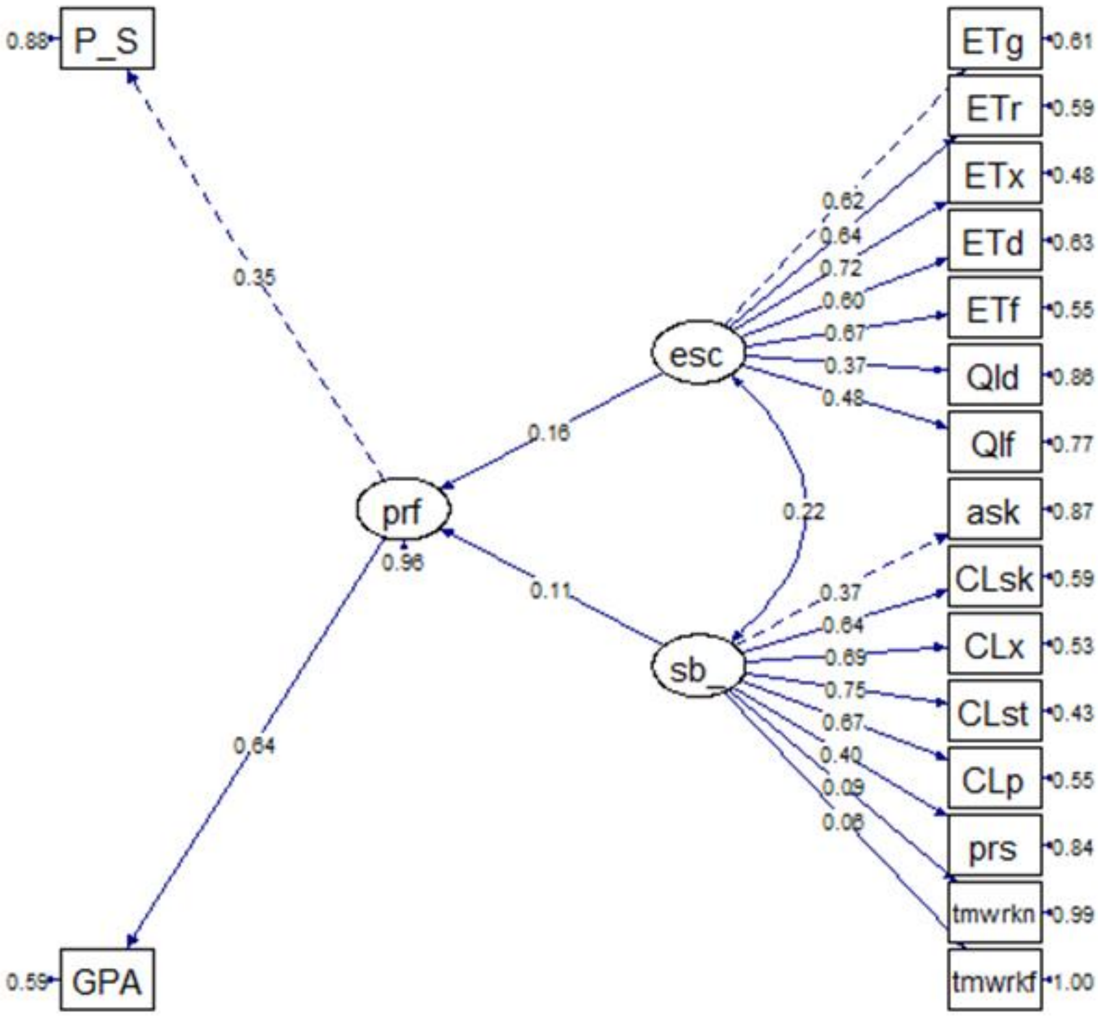
Structural Model (Standardized Path Coefficients) for RQ1E-Hispanic Students (N = 550)



Note. A revised theoretical model of the Expectancy-Value Model of Achievement Motivation. Latent constructs are represented by the ellipses. The arrowed lines signify the path of influence. Curved lines show correlations between latent variables. An observed indicator is characterized by a rectangle.

Figure A7

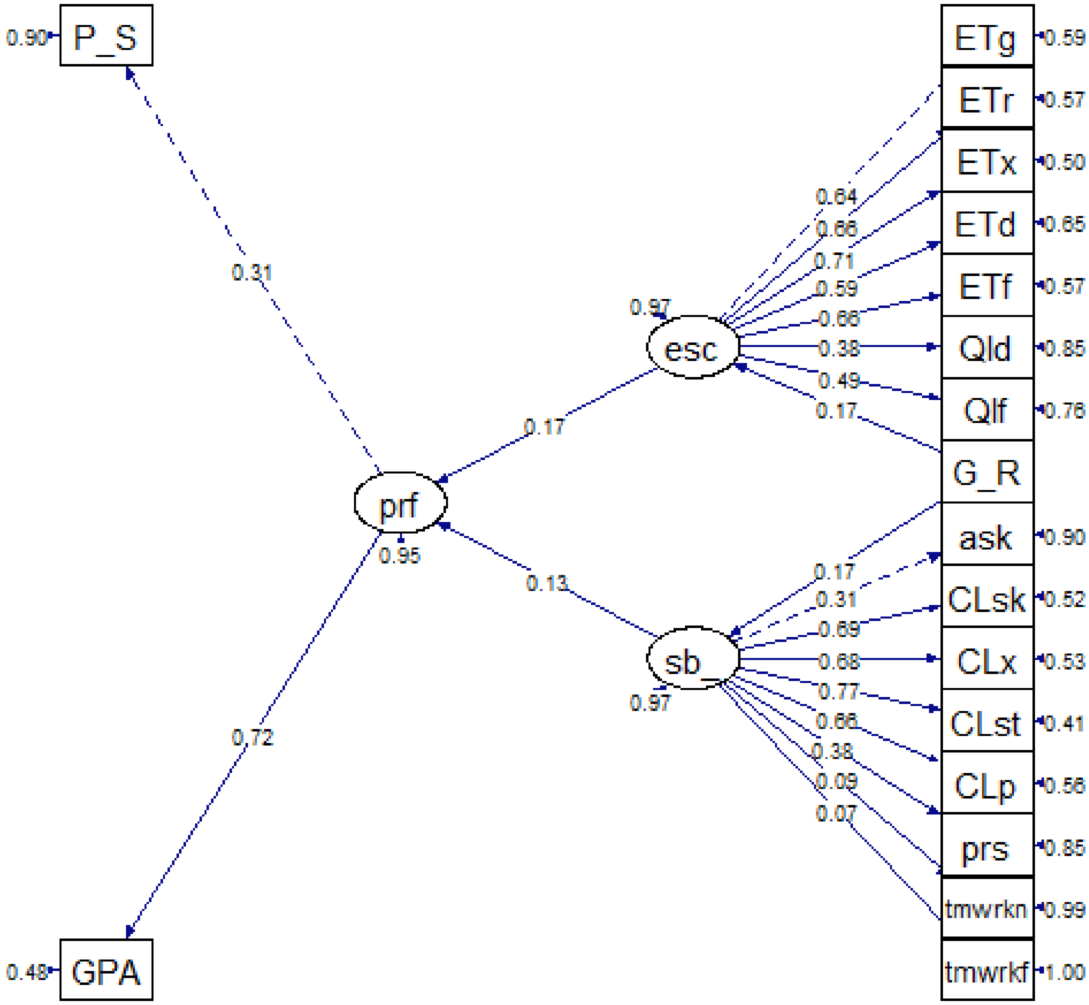
Structural Model (Standardized Path Coefficients) of First-Year STEM Major (RQ2A; N = 789)



Note. A revised theoretical model of the Expectancy-Value Model of Achievement Motivation. Latent constructs are represented by the ellipses. The arrowed lines signify the path of influence. Curved lines show correlations between latent variables. An observed indicator is characterized by a rectangle.

Figure A8

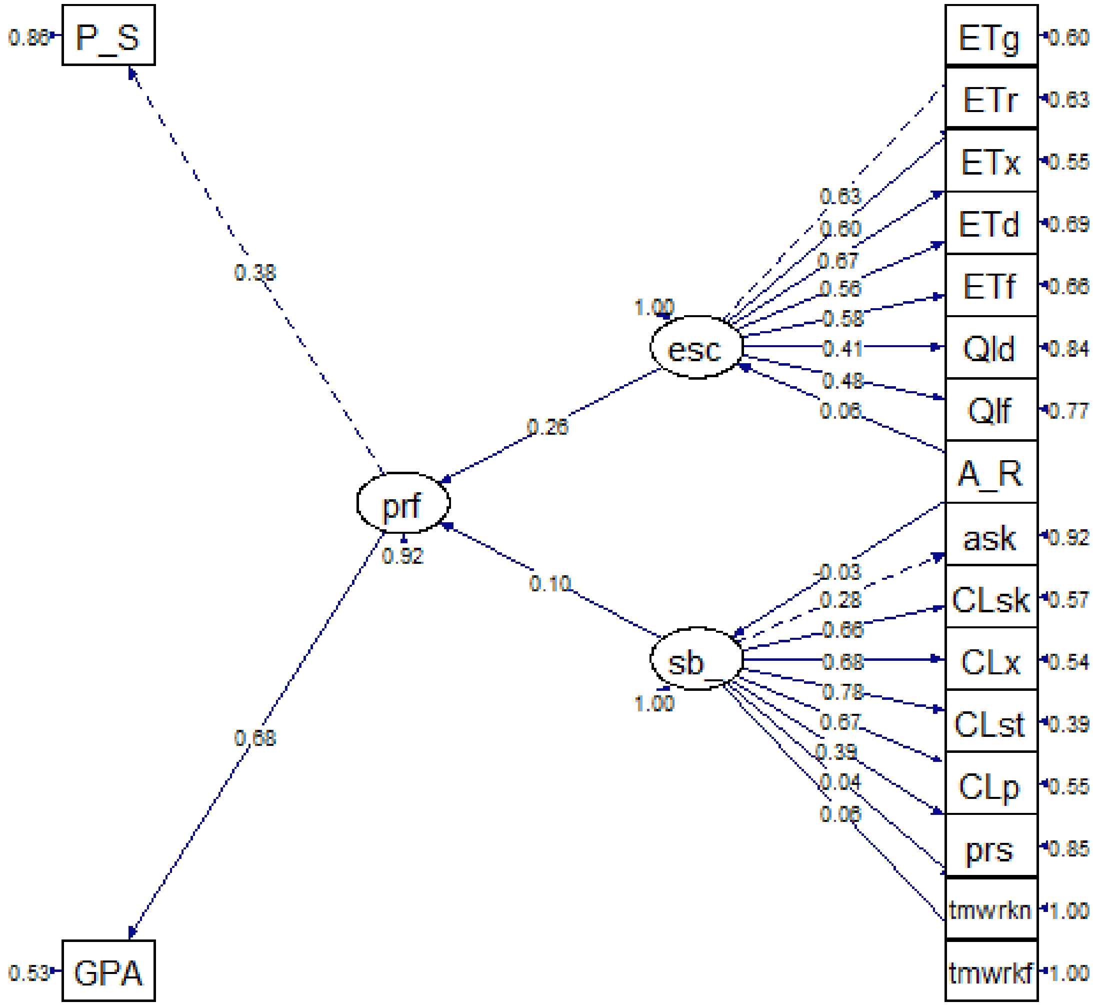
Structural Model (Standardized Path Coefficients) for RQ2B-Gender (N = 789)



Note. A revised theoretical model of the Expectancy-Value Model of Achievement Motivation. Latent constructs are represented by the ellipses. The arrowed lines signify the path of influence. Curved lines show correlations between latent variables. An observed indicator is characterized by a rectangle.

Figure A9

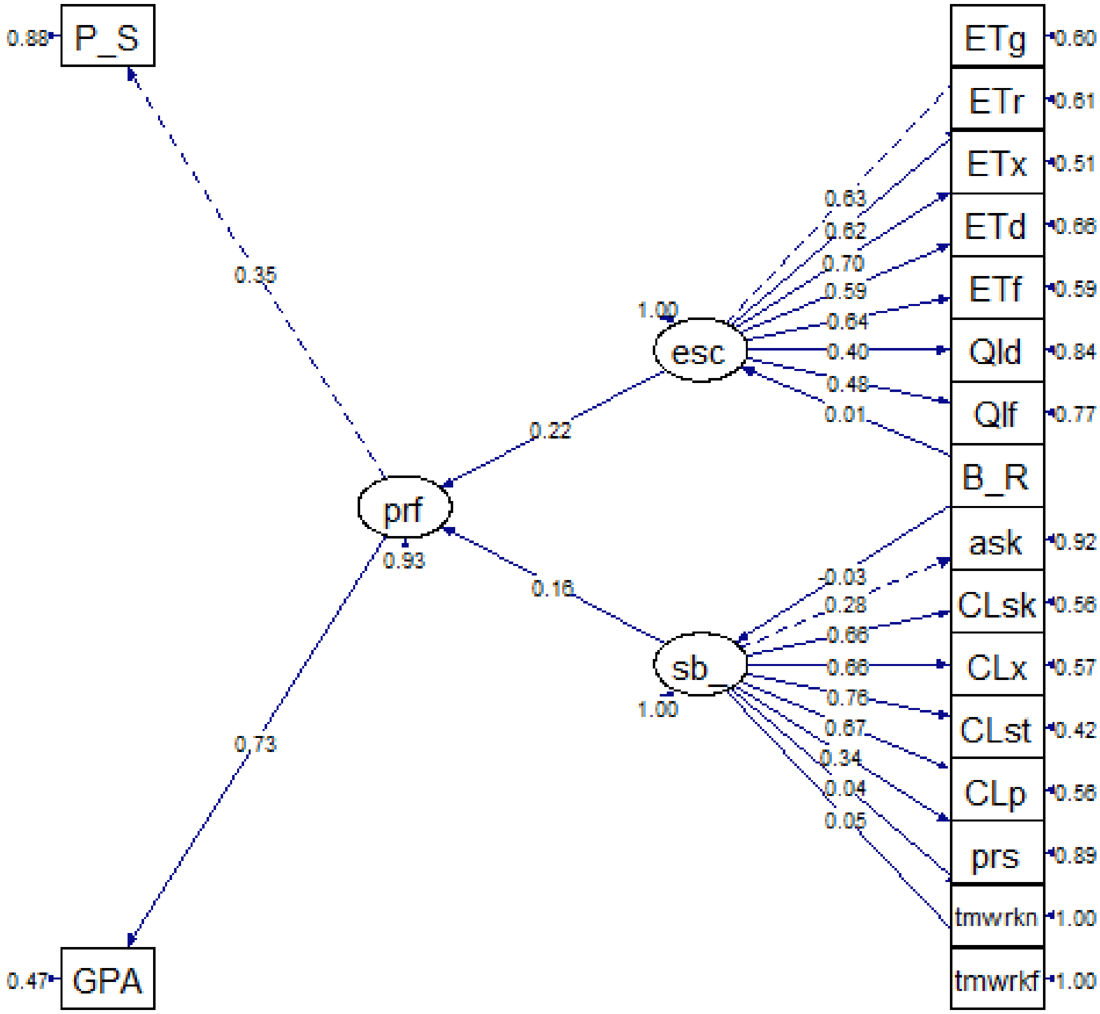
Structural Model (Standardized Path Coefficients) for RQ2C-Asian Students (N = 516)



Note. A revised theoretical model of the Expectancy-Value Model of Achievement Motivation. Latent constructs are represented by the ellipses. The arrowed lines signify the path of influence. Curved lines show correlations between latent variables. An observed indicator is characterized by a rectangle.

Figure A10

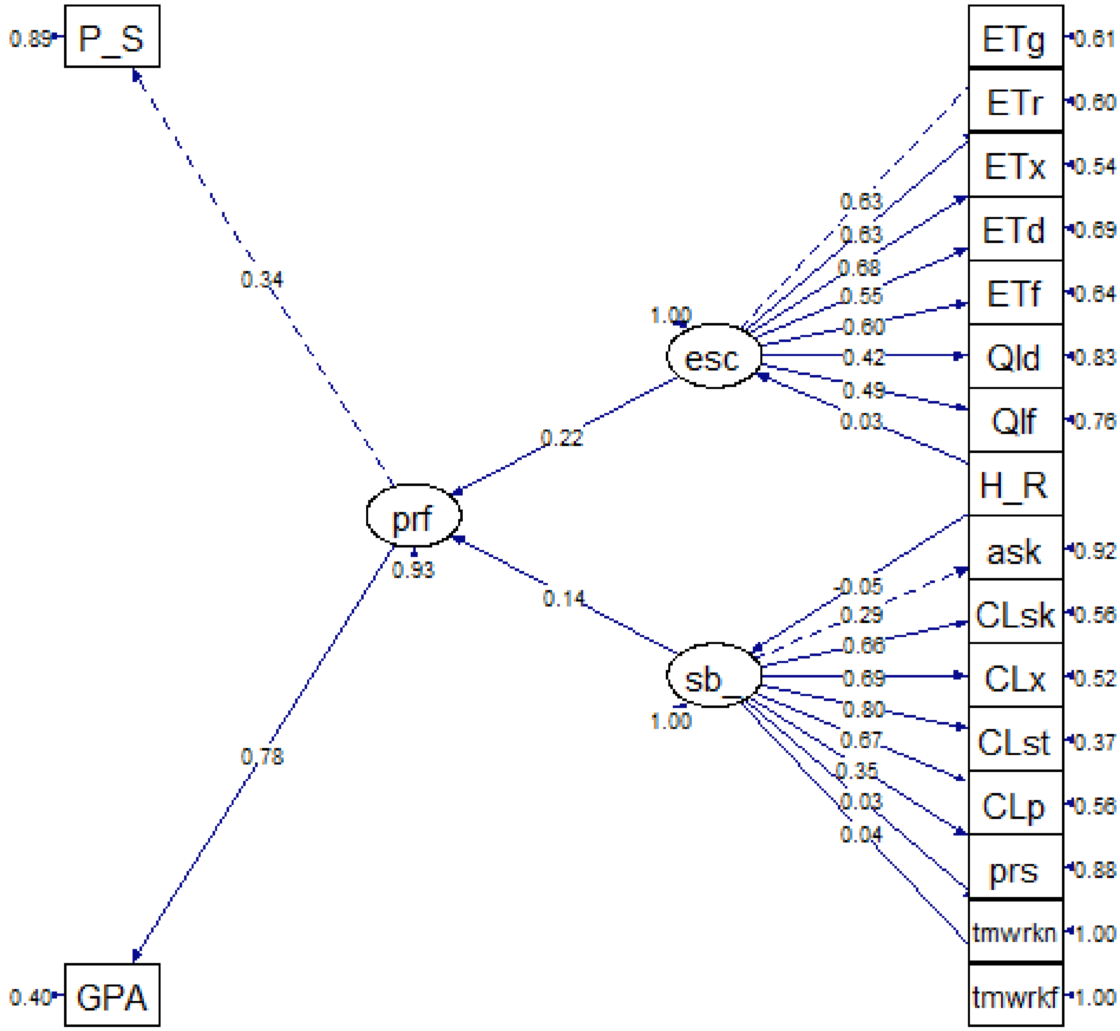
Structural Model (Standardized Path Coefficients) for RQ2D-Black Students (N = 565)



Note. A revised theoretical model of the Expectancy-Value Model of Achievement Motivation. Latent constructs are represented by the ellipses. The arrowed lines signify the path of influence. Curved lines show correlations between latent variables. An observed indicator is characterized by a rectangle.

Figure A11

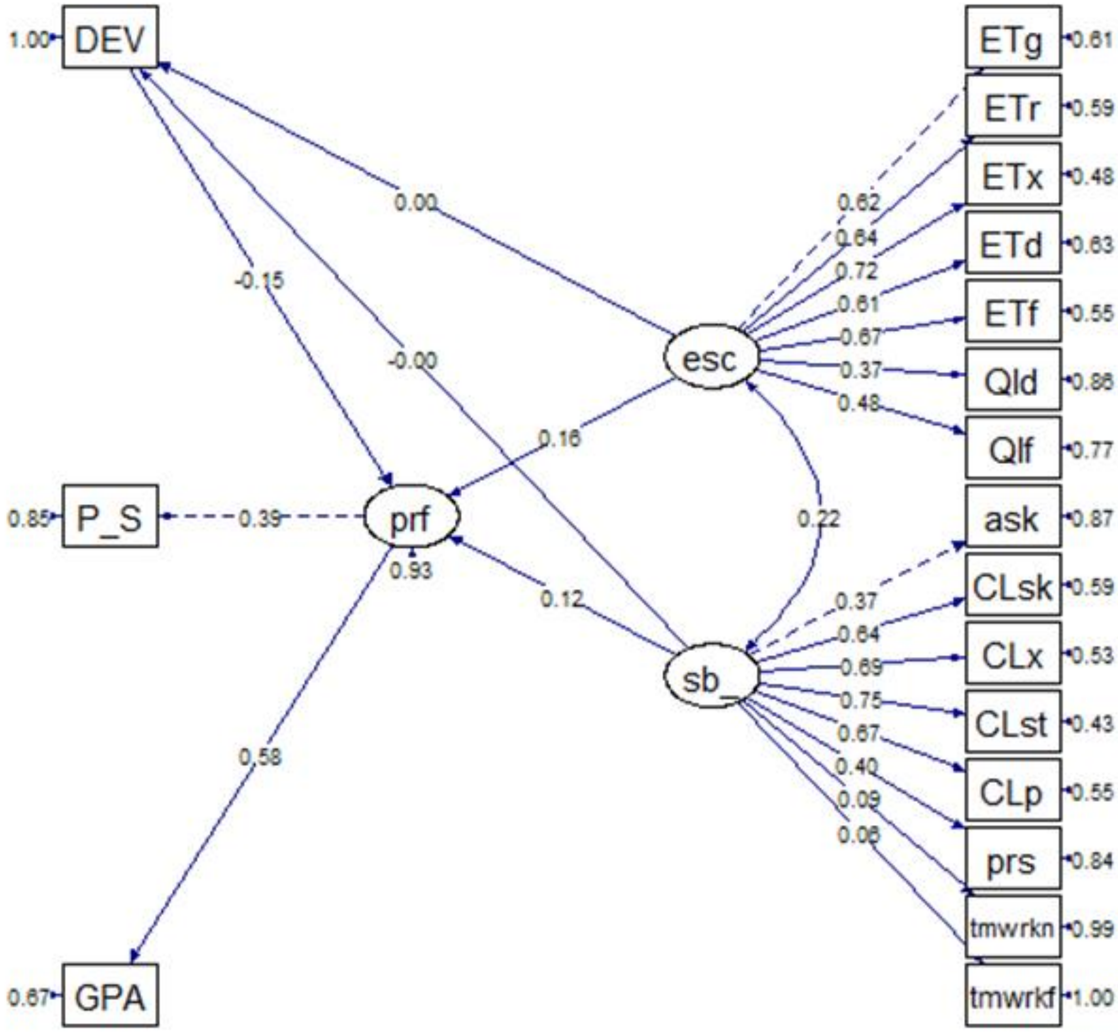
Structural Model (Standardized Path Coefficients) for RQ2E-Hispanic Students (N = 550)



Note. A revised theoretical model of the Expectancy-Value Model of Achievement Motivation. Latent constructs are represented by the ellipses. The arrowed lines signify the path of influence. Curved lines show correlations between latent variables. An observed indicator is characterized by a rectangle.

Figure A12

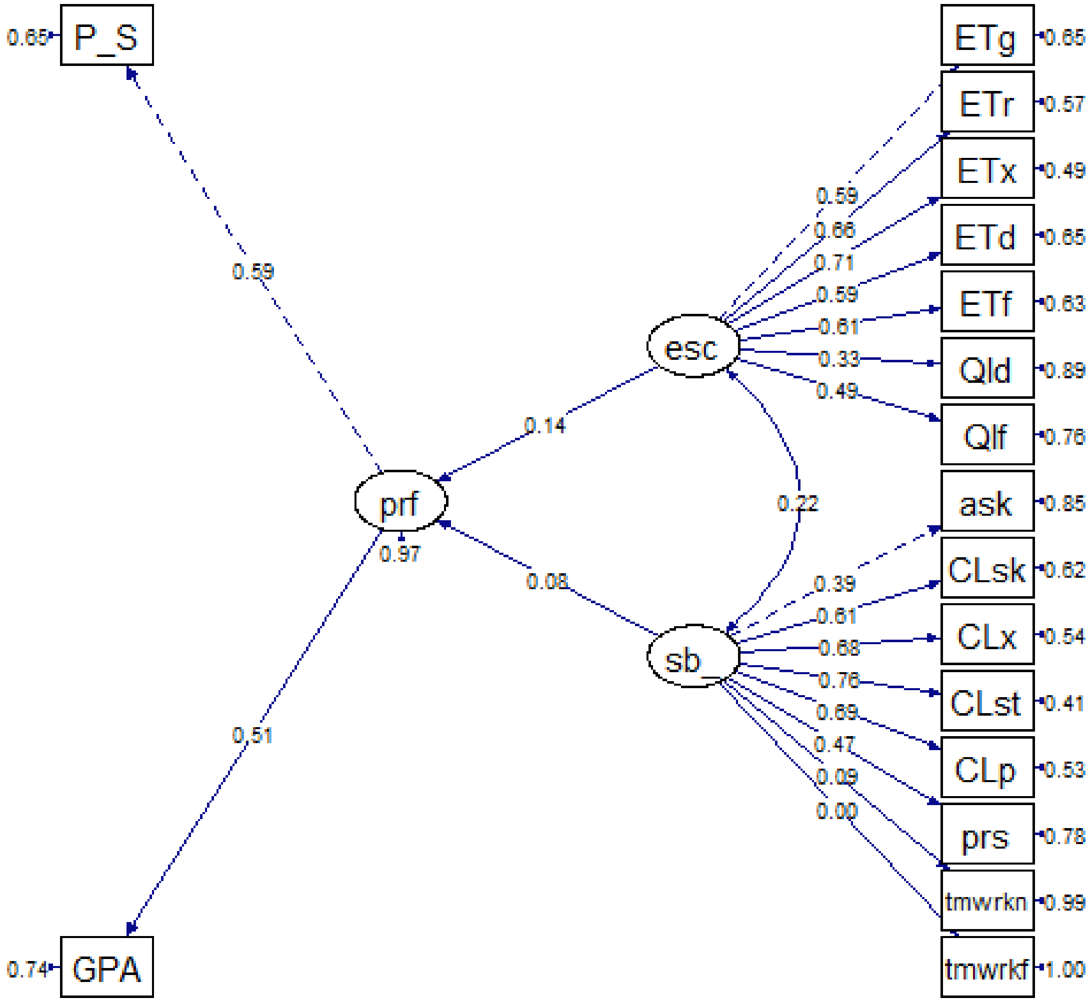
Structural Model (Standardized Path Coefficients) of First-Year STEM Major (RQ3; N = 789)



Note. A revised theoretical model of the Expectancy-Value Model of Achievement Motivation. Latent constructs are represented by the ellipses. The arrowed lines signify the path of influence. Curved lines show correlations between latent variables. An observed indicator is characterized by a rectangle.

Figure A13

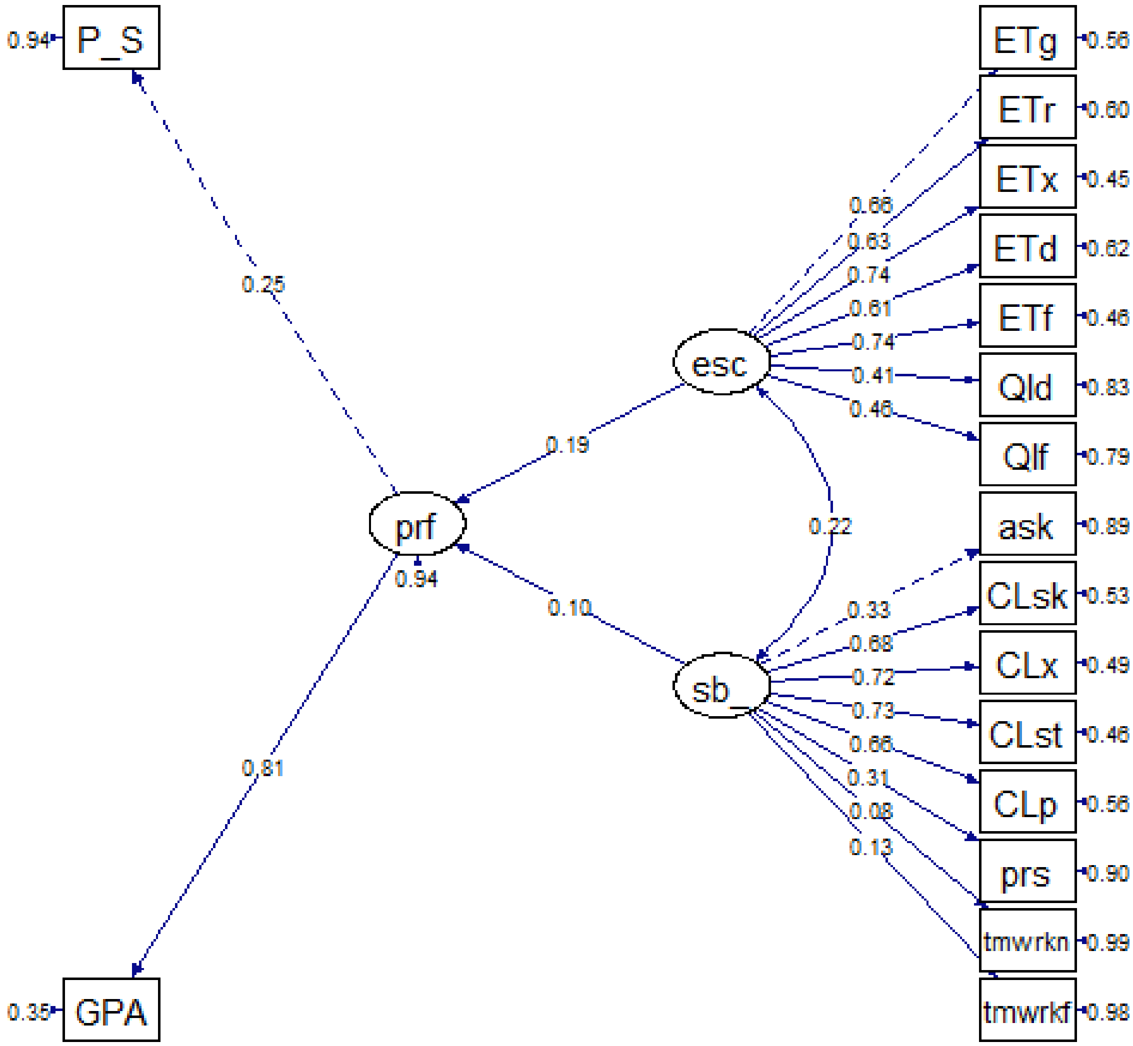
Structural Model (Standardized Path Coefficients) for RQ4-PEMC Majors (N = 444)



Note. A revised theoretical model of the Expectancy-Value Model of Achievement Motivation. Latent constructs are represented by the ellipses. The arrowed lines signify the path of influence. Curved lines show correlations between latent variables. An observed indicator is characterized by a rectangle.

Figure A14

Structural Model (Standardized Path Coefficients) for RQ4-Other-STEM Majors (N = 345)



Note. A revised theoretical model of the Expectancy-Value Model of Achievement Motivation. Latent constructs are represented by the ellipses. The arrowed lines signify the path of influence. Curved lines show correlations between latent variables. An observed indicator is characterized by a rectangle.