Integrating Self-Determination And Expectancy-Value Theories In Examining The Achievement Of First-Generation College Students: A Latent Profile Analysis Examining Relations Between Perceived Choice, School Valuing, And Perceived Competence And Academic Achievement

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INTEGRATING SELF-DETERMINATION AND EXPECTANCY-VALUE THEORIES IN EXAMINING THE ACHIEVEMENT OF FIRST-GENERATION COLLEGE STUDENTS: A LATENT PROFILE ANALYSIS EXAMINING RELATIONS BETWEEN PERCEIVED CHOICE, SCHOOL VALUING, AND PERCEIVED COMPETENCE AND ACADEMIC ACHIEVEMENT

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DEDICATION

This dissertation is dedicated with the deepest love from my heart to my
dearest mother, Ms. Cheryl Lytton for her physical, emotional, and financial support
throughout this journey. I hope I have made you proud.
ACKNOWLEDGEMENTS

This dissertation would not have been possible without the support of my mentors, family, and friends. Having Dr. Matthew Irvin as my advisor has been a true blessing, although he probably rue the day he gave me his cell phone number. His guidance, patience, and high expectations have molded me into a better researcher and writer. I also want to acknowledge my professor and committee member, Dr. Christine DiStefano, who was so helpful with the analysis and Mplus learning curve. I only wish I had her cell number too! I am so grateful to my entire committee, including Dr. Kellah Edens, Dr. Kelly Lynn Mulvey, and Dr. Judith Meece for their constructive feedback to make this dissertation better. I especially appreciate Dr. Meece who recommended I dichotomize my variables! I especially thank the professors at USC Upstate who helped me collect my data, including Dr. George Williams, Dr. Peter Caster, Susannah Waldrop, Sue Kolb, Ann Wadell, Rachel Hyder, Dr. Elizabeth Cole, Dr. Chuck Reback, and Michael Wooten. I would also like to thank Brian Smith for helping me get GPA data on students who had graduated and Adam Long for retrieving the achievement data from the system.

I also owe many thanks to my family. I thank my mother, who has set an example for me to always be strong and optimistic and has taught me the value of hard work. I feel grateful for my sister for taking me in as a housemate when my world came crashing down. Her generosity allowed me to continue taking classes
without disruption. Finally, I thank my friends in the program, including Sandy Rogelberg, Liyun Zhang, Erin Carson, and Adam Sokol, for always being so encouraging and making me laugh through the difficult times.
ABSTRACT

First-generation students, who represent more than 40% of entering college freshmen, have lower academic achievement and struggle to persist compared to their continuing-generation peers. Although previous studies have repeatedly shown a deficit model for first-generation students, there is still a lack of clear understanding about the heterogeneity that exists among these college students. While some do struggle to persist, others show marked resilience. Thus, drawing on Self-Determination Theory and Expectancy-Value Theory, this short-term longitudinal study examined whether perceived competence, perceived choice, and positive school value could moderate the risk of being a first-generation college student. A latent profile analysis on the motivational constructs revealed a three-class solution with one high competence class and two low competence and value classes. When considering if the latent profiles moderate the risk of being first-generation, no significant relationship with generation status was found when controlling for high school GPA, race/ethnicity, and socioeconomic hardship. Thus, this dissertation study specifically illustrates the resilience that can protect college students at risk of low academic achievement. The significance, limitations, and implications of this study for future research and practice on how at-risk college students can beat the odds on academic achievement are discussed.
# TABLE OF CONTENTS

Dedication ........................................................................................................................................ iii

Acknowledgements ........................................................................................................................... iv

Abstract ........................................................................................................................................ vi

List of Tables ...................................................................................................................................... ix

List of Figures .................................................................................................................................. x

List of Abbreviations ........................................................................................................................ xi

Chapter 1 Introduction ..................................................................................................................... 1
  1.1 First-Generation College Students ......................................................................................... 1
  1.2 Rural College Students ........................................................................................................... 3
  1.3 Race/Ethnicity and Socioeconomic Status ............................................................................. 4
  1.4 Collegiate Class and Motivation ............................................................................................ 5
  1.5 Theoretical Framework ........................................................................................................... 6
  1.6 Significance of the Study ......................................................................................................... 7

Chapter 2 Literature Review ........................................................................................................... 8
  2.1 Self-Determination Theory .................................................................................................... 9
  2.2 Expectancy-Value Theory ..................................................................................................... 13
  2.3 First-Generation College Students ....................................................................................... 15
  2.4 Rural College Students .......................................................................................................... 21
  2.5 Race/Ethnicity and Socioeconomic Status .......................................................................... 24
LIST OF TABLES

Table 3.1 Demographics by Cohort and in Total.................................................................39
Table 3.2 Codes for Race/Ethnicity in the Analysis ............................................................45
Table 3.3 Variable Treatment ...............................................................................................45
Table 3.4 Descriptive Statistics for Variables .........................................................................52
Table 3.5 Percent Representation by Major .........................................................................52
Table 4.1 Fit Values for the Different Class Solutions .............................................................55
Table 4.2 Motivational Profile Conditional Response Means ...............................................57
Table 4.3 Satorra-Bentler Log Likelihood Difference Tests for Covariates.........................58
Table 4.4 Logistic Regression Log Odds for Covariates .......................................................59
Table 4.5 Conditional Mean Differences Across the Classes by Generation Status...........60
Table 4.6 Conditional Mean Differences Across the Classes by Rural Status ....................61
Table 4.7 Conditional Mean Differences Across the Classes by Race ................................61
Table 4.8 Chi-Square Results for Each of the Covariates .....................................................62
Table 4.9 Conditional Mean GPA for Each Latent Class ......................................................62
Table 4.10 Slopes and p-values for Initial Model .................................................................63
Table 4.11 Slopes and p-values for Model Including a 3-way Interaction ............................65
Table 4.12 Slopes and p-values for the Final Model ..............................................................67
Table 4.13 Slopes & p-values for Multiple Regression Using Motivational Variables69
LIST OF FIGURES

Figure 2.1 Hypothesized SEM model..........................................................37

Figure 4.1 Motivational Profile Conditional Response Means ..........................57

Figure 4.2 The Interaction Effect of the Motivational Profiles on Race ...............67
LIST OF ABBREVIATIONS

CET ..............................................................Cognitive Evaluation Theory

EVT ..............................................................Expectancy-Value Theory

LPA ..............................................................Latent Profile Analysis

OIT ..............................................................Organismic Integration theory

SDT ..............................................................Self-Determination Theory

SES ..............................................................Socioeconomic Status
CHAPTER 1

INTRODUCTION

The purpose of this study is to explore the heterogeneity among first-generation and rural college students across different grades (freshman, sophomore, junior, and senior) among the latent classes created by perceived choice, school value, perceived competence through the lens of self-determination theory and expectancy-value theory. Although research has consistently shown a positive relationship between perceived choice/autonomy, school value, perceived competence and a variety of well-being, motivational, and academic measures (Assor, Roth, & Deci, 2004; Baker, 2004; Berndt & Miller, 1990; Burton, Lydon, D’alessandro, & Koestner, 2006; Chirkov, & Ryan, 2001; Eccles, Adler, & Meece, 1984; Grolnick, Ryan, & Deci, 1991; Legault, Green-Demers, & Pelletier, 2006; Ratell, Larose, Guay, & Senécal, 2005; Ryan, Stiller, & Lynch, 1994; Wentzel, 1998), a review of the literature revealed very few examinations of the relationship between autonomy, perceived competence, and school value specifically in first-generation and/or rural college students.

1.1 FIRST-GENERATION COLLEGE STUDENTS

Overwhelmingly, current research shows a deficit model applies to first-generation college students. First-generation students, who represent at least half of high school graduates, are less likely than their counterparts whose parents have
more education to be prepared academically for postsecondary education (Davis, 2004). As of fall 2015, 69% of high school graduates enrolled in a 2- or 4-year college, but the national 6-year college graduation rate is only 59% (National Center for Education Statistics, 2017). At a clear disadvantage, first-generation students are less likely to enroll in 4-year institutions and, if they do, are less likely to persist in college. Ishitani (2006) showed that first-generation students were half as likely to graduate within 4 years than students with college-educated parents. While enrolled in college, first-generation students have weaker academic performances compared to their peers with college-educated parents: The 2001 National Center of Education Statistics study (Warburton et al., 2001) reported that the average first-year GPA of non-first-generation students beginning in the fall 1995 semester was 2.7, and the first-year GPA for first-generation students was only 2.4. Because first-generation college students comprise more than 40% of entering college freshmen (Davis, 2010), the challenges experienced by this group of students have wide-reaching consequences not only to the students themselves, but also to their families, the institutions they attend, and our society as a whole, especially if they fail to persist. For the student, failure to persist likely means a low-paying service industry job, potentially with the burden of student loan debt (Porter, 2013). Affecting both the student and society, the drop-out misses out on important social, political and global knowledge that comes from being part of a student body on a college campus (Tabarrok, 2012). Low persistence rates also affect universities in both their ranking and federal funding (“College Dropouts”, 2010).
1.2 RURAL COLLEGE STUDENTS

Compared to first-generation students, rural college students may experience less disadvantage. Precollege factors, including family income, parents’ education and educational expectations, and academic preparation, do play a role in the rural college student’s ultimate academic success. Several studies show that these precollege factors predict college enrollment, persistence, and completion (Adelman, 2006; Bozick, 2007; Byun, Irvin, & Meece, 2012; Goldrick-Rab & Pfeffer, 2009; Lapan, 2017). While rural youth may be lacking in some of these precollege factors, other studies show that rural students experience unique forms of social capital. Several studies demonstrate how this beneficial social capital, such as supportive student-teacher relationships, close community-school relationships, and conversations with parents about careers and work, predicts rural youth’s educational aspirations (Byun, Meece, Irvin, & Hutchins, 2012; Schafft, Alter, & Bridger, 2006). Studies on rural youth prove that most aspire to obtain a two- or four-year college degree, and most perceive their parents want them to attend college (Irvin, Byun, Meece, Reed, & Farmer, 2016; Meece, et al., 2013). With regards to motivation, research on rural youth has emphasized the important role that perceived competence and instrumentality have on school completion and postsecondary plans (Hardre, Sullivan, & Crowson, 2009; Irvin, Meece, Byun, Farmer, & Hutchins, 2011; Irvin, Byun, Meece, Reed, & Farmer, 2016). More research needs to be done on the motivation and perceived competence of rural college students. In particular, this dissertation study examines whether rural background may compound the relation of first-generation status to college
achievement. It remains to be seen how many first-generation students are also rural educated compared to those that are non-rural educated.

1.3 RACE/ETHNICITY AND SOCIOECONOMIC STATUS

Studying academic achievement is difficult without considering the impacts of race and socioeconomic status. The National Center of Education Statistics (NCES) has shown that, on average, minority students academically underperform compared to their White peers on both grades and standardized tests (US Department of Education, 2000). More specifically, Black students on predominantly White campuses struggle with persistence, academic achievement, postgraduate study, and overall psychosocial adjustment compared to their White counterparts (Allen, Epps, & Haniff, 1991; Astin, 1982; Hall, Mays, & Allen, 1984; Nettles, 1988). In addition to race, a positive relationship exists between socio-economic status and academic achievement (Battle & Lewis, 2002; Hedges & Nowell, 1999; Sirin, 2005). But, according to Sirin’s (2005) meta-analysis, this relationship is contingent on other factors, including minority status. Thus, these variables need to be considered in tandem. Since first-generation students are more likely to be minority and more likely to be from lower socioeconomic levels (Davis, 2004; Pascarella, Pierson, Wolniak, Terenzini, 2004), the current study must consider the effects of race and socioeconomic status on academic achievement. Without controlling for race and socioeconomic status, any significant first-generation findings may simply be masking a minority or poverty effect. The 2001 National Center of Education Statistics study by Warburton et al. (2001) that showed a significant difference in GPAs of first-generation college students compared to continuing generation college
students only controlled for high school academic performance. By controlling for more demographic attributes, this dissertation study will delve deeper into the potential relation between first-generation college students and underperformance.

1.4 COLLEGIATE CLASS AND MOTIVATION

Collegiate class confounds the study of motivation, but disagreement exists as to how it muddles motivation. Research on students from elementary through high school confirms motivation decreases across school years (Blackwell & Trzesniewski, 2007; Bong, 2001; Gottfried, 1985; Neel & Fuligni, 2013; Wang & Eccles, 2013; Wigfield, Eccles, Yoon, Harold, Arbreton, Freedman-Doan, & Blumenfeld, 1997). Little longitudinal motivational research has been done on college students, but a few of these studies (Brouse, Basch, LeBlanc, McKnight, & Lei, 2010; Ryan & Deci, 2000) show that motivation decreases across college.

Most motivational studies at the collegiate level focus on persistence, especially between the first and second year (Allen, 1999; Allen, Robbins, Casillas, & Oh, 2008; Astin, 1984; Bean, 1980; Cruce, Wolniak, Seifert, & Pascarella, 2006; Kuh, Cruce, Shoup, Kinzie, & Gonyea, 2008; Tinto, 1975). These studies are grounded in attrition theories of Tinto, Astin, or Bean, and they overwhelmingly demonstrate that academic and student involvement predicts persistence (Allen, 1999; Allen, Robbins, Casillas, & Oh, 2008; Cruce, Wolniak, Seifert, & Pascarella, 2006; Kuh, Cruce, Shoup, Kinzie, & Gonyea, 2008). This result implies that less motivated students fail to persist, leaving more motivated upperclassmen. Whether in a positive or negative direction, the evidence above shows that between-class differences confound the study of collegiate motivation. Thus, this dissertation study
will employ collegiate class as an independent variable so that the interaction with motivation can be explored.

1.5 THEORETICAL FRAMEWORK

Two theoretical frameworks on academic motivation guide this study. First, the study focuses on a student’s sense of autonomy and competence as detailed by self-determination theory (SDT). A substantial body of research has linked self-determined motivation to engagement and optimal learning in educational contexts (Benware & Deci, 1984; Black & Deci, 2000; Grolnick & Ryan, 1987; Kage & Namiki, 1990; Niemiec & Ryan, 2009; Noels, Pelletier, Clement & Vallerand, 2000). I will discuss students’ basic psychological needs for autonomy and competence, which when supported are associated with academic engagement and better learning outcomes, but when unsatisfied are associated with academic disengagement and poorer learning outcomes. Second, the study draws on expectancy-value theory (EVT), which emphasizes beliefs in one’s abilities and the value placed on the learning activity. Eccles and her colleagues proposed that expectancy-related beliefs and subjective task values influence students’ achievement-related decisions about engaging in particular activities, the amount of effort exerted, persistence, and performance. A multitude of studies have since validated this model (Berndt & Miller, 1990; Bong, 2001; Malka & Covington, 2005; Meece, Wigfield, & Eccles, 1990; Wigfield & Eccles, 1992). I will discuss how perceived competence (or ability beliefs) and school value play a critical role in initiating and sustaining students’ achievement motivation and ultimately their performance. Finally, my study draws
on the person-oriented perspective, and I will also provide an overview of this perspective and motivation research employing this perspective.

1.6 SIGNIFICANCE OF THE STUDY

While a multitude of studies have shown disadvantages for first-generation college students, those studies have some major limitations, which my dissertation seeks to address. First, no studies have examined this population under the lens of SDT and EVT. Further, this study draws on the person-oriented perspective and specifically considers profiles of and the heterogeneity in first-generation students’ perceived competence, school value and autonomy. Second, few studies have employed advanced statistical techniques, like latent profile analysis and structural equation modeling when examining this population. Third, this study simultaneously considers the impact of generation status, rurality, race/ethnicity, socioeconomic status, and collegiate class on academic achievement. Thus, the study allows for a deeper understanding of the impact of these variables, as well as their interactions.

To sum, understanding the collegiate experience of first-generation students is imperative to the identification and implementation of effective support and interventions for this sizable population. Hence, this study attempts to explore how first-generation and rural college students may differ in their motivational profiles created from autonomy, school valuing and perceived competence. Furthermore, this study will also explore whether rural background, race/ethnicity, socioeconomic status, and/or collegiate class may compound the relation of first-generation status to college achievement.
CHAPTER 2  
LITERATURE REVIEW  

Understanding the heterogeneity in first-generation college students is critical for designing an appropriate intervention. First, first-generation students represent a large proportion of college students. According to Davis (2010) first-generation students comprise more than 40% of incoming freshman. Second, some first-generation students fail to succeed at the college level. Ishitani (2006) showed that first-generation students were half as likely to graduate within 4 years than students with college-educated parents. While enrolled in college, some first-generation students have weaker academic performances compared to their peers with college-educated parents. The 2001 National Center of Education Statistics study (Warburton et al., 2001) reported that the average first-year GPA of non-first-generation students beginning in the fall 1995 semester was 2.7, and the first-year GPA for first-generation students was only 2.4. However, heterogeneity exists within the first-generation population such that some students persist with strong academic achievement. This study attempts to explain this heterogeneity through perceived competence, perceived autonomy and school value. In essence, varying levels of motivation may moderate generation status on academic achievement. This study also considers how rurality and collegiate class may compound the relation of
first-generation status to collegiate achievement. This chapter provides a more in-depth review of previous findings and gaps in the research on first-generation college students, rural college students, and upperclassmen, as well as discusses the theoretical framework of my dissertation.

2.1 SELF-DETERMINATION THEORY

SDT is a broad theory that defines intrinsic and varied extrinsic sources of motivation, as well as the cognitive and social implications of the intrinsic and varied extrinsic sources of motivation. Research in SDT focuses on how social and cultural factors facilitate or undermine an individual’s sense of volition and initiative, in addition to his or her well-being and the quality of his or her performance. According to the theory, conditions supporting the individual’s experience of autonomy, competence and relatedness are reasoned to foster the most volitional and high quality forms of motivation and engagement for activities, including enhanced performance and persistence (Deci, Vallerand, Pelletier, & Ryan, 1991). SDT is a meta-theory that is comprised of several mini-theories. One, Cognitive Evaluation Theory (CET), concerns intrinsic motivation, motivation involved in self-determined acts (Deci & Ryan, 2012). CET specifically addresses the effects of social contexts on intrinsic motivation and interest. CET highlights the critical roles played by competence and autonomy supports in fostering intrinsic motivation (Niemiec & Ryan, 2009). The need for autonomy refers to the experience of behavior as volitional and reflectively self-endorsed. For example, students are autonomous when they willingly devote time and energy to studying. The need for competence refers to the learner’s ability to master knowledge and skills. For
example, students are competent when they feel able to meet the challenges of their coursework. Numerous experimental studies have supported the SDT hypothesis that both autonomy and competence are necessary conditions for the maintenance of intrinsic motivation (Deci et al., 1999).

A second mini-theory, Organismic Integration Theory (OIT), addresses the topic of extrinsic motivation in its various forms, defined by the degree to which an act is perceived as controlled or coerced (Deci & Ryan, 2012). There are distinct forms of extrinsic motivation, which include external regulation, introjection, identification, and integration, and these subtypes are seen as falling along a continuum of internalization. The more internalized the extrinsic behavior, the more autonomous the individual will be when engaging in the activity. OIT particularly highlights supports for autonomy and relatedness as critical to internalization (Niemiec & Ryan, 2009). Since not all motivation can be intrinsic, numerous studies have shown that internalization, meaning higher autonomous self-regulation for learning, supports greater psychological and academic functioning.

Many researchers have applied the SDT framework to intrinsic motivation in educational contexts. Benware and Deci (1984) had college students learn course material either with the expectation of teaching it to another student or of being tested on it. Results revealed that students who learned in order to teach, relative to those who learned to take the test, were more intrinsically motivated and showed better conceptual learning. Studies also show how the teacher can impact perceived competence and intrinsic motivation. Hollembeak and Amorose (2004) investigated college athletes under the lens of self-determination theory. They found specific
coaching behaviors, i.e. training and instruction, and positive feedback, significantly predicted perceived competence, autonomy and relatedness, which, in turn, predicted intrinsic motivation. Even more general studies demonstrate that students going to college to fulfill intrinsic motivation needs for autonomy and competence are positively associated with intention to persist and GPA (Guiffrida, Lynch, Wall, & Abel, 2013). Studies on younger students reveal the same results. In both the USA (Grolnick & Ryan, 1987) and Japan (Kage & Namiki, 1990), exam pressures undermined, and autonomy support facilitated, students’ intrinsic motivation for classroom material, as well as their performance in school. Jang et al. (2009) showed that South Korean public school students were more intrinsically motivated when they experienced feelings of autonomy and competence. Overall, these studies highlight CET and the important role of autonomy and competence for intrinsic motivation.

While intrinsic motivation is essential for learning, not all tasks in school are inherently satisfying or fun. For example, college students in calculus may not find fun or interest in arduous math problems. In this case, students need other incentives or reasons to learn. Extrinsic motivation refers to behaviors performed to obtain some outcome separable from the activity itself (Ryan & Deci, 2000). As previously mentioned, OIT posits four distinct types of extrinsic motivation that vary in the degree to which they are experienced as autonomous and that are differentially associated with learning outcomes. Numerous studies have examined the psychological and academic outcomes associated with autonomous self-regulation for learning. Grolnick et al. (1991) showed that elementary students who
reported higher autonomous self-regulation for learning were rated by their teachers as higher on both academic achievement and adjustment in the classroom. Niemiec et al. (2006) found that high school students who reported higher autonomous self-regulation for attending college reported higher well-being (life satisfaction) and lower ill-being (depression, anxiety). Black and Deci (2000) found that college students who reported higher autonomous self-regulation for learning organic chemistry reported higher perceived competence and interest/enjoyment for the course material, as well as lower anxiety. When intrinsic motivation is absent, internalization of extrinsic motivation is crucial for effective psychological and academic functioning.

Broadly speaking, the SDT model posits that when the need for autonomy is met, students’ active involvement or engagement in learning activities increases. In turn, engagement has direct implications for student achievement. By engaging themselves, students learn, develop skills and become more competent. Both the extent and quality of students’ engagement have been shown to predict various aspects of achievement, including course grades and standardized test scores (Alexander, Entwisle, & Dauber, 1993; Ladd & Dinella, 2009). Consequently, autonomy is critical for increasing perceived competence and ultimately performance. Perceived autonomy has been shown to be a direct predictor of students’ persistence (Vansteenkiste, Simons, Lens, Sheldon, & Deci, 2004), positive emotionality (Patrick, Skinner, & Connell, 1993), conceptual understanding and competence (Vansteenkiste et al., 2005), and sense of agency (Reeve & Tseng, 2011). Thus, the theory suggests that a college student who has higher autonomous
self-regulation for learning and higher perceived competence will undoubtedly have a higher GPA.

2.2 EXPECTANCY-VALUE THEORY

In SDT, Deci and Ryan (1985) include the need for competence as a basic need that individuals have and discussed how this need is a major reason why students seek out optimal stimulation and succeed at challenging activities. Beliefs about one's ability also emerge as a critical component in expectancy-value theory (EVT), along with subjective task value. According to Wigfield and Eccles (1992), expectancies and values directly influence performance and task choice. According to EVT, expectancies and values themselves are influenced by task-specific ability beliefs such as perceived competence, perceived task difficulty and individuals' goals. Wigfield and Eccles (2000) conceptually view ability beliefs as a student's evaluation of their competence, both in terms of their assessment of their own ability and also how they think they compare to other students. However, confirmatory factor analyses have demonstrated that expectancy and ability/competence beliefs are indistinguishable (Wigfield & Eccles, 2000) and, as such, can be and for the purposes of this study are used interchangeably.

Aside from ability beliefs, inherent in expectancy-value models of behavior is the assumption that task value influences behavioral choices. Historically, Atkinson connected the value of engaging in a task to the degree of difficulty inherent in the task. Success at harder tasks was related to greater value (Weiner, 1985). Atkinson's conception has since been broadened to include both characteristics of the task and the needs, goals and values of the person (Parsons & Goff, 1980). The degree to
which a particular task is able to fulfill needs, to facilitate reaching goals, or to affirm personal values influences the usefulness a person attaches to engaging in that particular task. Eccles et al. (1984) further elaborated on the conceptualization of task value by defining it in terms of four major components: attainment value, intrinsic value, utility value, and cost. Attainment value refers to the importance of performing well on the task for one’s identity. This particular component is similar to autonomous self-regulated behavior in SDT. Intrinsic value represents the enjoyment one gets from engaging in the activity. Utility value denotes how useful the task is in reaching a variety of long- and short-term goals. Attainment, intrinsic and utility value have been found to predict motivational outcomes such as course enrollment decisions (Harackiewicz, Durik, Barron, Meece, Wigfield, & Eccles, 1990; Wigfield, 1994), self-reported effort in science classes (Cole, Bergin, & Whittaker, 2006; Mac Iver, Stipek, & Daniels, 1991), and classroom interest (Hulleman, Durik, & Schweigert, 2008). Lastly, cost is what is given up or suffered as a result of engaging in the activity. To the extent the amount of effort needed to succeed in college is perceived to interfere with other salient adult roles (e.g. marrying, parenting, working), the perceived cost of pursuing a degree should increase.

According to Wigfield and Eccles (2000), research on EVT indicates that ability beliefs are better predictors of achievement, while value beliefs better predict persistence. For example, Meece, Eccles and Wigfield (1990) found that students’ expectancies for success and valuing of mathematics predict their performance in mathematics and their choices of whether to continue studying math. In the study, efficacy expectations, defined as the belief that one can
successfully execute the required behavior to produce the outcomes, directly predicted math performance, whereas subjective task value significantly predicted taking math courses in the future. Similarly, Bong (2001) used longitudinal path analyses to show that in the long run self-efficacy predicted students’ academic achievement and task value factors predicted enrollment intentions. Other studies indicate that there is a relationship between perceiving task value and subsequent performance, perhaps both directly and indirectly. For example, Malka and Covington (2005) found that the relevance of schoolwork to student’s future goals predicted classroom performance, whereas Bong (2001) demonstrated that the perceived usefulness of a course predicted self-efficacy in the course, which in turn predicted exam performance. Consequently, the theory suggests a college student with higher perceived competence will naturally have a higher GPA, whereas a college student who has higher school value will be more engaged and continue to enroll in courses.

2.3 FIRST-GENERATION COLLEGE STUDENTS

Although there is no standard definition of first-generation college student, the most commonly used definition is a student whose parents (father or mother) do not have bachelor’s degrees (Davis, 2010). Some researchers more narrowly define first-generation college student as a student whose parents (father and mother) never attended college. Regardless of the definition used, multiple studies have found first-generation college students to be at a disadvantage and face additional obstacles in college compared to continuing-generation college students and these will be discussed in more detail below. Broadly, research on first-
generation college students generally falls into one of three categories (Terenzini, Springer, Yaeger, Pascarella, & Nora, 1996) that resemble the chronological order of the college-going process.

One category typically compares potential first-generation college students to potential continuing generation college students in terms of demographic characteristics, high school preparation, the college choice process, and college expectations (e.g. Stage & Hossler, 1989, York-Anderson & Bowman, 1991). This research focuses on middle school and high school students that would be classified as first-generation or continuing-generation if he or she decides to go to college. The weight of evidence from this research indicates that, compared to their peers, potential first-generation college students tend to be at a distinct disadvantage with respect to basic knowledge about postsecondary education (e.g., costs and application process), level of family income and support, educational degree expectations and plans, and academic preparation in middle school and high school. Stage and Hossler (1989) found a positive relation between several parental characteristics, including educational level, which had a significant effect on their expectations for the educational attainment of their ninth-grade children and, in turn, on their children's own educational plans. Among middle-school students, prospective first-generation college students had lower self-efficacy, lower academic expectations, and a higher number of perceived barriers to college than their peers whose parents had attended college (Gibbons & Borders, 2010). When the time comes to select a school, first-generation college students were less likely
to attend academically selective colleges and universities compared to continuing-generation college students (Pascarella, Pierson, Wolniak, and Terenzini, 2004).

A second category of research on first-generation college students attempts to describe and understand first-generation students in the first-year following the transition from high school to college (e.g., Lara, 1992; Rendon, 1992; Rendon, Hope, & Associates, 1996; Terenzini et al., 1994; Weis, 1992). The collegiate experience has been shown to differ markedly for freshmen first-generation college students compared to the experiences of their continuing-generation peers. York-Anderson and Bowman (1991) found differences between freshmen first-generation and continuing-generation students with respect to their basic knowledge of college, personal commitment, and level of family support, with first-generation students being at a disadvantage. As summarized by Terenzini et al. (1996), the deficit model applies to first-generation students as a group, as they have a more difficult transition from high school to college than their peers. Not only do first-generation students confront all the anxieties, dislocations, and difficulties of any college student, their experiences often involve substantial cultural as well as social and academic transitions. Padgett, Johnson, and Pascarella (2012) found freshmen first-generation college students to experience deficits in several cognitive (i.e., enjoyment of reading and writing activities) and psychosocial outcomes (i.e., intercultural effectiveness and psychological well-being) compared to continuing-generation college students. Community college first-generation college students in their first two years tended to work more hours per week, complete fewer credit hours, live off-campus, interact less frequently with their fellow college students.
outside of class, earn lower grades, and participate less in extracurricular activities, athletics, and volunteer work (Pascarella et al., 2004; Pascarella, Wolniak, Pierson, & Terenzini, 2003). In one particular study, Terenzini and his colleagues (1996) found that, compared to their peers, freshmen first-generation students completed fewer first-year credit hours, took fewer humanities and fine arts courses, studied fewer hours and worked more hours per week, were less likely to participate in an honors program, were less likely to perceive that faculty were concerned about students and teaching, and made smaller first-year gains on a standardized measure of reading comprehension. These significant differences persisted even in the presence of statistical controls for a battery of background or precollege characteristics such as tested ability, family economic status, degree aspirations, and high-school social involvement. Moreover, for freshman first-generation college students, interaction with faculty was negatively correlated with psychological well-being and a desire to engage in intentional cognitive activities. Conversely, continuing-generation college students’ interaction with faculty had a positive relationship with these developmental dimensions. The authors suggested that upon entrance to college first-generation college students are not as well equipped as their peers to derive the potential developmental benefits that stem from interactions with an institution’s faculty.

The third category of research on first-generation college students examines their persistence in college, degree attainment, and early career labor market outcomes (e.g., Attinasi, 1989; Berkner, Horn, & Clune, 2000; Billson & Terry, 1982; Choy, 2001; Horn, 1998; Nunez & Cuccaro-Alamin, 1998; Richardson & Skinner,
1992; Warburton, Bugarin, & Nunez, 2001). These investigations relatively consistently indicate that, compared to students whose parents are college graduates, first-generation students are more likely to leave a four-year institution at the end of the first year, less likely to remain enrolled in a four-year institution or be on a persistence track to a bachelor’s degree after three years, and are less likely to stay enrolled or attain a bachelor's degree after five years. One interesting exception is the 2001 National Center for Education Statistics study (Warburton, Bugarin, & Nunez, 2001), which showed no significant difference between the GPAs of first-generation and non-first-generation students after controlling for high school achievement and preparation. Rigorous academic preparation in high school seemed to play a substantial role in narrowing the gap in postsecondary outcomes between first-generation students and their peers whose parents graduated college. However, the analysis showed that parents’ levels of education were associated with rates of students’ retention and persistence in college, even when controlling for measures of academic preparedness. First-generation students were less likely than their peers whose parents had a bachelor’s degree to be enrolled at their initial institution three years later and to stay on the persistence track to a bachelor’s degree. As previously mentioned, Ishitani (2006) showed that first-generation students were half as likely to graduate within 4 years than students with college-educated parents. In several first-generation studies, researchers examine both predictors and risks for persistence. Duggan (2003) found that coming from a family where English is not the primary language had a negative effect on persistence. Similarly, Lohfink and Paulsen (2005) revealed that being a Hispanic first-
generation student, a lower-income first-generation student, or a female first-generation student, made the first-to-second year persistence more problematic. In addition, Somers, Woodhouse and Cofer (2004) used national data and found that first generation students from low-income and multiethnic backgrounds were less likely to persist. However, few, if any, studies have examined rural background among first-generation students.

Several studies have investigated the role of motivational constructs among first-generation students. Hellman (1996) demonstrated that first-generation students at a community college have lower perceived self-efficacy compared to students whose parents have some college experience. However, studies confirm the importance of motivation for first-generation students. Majer (2009) performed a longitudinal study to show that self-efficacy is an important cognitive resource among ethnically diverse first-generation students during the first two years of community college. Similarly, Prospero and Vohra-Gupta (2007) showed that among first-generation college students motivation contributed significantly to academic achievement. In fact, their research revealed that extrinsic motivation and amotivation for these students contributed significantly to lower grades. Using national data, Somers et al. (2004) found first-generation students became more likely to persist if they had high degree aspirations. Vuong and colleagues (2010) used multiple regression to show that college self-efficacy beliefs affect GPA and persistence rates of sophomore students, and first-generation college sophomores underperform compared to their second-generation peers in both GPA and persistence rates. Ramos-Sanchez and Nichols (2007) examined whether self-
efficacy mediated the relationship between generation status and two academic outcome indicators: academic performance and college adjustment. No mediation effect was found, but they did show that for college students in general high self-efficacy was related to college adjustment. Only one moderator analysis was found. In a closely related study, Aspelmeier et al. (2012) investigated the role of generational status as a moderator of the relationship between psychological factors (self-esteem and locus of control) and college outcomes (GPA and academic adjustment) among college students enrolled in an introductory psychology course. Generally, they found that the relationship between psychological factors and academic outcomes was strongest for first-generation students. Further, for the interactions with locus of control, first-generation status acted as a sensitizing factor that strengthened both the positive and negative effects of locus of control. For self-esteem, they found that first generation status acted as a risk factor that only worsened the negative effects of low self-esteem.

2.4 RURAL COLLEGE STUDENTS

Numerous studies on rural youth follow a rural deficit model, portraying them as disadvantaged due to the lower socioeconomic and occupational status of rural families (Meece, et al., 2013). Unfortunately, rural youth, compared to nonrural youth, are more likely to experience a narrow school curriculum and limited access to career counseling and college preparatory programs (Griffin, Hutchins, & Meece, 2011). Numerous studies suggest that these precollege factors (i.e., family income, parents’ education and educational expectations, and academic preparation) predict college enrollment, persistence, and completion (Adelman,
Byun, Irvin and Meece (2012) showed that family income, parental educational expectations and the rigor of the high school curriculum significantly predicted bachelor’s degree attainment among rural college students. Lapan (2004) also associated postsecondary degree attainment with pre-college schooling experiences, such as a rigorous curriculum, availability of A.P. courses, and services to promote career development. More specifically, Irvin et al. (2017) demonstrated that rural students take advanced math at a significantly lower rate than urban students. Compared with urban students, the researchers revealed that rural students have less change in their math achievement from tenth to twelfth grade and are less likely to be enrolled in a 4-year college two years postsecondary. Furthermore, the study explains these differences by advanced math course taking.

In contrast, several recent studies do not necessarily follow a rural disadvantaged model because positives exist for youth coming from rural environments. Rural communities are high in social capital due to small size, shared values and norms, and connections between families, schools and religious institutions (Crockett et al., 2000). Rural youth often experience unique forms of social capital, such as enduring and supportive student-teacher relationships and close community-school relationships (Schafft, Alter, & Bridger, 2006). Byun et al. (2012) investigated the relationship between social capital and educational aspirations of rural youth. In particular, results showed that process elements of family social capital, including parental expectations of the child to attend college, conversations with parents about how to pay for college, and discussions with
parents about careers and work, predicted rural youth’s educational aspirations. Meece et al. (2013) showed that a majority of rural youth wants to obtain a two- or four-year college degree, and they aspire to adulthood occupations requiring college degrees. Furthermore, Irvin et al. (2016) found students’ perceptions of their parents’ educational expectations indicated that most believed their parents wanted them to go to college. Aspiring to and earning a postsecondary degree may also help rural communities because college graduates provide financial return to local areas and volunteer more in their community (Irvin et al., 2016). Furthermore, parents of African American adolescents in high-poverty rural communities often want youth to use the knowledge and skills they acquired to better the community (Petrin, Farmer, Meece, & Byun, 2011).

Research on motivation and rural high school youth has highlighted the important role that perceived competence and instrumentality have on school completion and postsecondary plans (Hardre, Sullivan, & Crowson, 2009). Meece et al. (2014) similarly showed the importance of motivational variables in predicting gender-related aspirations of rural high school youth. Two studies (Irvin, Meece, Byun, Farmer, & Hutchins, 2011; Irvin, Byun, Meece, Reed, & Farmer, 2016) demonstrate how school value and perceptions of competence predict educational aspirations and achievement among rural youth. Only one study appears to examine rural youth under the umbrella of SDT. Hardre and Reeve (2003) use SDT to test a motivational model to explain the conditions under which rural students formulate their intentions to persist in, versus drop out of, high school. Results demonstrated that the provision of autonomy support within classrooms predicted rural high
school students’ self-determined motivation and perceived competence. These motivational resources, consequently, predicted students’ intentions to persist, even after controlling for the effect of achievement.

More research needs to be done on intrinsic motivation and perceived competence, particularly with regards to rural college students, and whether rural background may compound the relation of first generation status to college achievement. Only one study considered both first-generation status and rural status simultaneously (Schultz, 2004). This qualitative study showed that first-generation status generated numerous problems for the participants in their first semester, where as rural status contributed to the students’ affective concepts of disconnectedness. By investigating the interaction of first-generation and rural college students, this dissertation study will examine if rural status moderates the risk of being first-generation.

2.5 RACE/ETHNICITY AND SOCIOECONOMIC STATUS

In the fall of 1982, the College Board published a statistical report that includes a large number of tables profiling the differences among racial and ethnic segments of SAT test takers (CEEB, 1982). Since this controversial release, four decades of research have examined how and why race relates to academic achievement. With regards to this dissertation study, race greatly confounds the study of first-generation students and academic achievement. According to Davis (2010) first-generation students are more likely to be minorities. Furthermore, Black college students are more often from urban areas and their parents have fewer years of education, work at lower status jobs, and earn less (Blackwell, 1982;
Nettles, 1988). Thus, rural and urban background and family socioeconomic status may also be confounded by race.

Research has consistently shown at all levels of education that minorities, particularly Black students, struggle to match the academic achievement of their White counterparts. Surveys conducted by the National Center of Education Statistics (NCES) indicated that, on average, Black and Hispanic students lagged behind their White peers in terms of academic achievement (Vanneman, Hamilton, Anderson, & Rahman, 2009). Black students on predominantly White campuses do not fare as well as White students in persistence, academic achievement, postgraduate study, and overall psychosocial adjustments (Allen, Epps, & Haniff, 1991; Astin, 1982; Hall, Mays, & Allen, 1984; Nettles, 1988). Murtaugh, Burns, and Schuster (1999), for example, examined patterns of dropout across ethnic/racial groups. They found that although African-American and Latino/a students had higher dropout rates than White students, when groups were matched on entering preparation factors, these differences disappeared. Despite social, economic, and educational disadvantages, Black college students have aspirations similar to (or higher than) their White counterparts; however, they attain these aspirations less often than White students (Allen, 1992; Irvin, Byun, Meece, Reed, & Farmer, 2016; Kao & Thompson, 2003). African-Americans who attend predominantly White colleges apparently experience considerable adjustment difficulties. Some of their adjustment problems are common to all college students, while others are unique to Black students due to perceived isolation, alienation and lack of support (Allen, 1986; Becker & Luthar, 2002; Hinderlie & Kenny, 2002; Thomas, 1984).
Regarding the race effect, a number of researchers have found that African Americans, on average, exhibit lower educational achievement than their White counterparts (Allen, 1992; Allen, Epps, & Haniff, 1991; Entwisle & Alexander, 1992; Roscigno, 2000). There is not a consensus on what accounts for this relationship, but several explanations have been proposed. Ogbu (1986) argued that being members of a group that has suffered extensive discrimination and exploitation, African Americans, predicting that such treatment will continue, do not expect to benefit as much from hard work in school as Whites do. They, therefore, invest less time and effort into doing well in school than their White counterparts and, consequently, end up not doing as well. Numerous studies have explored why African-Americans may devalue effort and high achievement in school (Graham, Taylor, & Hudley, 1998; Osborne, 1997; Steele, 1997). Another explanation for the lower achievement of African Americans has to do with teacher expectations. If White teachers do not expect African American students to do as well as Whites, then they may treat African American students differently, leading to a self-fulfilling prophecy of low performance (Farkas, Lleras, & Maczuga, 2002). A third explanation, a variant of the teacher expectations view, is that African American students, to a greater extent than Whites, are regarded by teachers as coming to school with a demeanor, work habits, and attitudes that are not conducive for learning. For example, African Americans are viewed as absent more often, exerting less effort, more often inappropriately dressed, etc. (Battle & Lewis, 2002). Teachers’ negative evaluation of these practices leads them to give African American students lower grades even
though these practices may be unrelated to academic performance (Dee, 2005; Farkas, 2003, Ferguson, 2003; Steele, 1997; Steele & Aronson, 1995).

In addition to race, a positive relationship between socioeconomic status and achievement is often implicated in predicting educational outcomes (Battle & Lewis, 2002; Hedges & Nowell, 1999; Sirin, 2005). Sirin (2005) conducted a meta-analysis on socioeconomic status and academic achievement in articles published from 1990-2000. The results showed a medium to strong relationship between socioeconomic status and academic achievement. According to the meta-analysis, this relationship is contingent upon school level, minority status, and school location (urban, rural, etc.). A frequently encountered explanation for this finding is that high socioeconomic status students have parents who can afford to allocate resources to those endeavors that increase the likelihood that their children will do well in school (Kozol, 1991).

There is also the relative importance of these two variables, race and socioeconomic status, in tandem. Minorities are more likely to live in low-income households or in single parent families; their parents are likely to have less education; and they often attend under-funded schools (National Commission on Children, 1991). Battle and Lewis (2002) considered these variables simultaneously to determine if African American students get an equal benefit for increases in socioeconomic status. They found that 12th grade performance of whites was better than that of African Americans, even after controlling for socio-economic status. Also, 12th grade performance of high socioeconomic status students was greater than that of low status students. However, they showed that two years after high
school African Americans outperformed Whites when they controlled for socioeconomic status; however, African American students did not get the same return for increases in socioeconomic status. Similarly, using a nationally representative sample of eighth graders from the National Education Longitudinal Study of 1988 (NELS), Kao et al. (1996) found that Asians had the highest GPA (3.24) versus 2.96 for Whites, 2.74 for Hispanics, and 2.73 for Blacks. After taking parental education, income, household status, immigrant status, and prior experiences at school into account, the mean GPA of Hispanics was no longer significantly different, whereas the mean GPA of Asians was still moderately significantly different from that of Whites. The mean GPA of Blacks, on the other hand, remained statistically significantly lower than that of Whites. Thus, one can see that race and socioeconomic status muddle the study of academic achievement. Since first-generation students are more likely to be minority and more likely to be from lower socioeconomic levels (Davis, 2010), the current study must consider the effects of race and socioeconomic status on academic achievement. Without controlling for race and socioeconomic status, any significant first-generation findings may simply be disguising a minority or poverty effect. When Warburton et al. (2001) showed a significant difference in academic performance between first-generation college students and continuing generation college students, they only controlled for high school academic performance. Furthermore, Stephens et al. (2012) found social class, not first-generation status, to predict academic performance. This dissertation study will extend current research by examining generation status simultaneously with rural status, race/ethnicity, socioeconomic
status, and collegiate class to see if any interactions pose greater risks to students with regards to academic performance.

2.6 COLLEGIATE CLASS AND MOTIVATION

In the review of the literature, motivation definitely varies across collegiate class but results differ on the direction. Historically, longitudinal studies of motivation have focused on grade school students (Blackwell, Trzesniewski, & Dweck, 2007; Bong, 2001; Neel & Fuligni, 2013; Wang & Eccles, 2013). These studies overwhelmingly confirm that motivation decreases across the school years. Neel and Fuligni (2013) determined that school belonging and academic motivation decreased across the high school years, more for girls than boys. Gottfried (1985) showed that intrinsic motivation for both specific school subjects and a general orientation for learning decreased from elementary to junior high. Similarly, Ryan and Patrick (2001) demonstrated that both academic motivation and engagement decreased across middle school. Even when examining elementary students, Wigfield et al. (1997) proved that both competence beliefs and subjective task values decrease from kindergarten through third grade. Relatively little research has longitudinally focused on the motivation of college students. Of the studies that do exist, a few show that motivation decreases across college. Ryan and Deci (2000) were the first to show levels of motivation tend to decline as students progress from freshman to senior year. Brouse et al. (2010) performed a cross-sectional study rooted in self-determination theory to compare intrinsic and extrinsic motivation levels between freshmen and seniors. They found that freshmen had significantly higher levels of intrinsic motivation to know and to experience stimulation.
Furthermore, they discovered that freshmen had significantly higher levels of identified, introjected and external regulation extrinsic motivation.

Most motivation research at the collegiate level is focused on persistence. Tinto’s interactive model of student departure (1975) explains the longitudinal process of students departing from institutions of higher education. The theory argues that the process of student departure from colleges is a longitudinal process of interactions among students’ personal attributes, prior educational experiences, and academic and social systems that students experience in college. Thus, the likelihood of persistence is directly related to students’ academic and social involvement at different points in time in college. Since Tinto’s seminal work, other theorists have developed related models of attrition, including Astin’s (1984) theory of student involvement and Bean’s (1980) student attrition model. Research grounded in one of these three theories tends to show that students lacking academic involvement and/or motivation fail to persist to matriculation. For example, Allen (1999) utilized Bean’s model to show a significant motivational effect on persistence for minority students. Allen et al. (2008) considered the effects of motivation and social connectedness beyond the first year of college. They found that academic performance has significant effects on likelihood of retention and transfer. Furthermore, college commitment and social connectedness have direct effects on retention, while academic self-discipline led to greater first-year academic performance, which suppressed its effect on retention and transfer. Most collegiate research examines the persistence from the first to the second year. In one such study, Kuh et al. (2008) showed that engagement has a compensatory effect on first-
year grades and persistence to the second year of college at the same institution. In other words, the effects are even greater for lower ability students and minority students. Cruce, Wolniak, Seifert, and Pascarella (2006) noted the same compensatory effect of engagement in their study. In conclusion, these studies paint a different picture of motivation levels by collegiate class. Tinto, Astin, and Bean, as well as studies grounded in these theories, argue students lacking appropriate levels of motivation, engagement, and involvement fail to persist. More often than not, this dropout occurs between the first and second year of college. In terms of studying motivation levels across collegiate class, one would expect to see higher levels of motivation in older students because they have persisted. Regardless of the direction, collegiate class confounds the study of motivation. In order to appropriately handle this situation, collegiate class will be treated as an independent variable so that the interaction with the motivational profiles can be explored.

2.7 PERSON-ORIENTED APPROACH

Within the Magnusson-Berman (1997) tradition, a person-oriented approach is one in which the focus is to understand development at the individual level by regarding the individual as a functioning whole operating at a system level and his/her components jointly contributing to what happens in development. By components, Magnusson and Berman (1997) referred to behaviors, biological factors, perceptions, goals, and values, among other aspects that make up the structure of the individual. Theoretically, the person-oriented approach considers the components all together as the individual evolves over time. The methodological
aspects of the person-oriented approach focus on identifying a subsystem relevant to the problem under study, measuring its components, and studying them all together as an undivided whole, which is done by applying some type of pattern-oriented approach like cluster analysis or latent class analysis (Bergman & Trost, 2006). When employing this methodology, one cannot solely go on the success of the classification in summarizing the individuals’ value patterns. Meehl (1992) strongly advocates person-oriented approaches for finding “natural clusters”, by which the approximate mean classes are not simply good summaries of multivariate data but also exhibit validity and generalizability. For the statistical model to be informative, it must be constructed in such a way that its characteristics match the important aspects of the driving theory and its subsystems are interpretable in a theoretically meaningful way. Variable-oriented approaches describe how variables relate to other variables on average, but Molden and Dweck (2006) noted, “by attempting to describe only the average, one runs the risk of describing nobody in particular” (p. 192). Consequently, research questions concerning psychological phenomena often deal with a person as a unit of analysis. For this reason, person-oriented approaches have oft been utilized in motivation studies.

Risk refers to variables that predict problematic outcomes like underachievement (Irvin, 2012). Researchers typically assume uniform risk across a high-risk group of individuals, like first-generation college students (Pascarella, Pierson, Wolniak, & Terenzini, 2004; Warburton, Bugarin, & Nunez, 2001). Researchers have criticized the use of a distal risk factor (e.g. poverty, minority status) as inaccurate and stereotyping because many individuals within such groups
are not at risk (Farmer et al., 2004). The solution to this criticism lies in utilizing the person-oriented approach. Person-oriented risk research has found that risk is variable across individuals that some have deemed high risk due to their group membership (Farmer et al., 2004). Thus, the current study aims to see if some high-risk individuals (e.g. first-generation status, low SES, minority status) can show resilience by being a member of a motivationally well-adapted profile, meaning possessing higher amounts of perceived competence, perceived choice, and school value. Furthermore, person-oriented analysis will confirm the heterogeneity that exists within these populations.

Numerous studies have been conducted using person-centered analyses to reveal profiles of students on various motivational constructs (Chen, 2012; Conley, 2012; Roeser, Strobel, & Quihuis, 2002; Tuominen-Soini, Salmela-Aro, & Niemivirta, 2011; Viljaranta, Nurmi, Aunola, & Salmela-Aro, 2009). Roeser et al. (2002) used a person-oriented approach to show between group variation in classroom engagement as a function of different patterns of motivation and mental health among different subgroups of adolescents. The results were used to identify broad patterns of promise or problems during early adolescence. Conley (2012) employed cluster analysis to integrate achievement goal and expectancy-value perspectives. Results revealed more- and less-adaptive patterns of mastery and performance-achievement goals, task values, and competence beliefs. In a longitudinal study, Tuominen-Soini, Salmela-Aro, and Niemivirta (2011) used a person-centered approach to examine the stability and change in students’ achievement goal orientations within a high school year. Again, results confirm both adaptive and
maladaptive patterns of achievement goals. In another high school study Viljaranta et al. (2009) examined the kinds of patterns of task values adolescents show by subject material. The patterns of task-values predicted adolescents’ occupational and educational expectations. In a study on college students, Ratelle et al. (2007) performed a person-oriented analysis under the framework of SDT that revealed self-determined students with low levels of both controlled motivation and amotivation were more persistent than students in the other two less-autonomous groups. Across these studies, focusing more on individuals instead of variables allowed for the identification of homogenous groups of students who share similar motivational characteristics. Results also detail how between group differences lead to different educational processes and outcomes (e.g. performance, persistence).

Revealing more homogenous profiles of adaptive and maladaptive levels of motivation, as well as between group differences, is so important in the study of first-generation and rural college students. This is because while some first generation and rural students show incredible resiliency, others fail to persist. Only a person-centered analysis will capture the variability in adaptive and maladaptive patterns of motivation within different groups of first-generation and rural students, as well as how these and other characteristics (generation status, rurality, race, SES) may co-vary. Furthermore, this study will reveal differences in motivational profiles across collegiate class so that motivation will be better understood in those students who have persisted. Previous variable-oriented analyses show first-generation students have significantly lower academic achievement and are half as likely to persist. With rural college students, variable-oriented analyses reveal much more
heterogeneity. Some studies highlight challenges that rural students face when going to college (Guiffrida, 2008; Maltzan, 2006), while other studies depict a resilient rural student that is actually more likely to persist (Byun, Irvin, & Meece, 2012; Gibbs, 1998; Schonert, Elliott, & Bills, 1991). If a first-generation student, a rural student, or an upperclassman has more motivationally adaptive behavior, does this translate into higher academic achievement? Recall, Kuh et. al. (2008) and Cruce, Wolniak, Seifert, and Pascarella (2006) showed that engagement has a compensatory effect on first-year grades and persistence to the second year of college at the same institution. In other words, the effects are even greater for lower ability students and minority students. While some studies have examined interaction effects between first-generation college students and college experiences (Pascarella, Pierson, Wolniak, Terenzini, 2004; Terenzini, Springer, Yaeger, Pascarella, Nora, 1996), no study has employed the results of a latent profile analysis as a moderator. SDT and EVT in conjunction with the person-oriented perspective guide the hypothesis that more motivationally adaptive profiles will buffer first-generation or rural students against lower academic achievement. Numerous studies have validated SDT and EVT, demonstrating how ability beliefs, autonomous self-regulation for learning and subjective task value lead to higher academic performance and persistence. Integrating both theories, this study specifically tests how the latent profiles influence the strength of the relationship between generation or rural status and academic achievement. In doing so, this study uniquely considers the first-generation, rural college student at varying
collegiate classes and his/her motivational pattern(s). Figure 1 presents a graphic depiction of the hypothesized structural equation model estimated by the study.
Figure 2.1
Hypothesized SEM model where PC is Perceived Competence, PCh is Perceived Choice, SV is School Value, and FEH is Family Economic Hardship
CHAPTER 3

METHOD

3.1 PARTICIPANTS

Data for the dissertation study has been collected at a small southeastern regional university located in an urban area but surrounded by rural areas. Fall 2016 total enrollment was 5,821. The data consists of 719 students from beginning of the 2015 fall semester through the 2017 fall semester. In total 988 students were given the option of completing the survey, so the completion rate is 74%. The survey was emailed to fifteen professors across campus. These professors were selected because they represented varied majors and classes. The sample was gathered in cohorts. The first cohort was from Fall 2016, which included 344 (48%) of the total students. The second cohort was from Spring 2017, which added 49 (7%) to the total sample. This cohort was smaller due to the fact that only two classes were sampled. Realizing more data was needed, the last cohort was from Fall 2017, which provided 326 (45%) more students. Among the 719 students, 42% of the students are male and 54% of the students are female. Of the sample, 29% are juniors, 27% are sophomores, 23% are freshmen, and 15% are seniors. Students are primarily Caucasian (52%) or Black/African-American (29%). On average students worked 16 hours per week. Among the 719 students, 46% are first-generation, and 24% were
educated at a rural high school. Lastly, 89% of the students were business majors, as shown in Table 3.5.

Table 3.1
Demographics by cohort and in total

<table>
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<tr>
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<th>Fall 2016 Cohort</th>
<th>Spring 2017 Cohort</th>
<th>Fall 2017 Cohort</th>
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<td>115</td>
<td>307 (44%)</td>
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<tr>
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<td>23</td>
<td>203</td>
<td>395 (56%)</td>
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<td>364 (52%)</td>
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<td>37</td>
<td>71 (10%)</td>
</tr>
</tbody>
</table>

3.2 MEASURES

**Perceived Choice.** Individual differences in autonomy were assessed with Deci and Ryan's (1996) 5-item Perceived Choice Scale that assessed the degree to which the student feels a sense of choice in his or her life. Most studies assess perceived autonomy using items referencing perceived choice (Hollembeak & Amorose, 2005; Sheldon, Ryan, & Reis, 1996; Thrash, & Elliot, 2002). The scale has good internal consistency (alphas ranging from .85 to .93 in numerous samples) and adequate test-retest reliability ($r = .77$ over an 8-week period) (Sheldon, Ryan, &
Reis, 1996). For each item, participants were asked to indicate which of two statements is truer for them (e.g. “A. I sometimes feel that it’s not really me choosing the things I do.” And “B. I always feel like I choose the things I do”). Participants responded on a 1 (only A feels true) to 7 (only B feels true) scale. After recoding reversed items, participants’ responses were summed. Mean-centered values were used in the analysis. An exploratory factor analysis indicated that four of the items formed a single composite accounting for 54% of the variance. A confirmatory factor analysis, removing the one uncorrelated item, yielded a RMSEA of 0.132, indicating that the model was an adequate fit of the predicted structures for the data. Cronbach’s alpha demonstrated that internal consistency reliability was 0.81. Standardized item loadings ranged from .468 to .840.

**Perceived competence for learning.** The Perceived Competence Scale (PCS) is a short, 4-item questionnaire, and is one of the most face valid of the instruments designed to assess concepts from self-determination theory. Two examples of studies that have used the PCS are Williams, Freedman, and Deci (1998) for management of glucose levels among patients with diabetes and Williams and Deci (1996) for medical students learning the material in an interviewing course. The alpha measure of internal consistency for the PCS items in these studies was above 0.80. Items on the PCS are typically written to be specific to the relevant behavior or domain being studied. In the current study, the PCS assesses students’ feelings of competence about graduating from college. For each item, participants were asked to indicate how true the statement appeared to them (e.g. “I feel confident in my ability to graduate from college.” and “I am capable of learning the
material in my coursework in order to graduate from college”). Participants responded on a 1 (not at all true) to 7 (very true) scale. Participants’ responses were summed. Mean-centered values were used in the analysis. An exploratory factor analysis indicated these items formed a single composite accounting for 80% of the variance. A confirmatory factor analysis yielded a RMSEA of 0.19 and a WRMSR of 0.774, indicating that the model was a good fit of the predicted structures for the data. Cronbach’s alpha demonstrated that internal consistency reliability was .945. Standardized item loadings ranged from .892 to .980.

**School value.** The School Value Scale is a 12-item questionnaire that assessed the student’s value for school and whether he/she viewed it as a pathway for later opportunities in life (e.g. “School is one of the most important things in my life.” and “School is often a waste of time.”). Participants responded on a 1 (Strongly Disagree) to 5 (Strongly Agree) scale. The twelve items were adapted from previous measures created by Voelkl (1996), and Lapan et al. (2001), and used in studies by Voelkl (1997) and Irvin et al. (2011) (α = .88). Confirmatory factor analysis indicated that a two-factor model provided an adequate fit as the CFI was 0.937 and the SRMR was 0.06. The first factor was positive school value as the 7-items that loaded on this factor referred to the positive value of school (e.g. “most of what I learn in school will be useful when I get a job,” “the kind of education I’m getting here will help me later on,” and “dropping out of school would be a huge mistake for me”). Cronbach’s alpha demonstrated that internal consistency reliability was 0.868 for positive school value. The second factor was labeled as negative school value as these five items referred to students’ negative views of school (e.g. “many of the
things we learn in class are useless,” and “school is often a waste of time”). The seven positive school values items were summed for each individual. Mean-centered values were used in the analysis. Cronbach’s alpha demonstrated that internal consistency reliability was 0.754 for negative school value.

**Generation Status.** Students provided the highest degree each parent obtained. First-generation is operationally defined as neither parent having a Bachelor’s degree. A “2” in the data signifies at least one parent having a Bachelor’s degree, and a “3” is defined as both parents having a Bachelor’s degree and at least one parent having an advanced or professional degree. According to Davis (2010) who surveyed all published first-generation material in his book, individuals can claim first-generation status if neither of their parents possesses a four-year degree. Furthermore, Pascarella et al. (2004) used a tripartite scheme for a more fine-grained analysis of non-first-generation students. They defined high parental postsecondary education as both parents having a Bachelor’s degree or above. They defined moderate postsecondary education as one parent completing some college, but no more than one parent had a Bachelor’s. Lastly, first generation was defined as neither parent having any college experience. Consequently, the three-way definition employed by the current study utilizes the most popular definition of first-generation, but uses a bipartite structure to capture the other students. In the analysis, the variable was dichotomized where “1” represented a first-generation student, and a “2” represented a continuing generation student.

**Rurality.** Students provided their graduating high school with city and state. The location of the high school was captured by the metro-centric locale codes.
*Rural fringe* was a rural territory less than or equal to 5 miles from an urbanized area (i.e. densely settled area with a population of 50,000 or more) or less than or equal to 2.5 miles from an urban cluster (i.e. area with a population between 25,000 and 50,000). *Rural distant* was a rural territory that was more than 5 miles but less than or equal to 25 miles from an urbanized area or more than 2.5 miles but less than or equal to 10 miles from an urban cluster. *Rural remote* was a rural territory that was more than 25 miles from an urbanized area and more than 10 miles from an urban cluster. These three urban-centric names were coded as “rural”. *Town fringe* was a territory inside an urban cluster that is less than or equal to 10 miles from an urbanized area. *Town distant* was a territory inside an urban cluster that is more than 10 miles and less than or equal to 35 miles from an urbanized area. *Town remote* was a territory inside an urban cluster that is more than 35 miles from an urbanized area. These three urban-centric names were coded as “town”. *Suburb, Large* was a territory outside a principal city and inside an urbanized area with population of 250,000 or more. *Suburb, Midsize* was a territory outside a principal city and inside an urbanized area with population less than 250,000 and greater than or equal to 100,000. *Suburb, Small* was a territory outside a principle city and inside an urbanized area with population less than 100,000. These three urban-centric names were coded as “suburb”. *City, Large* was a territory inside an urbanized area and inside a principal city with population of 250,000 or more. *City, Midsize* was a territory inside an urbanized area and inside a principal city with population less than 250,000 and greater than or equal to 100,000. *City, Small* was a territory inside an urbanized area and inside a principal city with population less
than 100,000. These three urban-centric names were coded as “city”. In the analysis, the variable was dichotomized, such that a “1” represented a rural-educated student, and a “0” represented a non-rural educated student.

**Family economic hardship.** Family economic hardship, used as a proxy for socio-economic status, was assessed using 3-items adapted from Irvin, Byun, Meece, and Farmer (2012) (α = .88). This measure asked how often (1 = “never” to 5 = “all the time”) their family had “difficulty paying bills,” “buying important items,” and “buying things the family wants or needs.” These items are similar to measures of financial hardship in anti-poverty intervention research (Huston et al., 2001) and studies of rural families (Conger et al., 1999; Elder et al., 1995). Items were summed such that a higher score indicated more family economic hardship. An exploratory factor analysis indicated these items formed a single composite accounting for 80% of the variance. A confirmatory factor analysis yielded a RMSEA of near zero, indicating that the model was a good fit of the predicted structures for the data. Cronbach’s alpha demonstrated that internal consistency reliability was .90. Standardized item loadings ranged from .891 to .954.

**Dependent variable.** College GPA was obtained from Information Technology & Services at the end of the Fall 2017 semester.

**Control Variables.** To more accurately estimate the effects of the interaction between the motivational profiles and first-generation status, student-level characteristics were also included in the analysis as covariates. Student race/ethnicity, family economic hardship, high school GPA and collegiate class were selected from the survey as student-level covariates. First-generation students are
more likely to represent a minority race/ethnicity (Lohfink & Paulsen, 2005; Somers, Woodhouse, & Cofer, 2004), and they are more likely to work more hours than their peers with college-educated parents (Pascarella et al., 2004; Pascarella, Wolniak, Pierson, & Terenzini, 2003). Table 3.2 represents how race/ethnicity was coded in the analysis. Gender was coded such that “0” represented a male and “1” represented a female. Collegiate class was also dichotomized. Under classmen, defined as freshmen and sophomores, were coded as “0”, and upper classmen, defined as juniors and seniors, were coded as “1”.

Table 3.2. 
*Codes for Race/Ethnicity in the Analysis*

<table>
<thead>
<tr>
<th>Race</th>
<th>Code</th>
</tr>
</thead>
<tbody>
<tr>
<td>Caucasian</td>
<td>1</td>
</tr>
<tr>
<td>African-American</td>
<td>2</td>
</tr>
<tr>
<td>Latino/a</td>
<td>3</td>
</tr>
<tr>
<td>Asian</td>
<td>4</td>
</tr>
<tr>
<td>Other</td>
<td>5</td>
</tr>
</tbody>
</table>

Table 3.3 summarizes how each variable was treated in the analysis.

Table 3.3. 
*Variable Treatment*

<table>
<thead>
<tr>
<th>Variable</th>
<th>Treatment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Race/Ethnicity</td>
<td>5-level Categorical</td>
</tr>
<tr>
<td>Collegiate Class</td>
<td>Dichotomized, 0/1</td>
</tr>
<tr>
<td>Generation Status</td>
<td>Dichotomized, 1/2</td>
</tr>
<tr>
<td>Rurality</td>
<td>Dichotomized, 0/1</td>
</tr>
<tr>
<td>Family Economic</td>
<td></td>
</tr>
<tr>
<td>Hardship</td>
<td>Continuous</td>
</tr>
<tr>
<td>Competence</td>
<td>Mean-centered Continuous</td>
</tr>
<tr>
<td>Choice</td>
<td>Mean-centered Continuous</td>
</tr>
<tr>
<td>School Value</td>
<td>Mean-centered Continuous</td>
</tr>
<tr>
<td>HS GPA</td>
<td>Continuous</td>
</tr>
</tbody>
</table>
**Missing Data.** Missing data will be handled with full-information maximum likelihood estimation in Mplus. As one of the best missing-data coping approaches that are available currently (Acock, 2005; Enders, 2010; Molenberghs, et al., 2014), full-information maximum likelihood estimation provides maximum likelihood estimation under MCAR (missing completely at random), MAR (missing at random), and NMAR (not missing at random) for continuous, categorical, or the combinations of these variable types (Little & Rubin, 2002; Muthén & Muthén, 1998-2015).

3.3 ANALYTIC APPROACH

Structural equation modeling (SEM) is an appropriate statistical analysis for this dissertation study for several reasons. First, latent profile analysis needs to be employed to build the clusters that categorize the students based on perceived competence, self-determination and school value. Second, family economic hardship (an SES proxy) is being treated as a control variable. SEM can handle the measurement errors since SES is imperfectly measured by survey items. Third, SEM can estimate the relationship between the latent profiles on the outcome variable of academic achievement, showing potential causation. Correlational studies cannot demonstrate such cause-and-effect. Lastly, this study tests whether the latent profiles moderate the relationship between generation status and academic achievement. Again, SEM is ideal because it is the primary tool used to examine moderators among constructs or variables.
Latent profile analysis is a type of mixture modeling, and is based on the assumption that a sample includes a mixture of subpopulations. Mixture models are part of the GSEM framework (Muthén, 2002; Skrondal & Rabe-Hesketh, 2004) that allows for the estimation of relations between any type of continuous or categorical observed and latent variables. Structural equation modeling, as a variable-oriented framework, yields results reflecting a synthesis of relations observed in the total sample and assumes that all individuals are drawn from a single population. GSEM relaxes this assumption by considering the possibility that all or part of any SEM model can differ across subgroups of participants. These subgroups are referred to as latent profiles and are represented in the model as the various categories of an underlying categorical latent variable. These profiles are referred to as latent because they are represented by an unmeasured categorical variable where each category represents an inferred subpopulation. LPA is one form of mixture model that aims to describe subgroups of participants differing from one another on their pattern on a series of indicators (e.g., perceived competence, perceived autonomy, and school value). LPA is similar to factor analysis, except that the latent variable is categorical (reflecting profiles that represent groupings of individuals) rather than continuous (reflecting factors that represent groupings of variables) (Lubke & Muthén, 2005). Finally, LPA allows for the direct inclusion of covariates in the model, helping to limit Type I errors by combining analyses, meaning the profiles and the relationships are estimated in a single step. This direct inclusion of covariates has been shown to reduce biases in the estimation of the relationships between covariates and the latent profiles (Lubke & Muthén, 2007).
Overall, structural equation modeling offers the capabilities to 1) more accurately estimate standard errors; 2) analyze observed and latent predictors and covariates at the student level; 3) take into account measurement error; 4) make the estimation of causal relationships possible through meditational testing (Kline, 2016). Furthermore, by including the covariates of race, gender, and hours worked, SEM handles this like logistic regression so odds-ratios can be interpreted. The longitudinal data and rigorous statistical analysis will allow this dissertation study to provide students, faculty and administrators with a more comprehensive understanding of the heterogeneity within first-generation students. It will enable the development of an intervention at the university to maximize first-generation student persistence.

The current study requires several models to be assessed for adequate fit. First, a decision will be required during the exploratory latent profile analysis as to the optimal number of classes. Second, covariates will be run one at a time so odd-ratios can be interpreted across classes. Third, the structural equation model with the moderator will need to be evaluated for fit. As the interactions among rural status, generation status, and collegiate class is explored, fit indices will need to be assessed to make the best decision as to the number of independent variables. Lastly, fit will be gaged as different control variables are added to the model. Assessment of fit essentially calculates how similar the predicted data are to matrices containing the relationships in the actual data. Individual parameters must also be examined within the estimated model to see how well the proposed model fits the driving theory. Because different measures of fit capture different elements
of the fit of the model, I will report a selection of different fit measures. Akaike Information Criterion (AIC) is a test of relative model fit and rewards parsimony. The preferred model is the one with the lowest AIC. The Bayesian Information Criterion (BIC) is another parsimony index like AIC. Root Mean Square Error Approximation (RMSEA) is a fit index where a value of zero indicates the best fit. Most researchers concur that a RMSEA of 0.1 or higher indicates poor fit. Standardized Root Mean Residual (SRMR) is a popular absolute fit indicator. It is suggested 0.08 or smaller as a guideline of good fit. Comparative Fit Index (CFI) is another popular fit index. The CFI depends on the average size of the correlations in the data. If the average correlation between variables is not high, then the CFI will not be very high. A CFI value of 0.9 or higher is preferred. For each measure of fit, a decision as to what represents a “good enough” fit between the model and the data must reflect other factors such as sample size, the ratio of items to factors and the overall complexity of the model. The model may need to be modified in order to improve fit. Most output includes modification indices which can guide minor modifications. Modification indices report the change in chi-square that result from freeing fixed parameters; therefore adding a path to the model, which is currently set to zero. Modifications to a model, especially the structural model, are changes to the driving theory. Modifications therefore must make sense in terms of the theory or be recognized as limitations of that theory. For the exploratory latent class analysis, there are a few extra fit indices to consider. I will examine entropy, where values approaching one indicate clear delineation of classes. Similarly, the Lo-Mendell-Rubin likelihood test (LMR) is particularly useful. It compares the
estimated model with a model with one less class. Thus, a non-significant p-value suggests that the additional class does not result in a significant improvement in fit. Lastly, I will evaluate parameter estimates. For example, I will reject a model as having too many latent profiles if some of the profiles are associated with very small prevalences.

When estimating the motivational profiles, I will use the estimator MLR, which is an option for maximum likelihood estimation with robust standard errors. It is primarily used when data is particularly non-normal, as seen with the motivational constructs. In the ANALYSIS section of the code, the TYPE=MIXTURE command specifies that a mixture model will be fit. Maximum likelihood optimization is done in two stages. The STARTS 250 50; and STITERATIONS = 50; commands tell Mplus to generate in the first stage 250 different random starting values for the parameters and to do 50 iterations of the maximization for all of them. Then in the second stage, it takes the parameter estimates associated with the best 50 likelihood values obtained from those partial optimizations in the first stage and uses them as starting values for an optimization that continues until default convergence settings are satisfied. This part of the code guards against finding local maxima.

Once the optimal class solution has been determined, class probabilities will be used to assign each student to a class. Currently, the only way to utilize a LPA as a moderator is through modal assignment. Unfortunately this method is not perfect, as each student is assigned to only a dominant class. There remains probability that the student belongs to another class. For the purpose of this dissertation, the
smaller probabilities will be ignored, and the dominant class will be assigned. I will discuss this further in the limitations section of the discussion. In this portion of the analysis, 2-way, 3-way, and 4-way interactions will be coded. The Mplus ANALYSIS setting will be specified as TYPE=COMPLEX to adjust the standard errors in the model to account for non-independence of observations (Muthén & Muthén, 1998-2015). In all, the rigorous structural equation modeling analysis with the adjustment of dependency of data in my study offers the capabilities to more accurately estimate standard errors, take into account measurement errors, and make estimation of causal relationships possible (Kline, 2016). Therefore, findings of my dissertation study will allow University decision makers to design a more accurate, evidence-driven intervention for first-generation students.

Variable-oriented analyses will also be run so as to compare results with the person-oriented analysis. Multiple regression will be run in Minitab on all motivational constructs, as well as significant predictors found in the structural equation modeling. According to Bergman and Trost (2006), person-oriented approaches should complement variable-oriented approaches. Even though the classes may significantly predicted end-of-semester GPA, I want to explore whether the motivational variables themselves will predict end-of-semester GPA. I want investigate how the motivational constructs predict end-of-semester GPA given all other significant predictors in the model. Since several predictors are categorical, Minitab is being used for the anlaysis. Minitab uses a coding scheme to make indicator variables out of the categorical predictor. Thus, I will be able to see specifically if certain classes or races predict end-of-semester GPA.
Table 3.4.
*Descriptive statistics for variables*

<table>
<thead>
<tr>
<th>Variable</th>
<th>Sample Size</th>
<th>Mean</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Standard Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gender</td>
<td>675</td>
<td>0.56</td>
<td>0.00</td>
<td>1.00</td>
<td>0.02</td>
</tr>
<tr>
<td>Age</td>
<td>703</td>
<td>20.74</td>
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<td>59.00</td>
<td>0.15</td>
</tr>
<tr>
<td>Race/Ethnicity</td>
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<td>1.90</td>
<td>1.00</td>
<td>5.00</td>
<td>0.05</td>
</tr>
<tr>
<td>Collegiate Class</td>
<td>675</td>
<td>0.47</td>
<td>0.00</td>
<td>1.00</td>
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<tr>
<td>Generation Status</td>
<td>705</td>
<td>1.54</td>
<td>1.00</td>
<td>2.00</td>
<td>0.02</td>
</tr>
<tr>
<td>Rurality</td>
<td>674</td>
<td>0.25</td>
<td>0.00</td>
<td>1.00</td>
<td>0.02</td>
</tr>
<tr>
<td>Family Economic Hardship</td>
<td>696</td>
<td>5.31</td>
<td>0.00</td>
<td>15.00</td>
<td>0.11</td>
</tr>
<tr>
<td>Competence</td>
<td>705</td>
<td>24.57</td>
<td>4.00</td>
<td>28.00</td>
<td>0.18</td>
</tr>
<tr>
<td>Choice</td>
<td>705</td>
<td>18.83</td>
<td>5.00</td>
<td>25.00</td>
<td>0.16</td>
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<tr>
<td>School Value</td>
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<td>29.12</td>
<td>9.00</td>
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</tr>
<tr>
<td>HS GPA</td>
<td>559</td>
<td>3.23</td>
<td>1.28</td>
<td>4.84</td>
<td>0.03</td>
</tr>
<tr>
<td>College GPA</td>
<td>670</td>
<td>2.99</td>
<td>0.00</td>
<td>4.00</td>
<td>0.02</td>
</tr>
</tbody>
</table>

Table 3.5.
*Percent representation by major*

<table>
<thead>
<tr>
<th>Major</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Art Studio</td>
<td>1.0%</td>
</tr>
<tr>
<td>Biology</td>
<td>0.5%</td>
</tr>
<tr>
<td>Business Administration</td>
<td>89.1%</td>
</tr>
<tr>
<td>Communications</td>
<td>0.6%</td>
</tr>
<tr>
<td>Computer Information Systems</td>
<td>0.2%</td>
</tr>
<tr>
<td>Criminal Justice</td>
<td>0.1%</td>
</tr>
<tr>
<td>Engineering Technology Mgmt</td>
<td>1.2%</td>
</tr>
<tr>
<td>Exercise &amp; Sport Science</td>
<td>0.7%</td>
</tr>
<tr>
<td>Experimental Psychology</td>
<td>0.4%</td>
</tr>
<tr>
<td>Information Mgmt and Systems</td>
<td>3.1%</td>
</tr>
<tr>
<td>Interdisciplinary Studies</td>
<td>2.8%</td>
</tr>
<tr>
<td>Mathematics</td>
<td>0.1%</td>
</tr>
<tr>
<td>Nursing</td>
<td>0.1%</td>
</tr>
</tbody>
</table>
CHAPTER 4

RESULTS

4.1 LATENT PROFILE ANALYSIS

**Exploratory Latent Profile Analysis.** Latent profile analysis (LPA) was employed to obtain typologies of motivation within this university sample, and then relate these typologies to the specific outcome measure, GPA, as well as interactions with other independent variables aforementioned. LPA first utilizes all observations that are associated with the dependent variables (the three motivational constructs) and performs maximum likelihood estimation. LPA also allows for the probability of an individual’s membership in a motivational profile to be estimated in the same model as the estimation of that profile (Hill, Degnan, Calkins, & Keane, 2006). The flexibility of LPA accounts for the likelihood that there is uncertainty in class membership by allowing both prediction of the probability of membership in a particular group while simultaneously estimating the motivational classes. Consequently, each individual’s probability of class membership can be estimated so the person may be classified into the most appropriate class (Hill, Degnan, Calkins, & Keane, 2006). Although the points of the distribution are occupied by individuals in different latent classes, it is up to the analysis interpretations, in light of possible covariates and substantive theory, to decide if these classes can be seen as
substantively different categories or simply representative of a single, non-normal distribution (Muthén, 2006). As a result of the flexibility and maximal information accounted for within this analysis, LPA was utilized to derive the optimal number of motivational typologies within this university sample.

Before the analysis, mean-centered, summed values of perceived competence, perceived choice, and school value were assessed for normality. In all three cases, the Anderson-Darling test confirmed non-normal data. Due to non-normality, the MLR estimator was used for the exploratory latent profile analysis. Robust standard errors associated with the maximum likelihood estimates are output because of the inclusion of the ESTIMATOR=MLR command. LPA was used to investigate the plausibility of 2-, 3-, 4-, and 5-class solutions. Classes were added iteratively to determine the best model fit for the data according to both statistical and interpretive perspectives. The purpose of this analysis was to derive latent classes that describe different categorical types of participants based on the response pattern associated with continuously measured observed variables. LPA assumes a simple parametric model and uses the observed data to estimate parameter values for the model (Mplus, Version 8). Model fit was evaluated using the Lo-Mendell-Rubin Adjusted Likelihood Ratio Test (LMRT) that is a statistical indicator of the number of classes that best fit the data. The LMRT statistically compares the fit of a target model (e.g. a 3-class model) to a model that specifies one fewer class (e.g. a 2-class model). P-values less than .05 indicate that the “higher class” solution fits better (e.g. 3-class better than the 2-class). P-values greater than .05 indicate the “lower class” solution fits better. The Vuong-Lo-Mendell-Rubin
Likelihood Ratio Test and the Parametric Bootstrap Ratio Test are two more similar tests used in the decision of fit. Both the Akaike Information Criterion (AIC) and the sample-size adjusted Bayesian Information Criterion (BIC) were also examined to ascertain the optimal class solution. Optimal model fit is defined by lower AIC and BIC values. Finally, the Entropy criterion was also examined. Entropy is an index that determines the accuracy of classifying people into their respective profiles, with higher values (i.e. closer to 1.0) indicating that this solution fits better. Table 4.1 contains the AIC, BIC, LMRT, Vuong-Lo-Mendell-Rubin Ratio Test, Parametric Bootstrap Test, and Entropy values for the latent profile analyses conducted.

Table 4.1  
*Fit Values for the Different Class Solutions*

<table>
<thead>
<tr>
<th></th>
<th>2-class</th>
<th>3-class</th>
<th>4-class</th>
<th>5-class</th>
</tr>
</thead>
<tbody>
<tr>
<td>Loglikelihood</td>
<td>-6054.39</td>
<td>-5968.11</td>
<td>-5900.77</td>
<td>-5866.41</td>
</tr>
<tr>
<td>AIC</td>
<td>12128.77</td>
<td>11964.22</td>
<td>11837.53</td>
<td>11776.82</td>
</tr>
<tr>
<td>BIC</td>
<td>12174.35</td>
<td>12028.03</td>
<td>11919.58</td>
<td>11877.10</td>
</tr>
<tr>
<td>Sample-Size Adjusted BIC</td>
<td>12142.60</td>
<td>11983.58</td>
<td>11862.43</td>
<td>11807.25</td>
</tr>
<tr>
<td>Entropy</td>
<td>0.91</td>
<td>0.92</td>
<td>0.92</td>
<td>0.94</td>
</tr>
<tr>
<td>Vuong-Lo-Mendell-Rubin p-value</td>
<td>&lt;0.01</td>
<td>0.01</td>
<td>0.19</td>
<td>0.10</td>
</tr>
<tr>
<td>Lo-Mendell-Rubin p-value</td>
<td>&lt;0.01</td>
<td>0.01</td>
<td>0.20</td>
<td>0.10</td>
</tr>
<tr>
<td>Parametric Bootstrap p-value</td>
<td>&lt;0.01</td>
<td>&lt;0.01</td>
<td>&lt;0.01</td>
<td>&lt;0.01</td>
</tr>
</tbody>
</table>

LPA revealed that the 3-class solution was better than the 2-class solution, evidenced by the significance of the LMRT and Vuong-Lo-Mendell-Rubin test. The 3-class solution was considered better than the 2-class solution due to both lower AIC and BIC values, a higher Entropy value, and a significant LMRT value. The 4-class solution, despite having slightly lower AIC and BIC values than the 3-class solution, was not statistically different from the 3-class solution according to the LMRT and Vuong-Lo-Mendell-Rubin test. The same result held true for the 5-class solution as.
well. As a result, the 3-class solution was deemed the best-fitting model. Class 1 was composed of 134 students (19%), Class 2 was composed of 24 individuals (3.4%), and Class 3 was composed of 547 students (77.6%).

To substantively interpret each class, the conditional response means and the overall sample means were evaluated (see Table 4.2 and Figure 4.1). For class 1, perceived competence was one standard deviation below the mean (z-score = -1.21), and school value was nearly half a standard deviation below the mean (z-score = -0.45). Thus, this profile class was referred to as low competence and value students. Interpretation of the conditional response means indicated that class 2 reflected individuals who had extremely low perceived competence and very low school value. For class 2, perceived competence was over three standard deviations below the mean (z-score = -3.23), and school value was two standard deviations below the mean (z-score = -2.01). Accordingly, this class was referred to as very low competence and value students. Conditional response means indicated that class 3 reflected individuals who possess above average levels of perceived competence. For class 3 perceived competence was nearly half a standard deviation above the mean (z-score = 0.45). Consequently, this class was referred to as high competence students. This final model without any covariates was used to generate conditional probabilities that give the probability for being a member of each latent class and the class assigned for the individual. These were used in the regression analyses to follow. Covariates were not included in the final model because they were used as control variables in the regression analysis; however, covariates were analyzed with regards to the latent profile analysis.
Table 4.2
Motivational Profile Conditional Response Means and Overall Sample Means

<table>
<thead>
<tr>
<th>Motivational Construct</th>
<th>Sample Mean (n=705) (SD)</th>
<th>Class 1: Low Competence and Value Students (n=134) (SD)</th>
<th>Class 2: Very Low Competence and Value Students (n=24) (SD)</th>
<th>Class 3: High Competence Students (n=547) (SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Perceived Competence</td>
<td>0 (4.65)</td>
<td>-5.61 (2.11)</td>
<td>-15.01 (2.11)</td>
<td>2.08 (2.11)</td>
</tr>
<tr>
<td>Perceived Choice</td>
<td>0 (4.19)</td>
<td>-1.86 (4.08)</td>
<td>-1.33 (4.08)</td>
<td>0.53 (4.08)</td>
</tr>
<tr>
<td>School Value</td>
<td>0 (5.16)</td>
<td>-2.33 (4.58)</td>
<td>-10.39 (4.58)</td>
<td>1.06 (4.58)</td>
</tr>
</tbody>
</table>

Note. LCV is Low Competence and Value Class, VLCV is Very Low Competence and Value Class; HC is High Competence Class

Figure 4.1
Motivational Profile Conditional Response Means

Covariates as predictors of class membership. To further describe the latent classes, covariate analyses were conducted to determine whether class membership could be predicted by characteristics of individuals. Five different types of demographic variables were used: generation status, rural status, race, family economic hardship, and collegiate class. Recall, generation status was dichotomously coded where one signified first-generation. Rural status was dichotomously coded where one signified rural-educated. Race was coded as a five-
level categorical variable where one was Caucasian, two was African-American, three was Latino/a, four was Asian, and five was other. Family economic hardship was a continuous variable where higher values signified greater hardship. Lastly, collegiate class was dichotomously coded where one signified upperclassmen. Covariates were added to the model one variable at a time. After each addition, the models were examined to make sure the fit statistics and classification probabilities continued to significantly improve. Satorra-Bentler log likelihood difference tests were utilized to make sure that each covariate was a significant predictor of class composition in the model. The test statistic must be calculated manually by using Satorra-Bentler scaled chi-square values from the null model (base model) and the alternative model (base model with covariate added). The results of the significance tests for covariates are shown in Table 4.3. All demographic variables were found to be significant.

Table 4.3
Satorra-Bentler Log Likelihood Difference Tests for Covariates

<table>
<thead>
<tr>
<th>Covariate</th>
<th>Parameters Estimated</th>
<th>Satorra-Bentler Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Generation Status</td>
<td>16</td>
<td>419.55**</td>
</tr>
<tr>
<td>Rural Status</td>
<td>18</td>
<td>505.46**</td>
</tr>
<tr>
<td>Race</td>
<td>20</td>
<td>1116.74**</td>
</tr>
<tr>
<td>Family Economic Hardship</td>
<td>22</td>
<td>292.17**</td>
</tr>
<tr>
<td>Collegiate Class</td>
<td>24</td>
<td>239.57**</td>
</tr>
</tbody>
</table>

**p<.01

Covariate Analyses. The results of the covariate analyses are shown in Table 4.4.
Table 4.4
Logistic Regression Log Odds for Covariates

<table>
<thead>
<tr>
<th></th>
<th>Generation Status</th>
<th>Rural Status</th>
<th>African-American</th>
<th>Family Economic Hardship</th>
<th>Collegiate Class</th>
</tr>
</thead>
<tbody>
<tr>
<td>Very Low Competence And Value Class</td>
<td>1.86*</td>
<td>0.43**</td>
<td>0.79*</td>
<td>1.20**</td>
<td>0.91</td>
</tr>
<tr>
<td>Low Competence and Value Class</td>
<td>0.72</td>
<td>1.60</td>
<td>1.20*</td>
<td>1.18**</td>
<td>1.34</td>
</tr>
</tbody>
</table>

*p<.05; **p<.01
Note. The high competence class was used as the reference class

Generation status, rural status, race, family economic hardship and collegiate class were run one at a time as covariates on the three-class solution using multinomial logistic regression. With regards to generation status and using the high competence class as the reference class, continuing generation students have 1.9 times greater odds of being in the very low competence and value class ($OR = 1.86$, $p = .043$). Non-Rural educated students have 2.3 times greater odds of being in the very low competence and value class compared to rural educated students ($OR = 0.43$, $p < .001$). African-Americans have 1.2 times greater odds of being in the low competence and value class ($OR = 1.20$, $p = .002$) but Caucasians have 1.3 greater odds of being in the very low competence and value class ($OR = 0.79$, $p = .004$). For each unit increase in family economic hardship (i.e. going from 1 to 2, 2 to 3, etc.) the odds are 1.2 times more likely that the student will be in the low competence and value class and the very low competence ($OR = 1.18$, $p = .005$) and value class ($OR = 1.20$, $p = .038$). Thus, a student with a family economic hardship score of ten is twelve times more likely to be in the low competence and value class. With regards to collegiate class, no log odds were found to be significant.
Subsequently, I examined generation status, rural status, and race differences between the three classes. Analyses of variance (ANOVAs) were run to determine whether generation status, rural status, or race explained a significant portion of the variation in the conditional means of perceived competence, perceived choice, and school value. After running these ANOVAs, only a few significant differences were found. First-generation students have significantly lower perceived competence compared to continuing generation students across the three classes (F = 145.95, $\eta^2 = .243, p = .0347$). No significant differences were found between rural and non-rural educated students. As for race, African-American students have significantly lower perceived competence (F = 42.20, $\eta^2 = .441, p = .0195$) and school value (F = 17.85, $\eta^2 = .142, p = .0492$) compared to Caucasians in the low competence and value class, as well as the very low competence and value class. Tables 4.3, 4.4, and 4.5 show the conditional mean differences across the classes for each of these variables.

Table 4.5

*Conditional Mean Differences Across the Classes By Generation Status*

<table>
<thead>
<tr>
<th></th>
<th>Low Competence and Value Class</th>
<th>Very Low Competence and Value Class</th>
<th>High Competence Class</th>
</tr>
</thead>
<tbody>
<tr>
<td>First generation</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Competence</td>
<td>-6.0*</td>
<td>-18.4*</td>
<td>2.1</td>
</tr>
<tr>
<td>Choice</td>
<td>-2.2</td>
<td>-1.5</td>
<td>0.7</td>
</tr>
<tr>
<td>Value</td>
<td>-2.0</td>
<td>-8.5</td>
<td>1.0</td>
</tr>
<tr>
<td>Continuing generation</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Competence</td>
<td>-4.7</td>
<td>-13.4</td>
<td>2.2</td>
</tr>
<tr>
<td>Choice</td>
<td>-1.3</td>
<td>-1.5</td>
<td>0.4</td>
</tr>
<tr>
<td>Value</td>
<td>-2.5</td>
<td>-10.0</td>
<td>1.1</td>
</tr>
</tbody>
</table>

*p<.05
Table 4.6
*Conditional Mean Differences Across the Classes By Rural Status*

<table>
<thead>
<tr>
<th></th>
<th>Low Competence and Value Class</th>
<th>Very Low Competence and Value Class</th>
<th>High Competence Class</th>
</tr>
</thead>
<tbody>
<tr>
<td>Non-rural</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Competence</td>
<td>-5.8</td>
<td>-15.2</td>
<td>1.9</td>
</tr>
<tr>
<td>Choice</td>
<td>-1.7</td>
<td>-0.6</td>
<td>0.4</td>
</tr>
<tr>
<td>Value</td>
<td>-2.7</td>
<td>-7.1</td>
<td>1.0</td>
</tr>
<tr>
<td>Rural</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Competence</td>
<td>-4.3</td>
<td>-15.1</td>
<td>2.4</td>
</tr>
<tr>
<td>Choice</td>
<td>-1.2</td>
<td>-2.4</td>
<td>0.9</td>
</tr>
<tr>
<td>Value</td>
<td>-2.0</td>
<td>-13.4</td>
<td>1.2</td>
</tr>
</tbody>
</table>

Table 4.7
*Conditional Mean Differences Across the Classes By Race*

<table>
<thead>
<tr>
<th></th>
<th>Low Competence and Value Class</th>
<th>Very Low Competence and Value Class</th>
<th>High Competence Class</th>
</tr>
</thead>
<tbody>
<tr>
<td>Caucasian</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Competence</td>
<td>-4.5</td>
<td>-12.9</td>
<td>2.2</td>
</tr>
<tr>
<td>Choice</td>
<td>-1.1</td>
<td>-1.9</td>
<td>0.9</td>
</tr>
<tr>
<td>Value</td>
<td>-1.7</td>
<td>-7.9</td>
<td>1.1</td>
</tr>
<tr>
<td>African-American</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Competence</td>
<td>-7.6*</td>
<td>-18.6*</td>
<td>2.0</td>
</tr>
<tr>
<td>Choice</td>
<td>-1.7</td>
<td>0.5</td>
<td>0.3</td>
</tr>
<tr>
<td>Value</td>
<td>-4.0*</td>
<td>-14.1*</td>
<td>1.0</td>
</tr>
</tbody>
</table>

*p<.05

I also ran several chi-square tests on the covariates to examine whether the covariates were related to the latent classes. This goodness-of-fit statistic measures how well the observed distribution of the data fits with the distribution that is expected if the variables are independent. Table 4.6 summarizes the chi-square statistic for each of the categorical covariates.
Table 4.8
*Chi-Square Results for Each of the Covariates*

<table>
<thead>
<tr>
<th>Covariate</th>
<th>Chi-square Statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Generation Status</td>
<td>4.49</td>
</tr>
<tr>
<td>Rural Status</td>
<td>8.40</td>
</tr>
<tr>
<td>Collegiate Year</td>
<td>4.00</td>
</tr>
<tr>
<td>Race</td>
<td>21.49**</td>
</tr>
</tbody>
</table>

**p<.01

Only race had a significant p-value ($\chi^2 = 21.49, p = .005$), which says that the classes depend on race.

Lastly, using the class probabilities and class assignment, each individual was assigned to a class. The end-of-semester GPA was then regressed on the classes to see if the motivational typologies predicted GPA. The low competence and value class ($b = 0.199, se = .153, p = .0138$) and the high competence class ($b = 0.486, se = 0.145, p = .0009$) significantly predict end-of-semester GPA. Table 4.7 summarizes the conditional mean GPA for each class.

Table 4.9
*Conditional Mean GPA for Each Latent Class*

<table>
<thead>
<tr>
<th>Low Competence and Value Class</th>
<th>Very Low Competence and Value Class</th>
<th>High Competence Class</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean (SD)</td>
<td>Mean (SD)</td>
<td>Mean (SD)</td>
</tr>
<tr>
<td>GPA</td>
<td>2.57 (0.60)</td>
<td>2.78 (0.68)</td>
</tr>
</tbody>
</table>

4.2 INITIAL STRUCTURAL EQUATION MODEL

Built on the latent profile analysis, the structural equation model incorporated regressions among variables, including generation status, rural status, and collegiate class. In predicting end-of-semester GPA, I controlled for race/ethnicity, high school GPA, and family economic hardship. I also explored
several interaction terms, including rurality and generation status, generation status and the latent classes, and race and the latent classes. The model yielded excellent fit, $\chi^2(15) = 302.59$, AIC = 727.75, BIC = 800.13, CFI = 1.00, and RMSEA = 0.00. Table 4.8 summarizes the slopes and associated $p$-values. All of the control variables, race ($b = -0.05, se = 0.02, p = 0.006$), high school GPA ($b = 0.53, se = 0.03, p < 0.001$), collegiate class ($b = -0.10, se = 0.05, p = 0.028$), and family economic hardship ($b = -0.02, se = 0.01, p = 0.018$), were significant. As already expected, the low competence and value class ($b = -0.33, se = 0.72, p = 0.017$) and the high competence class ($b = -0.05, se = 0.02, p = 0.006$) significantly predicted end-of-semester GPA. The interaction of race on the low competence and value class ($b = 0.06, se = 0.05, p = 0.032$) was significant, as well as the interaction of generation status on the low competence and value class ($b = 0.27, se = 0.12, p = 0.025$). No other variables or interactions were significant in this model.

Table 4.10

<table>
<thead>
<tr>
<th></th>
<th>Estimate</th>
<th>s.e.</th>
<th>$p$-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Race</td>
<td>-0.05</td>
<td>0.02</td>
<td>0.01</td>
</tr>
<tr>
<td>HS GPA</td>
<td>0.53</td>
<td>0.03</td>
<td>0.00</td>
</tr>
<tr>
<td>Family Economic Hardship</td>
<td>-0.02</td>
<td>0.01</td>
<td>0.02</td>
</tr>
<tr>
<td>Collegiate Class</td>
<td>-0.10</td>
<td>0.05</td>
<td>0.03</td>
</tr>
<tr>
<td>Rural Status</td>
<td>-0.02</td>
<td>0.17</td>
<td>0.90</td>
</tr>
<tr>
<td>Generation Status</td>
<td>-0.05</td>
<td>0.05</td>
<td>0.32</td>
</tr>
</tbody>
</table>
Another model was run exploring a three-way interaction between race, generation status and the latent profiles. This model also had good fit, RMSEA = 0.064, CFI = 0.978, TLI = 0.941, and SRMSR = 0.024. Table 4.9 summarizes the slopes and associated p-values for each of the variables. For first-generation students, race \((b = -0.09, \text{se} = 0.03, p = .011)\), the low competence and value class \((b = -0.25, \text{se} = 0.11, p = .026)\), the high competence class \((b = -0.09, \text{se} = 0.03, p = .011)\), and high school GPA \((b = 0.57, \text{se} = 0.05, p < .001)\) significantly predict end-of-semester GPA. For continuing generation students, the low competence and value class \((b = -0.25, \text{se} = 0.11, p = .026)\), high school GPA \((b = 0.50, \text{se} = 0.04, p < .001)\), and family economic
hardship ($b = -.02, se = 0.01, p = .034$) significantly predict end-of-semester GPA.

There is a significant difference in the slopes for each generation status across race ($b = .08, se = 0.03, p = .015$). Consequently, first-generation students of every race/ethnicity have significantly lower end-of-semester GPAs than continuing-generation students of every race/ethnicity. More details about the meanings of these interactions will be discussed in the next chapter.

Table 4.11  
*Slopes and p-values for Model Including a 3-way Interaction*

<table>
<thead>
<tr>
<th></th>
<th>Estimate</th>
<th>s.e.</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>First-Generation Students</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Race</td>
<td>-0.09</td>
<td>0.03</td>
<td>0.01</td>
</tr>
<tr>
<td>HS GPA</td>
<td>0.57</td>
<td>0.05</td>
<td>&lt;0.01</td>
</tr>
<tr>
<td>Family Economic Hardship</td>
<td>-0.01</td>
<td>0.01</td>
<td>0.23</td>
</tr>
<tr>
<td>Collegiate Class</td>
<td>-0.12</td>
<td>0.07</td>
<td>0.07</td>
</tr>
<tr>
<td>Rural Status</td>
<td>0.00</td>
<td>0.08</td>
<td>0.97</td>
</tr>
<tr>
<td>Very Low Competence and Value Class</td>
<td>-0.38</td>
<td>0.25</td>
<td>0.13</td>
</tr>
<tr>
<td>Low Competence and Value Class</td>
<td>-0.25</td>
<td>0.11</td>
<td>0.03</td>
</tr>
<tr>
<td>Race*Very Low Competence and Value Class</td>
<td>0.08</td>
<td>0.17</td>
<td>0.65</td>
</tr>
<tr>
<td>Race*Low Competence and Value Class</td>
<td>0.05</td>
<td>0.05</td>
<td>0.28</td>
</tr>
<tr>
<td><strong>Continuing Generation Students</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Race</td>
<td>-0.01</td>
<td>0.02</td>
<td>0.55</td>
</tr>
<tr>
<td>HS GPA</td>
<td>0.50</td>
<td>0.04</td>
<td>&lt;0.01</td>
</tr>
<tr>
<td>Family Economic Hardship</td>
<td>-0.02</td>
<td>0.01</td>
<td>0.03</td>
</tr>
<tr>
<td>Collegiate Class</td>
<td>-0.09</td>
<td>0.06</td>
<td>0.15</td>
</tr>
</tbody>
</table>
### Generation Status Across Race

<table>
<thead>
<tr>
<th></th>
<th>Rural Status</th>
<th>Very Low Competence and Value Class</th>
<th>Low Competence and Value Class</th>
<th>Race*Very Low Competence and Value Class</th>
<th>Race*Low Competence and Value Class</th>
<th>Difference in slopes</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>-0.02</td>
<td>0.06</td>
<td>0.80</td>
<td>-0.38</td>
<td>0.25</td>
<td>0.13</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.11</td>
<td>0.03</td>
</tr>
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<td></td>
<td></td>
<td></td>
<td>0.08</td>
<td>0.17</td>
</tr>
<tr>
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<td></td>
<td>0.05</td>
<td>0.05</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.08</td>
</tr>
</tbody>
</table>

### 4.3 FINAL STRUCTURAL EQUATION MODEL

In the final model, only known significant variables were added to the model. This final model provides a more concise analysis and estimates of focal constructs. Thus, this model employed the control variables, race, family economic hardship, and high school GPA, as well as collegiate class and the latent profile classes. The interaction between race and the latent classes was also included. The final model had excellent fit with AIC = 737.66, BIC = 780.42, CFI = 1.00, and RMSEA = 0.00. This model explains 44% of the total variation in end-of-semester GPA. Table 4.10 summarizes the slopes and p-values of the final model. All variables were significant, including the slope of the low competence and value class across race and the slope of the high competence class across race. Figure 4.3 demonstrates the interaction between race and the latent classes on GPA.
For minorities in the low competence and value class, they have significantly lower end-of-semester GPAs than their Caucasian counterparts ($b = -0.20, se = 0.022, p = 0.044$). On the other hand, minority students in the high competence class had significantly higher end-of-semester GPAs than minority students in the low competence and value class, but minority students in the high competence profile had significantly lower end-of-semester GPAs than their Caucasian counterparts ($b = -0.06, se = 0.02, p = 0.007$).

**Table 4.12**

*Slopes and p-values for the Final Model*

<table>
<thead>
<tr>
<th>Variables</th>
<th>Estimate</th>
<th>s.e.</th>
<th>p-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Race</td>
<td>-0.05</td>
<td>0.02</td>
<td>0.01</td>
</tr>
<tr>
<td>Model</td>
<td>Estimate</td>
<td>Standard Error</td>
<td>p-value</td>
</tr>
<tr>
<td>-------------------------------</td>
<td>----------</td>
<td>----------------</td>
<td>---------</td>
</tr>
<tr>
<td>Family Economic Hardship</td>
<td>-0.02</td>
<td>0.01</td>
<td>0.02</td>
</tr>
<tr>
<td>Collegiate Class</td>
<td>-0.10</td>
<td>0.05</td>
<td>0.04</td>
</tr>
<tr>
<td>HS GPA</td>
<td>0.59</td>
<td>0.05</td>
<td>&lt;0.01</td>
</tr>
<tr>
<td>Low Competence and Value Class</td>
<td>-0.36</td>
<td>0.12</td>
<td>0.04</td>
</tr>
<tr>
<td>Very Low Competence and Value Class</td>
<td>-0.28</td>
<td>0.31</td>
<td>0.02</td>
</tr>
<tr>
<td>Race*Low Competence and Value Class</td>
<td>0.04</td>
<td>0.05</td>
<td>0.65</td>
</tr>
<tr>
<td>Race*Very Low Competence and Value Class</td>
<td>0.04</td>
<td>0.22</td>
<td>0.38</td>
</tr>
<tr>
<td>Intercepts</td>
<td>GPA</td>
<td>3.41</td>
<td>0.00</td>
</tr>
<tr>
<td>Interaction slopes</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Slope of Low Competence and Value Class across race</td>
<td>-0.20</td>
<td>0.22</td>
<td>0.04</td>
</tr>
<tr>
<td>Slope of Very Low Competence and Value Class across race</td>
<td>0.00</td>
<td>0.05</td>
<td>0.93</td>
</tr>
<tr>
<td>Slope of High Competence Class across race</td>
<td>-0.06</td>
<td>0.02</td>
<td>0.01</td>
</tr>
</tbody>
</table>
4.4 VARIABLE-ORIENTED ANALYSIS

According to Bergman and Trost (2006), person-oriented approaches should complement variable-oriented approaches. Even though the classes significantly predicted end-of-semester GPA, I wanted to explore whether the motivational variables themselves would predict end-of-semester GPA. Table 4.11 summarizes the slopes and p-values for the multiple regression.

Table 4.11
Slopes and p-values for Multiple Regression Using Motivational Variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Estimate</th>
<th>S.E.</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>HS GPA</td>
<td>0.51</td>
<td>0.03</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Family Economic Hardship</td>
<td>-0.02</td>
<td>0.01</td>
<td>0.02</td>
</tr>
<tr>
<td>Under Classmen</td>
<td>0.09</td>
<td>0.14</td>
<td>0.53</td>
</tr>
<tr>
<td>Upper Classmen</td>
<td>-0.16</td>
<td>0.14</td>
<td>0.25</td>
</tr>
<tr>
<td>African-American</td>
<td>-0.25</td>
<td>0.05</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Latino/a</td>
<td>0.01</td>
<td>0.10</td>
<td>0.91</td>
</tr>
<tr>
<td>Asian</td>
<td>-0.01</td>
<td>0.10</td>
<td>0.39</td>
</tr>
<tr>
<td>Other</td>
<td>-0.11</td>
<td>0.08</td>
<td>0.14</td>
</tr>
<tr>
<td>Perceived Competence</td>
<td>0.01</td>
<td>0.01</td>
<td>0.03</td>
</tr>
<tr>
<td>School Value</td>
<td>0.01</td>
<td>0.01</td>
<td>0.02</td>
</tr>
<tr>
<td>Perceived Choice</td>
<td>0.01</td>
<td>0.01</td>
<td>0.27</td>
</tr>
</tbody>
</table>

As was the case with the person-oriented analysis, high school GPA and family economic hardship were both significant. Interestingly, collegiate class was no longer significant. With regards to race, African-American status significantly predicted end-of-semester GPA. Lastly, two of the motivational variables, perceived competence and school value, were significant predictors, which confirms variable-oriented expectancy-value research (Bong, 2001; Malka & Covington, 2005; Meece, Eccles & Wigfield, 1990).
CHAPTER 5
DISCUSSION

Using Self-Determination Theory and Expectancy-Value Theory, this short-term longitudinal study examined the degree to which perceived competence, perceived choice, and school value could moderate academic achievement among first-generation college students and rural-educated college students. Specifically, my study employed a person-oriented approach to develop motivational profiles for the college students in the sample. I then ran multiple structural equation models exploring various interactions among the variables, including generation status with rural status, the latent profiles with generation status, the latent profiles with race, and the latent profiles with both race and generation status. Lastly, I ran a variable-oriented multiple regression model to investigate the degree to which the variable-oriented and person-oriented approaches agree. Results from the analyses yielded five main findings. First, the latent profile analysis resulted in a three-class solution. With regards to the solution, demographics predicted class membership, and demographics provided significant probabilities for inclusion in the classes. Second, a structural equation model exploring only two-way interactions among the variables revealed control variables and the classes as significant predictors of end-of-semester GPA, as well as conditional effects with race and generation status. Interestingly, generation status was not a significant predictor of end-of-semester
GPA. Third, a structural equation model incorporating a three-way interaction among race, generation status and the latent profiles revealed varying significance among the control variables depending on generation status. Fourth, in the final structural equation model incorporating only significant variables, results show that the latent profiles serve as a moderator for race on end-of-semester GPA. Finally, the variable-oriented multiple regression confirmed results of the final structural equation model, as well as previous expectancy-value research. Perceived competence and school value, along with control variables, significantly predict end-of-semester GPA. This chapter discusses each of these findings, along with implications of the results, limitations, and suggestions for future research.

5.1 CHARACTERIZING THE THREE-CLASS SOLUTION

One of the primary goals of the current study was to identify motivational typologies in college students using constructs from self-determination theory and expectancy-value theory. Secondarily, the emergent motivational typologies classified college students based on their patterns of motivation and related these classes to end-of-semester GPA. Overall, the study found three motivational profiles that represented a large sample of college students. Two of the three groups can be characterized according to the traditional dimensions of perceived competence and school value (Pintrich, 1989, Conley, 2012). However, a third class (very low perceived competence and value) is not represented by existing motivational taxonomies. Interestingly, perceived choice was not a significant factor in any of the classes. In other words, all three classes demonstrated average perceived choice. This contradicts the typologies found by Vansteenkiste et. al. (2009) when they
examined motivational profiles solely according to self-determination theory. In their study, they found four clusters with varying degrees of perceived autonomy and controlled motivation. The difference between the two studies likely stems from the scale utilized for measuring autonomy. I used a proxy for perceived autonomy, namely Deci and Ryan’s 5-item Perceived Choice Scale, where as Vansteenkiste et al. used Deci and Connell’s 16-item Academic Self-Regulation Scale.

Overall, race and generation status explained significant variation in the conditional means across all three of the typologies. First-generation students had significantly lower perceived competence across all three classes. In fact, generation status explained 24% of the variation in perceived competence conditional means. This is in line with Hellman’s (1996) study that showed first-generation college students have lower perceived self-efficacy compared to continuing-generation college students. Furthermore, African-American students had significantly lower perceived competence and school value compared to Caucasian students across all three classes. Race (as either Caucasian or African-American) explained 44% of the variation in perceived competence conditional means. Similarly, it explained 14% of the variation in school value conditional means. This could support Ogbu’s (1986) theory that African Americans do not expect to benefit as much from hard work in school as Whites do, and, therefore, invest less time and effort into doing well in school. It could also imply that African American college students do not value school as much because of lower perceived competence. In fact, nonparametric results confirm that the classes are dependent on race. This replicates the
dependence Conley (2012) found between her motivational clusters and ethnicity, but her sample primarily included Latino/a and Vietnamese students.

**High Competence Class.** The largest class (78%) had significantly above average perceived competence, and both average perceived choice and school value. This class possessed a heterogeneous mix of students. In fact, 76% of all first-generation students appeared in this class. Furthermore, 68% of all minorities were in this motivationally well-adapted class. These percentages demonstrate that though first-generation and minority background are often viewed from a deficit perspective this indicates that a majority of such youth are well-adapted in terms of motivation. This class had the highest conditional mean GPA (3.05) among the three classes. From previous research, this typology was expected. Conley (2012) utilized a person-oriented approach to integrate achievement goal and expectancy-value perspectives. She measured perceived competence and task value in middle school math classrooms. She found seven clusters with her very large sample ($n = 1,870$), and three of the clusters possessed high competence. However, she did not do any significance testing on the conditional means. In fact, only two of the clusters had perceived competence at least half a standard deviation above the mean. Furthermore, Conley labeled a cluster as high competence and high task value, but the task value conditional mean was not significantly above the true mean. Technically, she had one high-perceived competence cluster that mirrored mine because the two high competence clusters had the same conditional mean.

**Low Competence and Value Class.** The second largest class (19%) had significantly below average perceived competence and below average school value.
Perceived competence was approximately one standard deviation below the mean, while school value was half of a standard deviation below the mean. This class had the lowest predicted end-of-semester GPA of 2.57, which was two-thirds of a standard deviation below the average GPA. This class contained 22% of all first-generation students, and it was represented by 15% of the African-Americans. In fact, Black students had a 55% greater chance of being in this class compared to White students (using the High Competence Class as the reference class). This result confirms the numerous studies that have explored African Americans devaluing effort and high achievement in school (Graham, Taylor, & Hudley 1998; Osborne, 1997; Steele, 1997). Furthermore, the conditional mean family economic hardship in this class was half a standard deviation below the mean. For each point increase in family economic hardship, a student had a 55% greater chance of being in the class (using the High Competence Class as the reference class). Conley (2012) also found a cluster that possessed low perceived competence and task value. For her low cluster, the conditional means of perceived competence and school value were a full standard deviation below the mean. Pintrich (1989) also found a cluster that was low in both intrinsic motivation and task value. As previously stated, due to previous research, this motivational typology was expected.

**Very Low Competence and Value.** The smallest class (3%) had significantly below average perceived competence and below average school value. The conditional mean for perceived competence was approximately three standard deviations below the mean, and the conditional mean for school value was approximately two standard deviations below the mean. This motivational typology
has not been seen in previous research. Both Pintrich (1989) and Conley (2012) found only one low cluster that matched the conditional means for the Low Competence and Value Class. While the predicted end-of-semester GPA was low for this group (2.78), it was not as low as the GPA for the Low Competence and Value Class. Furthermore this class did not significantly predict end-of-semester GPA, like the other two classes. This non-significance could be due to a power problem since the class only contains 24 students. Overall, Caucasians comprised 62% of this class. In fact, White students had a 57% greater chance of being in this class compared to Black students (using the High Competence Class as the reference class). This is an interesting result because combining this result with the fact African-Americans are more likely to be in the Low Competence and Value Class, it appears African-American students can somewhat devalue school, but Caucasian students can devalue school a lot. Similarly, non-rural-educated students comprised 61% of this class. They had a 70% greater chance of being in this class compared to rural-educated students (using the High Competence Class as the reference class). As for generation status, continuing-generation students comprised 75% of this class, and they had a 66% greater chance of being in this class compared to first-generation students (using the High Competence Class as the reference class). Lastly, socioeconomic status did play a role in this class. For each point increase in family economic hardship, a student had a 55% greater chance of being in the class (using the High Competence Class as the reference class). Thus, if a student had a family economic hardship score of ten (where 15 is the maximum score), then he/she has a 92% chance of being in this class (using the High Competence Class as the reference class).
class). This class has not been seen in existing research; in fact, it even contradicts variable-oriented studies (Anderman & Midgley, 1997; Miserandino, 1996). However, results must be cautiously interpreted due to the small size of the class. Miserandino (1996) demonstrated that lower perceived competence predicted lower test scores in third and fourth graders, where as Anderman and Midgley (1997) demonstrated the same result with sixth graders. Interestingly, Conley (2012) found that her low competence and value cluster did not have significantly lower achievement from one of her average clusters, which matches the end-of-semester GPA anomaly seen here.

5.2 THE INITIAL STRUCTURAL EQUATION MODEL

**Two-Way Interactions.** The first structural equation model employed the control variables (race, high school GPA, family economic hardship, and collegiate class), the latent profiles, generation status, and rural status, as well as all two-way interactions between generation status, rural status, race and collegiate class. As expected, all control variables were significant predictors of end-of-semester GPA. Race was negatively significant. With all other variables held to zero, the unique effect of race was negative. This may reflect previous research that Black students on predominantly White campuses do not fare as well as White students in academic achievement (Allen, Epps, & Haniff, 1991; Nettles, 1988; Vanneman, Hamilton, Anderson, & Rahman, 2009). This study cannot confirm these results as this study only includes one campus. To confirm the results, a future study would need multiple campuses with each of the student distributions and then test if there is a difference across several predominantly White campuses. With all other
variables held to zero, the unique effect of family economic hardship was negative two-hundredths of a GPA point for each incremental increase in family economic hardship. Thus, a student with a family economic hardship score of ten (with a maximum score of 15) could see a predicted GPA two-tenths lower than a student with no family economic hardship. This supports the results of Sirin’s (2005) meta-analysis showing a medium to strong relationship between socioeconomic status and academic achievement. Lastly, among the control variables, with all other variables held to zero, as a student moved from underclassman to upperclassman, the predicted GPA decreased by a tenth of a GPA point. This is likely explained by taking upper division courses, as opposed to general education requirements. Both the High Competence Class and the Low Competence and Value Class significantly predicted end-of-semester GPA. A student moving from the High Competence Class to the Low Competence and Value Class would see a predicted drop of seven-tenths of a GPA point. This supports the variable-oriented expectancy-value theory studies linking perceived competence and task value to academic achievement (Bong, 2001; Malka & Covington, 2005; Meece, Eccles, & Wigfield, 1990). This also corroborates Conley’s (2012) person-oriented research that showed lower perceived competence, lower utility value, and higher perceived cost resulted in lower academic achievement among seventh graders. The interaction between race and the Low Competence and Value Class was significant. Thus, the effect of the Low Competence and Value Class on end-of-semester GPA is different for each race. Similarly, the interaction between generation status and the Low Competence and Value Class was significant, implying that the effect of the Low Competence and
Value Class on end-of-semester GPA is different for first-generation students. With both of these interactions, minorities and first-generation students in the Low Competence and Value Class have lower predicted GPAs compared to their Caucasian and continuing-generation counterparts, respectively.

Rarely in a discussion does a researcher spend time talking about the non-significant variables, but the non-significant variables are of great interest to this study. One must be cautious when interpreting the null effect because one cannot be sure if there really is no significant difference or if the study simply did not have the power to detect. First, generation status did not significantly predict end-of-semester GPA. This contradicts a study by Strayhorn (2006) where he showed first-generation status significantly explains differences in GPA after controlling for a gamut of precollege and college factors. However, he did not control for high school GPA, only SAT score. Furthermore, he defined first-generation as a student whose parents never attended college, where as this study defines first-generation as not having a parent with a Bachelor’s degree. Furthermore, Strayhorn used the Baccalaureate and Beyond national database, whereas the current study uses a local sample that could lead to different results. The current results do support the National Center for Education Statistics study by Warburton, Burgarin, and Nunez (2001), which showed no significant difference between the GPAs of first-generation and continuing-generation students after controlling for high school achievement and preparation. Furthermore, the current study defines first-generation identically to Warburton et al., as a student whose parents do not have a 4-year degree. Unlike Strayhorn’s national database study, this national sample led
to similar results of the current study. The results of this study suggest that
generation status is a marker for other variables. In other words, generation status
captures other influences, like minority status and socioeconomic level. Aside from
generation status, rural status was also a non-significant predictor of end-of-
semester GPA. This is in line with current research on rural-educated college
students. Several studies show that precollege factors, including family income,
parents’ education and educational expectations, and academic preparation, predict
college enrollment, persistence, and completion (Adelman, 2006; Bozick, 2007;
Byun, Irvin, & Meece, 2012; Goldrick-Rab & Pfeffer, 2009; Lapan, 2017). In other
words, the precollege factors are the significant variables, which explain why rural
status is not significant after controlling for race, family economic hardship, and
high school GPA.

One of the primary aims of the current study was to explore the interaction
between generation status and rural status. In particular, this dissertation study
examined whether rural background compounded the relation of first-generation
status to college achievement. In the end, 24% of the sample was rural-educated. Of
those 24%, 43% were first-generation students. However, like generation status and
rural status individually, the interaction of the two variables was non-significant.
This is a unique contribution of this study, as no quantitative research exists that
examines the confounding impact of both rural background and first-generation
status. The current study demonstrates that control and motivational variables are
the more focal constructs.
5.3 RACE, GENERATION STATUS AND LATENT CLASS INTERACTION

The second structural equation model took significant variables from the first model and added a three-way interaction between race, generation status and the latent profiles. For first generation students, race, high school GPA, and collegiate class were significant control variables. With all other variables held to zero, first-generation upperclassman compared to first-generation underclassmen have a significant decrease in predicted GPA. This is interesting as it may be a factor that plays into the lower persistence seen among first-generation in a multitude of studies (Attinasi, 1989; Berkner, Horn, & Clune, 2000; Billson & Terry, 1982 Choy, 2000; Horn, 1998; Nunez & Cucarro-Alamin, 1998; Richardson & Skinner, 1992; Warburton et al., 2001). These studies repeatedly show that first-generation students struggle with persistence after their freshman year compared to continuing-generation students. The current study shows that GPA is lower for upperclassmen first-generation students, which could factor into the lower persistence among this group of college students. Aside from the control variables, the High Competence Class and the Low Competence and Value Class significantly predicted GPA. A first-generation student moving from the High Competence Class to the Low Competence and Value Class had a predicted decrease in GPA of nearly three-tenths of a GPA point. These results both confirm and contradict previous variable-oriented research on first-generation students. Majer (2009) showed that self-efficacy is an important resource among ethnically diverse first-generation students during the first two years of community college. The above results confirm that first-generation students in the High Competence Class have higher end-of-
semester GPAs than first-generation students in the Low Competence and Value Class. Furthermore, this study supports the work by Prospero and Vohra-Gupta (2007) that demonstrated that among first-generation college students motivation contributed significantly to academic achievement. The unique contribution of this study is in showcasing the inherent heterogeneity among first-generation students. For example, Vuong and colleagues (2010) used multiple regression to show that college self-efficacy beliefs affect GPA, and first-generation students underperform compared to their continuing-generation peers. The current study argues against that conclusion, as first-generation students in the High Competence Class are outperforming their continuing-generation peers in the Low Competence and Value Class with regards to end-of-semester GPA. Again, this points to the heterogeneity of first-generation students that can only be explored with a person-oriented approach.

For continuing-generation students, the control variables of race, high school GPA, and family economic hardship significantly predicted end-of-semester GPA. This result supports numerous studies that have shown that race, socioeconomic status and high school preparation are predictors of academic achievement (Battle & Lewis, 2002; Kao et. al., 1996). For continuing-generation students, the High Competence Class and the Low Competence and Value Class were also significant predictors of GPA, as was the case for first-generation students. This result validates a multitude of variable-oriented studies involving expectancy-value theory (Bong, 2001; Malka & Covington, 2005; Meece, Eccles, & Wigfield, 1990). For example, Bong (2001) showed that self-efficacy predicted students’ academic achievement and task
value factors predicted enrollment intentions. Furthermore, Meece, Eccles, and Wigfield (1990) demonstrated that low expectancies for success undermined performance in mathematics. With both first-generation students and continuing generation students, there was a significant drop in predicted GPA when moving from the High Competence Class to the Low Competence and Value Class. As Bergman and Trost (2006) recommend, this person-oriented study supports the results seen from variable-oriented studies. The advantage of the current study is that it does more than trends a variable. Motivational typologies of students demonstrate the heterogeneity that exists among first-generation students, minority students, and low socioeconomic students. Whereas variable-oriented research tends to show all of these groups at a disadvantage compared to their respective counterparts. The current study reveals that the risk profile stemming from variable-oriented research can be averted by being in the High Competence Class.

Lastly, this structural equation model explored a three-way interaction among generation status, race, and the latent classes. While no significant difference was found for the Low Competence and Value Class or the Very Low Competence and Value Class, a significant difference did exist for the High Competence Class. First-generation, minority students in the High Competence Class have significantly lower end-of-semester GPAs than continuing-generation, minority students. Race serves as a risk factor for continuing-generation students, as minorities have lower predicted GPAs than their Caucasian counterparts. However, first-generation status and minority status together is a double risk factor that weakens the positive effects of high perceived competence. This result does support the work by Vuong and
colleagues (2010) that showed first-generation college students underperform compared to their continuing-generation peers in GPA with self-efficacy held equal. The current study contradicts the moderator study by Aspelmeier et. al. (2012). In their study, they found that first-generation status acted as a risk factor that only worsened the negative effects of low self-esteem. This study did not find that to be the case as there was no significant difference between first-generation students in the Low Competence and Value Class and continuing-generation students in the Low Competence and Value Class. However, this study did find a significant difference by race and generation status in the High Competence Class. Due to the significantly negative slopes, race is a risk factor that weakens the positive effects of perceived competence across both first-generation and continuing generation students. While the impact is significantly greater for first-generation students, the overall impact is much less in the High Competence Class. In other words, perceived competence works to buffer minorities and first-generation students. To date, no research has quantitatively explored the interaction among race, generation status and motivational typologies. This dissertation is contributing to existing research by revealing a double risk factor even when high-perceived competence is present.

5.4 FINAL STRUCTURAL EQUATION MODEL

After exploring several different models, the final model gives a more precise analysis of the focal constructs. Overall, this model explains 44% of the total variation in end-of-semester GPA. All control variables remained significant, including race, high school GPA, family economic hardship, and collegiate year. All three latent classes significantly predicted end-of-semester GPA. Interestingly, the
negative impact was greater for students in the Low Competence and Value Class compared to the Very Low Competence and Value Class. Variable-oriented studies have typically shown a linear relationship between perceived competence and school value on academic achievement (Bong, 2001; Malka & Covington, 2005; Meece, Eccles, & Wigfield, 1990). In other words, one would expect students in this extreme motivationally mal-adjusted class to have the lowest predicted GPAs. However, as previously stated, this motivational typology is new compared to other expectancy-value, person-oriented studies (Conley, 2012; Pintrich, 1989). Furthermore, this class represents only 3% of the sample or 21 students. While they are significantly different from the students in the other classes, their representation is too small to draw any major conclusions about this motivational typology. Lastly, this final model included the interaction between race and the latent profiles to explore a potential moderator relationship. High competence served to buffer minority students from lower academic achievement. In other words, minority students had lower predicted GPAs than their Caucasian counterparts in the Low Competence and Value Class. Minorities in the High Competence Class had significantly higher predicted GPAs than students in the Low Competence and Value Class, but their GPAs were still lower than their Caucasian counterparts in the High Competence Class. While minorities are at a disadvantage compared to their Caucasian peers, this disadvantage is significantly less for minorities in the high competence profile.

This result concerning African-American students coincides with previous race and motivation research (Allen, 1992; Harris-Britt, Valrie, Kurtz-Costes &
Rowley, 2007; Hudley & Graham, 2001; Ogbu, 1992; Ogbu, 2004; Rowley, Sellers, Chavous & Smith, 1998; Solorzano, Ceja & Yosso, 2000, Wong & Eccles, 2003). Graham (1989) performed a meta-analysis showing that Whites have higher achievement needs than Blacks, Whites were reported to be more internal than Blacks, and Black children attach less value to effort as a cause of achievement outcomes. With regards to academic achievement, Wong and Eccles (2003) demonstrated that experiences of racial discrimination at middle school from one’s teachers and peers predicted declines in grades, academic ability self-concepts, and academic task values. Ogbu (1992, 2004) has extensively studied how African-Americans navigate the academic environment. He has argued that a minority group’s cultural frame of reference and collective identity may lead its members to interpret the cultural and language differences they encounter as barriers to be overcome or as markers of group identity to be maintained (1992). He refers to five different types of minority group behavior: assimilationists, accommodators without assimilation, ambivalents, resisters, and the encapsulated (2004). Ambivalents, resisters and the encapsulated will all resist “acting White”, which academically refers to making good grades, studying, doing homework, and enrolling in advanced coursework. Furthermore, Black students receive peer pressure from the Black community for the above-mentioned “White” behaviors, but they also receive other unrelated peer pressure that contributes to low school performance (2004). The way a student perceives and responds to events in the college setting will differentiate his or her college experience and shape his or her college outcomes. Characteristics of the individual and characteristics of the
institution combine to influence academic performance, extent of social involvement, and occupational goals. Allen (1992) showed that students who attended historically Black universities reported better academic performance, greater social involvement, and higher occupational aspirations than Black students who attended predominantly White institutions. On predominantly White campuses, Black students emphasize feelings of alienation, sensed hostility, racial discrimination, and an overall lack of integration (Allen, 1992). Solorzano (2000) performed a critical race theory qualitative study revealing that faculty has low expectations that instill self-doubts among Black students. All of the students in the study reported a generalized feeling of discomfort and racial tension as a result of microaggressions experienced both inside and outside the classroom on predominantly White campuses. Fischer and Shaw (1999) worked with college students to reveal a significant negative relationship between perceived racism and overall mental health. Research shows Blacks on predominantly White campuses can be buffered from the discrimination by racial identity, messages about race pride and preparation for bias (Harris-Britt, Valrie, Kurtz-Costes & Rowley, 2007; Rowley, Sellers, Chavous & Smith, 1998). Rowley et al. (1998) showed that racial identity explains a significant portion of the variability in global self-esteem. Similarly, Harris-Britt et al. (2007) demonstrated that messages about race pride and preparation for bias moderate the relationship between discrimination and self-esteem in 8th grade African-American students. This study shows that perceived competence can buffer minorities from decreased academic achievement, but more research needs to be done on to see if perceived competence buffers these students
from perceived racial discrimination. More research needs to be completed to better understand how the predominantly White campus can promote racial identity and perceived competence in its Black students.

In a related study on risk factors, Aspelmeier et al. (2012) showed that first-generation status was a risk factor worsening the negative effects of low self-esteem. However, in their regressions they did not control for race. By controlling for race, high school GPA, family economic hardship, and collegiate class, this study failed to show any significance between generation status and academic achievement or between interactions comprising generation status and the latent profiles. One major contribution of the current study is that no study has employed a person-oriented approach to study the impact of minority status on academic achievement with a malleable moderator. This study confirms that minority students at risk of lower GPAs can be buffered by possessing above average perceived competence and school value. Furthermore, this study calls into question the studies that have shown significant academic disadvantages for first-generation students, including academic achievement and college persistence, without controlling for race (Aspelmeier et al., 2012; Prospero & Vohra-Gupta, 2007; Vuong et al., 2010).

5.5 A VARIABLE-ORIENTED COMPARISON

**Multiple Regression Model.** Until now the study has employed a person-oriented approach with regards to the motivational constructs. This approach takes a holistic and dynamic view of the individual as an integrated totality over time. Thus, the approach revealed motivational typologies for each student. The latent
profile analysis allowed for a qualitative and quantitative understanding of different motivational typologies, as well as how these profiles interact with other variables to predict end-of-semester GPA. The variable-oriented approach views the individual as a summation of variables over time. Bergman and Trost (2006) discuss how the two methods should complement each other by providing similar predictions. Thus, this study ran a multiple regression of all control variables, including race, high school GPA, family economic hardship, and collegiate class, as well as generation status, perceived competence, perceived choice, and school value on end-of-semester GPA. The results mirrored much of what was seen in the final structural equation model. Compared to 44% for the structural equation model, this model explains 46% of the total variation in end-of-semester GPA. Of the control variables, high school GPA and family economic hardship were significant predictors. In fact, the unique effect of family economic hardship was significantly negative as hardship increased. With regards to race, Caucasian and African-American significantly predicted end-of-semester GPA. Compared to Caucasians, African-Americans have a predicted GPA that is a quarter of a GPA point lower with all other variables held to the same level. Numerous variable-oriented studies have demonstrated that Black students do not perform as well as White students in collegiate academic achievement (Allen, Epps, & Haniff, 1991; Graham, Taylor, & Hudley, 1998; Hall, Mays, & Allen, 1984; Nettles, 1988; Vanneman, Hamilton, Anderson, & Rahman, 2009). As for the motivational variables, only perceived competence and school value were significant predictors. Again, this complements the results seen with the latent profiles, as the typologies were defined by
quantitatively different values of perceived competence and school value. This result mirrors numerous variable-oriented studies in expectancy-value theory that showed self-efficacy and task value to be predictors of academic achievement and course enrollment (Bong, 2001; Malka & Covington, 2005; Meece, Eccles, & Wigfield, 1990). While perceived competence was a significant predictor, perceived autonomy was non-significant which contradicts studies in self-determination theory (Alexander, Entwisle, & Dauber, 1993; Vansteenkiste, Simons, Lens, Sheldon, & Deci, 2004). The likely reason stems from the measure used by the studies. Vansteenkiste et. al. (2004) used Ryan and Connell’s (1989) 16-item self-regulation questionnaire that assesses the degree to which an individual’s motivation for learning tends to be relatively autonomous versus relatively controlled. The current study uses Deci and Ryan’s (1996) 5-item perceived choice questionnaire that reflects feeling a sense of choice with respect to one’s behavior. This 5-item survey did not provide enough variance across the students to be a significant predictor.

**Person-Oriented Versus Variable-Oriented.** Overall, the two models have similarities and appear, on face-value, to complement one another. However, there are also some stark differences. Both models demonstrate the significance of race, family economic hardship and high school GPA in predicting end-of-semester GPA. The way multiple regression employs a categorical variable allows one to specifically see the decreased prediction in performance for African-American students. Both models also show the importance of perceived competence and school value. With the variable-oriented model, both motivational constructs are significant predictors. With the person-oriented approach, all three motivational
Typologies are significant predictors. However, this is where the similarities end because for the variable-oriented model there is nothing more to discuss. The model reveals what significantly predicts end-of-semester GPA, but there is no understanding how the variables relate to one another. On the other hand, the structural equation model demonstrates how the high competence motivational typology buffers the minority student with regards to his/her academic performance. The model specifically shows that possessing competence values of only half a standard deviation above average will result in a significantly higher end-of-semester GPA. While minorities are at a disadvantage compared to their Caucasian peers, this disadvantage is significantly less for minorities in the high competence profile. The structural equation model with the motivational typologies does so much more for facilitating the development of either an intervention or a first-year seminar because competence can be taught to students. It reveals what is motivationally needed for all students, but specifically minorities, to have significantly higher academic performance. Lastly, the motivational typologies reveal the inherent heterogeneity among first-generation students, rural-educated students, and minority students. While the variable-oriented approach makes it look like all African-American students are at a severe disadvantage, the structural equation model reveals that disadvantage is significantly less for Black students possessing high-perceived competence.

5.6 IMPLICATIONS FOR FUTURE POLICY AND PRACTICE

My study made unique contributions to the understanding of motivational typologies and how these typologies interact with race, generation status, and rural
status to predict academic performance. Results from the moderation analyses support the extant conclusion that perceived competence and school value are essential for having significantly higher predicted GPA. Minority students at risk of lower GPAs can be buffered by possessing a high competence motivational profile. These findings have significant implications for administrators, professors, advisors, and students.

**Promoting Understanding.** Administrators, professors, advisors and students need to know the huge role perceived competence and school value play with regards to academic performance. In particular, they need to be aware of the detrimental effects of low perceived competence and low school value on GPA. Motivation is malleable, unlike the significant control variables. The university can design both teaching seminars and first-year seminars that both discuss expectancy-value theory but, also, teach how to develop competence and value. Advisors and tutors working in Student Services need to know how to mentor in ways that develop competence and value.

**Faculty Seminars.** From the results of this study, the Center for Excellence in Teaching and Learning needs to offer a seminar with regards to motivation. The motivation seminar needs to inform faculty about the crucial role expectancy-value theory plays in academic performance. The seminar needs to discuss how to pedagogically create a teaching environment that is conducive in developing competence and school value. This can be done by employing Keller’s (1979) ARCS Model of Motivation. According to Keller, faculty can learn how to foster active participation and establish relevance in order to motivate learners. Faculty should
be made aware of the results of the current study. Based on the results of both the person-oriented analyses and the variable-oriented analyses, African-American students are at a disadvantage compared to their Caucasian counterparts, but this disadvantage is significantly lessened by the presence of perceived competence.

**First-Year Seminars.** Students need to know the pivotal role motivation plays in their academic performance. The best opportunity to teach students about the role of competence and value is in the first-year seminar. As of now the curriculum focuses on relationships, organization, work ethic, and emotional intelligence. In light of this study the curriculum needs to be revised to incorporate several weeks on developing competence in the classroom and school value. From study habits to seeking feedback from professors to working with tutors and mentors, students can actively develop perceived competence in any given course. Students need to be made aware of all the benefits of a college degree and the material they are learning in each class. Students low in school value tend to think the degree is a waste of time and that they learn more from friends and family. Peer leaders in the first-year seminar need to be selected because they possess significantly high levels of perceived competence and school value so that they can mentor the freshmen in these areas.

First-year seminars need to be developed around Dweck’s theory of intelligence and the growth mindset. Dweck has shown it is possible to develop a belief that ability is malleable versus the thought that ability is fixed (Dweck, 2006; Yeager and Dweck, 2012). Her research confirms that this growth mindset can lead to more effort, greater task persistence, and a master orientation. Dweck’s latest
research involves larger, more rigorous field trials that provide some of the first evidence that the social psychology strategy can be effective when implemented in institutions on a wide scale (Yeager, et al., 2016). This strategy involves teaching students to acknowledge and embrace imperfections, to view challenges as opportunities, to seek constructive criticism, and to value the process over the end result (Yeager and Dweck, 2012). These are just a few of the ways to teach students how to foster a mindset that is focused on learning, development, and improvement, not just on outscoring a classmate.

5.7 LIMITATIONS AND FUTURE RESEARCH

Of note are some limitations of this study that warrant discussion. First, the sample was rather small \( n = 705 \) for investigating motivational typologies. Future studies should aim to have more students, which could reveal more typologies, as well as more information about the new typology with very low perceived competence and school value. Both Pintrich (1989) and Conley (2012) found an average motivation cluster that did not appear in this study. However, both Pintrich (1989) and Conley (2012) \( n = 1,870 \) had large samples of students. Furthermore, this sample comes from a small, regional university. Therefore, findings should be interpreted with caution when generalizing to other populations, like larger, research-based institutions.

Second, this study utilized Deci and Ryan’s (1996) 5-item perceived choice questionnaire as a proxy for perceived autonomy in learning. Since the survey contained only five items, there was not enough variation in scores to contribute to the motivational typologies. Recall, a typical question reads as
Please read the pairs of statements, and think about which statement within the pair seems more true to you at this point in your life. Indicate the degree to which statement A feels true, relative to the degree that statement B feels true, on the 5-point scale. [A. "I always feel like I choose the things I do." VERSUS B. "I sometimes feel that it's not really me choosing the things I do." ]

Future studies should use Ryan and Connell’s (1989) 16-item self-regulation questionnaire. This questionnaire actually assesses controlled versus autonomous motivation for learning. Vansteenkiste et al. (2009) conducted a person-oriented study using the self-regulation questionnaire and found four different profiles. Thus, variation in perceived autonomy exists, and future studies need to examine how it interplays with perceived competence and school value in creating motivational typologies. By better incorporating perceived autonomy for learning, the effect size could be even greater. The current study explains 44% of the total variation in end-of-semester GPA.

Third, the sample was collected in three cohorts across three semesters and primarily contained business majors (89%). All four collegiate classes were represented which confounded motivation, as well as end-of-semester GPA. Freshmen GPAs are significantly different from upperclassmen GPAs, which is not necessarily something this study was interested in capturing. No research exists on the specific motivational profile of business majors, but one needs to be cautious generalizing the results of this study to non-business majors. Future studies should sample from one class, like freshmen, have a more heterogeneous survey of majors,
and follow them through college. This potential study could then examine motivational typology changes, as well as persistence. By incorporating a latent transition analysis, this future study could examine the stability of the motivational typology.

Fourth, this study did not show any significance with generation status. However, parents’ education is a known significant control variable. A future study should numerically code parents’ education level and incorporate it as a control variable. Similarly, this study coded rural status based on high school location. Rural-educated was coded on high school location and perhaps results would have been different if coded it on home zip code. By coding rural status from home zip code, a future study could examine whether rural-based students are at a disadvantage in terms of academic performance and persistence.

Fifth, this study incorporated only self-determination theory and expectancy-value theory with regards to motivation. Subsequently, the small sample coupled with only three motivational constructs resulted in only three typologies. Other person-oriented motivational studies have revealed four or more typologies, but recall these studies used several more motivational variables (Conley, 2012; Pintrich, 1989; Vansteenkiste, sierens, Soenens, Luyckx, & Lens, 2009). A future study could incorporate more motivational constructs, like achievement goals and cost, to better develop motivational typologies among college students.

Sixth, this study incorporated the latent profile analysis into a structural equation model. Specifically, the study wanted to examine how the motivational profiles moderated predictors of academic achievement. Using Mplus for the
analysis, modal assignment was the only way to employ the motivational profiles. In the results of the latent profile analysis, each student is given a class probability and a class assignment. The class assignment is based on the highest class probability. Thus students possess probabilities of being assigned to other classes. While some students are dominantly in one class, other students have 20-30% chance of being in a different typology. Consequently, typology results need to be interpreted with caution, as they only represent the dominant class, as opposed to the unique class.

5.8 CONCLUSIONS

With the tremendous increase of college students across campuses in the U.S., the number of first-generation students has also been rising. Research staggering shows that first-generation students are academically at a disadvantage compared to their continuing-generation peers in preparation, performance, persistence, and degree attainment (Berkner, Horn, & Clune, 2000; Ishitani, 2006; Lara, 1992; Nunez & Cuccaro-Alamin, 1998; Padgett, Johnson, & Pascarella, 2012; Rendon, 1992; Rendon, Hope, & Associates, 1996; Terenzini et al., 1994; Weis, 1992; York-Anderson & Bowman, 1991). The purpose of my study was to examine how motivational typologies could moderate the relationship between generation status and academic performance, as guided by self-determination theory and expectancy-value theory. Findings of my study disagree with the previous findings by Prospero and Vohra-Gupta (2007) and Vuong and colleagues (2010) regarding the relationship between first-generation students and GPA. Both of these studies showed first-generation students underperform compared to their continuing-generation peers, but both studies failed to control for race and socioeconomic
status. By controlling for race, high school GPA, family economic hardship, and collegiate class, this study failed to show a significant relationship between generation status and academic performance. This study did show that generation status interacts with race, such that first-generation minority students have significantly lower predicted GPAs than continuing-generation minority students. Findings from my study have made unique contributions to the research on first-generation students by quantifying the heterogeneity among this group. While some first-generation students struggle with low perceived competence and school value and subsequently have lower GPAs, other first-generation students possess high-perceived competence and have higher GPAs. In other words, first-generation students with high competence outperform continuing-generation students with low competence and school value.

Findings from this study have also contributed to the understanding of motivational typologies, as this is the only person-oriented study incorporating both self-determination theory and expectancy-value theory. While future studies need to better measure autonomous motivation for learning, expectancy-value findings from this study support previous research by Pintrich (1989) and Conley (2012). Furthermore, findings from this study add to existing research on the interaction between race and motivation. This person-oriented study reveals the heterogeneity among minority college students by showing that minority students with high competence outperform minority students with low competence and school value in terms of GPA. This study highlights the importance of motivation with regards to academic performance, especially for students at-risk of struggling. These results
lend themselves to revising the curriculum in first-year seminars and educating faculty on how to develop perceived competence and school value.
REFERENCES


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APPENDIX A – VARIABLES AND DESCRIPTIONS

<table>
<thead>
<tr>
<th>Variable Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dependent Variable</td>
<td></td>
</tr>
<tr>
<td>End-of-semester GPA</td>
<td>A continuous variable</td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td>Predictors</td>
<td></td>
</tr>
<tr>
<td>Generation Status</td>
<td>A categorical variable (first-generation, continuing-generation)</td>
</tr>
<tr>
<td>Rural Status</td>
<td>A categorical variable (rural, non-rural)</td>
</tr>
<tr>
<td>Perceived Competence</td>
<td>A continuous variable</td>
</tr>
<tr>
<td>Perceived Choice</td>
<td>A continuous variable</td>
</tr>
<tr>
<td>School Value</td>
<td>A continuous variable</td>
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<tr>
<td></td>
<td></td>
</tr>
<tr>
<td>Covariates</td>
<td></td>
</tr>
<tr>
<td>Race/Ethnicity</td>
<td>A categorical variable (Caucasian, African-American, Latino/a, Asian, Other)</td>
</tr>
<tr>
<td>Collegiate Class</td>
<td>A categorical variable (underclassman, upperclassman)</td>
</tr>
<tr>
<td>Family Economic Hardship</td>
<td>A continuous variable</td>
</tr>
<tr>
<td>High School GPA</td>
<td>A continuous variable</td>
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