IDENTIFYING PROFILES OF MOTIVATIONAL PROCESSES IN ONLINE COLLEGE STUDENTS AND THEIR RELATION TO MULTIPLE INDICATORS OF ACADEMIC SUCCESS

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Abstract

Motivational processes are important for academic success in college because they enable students to learn independently and overcome challenges to learning. In particular, when students exhibit poor academic or self-regulation skills, are non-traditional in age, and/or enroll in online learning environments, they are more likely to encounter challenges that can interfere with learning. In the current study, person-centered statistical approaches were used to identify patterns of self-efficacy for online learning, mindset, mastery orientation, test anxiety, and grit in a sample of non-traditional college students (N = 5,952), and to examine whether these motivation profiles differentially related to indicators of academic success, engagement, and persistence. Additionally, this study aimed to validate the cluster solution by conducting multiple types of person-centered analyses (i.e., cluster analysis, latent profile analysis) across two random subsamples (i.e., 80% and 20% of the overall sample) of students. Results indicated that a four-profile solution was most meaningful and interpretable and was validated across two random samples. The four clusters also differed on measures of academic success and engagement with online resources, but not with term-to-term retention. Results are discussed in terms of the meaningfulness of motivation profiles in relation to achievement, how the profiles elicited from each statistical technique were compared, and the implications for future research and practical application of the motivation profiles.

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When I was growing up, my family taught me two important lessons: *you can do anything you set your mind to* and *you can always find the energy to accomplish your dreams if you try*. As I have encountered the many challenges and triumphs of graduate school, I have carried these lessons with me. Now, as my graduate education comes to a close, I would like to thank the people who have helped me along with way. First, to my dissertation chair and mentor of nearly four years, Dr. Timothy Cleary, thank you for your guidance, support, and encouragement throughout graduate school. You have always challenged me to grow, believed in my potential, and helped shape me into the professional I am today. Throughout our many conversations about research and my career, I will always remember how you taught me to consider when I love something because I am good at it, compared to when I am good at something because it is what I love.

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Introduction

Motivation for learning and achievement refers to students' desire to initiate and sustain adaptive behaviors in the pursuit of an academic goal (Schunk, Meece, & Pintrich, 2014). Students' motivation to learn and achieve is influenced by what they think, feel, and believe about their academic abilities. That is, cognitive processes, such as confidence, interest, goals, affect, and beliefs about one's abilities, underlie students' motivated behaviors (Schunk et al., 2014), such as using effective study strategies (e.g., setting study goals), putting forth additional effort when confronted with challenges, and seeking help from others when these challenges become too difficult (e.g., Blackwell, Trzesniewski, & Dweck, 2007; Shih, 2008; Zimmerman, 2000). Subsequently, these motivated behaviors and the processes that underlie them are key factors that influence academic performance and achievement (Cleary & Kitsantas, 2017; Guay, Ratelle, Roy, & Litalien, 2010; Zimmerman, Bandura, & Martinez-Pons, 1992).

Most researchers examining the relations between motivational processes and achievement have used variable-centered statistical approaches to understand how motivation variables relate to each other and/or to achievement (e.g., Barron & Harackiewicz, 2001; Pintrich & De Groot, 1990). Variable-centered statistical approaches, such as correlations, regression analyses, and path analyses, allow researchers to examine associations between multiple variables (Marsh, Lüdtke, Trautwein, & Morin, 2009). Variable-centered statistical approaches, however, are limited in that they focus on the variable as the unit of analysis rather than the person. Thus, variable-centered approaches cannot identify patterns of motivation constructs that coexist within individuals and which may collectively influence achievement-related behaviors or achievement.

To address these limitations, researchers have begun to rely on person-centered statistical approaches to understand patterns of motivation in students and how these patterns or clusters relate to achievement (e.g., Liu et al., 2014; Putwain & Sander, 2016). Person-centered statistical approaches (e.g., cluster analysis, latent profile analysis) aim to identify clusters of individuals from a given sample that exhibit a similar pattern of characteristics relative to a set of characteristics exhibited by other participants from the sample (Lubke & Muthén, 2005). Person-centered approaches are beneficial because they can help researchers and practitioners better understand how clusters of different motivation variables relate to achievement, and whether certain clusters suggest students have a greater chance of encountering academic struggles or success. In this study, I utilize a person-centered approach to identify various motivation clusters that emerge among a unique sample of college students, and explore how these clusters differentially relate to indicators of academic success, engagement, and persistence.

Motivation and Achievement

Students' learning and academic achievement is fundamentally influenced by the motivated behaviors that students engage in to support their learning (Dweck, 2006; Liem, Lau, & Nie, 2008). For example, students may put forth effort to engage in learning, approach and persist through challenges, and utilize effective strategies to help them learn. Motivational processes, such as a student's confidence in their abilities or interest and desire to put forth effort towards their interests over time, can drive students to engage in these motivated behaviors (e.g., Dweck, 2006; Walker, Greene, & Mansell, 2006). The important distinction between motivated behaviors and motivational processes is that motivated behaviors reflect the more overt and often observable actions that students engage in throughout their learning, whereas motivational processes refer to the cognitive beliefs that may influence behavior. Motivation theorists agree that these cognitive processes impact the extent to which students engage in adaptive behaviors in pursuit of their academic goals; although these theorists may disagree about the level of importance for each specific motivational belief (Schunk et al., 2014). Of importance for learning and achievement in college are motivational processes (e.g., self-efficacy, mindset) that enable students to study and learn independently and to overcome the many challenges that they may experience during their college years.

Motivational processes are important for academic performance and achievement because these cognitive beliefs can influence the extent to which students engage in adaptive, motivated behaviors toward their learning, which, in turn, can improve future academic success (e.g., Dweck, 2006; Liem et al., 2008). For example, when students exhibit adaptive motivational processes, such as confidence in their ability to attain goals (i.e., self-efficacy), belief that they can improve their intelligence with time and effort (i.e., growth mindset), or interest in attaining and working toward long-term goals (i.e., grit), they are more likely to initiate and sustain their efforts towards a learning goal or persist through challenges and setbacks (Brewer & Yucedag-Ozcan, 2013; Dweck, 2006). They may also work harder and longer, remain focused on tasks, and embrace challenges and feedback, as well as engage in more adaptive cognitive and self-regulation strategies (e.g., study strategies, adaptive inferences; Ames, 1992; Duckworth, Peterson, Matthews, & Kelly, 2007; Dweck, 2006; Hembree, 1988; Liem et al., 2008; Walker et al., 2006; Zimmerman, 2000). These behaviors are particularly important for students in college because these students are challenged with learning independently and persisting through setbacks. In short, it is important and valuable for college students to exhibit key motivational processes, such as self-efficacy for learning and a growth mindset, in order to help them independently learn and overcome challenges.

In this study, five motivational processes were used to identify motivation clusters: *self-efficacy*, *goal orientation*, *mindset*, *test anxiety*, and *grit*. In addition to their relevance and importance to achievement in college, these specific five processes were selected given their inclusion in the extant dataset that was utilized for the current dissertation study. This dataset was generated from a randomized control trial examining the impact of an academic intervention on the achievement of college students enrolled in an online college (Lui et al., 2018). Although other motivational beliefs (e.g., a student's interest in a topic or foreseen value of that topic to their future) may influence learning and achievement (Schunk et al., 2014), only the five motivational processes were included in the current study. In the following paragraphs, I provide a brief definition and description for each construct.

Self-efficacy for learning refers to the extent to which students feel confident in their ability to learn and succeed academically. These types of beliefs tend to be specific to a single topic or learning activity; therefore, students can feel very self-efficacious for one task or topic and less confident for others (Bandura, 1977; Zimmerman, 2000). Self-efficacy is crucial for learning and achievement because students who feel confident in their abilities are also likely to put forth effort toward their learning, engage in adaptive cognitive or self-regulation strategies, persist through challenges to their learning, and be more interested in and satisfied with their learning (Brewer & Yucedag-Ozcan, 2013; Walker et al., 2006; Zimmerman, 2000).

Goal orientation refers to the patterns of beliefs, attitudes, and reasons students have for engaging in achievement-related behaviors. Traditionally, there are two broad types of goals: mastery-oriented and performance-oriented. Students' goals may be mastery-oriented in that they aim to master learning materials, gain knowledge, and learn for the sake of learning. Alternatively, performance-oriented goals tend to reflect an interest in outperforming others or achieving a particular grade or benchmark (Senko, 2016). Both mastery and performance goal orientations can help students initiate goal-directed behaviors (Liem et al., 2008), albeit toward different goals (i.e., mastering material vs. outperforming others); however, many researchers and theorists agree that mastery-oriented goals may have a greater importance for long-term learning than performance-goals (Schunk et al., 2014). Mastery goals are important for learning because students who set these goals may also view their successes and failures in terms of controllable, changeable factors, use more adaptive self-regulation strategies to attain their mastery-oriented goals, and persist through setbacks they encounter (Ames & Archer, 1988; Liem et al., 2008; Shih, 2008). On the contrary, students who set performance goals may avoid challenges that could ultimately help them learn, attribute failures to a lack of innate ability, or use less adaptive self-regulation strategies when working toward their academic goals than students who have a mastery goal orientation (Ames & Archer, 1988; Liem et al., 2008; Shih, 2008).

Mindset refers to students' beliefs about the nature of intelligence; that is, whether students believe their intelligence can change over time and improve with effort (i.e., growth mindset) or believe their intelligence is fixed and unchangeable (i.e., fixed mindset; Dweck, 2006). Mindset is critical for learning because it can influence the extent to which students approach challenges, persevere after setbacks, view successes and failures in terms of controllable factors, and feel confident in their ability to succeed (Dweck, 2006).

Another process that is often associated with motivation and learning is test anxiety (Schunk et al., 2014). *Test anxiety* refers to the apprehension or fear that students experience prior to or during tests or other academic evaluations. Test anxiety includes both the emotional reaction to evaluations (e.g., fear) and cognitive appraisals of anxiety-provoking situations (e.g., worry; Hembree, 1988; Zeidner, 1998). Low anxiety is important for learning and achievement because if students feel too anxious before or during evaluations, they may avoid preparing for the evaluation, give up, or have difficulties focusing their attention or working memory on their learning, which could ultimately hinder their academic success (Chapell et al., 2005; Hayes, MacLeod, & Hammond, 2009; Hembree, 1988).

Lastly, *grit* refers to students' persistence of effort and their sustained interest in a task or topic over time in the pursuit of long-term goals. While grit partly reflects motivated behaviors (i.e., persistence), it also refers to the cognitive factors that contribute to students' interest for a task, desire to put forth effort to persist in the face of challenges, and resilience in working through challenges (Duckworth et al., 2007). Grit can improve students' learning and achievement because students who are grittier may work for longer and harder on academic tasks, sustain their attention on the same task over time, and persist despite challenges or failures (Duckworth et al., 2007).

Motivation's Role in Overcoming Challenges to Learning in College

Motivated behaviors for learning and motivational processes are important for academic success in college, particularly when students encounter challenges during learning. Most students will encounter some type of challenge or struggle in college; some are experienced by most students (e.g., learning to work independently and manage a schedule), while other challenges are more idiosyncratic to specific groups of students or situations. Students who will likely encounter many personal or contextual barriers to learning include those who: (a) display poor academic skills (e.g., basic reading, writing, or mathematics) or self-regulation skills (e.g., time management, help seeking strategies), (b) are considered non-traditional students (i.e., those who are older, took a hiatus from college, and/or are working full time or have family or other demands while enrolled in college) and/or (c) enroll in online courses or a degree program with minimal in-person supports. As a result of these challenges, these students may achieve less, as they often enroll in fewer semesters, complete fewer course credits, drop out before completing their degree, and/or have a lower grade point average (GPA) than more typical college students (Grimes & David, 1999).

To understand why students who encounter personal or contextual challenges may achieve less, and how motivational processes intersect with the challenges these students encounter, many researchers have turned to variable-centered statistical approaches. Variable-centered approaches, such as when researchers employ correlations, regressions, or path analyses, are used to examine associations between multiple variables. These statistical approaches consider each variable as the unit of analysis and aim to understand how these variables correlate with each other, predict other variables, or impact dependent variables (Marsh et al., 2009). Researchers have employed variable-centered techniques to explore how different motivational processes (e.g., goal orientation, mindset, and self-efficacy) reciprocally influence each other and a variety of achievement outcomes (Barron & Harackiewicz, 2001; Cleary & Kitsantas, 2017; Guay et al., 2010; Pintrich & De Groot, 1990; Zimmerman et al., 1992). As an example, some research has explored how mindset related to grades and other motivation beliefs. Blackwell and colleagues (2007) assessed the growth and fixed mindset and four motivation beliefs (i.e., learning goals, beliefs about effort, causal attributions, and beliefs about strategy use) of 373 seventh graders, as well as tracked their grades over two years. The researchers found that students who exhibited a growth mindset had more improvement in their grades over two years than students with a fixed mindset. Additionally, researchers found that students' learning goals, beliefs about effort, causal attributions, and beliefs about strategy use mediated the relationship between their mindset and achievement (Blackwell et al., 2007).

Researchers have also used variable-centered statistical techniques to understand how motivational processes differ between students who encounter challenges due to personal (i.e., those who exhibit poor skills or are non-traditional college students) or contextual (i.e., those who are enrolled in online-only learning environments) barriers to their learning, compared to students who are more typical, college-ready students. In regards to students who exhibit poor academic or self-regulation skills, Moore (2007) compared the time management, effort regulation, and self-efficacy of 97 students who exhibited adequate academic and/or self-regulatory skills and 524 students who did not. Results indicated that students who exhibited poor academic skills also exhibited less adaptive self-efficacy, time management, and effort regulation than students with more adequately-developed skills (Moore, 2007). Similarly, Grimes and David (1999) compared the beliefs of traditional college students to those of students with poor academic skills in a sample of 500 first-year community college students. The authors found that students who displayed poor academic skills also believed they were less able to achieve, less confident in their abilities, less driven to succeed, and more likely to fail one or more classes than traditional college students with adequate academic skills (Grimes & David, 1999).

Similarly, researchers have examined how motivational processes relate to achievement in samples of non-traditional college students (e.g., those who are older or have a full-time job or family). For example, researchers examined the relation between motivational beliefs (e.g., goal orientations, mindset), effort expenditure, cognitive strategy use, and academic achievement in a sample of 76 adult learners who chose to return to school later in life to complete a high school degree equivalent. Correlational analyses indicated that mastery goals were positively related to achievement (i.e., final course grade). Although path analyses did not find a relation between mindset or cognitive strategy use and the other variables or achievement, they did indicate that students who reported more mastery goals put forth more effort toward their learning, which in turn related to better academic achievement (Dupeyrat & Mariné, 2005).

Additional research has reported similar results regarding the link between adaptive motivational processes and academic success for students in online learning environments. In one study, Lynch & Dembo (2004) examined how students' self-efficacy, intrinsic motivation, help seeking, time and study environment management, and verbal ability related to achievement in 94 students enrolled in a class where 75% of the course occurred online. Most notably, the authors found that self-efficacy for learning alone accounted for 7% of the variance in students' course grades (Lynch & Dembo, 2004). Other research suggests that students who achieved more in online courses were more likely to plan, manage their time and environment, feel confident in their ability to use technology, use metacognitive strategies, and use adaptive learning strategies (e.g., elaboration) than students who did not achieve as well (e.g., Puzziferro, 2008; Wang, Shannon, & Ross, 2013). Collectively, this research underscores the importance of adaptive motivational processes for students who struggle to overcome a variety of challenges in college.

In online learning contexts, these adaptive motivational beliefs are particularly relevant to academic success given the inherent challenges in a virtual, distance education. Online courses are designed to be largely run without an instructor (McMahon & Oliver, 2001); thus, students must self-direct their learning and determine when, where, and for how long to access their online course materials. As a result, these students must be motivated to both persevere through challenges and engage in self-regulation strategies to help manage the independent learning time and seek help when needed. Without the frequent, in-person interactions with an instructor as in traditional college courses, students enrolled in online classes may become isolated and may more easily succumb to challenges navigating and understanding course content.

Research supports the link between self-regulation and/or motivation and achievement in online classes. For example, one study found that students who were more likely to plan and manage their time, manage their environment, and regulate their effort toward learning achieved more in online courses than students who did not (Puzziferro, 2008). If students do not exhibit adaptive motivational processes, including a growth mindset, mastery goal orientation, and grit, they may have difficulties with the increased demands for autonomy in an online class. Additionally, when students lack the basic academic or self-regulation skills needed for college or are met with personal demands that conflict with their ability to self-regulate and motivate themselves, and elect to enroll in online education, their chance at academic success may drop dramatically (Artino & Stephens, 2009; Lynch & Dembo, 2004; Moore, 2007; Moylan, 2013).

Intersection of Motivational Processes in Overcoming Challenges

In order for students to persevere through challenging learning contexts and succeed in online courses, students must exhibit adaptive motivational processes, such as the five discussed previously (Artino & Stephens, 2009; Lynch & Dembo, 2004; Wang et al., 2013). In particular, success in distance (i.e., online) learning environments involves engaging in course content and persevering through setbacks, such as difficulties understanding new topics. In order to engage with and put forth effort toward learning, students should possess the desire to learn for the sake of learning (i.e., mastery orientation; Dupeyrat & Mariné, 2005). Simultaneously, students need to manage any emotions that could influence their learning, including anxiety about upcoming evaluations (i.e., test anxiety) and confidence in their academic abilities (i.e., self-efficacy; Artino & Stephens, 2009; Lynch & Dembo, 2004; Wang et al., 2013). Similarly, students may be more likely to use adaptive learning strategies to help them overcome challenges to learning when they are interested in pursuing long-term goals and have the drive to put for effort despite being met with resistance (i.e., grit; Wolters & Hussain, 2015). In online learning contexts, it is essential for students to be driven to engage and persevere, because they may often be isolated from peers and instructors and can easily fall behind or drop out if they are not intrinsically motivated to learn.

For students to have the best chance of success in online learning environments, they need to possess adaptive levels of motivational process. It is also important to recognize that these motivational processes are often inter-related. For example, a large body of literature has found a strong relationship between mindset and goal orientations, such that a growth mindset often predicts the extent to which students engage in mastery—and performance—goals (Blackwell et al., 2007; Chen & Wong, 2014; Magno, 2012). Additionally, research has found that one aspect of grit, perseverance of effort, correlated with students' mindset, as well as with self-efficacy, and goal orientation (Muenks, Yang, & Wigfield, 2018). Grit's perseverance of effort component also predicted students' level of self-efficacy (Wolters & Hussain, 2015). Simultaneously, self-efficacy is related to test anxiety because it can mediate the relationship between test anxiety and academic performance, and, in general, an increase in the use of these adaptive motivational processes relates to achievement (Barrows, Dunn, & Lloyd, 2013; Blackwell et al., 2007; Chen & Wong, 2014; Nie, Lau, & Liau, 2011).

Although exhibiting adaptive motivation across multiple processes is ideal, the reality is that students often exhibit variable patterns of motivation beliefs (e.g., Chen, 2012; Liu et al., 2014; Putwain & Daly, 2013). That is, students may be confident in their abilities and aim to master the material they learn, but feel too anxious to perform well on evaluations. Alternatively, students may believe they can grow and improve their intelligence with time and do not exhibit high anxiety, but are not very interested in learning or working towards long-term goals that would improve their skills. A critical question involves whether certain patterns of motivational processes will lead to academic success or failure, and whether strengths in certain processes of motivation are particularly important to academic success.

To answer this type of question, researchers must look beyond traditional variable-centered statistical approaches–which focus on each variable as the unit of analysis, rather than examining the pattern of variables that exist within individuals–and focus instead on the person as the unit of analysis. When research is applied to practice, variable-centered studies fall short on providing guidance to practitioners about how to integrate across multiple motivation variables when students display high levels of some motivational processes, but lower levels of others.

Person-Centered Studies of Motivation and Achievement in College Students

To address the limitations of variable-centered statistical techniques, some researchers have begun to use person-centered approaches. Person-centered statistical approaches (e.g., cluster analysis, latent profile analysis) aim to identify patterns of variables within individuals and identify clusters of individuals who exhibit similar patterns. These approaches can be used to categorize individuals from a given sample into subgroups so that those from a given subgroup exhibit a similar set of skills or characteristics but that differ from the pattern of skills of other subgroups (Lubke & Muthén, 2005). These subgroups of patterns across multiple variables are often referred to as “clusters” and/or “profiles.” Unlike variable-centered approaches, person-centered approaches focus on the individual and their pattern of the variables being measured as the unit of analysis. Person-centered approaches can inform researchers and practitioners about how multi-component constructs, such as motivation, can influence academic outcomes, and can help identify the key profiles that make students more or less likely to succeed.

Person-centered statistical approaches have been used broadly across a variety of fields including self-regulation and motivation. Within the motivation field, the majority of the person-centered literature has focused on the different variations in motivation clusters that emerge depending upon the specific variables included in analyses, and how these clusters compare to traditional measures of achievement. For instance, researchers may examine the patterns across three motivational processes and how these relate to students' overall GPA. To a lesser degree, the authors of other person-centered studies have focused their attention on identifying motivation clusters in students who may experience more challenges to learning than the typical student, such as the personal or contextual barriers to learning identified previously. Similarly, few person-centered studies have included comparisons of motivation clusters across diverse measures of academic performance and achievement, such as including less-traditional indicators of academic achievement (e.g., credit attainment) or engagement and persistence in addition to more traditional measures, like grades or GPA. Lastly, even fewer studies have validated their cluster solutions across multiple random samples or types of statistical analyses. Although person-centered motivation research is expanding, there are still gaps in the literature. The following sections explore the existing person-centered literature with a primary focus on four key concepts: (1) the motivation clusters that emerge when different combinations of variables are included in analyses, (2) identifying motivation clusters with students who encounter personal or contextual challenges to their learning, (3) the relation between motivation clusters and a variety of outcomes that relate to academic success, and (4) comparing the results of person-centered analyses across multiple samples or statistical techniques.

Motivation clusters based on the various motivational processes examined. The motivation literature has highlighted how person-centered techniques can be used successfully to identify motivation clusters with a variety of motivation variables. Some studies have involved a nuanced examination of clusters for a single type of motivational process (e.g., types of goal orientations), whereas others have sought to identify clusters based on patterns across two different but related motivation variables, or capture patterns across a more comprehensive set of motivational processes. As an example of a person-centered study that focused on multiple aspects of a single motivational process, Putwain and Sander (2016) examined clusters of different types of goal orientations within 434 first-year honors college students. The authors observed four clusters based on the following four dimensions of goal orientations: mastery-avoidance (MV), mastery-approach (MP), performance-avoidance (PV), and performance-approach (PP). The clusters were (1) moderate MV, PP, PV and high MP, (2) low MV, moderate PP and PV, and high MP, and (3) moderate MV and high MP, PP, and PV. Although the authors did not attempt to differentiate these clusters across academic achievement, they did explore if the clusters were differentially associated with students' academic behavioral competence (i.e., confidence in the ability to attain desired grades, study independently, and talk with others about course material). The authors reported that students in the low MV with moderate PP/PV and high MP cluster were more confident than students in the other clusters at the start of the academic year, but that students in all three clusters displayed similar levels of confidence by the end of the year. Additionally, the authors hypothesized that the second cluster would be the most adaptive, as students endorsed both mastery and performance goals, and endorsed both types of approach goals more than avoidance goals (Putwain & Sander, 2016).

For other person-centered studies, researchers have elected to examine patterns across two motivational or related processes. Chen (2012) measured the mindset and epistemological beliefs about science in 1,225 middle and high school students and found four clusters: thriving (47% of the sample who reported a growth mindset and adaptive epistemic beliefs), fixed/sophisticated (15.8% with fixed mindset and adaptive epistemic beliefs), growth/passive (31.2% with growth mindset and passive epistemic beliefs), and uncommitted (6% with uncommitted mindset or type of epistemic beliefs). These clusters were differentially associated with other types of motivation processes (i.e., goal orientation, self-efficacy) and grades, with students in the thriving and growth/passive clusters reporting more adaptive goal orientations, and students in the uncommitted cluster reporting lower self-efficacy than students in the other clusters. Additionally, students with adaptive science beliefs in the thriving and fixed/sophisticated clusters attained higher grades, on average, than those in the passive and uncommitted clusters (Chen, 2012). Similarly, Putwain and Daly (2013) identified clusters using test anxiety and academic buoyancy (i.e., resilience). In this study with 469 secondary school students, the authors found five distinct clusters of anxiety and buoyancy. Based on how the profiles related to achievement, the authors concluded that students demonstrated lower academic performance (i.e., mean grades across English, mathematics, and science) when they were anxious and not buoyant, and that buoyancy levels appeared to have a greater impact on academic performance than test anxiety (Putwain & Daly, 2013).

Other lines of person-centered motivation research have focused on a more comprehensive set of motivation processes to identify clusters. Bråten and Olaussen (2005) assessed the interest, perceived value, mastery goals, and self-efficacy of 86 nursing college students and 105 business graduate students. The cluster analysis suggested three profiles of students in both samples: positive motivation (i.e., high interest, value, mastery goals, and self-efficacy; most adaptive cluster), moderate motivation (i.e., moderate interest, value, mastery goals, and self-efficacy; moderately adaptive cluster), and low motivation (i.e., low interest, value, mastery goals, and self-efficacy; least adaptive cluster). The authors also found that, in most cases, students in the more adaptive clusters used more self-regulation strategies (i.e., elaboration, rehearsal, metacognition) than students in the less adaptive clusters. Collectively, these person-centered studies demonstrate how different clusters of motivation emerge when multiple variables are studied jointly, and, in some cases, how these clusters relate to other motivation variables and achievement outcomes.

Motivation clusters in students who experience personal or contextual challenges to learning. A smaller portion of the existing person-centered literature aimed to identify the motivation clusters that emerged in students who may experience personal and/or contextual barriers to their learning. Specifically, these studies focused on students such as those who enter college with poor academic or self-regulation skills, are non-traditional or older students, and those who are enrolled in online courses. For example, Artino and Stephens (2009) divided a sample of 481 college students enrolled in a brief, self-paced online course into the highest, lowest, and middle third based on students' scores for motivation (i.e., self-efficacy and task value) and academic emotions (i.e., boredom and frustration). When the highest and lowest groups were retained, the authors found that students with the highest levels of motivation along with the lowest negative emotions reported using more adaptive self-regulation skills (e.g., elaboration) and achieved higher course grades than students with less adaptive motivation and academic emotions (Artino & Stephens, 2009).

Another study by Pawlo et al. (2019) explored the self-regulated learning (SRL) skills (i.e., metacognitive skills, motivational processes, and learning strategies) skills of 6,176 students at an online university who also exhibited poor academic or self-regulation skills and/or were non-traditional students (e.g., returning to school as an older adult). The authors found four clusters of self-regulation, two of which were consistent across the three self-regulation dimensions, and two of which exhibited more variable patterns, with students' metacognitive skills presenting as significantly lower than students' motivation or learning strategies. Additionally, students in the most adaptive cluster (i.e., consistently high SRL) attempted and earned more college credits than students with consistently moderate SRL skills or students with variable but lower SRL skills (Pawlo et al., 2019).

Motivation clusters' relation to multiple indicators of academic achievement. In both variable-centered and person-centered studies, researchers have compared motivational processes to a variety of different outcomes, such as students' achievement, school engagement, or well-being. In terms of the person-centered studies of motivational processes, most of the existing literature examined how clusters differ in traditional measures of academic achievement, such as grades or GPA. However, there is value in considering alternative and additional methods to examine how students are performing and achieving academically. Although GPA is a common marker of achievement, there are many indicators of academic success that should be considered and utilized when examining how motivation clusters differentially relate to achievement. Academic success may include students' satisfaction with their learning, skill or knowledge acquisition, persistence and retention, engagement in learning-related activities, and attainment of learning objectives (Kuh, Kinzie, Buckley, Bridges, & Hayek, 2006; York, Gibson, & Rankin, 2015). Two types of success indicators, persistence (e.g., enrollment in and completion of courses) and engagement (e.g., engagement in class or skill-development and support programs), may be particularly important to consider for college students who are tasked with learning and overcoming challenges independently. That is, when students attempt to learn autonomously online, they must determine how to both engage in the learning material and persist through barriers to their learning without the help of an in-person instructor. If students do not engage in their learning and/or persist from one academic term to the next, their course grades and other traditional measures of achievement may not accurately reflect the effort and success—or failure—of students learning online. Therefore, measures of student achievement (e.g., credits attained), engagement, and persistence should all be considered in relation to patterns of motivation within students.

A few prior person-centered studies have included measures of engagement as outcome variables (Abar & Loken, 2010; Hsieh, 2016). Hsieh (2016) examined students' engagement in class (i.e., class participation, cognitive effort) across three motivation clusters (i.e., high intrinsic, high extrinsic, high intrinsic and extrinsic) using a sample of 231 Taiwanese college students. The author found that students with high intrinsic and extrinsic motivation actively participated in class more than students in the other two clusters, and exerted more cognitive effort and achieved a higher GPA than students with only high intrinsic motivation (Hsieh, 2016). Abar and Loken (2010) also explored how motivation and self-regulation profiles differentially related to alternative achievement outcomes using students' engagement in an online intervention (i.e., duration and extent of using online resources), albeit mixing motivation and other self-regulation variables. The authors examined the metacognition, effort management, time and study environment strategies, test anxiety, and academic beliefs (i.e., efficacy, self-handicapping, and skepticism) of 205 high school students and identified three clusters of self-regulation: high SRL (i.e., students displayed primarily adaptive SRL skills), low SRL (i.e., students displayed primarily maladaptive SRL skills), and average SRL (i.e., all SRL skills were average). Results suggested that students who exhibited primarily adaptive SRL skills also studied materials on the intervention website for a longer time and attempted more online tutorials and practice questions than students in the other clusters (Abar & Loken, 2010).

Validating cluster results across multiple samples and statistical techniques. Nearly all prior person-centered studies of motivation and/or self-regulation have utilized a single person-centered analysis (i.e., a cluster analysis; latent profile analysis) to identify clusters of students who exhibit similar patterns of variables in a given study. Although a single cluster analysis, for example, may involve conducting multiple rounds of analyses with a varying number of clusters, this is still considered a single statistical technique since the analysis only yields one final cluster solution as the best fit for the data. However, researchers have questioned the validity of the patterns identified by a single person-centered statistical technique, and have suggested conducting multiple analyses to validate the solution across multiple random samples or statistical techniques (DiStefano & Kamphaus, 2006).

Only a handful of researchers have conducted person-centered studies that have validated cluster solutions across multiple random samples or statistical techniques, and, to my knowledge, none have attempted to validate a cluster solution across both multiple samples and statistical techniques. In regards to replicating results across random samples, one group of researchers attempted to validate the results of a cluster analysis across two random subsamples, each representing 50% of the overall sample, and found that the results were highly similar across both subsamples (Pawlo et al., 2019).

However, in regards to replicating across statistical techniques, researchers have often found differences in results between techniques. For example, Pastor, Barron, Miller, and Davis (2007) conducted a cluster analysis (CA) in one study and a latent profile analysis (LPA) for similar data in a subsequent study. While the authors found that both the CA and LPA yielded a final solution with the same number of profiles, the pattern of variables within each solution differed between the results of the CA and the results of the LPA (Pastor et al., 2007). DiStefano and Kamphaus (2006) took a slightly more rigorous approach to validate their cluster solution by conducting both a CA and LPA using the same data and sample in a single study. Unlike the study by Pastor and colleagues (2007), DiStefano and Kamphaus found that the CA produced a best-fit solution with seven clusters, whereas the best-fit solution from the LPA had only three clusters. Both sets of researchers ultimately decided that the results of the LPA were superior to that of the CA because the LPA technique provides fit statistics to guide researchers in making a more objective decision about the number of clusters that best fit the data, compared to the CA which resides primarily on the researchers' decision about the meaningfulness of the results (DiStefano & Kamphaus, 2006; Pastor et al., 2007; see the Data Analysis section for a more detailed description of each statistical technique). Most notably, the authors of both studies were not able to replicate their results across multiple statistical techniques. This draws into question the validity of cluster solutions in studies that only utilize a single statistical technique and highlights the importance of attempting to replicate results across both multiple random samples and statistical techniques within a single study.

Limitations of existing person-centered research. Previous person-centered research addressing motivation is important, but there are several gaps. First, even though these studies addressed a variety of different motivational processes, no single study included a comprehensive array of motivation variables within the same person-centered analysis. That is, there are many important motivational processes that can influence learning, particularly those that can assist college students in learning independently and overcoming challenges, yet few studies included many of these key motivational variables within the same person-centered analysis. Future research should address key motivational processes including self-efficacy, mindset, goal orientation, test anxiety, and grit—five cognitive processes that can greatly influence motivation for learning and achievement.

Second, as evidenced by the studies previously discussed, most person-centered studies of college students utilized samples of traditional college students, rather than focusing on populations that may experience more barriers to their learning because of personal or contextual challenges. There is a great need to understand the patterns and clusters of motivation in populations who are more likely to experience repeated challenges or failures and, as a result, may exhibit worse or different profiles of motivation.

Third, the studies that examined cluster group differences in achievement tended to rely only on single measures of achievement, such as students' grades or GPA. There is a significant need to expand the conceptualization of achievement in the person-centered literature and examine how credit attainment, engagement with resources and feedback, and persistence from one term to the next relate to motivation profiles.

Lastly, the majority of the existing person-centered studies relied on a single person-centered analysis, such as one cluster analysis or latent profile analysis, to identify their profiles or clusters of students. However, some researchers recommend that studies should include results across multiple random samples and/or statistical techniques in order to compare and validate the results (DiStefano & Kamphaus, 2006).

The Current Study

The current study aimed to identify motivation profiles within a large sample of non-traditional students enrolled in an online college. Understanding these motivation profiles is important because students who are non-traditional, exhibit poor self-regulation skills, and/or are enrolled in an online college may be more likely to encounter challenges and barriers to their learning than traditional college students, and motivational processes are essential for helping students overcome challenges and increase their chances of achieving academic success. Further, this study addressed four gaps in the person-centered motivation literature: a need for comprehensive measures of motivation, inclusion of less-traditional student populations, consideration of multiple indicators of academic success, and comparison of cluster results from multiple random samples and statistical analyses. The purposes of the current study were to: (a) use person-centered statistical approaches to identify clusters of motivational processes in a unique sample of college students (i.e., students who are non-traditional, lack basic academic or self-regulation skills, and/or are enrolled in an online college) across five core cognitive beliefs (i.e., self-efficacy, mastery goal orientation, mindset, test anxiety, grit), and (b) explore how these clusters differentially relate to multiple indicators of academic success, engagement, and persistence. Six broad research questions (RQ) were explored in the current study:

RQ1: How many clusters of motivational processes will emerge from cluster analyses (CA) for two random samples of students enrolled in an online college? Do the results converge across samples?

RQ2: Can the results of the CA be replicated with latent profile analyses (LPA) using the same two random samples? Do the results converge across the LPA with each sample?

RQ3: What are the key characteristics or patterns among motivation variables within each of the observed clusters?

RQ4: Do the motivation clusters differ in terms of achievement (i.e., ratio of credits earned to credits attempted)?

RQ5: Do the motivation clusters differ in terms of students' engagement in an academic and self-regulation intervention?

RQ6: Do the motivation clusters differ in terms of student term-to-term retention at an online college?

The current study was part of a larger research project focused on an academic and self-regulation intervention, the Diagnostic Assessment and Achievement of College Skills (DAACS). The DAACS intervention assesses students' academic and self-regulation skills shortly after students enroll in college, and then provides personalized, actionable feedback and recommendations for how students can improve their weaknesses (Bryer, Cleary, & Andrade, 2015). The DAACS intervention was developed under grant # P116F150077 from the U.S. Department of Education. The current study does not necessarily represent the policy of the U.S. Department of Education, nor is it endorsed by the Federal Government.

Methodology

Sample

All students included in the current study were participants in a large, federally-funded grant project, the Diagnostic Assessment and Achievement of College Skills (DAACS). Participants included 5,952 students from an online college located in Western United States.

The online college offers bachelors and master's degrees in business, education, information technology, and health and nursing. Students at the college are typically non-traditional in that they are older (i.e., in their mid-30's) than most college students, are employed full time, and/or are returning to college to finish a degree. The target sample displayed a mean age of 33.43 years (*SD*=8.86) and was 58.5% female. In terms of ethnicity, the participants were primarily White (75.4%), but included Black (11.4%), Multiple Races (3.7%), Hispanic (3.1%), Asian (2.8%), American Indian (0.8%), Hawaiian (0.6%), Other (0.1%), or Unknown (0.1%) ethnicities.

In selecting the sample, two steps were conducted to ensure adequate statistical power for the statistical approaches: cluster analysis (CA), latent profile analysis (LPA), and one-way ANOVAs. Regarding the CA and LPA, I first descriptively analyzed the samples used in prior person-centered studies. The CA and LPA are clustering techniques that were used to categorize individuals into similar groups based on a variety of motivation characteristics. Since these clustering techniques do not involve hypothesis testing or effect sizes, there are no guidelines on what is generally acceptable for a minimum or maximum sample size. Prior research has included between roughly 200 and 7,000 subjects in CAs and LPAs (e.g., Abar & Loken, 2010; Korpershoek, Kuyper, & van der Werf, 2015), which suggests that the technique is appropriate for at least moderate-large (e.g., 300) and very large (e.g., 6,000) sample sizes. As the current extant dataset contains nearly 6,000 participants, it is acceptable to include data from all the participants in a single CA or LPA. Prior research using person-centered techniques has often found anywhere between three to six clusters of motivation or self-regulation, often with the smallest cluster containing as little as 5% of the sample (e.g., Bråten & Olaussen, 2015; Putwain & Sander, 2016; Ratelle, Guay, Vallerand, Larose, & Senécal, 2007; Smith, Deemer, Thoman, & Zazworsky, 2014). Since it is possible for a cluster to contain a significantly smaller percentage of the sample than other clusters, the sample size must be large enough that significant effects can still be detected even with one small cluster.

Power analyses were also conducted for one-way ANOVAs. In the current study, ANOVAs were used to examine differential effects of cluster membership on multiple indicators of academic success. Based on prior literature, it was expected that three- to six-groups would emerge from the LPA; therefore, power analyses were conducted for ANOVAs with three to six groups. In order to detect a small effect with 80% power at $\alpha = .05$, 966 (322 per group), 1,096 (274 per group), 1,200 (240 per group), or 1,290 (215 per group), participants were needed for three, four, five, or six groups, respectively (Cohen, 1992). The almost 6,000 participant sample size in the extant dataset was large enough to detect very small effects of cluster membership on a variety of academic achievement indicators. If the smallest cluster found was only 5% of the sample ($n = 298$), this sample size would have been sufficient to detect small effects for ANOVAs with four through six groups. If only three clusters emerged from the CA or LPA, the smallest cluster would have needed to contain more than 5% of the sample ($n = 322$) in order to detect small effects.

Procedures

Data for the current study was obtained from an extant dataset generated from a federally-funded randomized controlled trial with college students. Upon enrolling in an online college and prior to receiving the DAACS intervention supports (i.e., feedback and resources to improve self-regulation skills), participants in the treatment group completed an online assessment of their motivation, metacognitive, and strategic skills (i.e., DAACS-SRL survey) as well as their academic skills (i.e., reading, mathematics, writing). The extant dataset used for this study included de-identified data about students' DAACS assessment results (i.e., motivation scores), demographic characteristics, college credit and enrollment information, and trace data on usage of the DAACS intervention website. The dataset was provided by the principal investigator of the DAACS project, who has granted permission for use of the dataset for the current dissertation study. The original DAACS project had received approval by the Institutional Review Board (IRB) of a different institution and the current study was approved by the Rutgers University IRB (ID# Pro2019000170).

Measures

DAACS-SRL survey. The DAACS-SRL assessment is a comprehensive 47-item self-report measure of students' SRL skills. It was developed to address three core dimensions of SRL: metacognition, motivation, and learning strategies (Bryer et al., 2015) In addition to these three second-order variables, the scale contains 11 first-order variables: *metacognition* included planning, monitoring, and evaluation; *motivation* included mastery goal orientation, test anxiety, mindset, and self-efficacy; *learning strategies* included time management, environmental structuring, help seeking, and tactics to manage learning and understanding (Lui et al., 2018). Given that the purpose of the current study was to identify motivation clusters or profiles, I elected to include the four measures subsumed within the motivation factor. The motivation composite demonstrated adequate internal consistency reliability (α = 0.87; Lui et al., 2018).

It is important to note that I also decided to include a grit scale as a fifth motivation measure in the current study. Although this measure was not included in the original factor analyses conducted by Lui and colleagues (2018), it was included in the DAACS-SRL survey for predictive validity purposes (Bryer et al., 2015). Further, given that grit corresponds to an individuals' perseverance and is consistent with the other motivation constructs included in the

DAACS-SRL survey (e.g., mastery goal orientation, mindset), it was deemed appropriate to include this measure in the current study.

Across all five motivation measures, students were asked to respond to items using a five-point Likert scale. All items were scored so that higher scores reflect more adaptive motivational processes. For most subscales, the wording of some items were adapted from the originally published items in order to best coincide with the educational experiences of students at an online college. Measures of internal consistency reliability are reported from a prior study that evaluated the validity and reliability of the DAACS-SRL survey, with the exception of grit (Lui et al., 2018).

Mindset. The mindset subscale assesses students' beliefs about the nature and plasticity of their intelligence (Dweck, 2006). The four items in this subscale address both growth and fixed mindset and were adapted from a Mindset Assessment Profile Tool (Mindset Works Inc., 2015). Items include, "You can always change how intelligent you are (growth mindset)" and "You can learn new things, but you can't really change your basic intelligence (fixed mindset)." All items pertaining to a fixed mindset were reverse scored so that higher scores reflected more growth mindset and lower scores reflect more fixed mindset. The mindset subscale demonstrated adequate internal consistency reliability (α = .86; Lui et al., 2018).

Self-efficacy for online learning. The self-efficacy for online learning subscale measures students' confidence in their ability to learn online without support from teachers or in person classroom instruction. The subscale contains four items adapted from the self-efficacy subscale of the Online Learning Value and Self-Efficacy Scale (Artino & McCoach, 2008). Example items include, "I am confident I can learn without the physical presence of an instructor to assist me" and "I am confident I can do an outstanding job on the activities in an online course"

(Artino & McCoach, 2008). The self-efficacy subscale demonstrated adequate internal consistency reliability (α = .82; Lui et al., 2018).

Mastery goal orientation. The mastery goal orientation subscale measures the reasons students provide for engaging in achievement-related activities. That is, whether students desire to learn course material for the sake of learning or to attain a particular grade and/or outperform others. Unlike other measures of goal orientation which often include both performance- and mastery-goal items, this measure only includes items that reflect mastery goal orientation. The four-item subscale was adapted from the Intrinsic Motivation subscale of the Survey of Academic Self-Regulation (SASR; Dugan & Andrade, 2011). Students responded to items including, "I want to master the things I am learning" and "What I am learning is relevant to my life." The mastery goal orientation subscale demonstrated adequate internal consistency reliability (α = .71; Lui et al., 2018).

Test anxiety. The test anxiety subscale assesses students' anxiety regarding tests and academic evaluations. Four items were adapted from the Westside Test Anxiety Scale (Driscoll, 2007) and include, "When I study for my exams, I worry that I will not remember the material on the exam" and "The closer I am to a major exam, the harder it is for me to concentrate on the material" (Driscoll, 2007). All items were reverse scored so that higher scores reflect lower, and thus more adaptive, test anxiety. The test anxiety subscale demonstrated adequate internal consistency reliability (α = .91; Lui et al., 2018).

Grit. The grit scale addresses students' persistence of effort (i.e., perseverance) and consistency of interest (i.e., passion) toward long-term goals (Duckworth et al., 2007). Ten items were taken from Duckworth's 12-item Grit Scale; the wording of two of the 10 items was modified. Items include, "I finish whatever I begin" and "I have overcome setbacks to conquer an important challenge." Duckworth's initial 12-item Grit Scale has previously demonstrated adequate internal consistency reliability (α = .85) in a large sample of adults (Duckworth et al., 2007).

Academic success. Three indicators of academic success in online learning environments were selected for the current study in order to provide a comprehensive account of students' academic performance and achievement: credit attainment, engagement with online SRL resources, and term-to-term retention.

Credit attainment. The ratio of the number of program course credits that students earned (i.e., completed the course) compared to the number of credits that students attempted (i.e., enrolled in) within the first six-month term was used as a behavioral indicator of academic success. Scores ranged from 0 to 1, with higher scores meaning students completed a greater percentage of the credits they attempted than students with lower scores. This information was provided by the participating college.

Engagement with online SRL resources. Data regarding students' engagement with online SRL resources through the DAACS intervention were collected. Specifically, the frequency with which students accessed information or recommendations from the online DAACS intervention website was measured.

Term-to-term retention. Data were collected regarding the amount of credits that students' enrolled in during the first and second six-month terms. Whether or not students enrolled in credits during both terms, or if they only enrolled in credits during the first term, was used as a measure of persistence and retention from one term to the next.

Results

Data Analysis Plan

To address the first research question (i.e., "RQ1: How many clusters of motivational processes will emerge from cluster analyses (CA) for two random samples of students enrolled in an online college? Do the results converge across samples?") k-means cluster analyses (CAs) were run as the primary clustering technique in order to identify the number and nature of motivation profiles across the five motivation variables (i.e., self-efficacy for online learning, mastery orientation, mindset, grit, and test anxiety). Cluster analyses aim to create homogenous clusters where the within-cluster differences are minimized, and the between-cluster differences are maximized (for an overview, see Pastor et al., 2007).

To enhance the validity of the cluster solutions, two k-means CAs were separately conducted for two random subsamples; one with 80% of the entire sample (i.e., primary subsample), and another with 20% of the entire sample (i.e., validation subsample). This split of the sample allowed for a large percentage (80%; *n* = 4,771) of the data to be used for identifying the initial CA solution (i.e., the training dataset), while maintaining a large enough sample (20%; *n* = 1,178) to conduct the second CA (i.e., the test dataset). ANOVAs were used to determine group equivalence for the two random samples across participant age, gender, and ethnicity, as well as each motivation and academic outcome variable. As discussed previously, conducting multiple analyses across two random samples can greatly enhance the validity of the cluster solutions, and has been cited as a limitation of prior person-centered studies (DiStefano & Kamphaus, 2006), as most studies do not attempt to replicate their results across multiple random samples from a single population. Given that prior research suggests three to six clusters of motivation variables can emerge as the most interpretable solution for the data (e.g., Bråten &

Olaussen, 2015; Putwain & Sander, 2016; Korpershoek et al., 2015), CAs were conducted with the primary subsample (i.e., 80%) for three, four, five, and six cluster solutions. The most meaningful cluster solution from the primary subsample results was used as the basis for the second CA with the validation subsample.

To address the second research question (i.e., “RQ2: Can the results of the CA be replicated with latent profile analyses (LPA) using the same two random samples? Do the results converge across the LPA with each sample?”) latent profile analyses (LPAs) were conducted as the secondary statistical technique to determine if the motivation profiles that emerged across two statistical techniques converged, and which technique produced a solution that better fit the data (see Figure 1). As with the CAs, the LPAs were conducted for two random subsamples (i.e., 80% and 20%); participants from the same two subsamples were used with the CA and LPA.

To conduct the LPA, the open-source statistical software, R, with the tidyLPA package, was used to run the LPA (R Core Team, 2018; Rosenberg, 2018), consistent with prior research (e.g., Jokić & Purić, 2019; Machimbarrena et al., 2018). An LPA assumes that a sample or population is comprised of a variety of probability distributions, with each cluster having its own probability distribution and parameters (Magidson & Vermunt, 2002; Pastor et al., 2007). Three population parameters are estimated within an LPA model (i.e., means, variances, and covariances) where typical assumptions (e.g., the assumption of local independence) can be relaxed in order to examine which model best fits the data. Some researchers caution against relaxing these assumptions without a valid, prior rationale, because the analyses are no longer a typical LPA (Marsh et al., 2009). However, relaxing these assumptions can also produce a solution with fewer profiles and better model fit than when variances and covariances are constrained, if the true nature of the data includes varying variances and/or covariances

(Vermunt & Magidson, 2002). For the current study, it was expected that the variances may differ between clusters, as each cluster could theoretically correspond to a different sub-population; therefore, the assumption of equal variances was relaxed. Additionally, since the motivation variables were expected to correlate, and may correlate with each other to varying degrees, the covariances were also allowed to vary. Given these hypotheses and the nature of the cluster analysis, which can sometimes constrain both the variances and covariances in its attempt to create homogenous groups, the LPA was run using the most lenient model that allows for both varying variances and covariances. For this model, LPA solutions with three through six profiles were estimated for the primary subsample, as is typical with prior research (e.g., Pastor et al., 2007). For the validation subsample, only one LPA solution was estimated based on the number of clusters from the best-fit LPA with the primary subsample. In order to attain convergence for all expected solutions, the prior control for the LPA was set at a specific point for each estimated solution.

To evaluate the fit of each solution, multiple fit statistics (i.e., Bayesian Information Criteria, BIC; entropy; Bootstrap Likelihood Ratio Test, BLRT) were considered, along with the sample size of each profile within a solution and the interpretability or meaningfulness of the pattern of motivational processes for each solution. This approach to evaluating the fit of an LPA solution is consistent with much of the prior LPA research in the field (e.g., Dörrenbächer & Perels, 2016; Pastor et al., 2007). The BIC was used to compare the model fit across multiple models and number of profiles and penalize for more complex models (e.g., where assumptions are relaxed); lower BIC numbers reflect better model fit. The entropy statistics provided a value of combined classification probabilities (i.e., the likelihood that a participant would be classified into their current profile) that were used to measure the acceptability of a solution to the data;

higher entropy values between 0 and 1 indicate better fit. The BLRT measured the model fit between a solution with *k* clusters and *k*-1 clusters; small *p*-values indicate that the solution with more (i.e., *k*) clusters was a better fit. Although these fit statistics provided a statistically objective basis for determining the best cluster solution, the sample size and interpretability of clusters may sometimes supersede the fit statistics (e.g., if a profile is too small to be meaningful and another solution should be considered), and were also considered in selecting the best solution for the data. Marsh et al. (2009) highlight how there is no “golden rule” for determining a final solution and that all available information (e.g., fit statistics, interpretability) must be considered in this process.

Results from the CA and LPA were then compared and the best solution for the data was selected based on whether or not results of the CA and LPA converged and/or if one type of analysis produced results that could be replicated across the primary and validation subsamples. No hypotheses were made regarding which statistical technique would produce the more favorable results, as the CA and LPA rely on different underlying assumptions to form groups. That is, the LPA makes assumptions regarding the underlying probability distribution of each cluster, with the current study using an LPA model that allows for varying variances and covariances. On the other hand, the CA aims to find the most homogenous groups regardless of the probability distribution of each cluster (Magidson & Vermunt, 2002; Pastor et al., 2007; Vermunt & Magidson, 2002). Although the CA can be considered to be most similar to an LPA model where variances vary but covariances are constrained to zero, the CA does not make any assumptions regarding the underlying probability distributions (Pastor et al., 2007), and therefore may produce different results than the LPA.

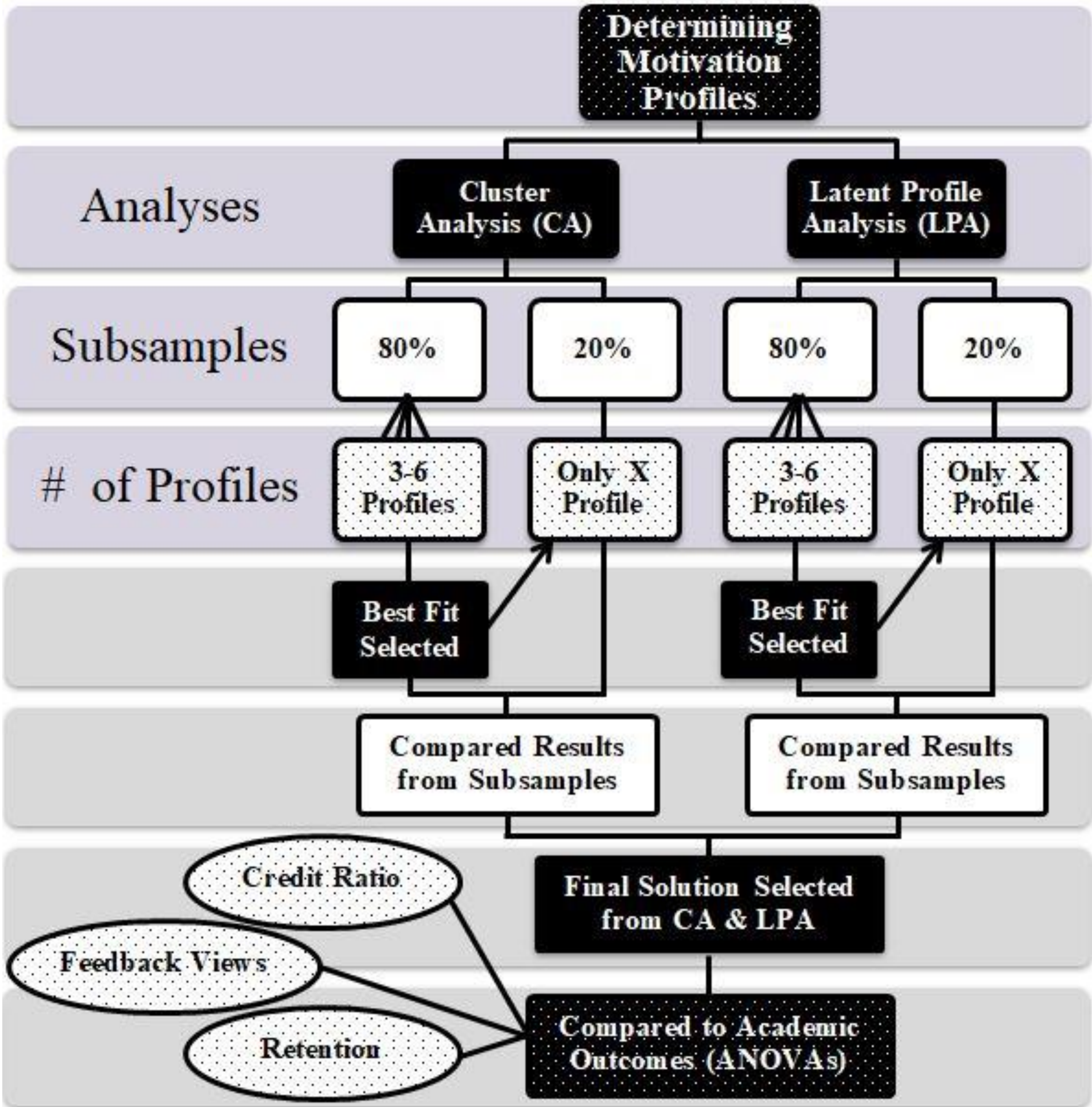


Figure 1. Data analysis process. X profile = the best fit profile solution selected from the 80% subsample.

Table 1

Research Questions and Data Analyses

Research Question (RQ)	Variables (IV, DV)	Analyses
RQ1: How many clusters of motivational processes will emerge from cluster analyses (CA) for two random samples of students enrolled in an online college? Do the results converge across samples?	Subscale scores for self-efficacy, mastery orientation, mindset, test anxiety, and grit for all students in the sample	Cluster Analysis (CA)
RQ2: Can the results of the CA be replicated with latent profile analyses (LPA) using the same two random samples? Do the results converge across the LPA with each sample?	Subscale scores for self-efficacy, mastery orientation, mindset, test anxiety, and grit for all students in the sample	Latent Profile Analysis (LPA)
RQ3: What are the key characteristics or patterns among motivation variables within each of the observed clusters?	Subscale scores for self-efficacy, mastery orientation, mindset, test anxiety, and grit for all students in the sample	Descriptive Analyses
RQ4: Do the motivation clusters differ in terms of achievement (i.e., ratio of credits earned to credits attempted)?	IV: Cluster membership DV: Credit ratio	ANOVA
RQ5: Do the motivation clusters differ in terms of students' engagement in an academic and self-regulation intervention?	IV: Cluster membership DV: Frequency of use of online resources	ANOVA
RQ6: Do the motivation clusters differ in terms of student term-to-term retention at an online college?	IV: Cluster membership DV: Retention from term-one to term-two	ANOVA

To address the third research question (i.e., "RQ3: What are the key characteristics or patterns among motivation variables within each of the observed clusters?"), descriptive analyses of the profiles from the final cluster solution (i.e., the solution selected between the CA and LPA results) were conducted to understand the key motivation characteristics of each cluster. To address research questions four, five, and six (i.e., "Do the motivation clusters differ in terms of achievement (RQ4), engagement in an academic and self-regulation intervention (RQ5), and term-to-term retention (RQ6)?") one-way ANOVAs and post-hoc tests were used to determine cluster group differences across all dependent measures. Levene's test of homogeneity of variances was conducted and Tamhane's T2 post-hoc tests were used to identify specific cluster differences on outcome variables when variances were significantly different.

Preliminary Statistics

The extant dataset used for the current study originally contained data for students in both the treatment and control group of the randomized control trial study where the data originated. Given that students in the control group did not have motivation scores, as they did not complete the DAACS-SRL assessment, only students with scores for the five motivation variables were retained for the current study. Upon analyzing descriptive statistics, the scores for three students represented extreme outliers as evidenced by multiple motivation variable scores of zero and a survey completion time of two minutes or less; the latter suggest suggests that the participants simply clicked through the survey rather than responding in a thoughtful and appropriate manner. As a result, these three students were eliminated from the current sample.

The two random subsamples were drawn using the *select cases* function in SPSS. The primary subsample included 4,771 students (80.2% of overall sample), while the validation sample consisted of 1,178 students (19.8%). One-way ANOVA's revealed that the two subsamples did not significantly differ across the following demographic variables: age ($F(1, 5946) = 0.148$; $p = 0.700$), gender ($F(1, 5947) = 3.577$; $p = 0.59$), and ethnicity ($F(1, 5947) = 1.218$; $p = 0.270$). The groups also did not differ across the five motivation variables: mindset ($F(1, 5947) = 0.000$; $p = 1.000$), self-efficacy for online learning ($F(1, 5947) = 0.338$; $p = 0.561$), mastery orientation ($F(1, 5947) = 1.785$; $p = 0.182$), test anxiety ($F(1, 5947) = 1.976$; $p = 0.160$), and grit ($F(1, 5947) = 0.971$; $p = 0.325$). Finally, no group differences emerged across the following academic outcomes: first-term credits earned to attempted ratio ($F(1, 5947) = 0.191$; $p = 0.662$) and feedback views (log(10) transformed; $F(1, 5944) = 1.120$; $p = 0.290$). However, statistically significant group differences did emerge for term-to-term retention ($F(1, 5931) = 7.051$; $p = 0.008$; $d = 0.09$) with the 80% primary subsample returning for a second term slightly more ($M = 0.77$; $SD = 0.43$) than the 20% validation subsample ($M = 0.73$; $SD = 0.44$). Despite the very small ($d = 0.09$) difference between groups on term-to-term retention, the two subsamples were broadly similar across demographic, motivation, and most outcome variables, and were considered equivalent for the purposes of the current study.

Descriptive Statistics

Descriptive statistics and correlations between the motivation variables included in this study are provided in Table 2 and Table 3. As expected, all motivation variables significantly ($p < .001$) correlated with each other. Descriptive statistics are also presented for the outcome variables measured in this study (Table 2). All skewness and kurtosis values were within accepted limits except for feedback views (skewness = 2.481; kurtosis = 16.479). Given these values, a log(10) transformation was conducted for this variable prior to use in analyses.

Table 2

Descriptive Statistics for Motivation and Academic Outcome Variables

Variable	Mean	SD	Min	Max	Skew	SE Skew	Kurtosis	SE Kurtosis
Motivation Variables								
Self-efficacy	3.310	0.525	0.00	4.00	-0.439	0.032	0.197	0.063
Mindset	3.084	0.634	0.00	4.00	-0.699	0.032	1.043	0.063
Mastery goal orientation	3.321	0.458	0.00	4.00	-0.627	0.032	1.007	0.063
Test anxiety	2.837	0.774	0.00	4.00	-0.845	0.032	0.908	0.063
Grit	2.860	0.459	0.90	4.00	-0.371	0.032	-0.031	0.063
Academic Outcomes								
Credit ratio	0.796	0.304	0.00	1.00	-1.390	0.032	0.715	0.063
Feedback views	1.069	0.403	0.00	2.40	-0.566	0.032	0.112	0.064
Term-to-term retention	0.760	0.426	0.00	1.00	-1.229	0.032	-0.491	0.064

Note. SD = Standard Deviation. Skew = Skewness. SE = Standard Error. Values presented for feedback views were transformed by log(10).

Table 3

Pearson Correlations between Motivation Variables

Variable	1	2	3	4	5
1. Self-efficacy	—	0.268	0.524	0.388	0.445
2. Mindset		—	0.250	0.150	0.298
3. Mastery goal orientation			—	0.311	0.411
4. Test anxiety				—	0.415
5. Grit					—

Note. All correlations significant at $p < .001$ (2-tailed).

Research Question 1: Motivation Profiles through Cluster Analysis

Overall, the results suggested that a four-profile solution best fit the data when three through six profiles were examined across multiple subsamples (i.e., primary and validation subsamples). The results for each subsample and type of analysis are presented in the following sections.

Cluster analysis with primary subsample. The cluster analysis with the primary 80% subsample suggested that a four-profile solution was the most meaningful solution for the data (Figure 2; Table 4). The four-cluster solution demonstrated the most interpretable pattern across the four profiles where each cluster had a unique, defining characteristic. That is, the four clusters represented unique groups of students who appeared to differ across several variables, such as higher test anxiety, an uncommitted mindset, or consistently high motivational beliefs, for example. Additionally, ANOVAs indicated that each cluster differed significantly ($p < .05$) from the other clusters across all five motivation variables, with the exception of two clusters, which exhibited similar scores on the grit measure.

In determining the number of profiles that best fit the data, solutions for three, five, and six clusters were also considered. Although the three-profile solution yielded three distinct patterns of motivation, the four-profile solution added an additional profile that provided more insight into the patterns of motivation in the current sample than the three-profile solution. Specifically, the four-profile solution identified a profile of students with considerably different levels of mindset than the other clusters, which did not emerge with the three-profile solution. The five-profile solution produced clusters that overlapped to some degree with other clusters, and therefore did not provide a more meaningful and distinct pattern of motivational processes than the four-profile solution. Lastly, the six-profile solution further differentiated between some motivation profiles, but again produced multiple clusters that were not descriptively distinct from other profiles. Therefore, the four-profile solution was retained as the most meaningful and interpretable solution for the data.

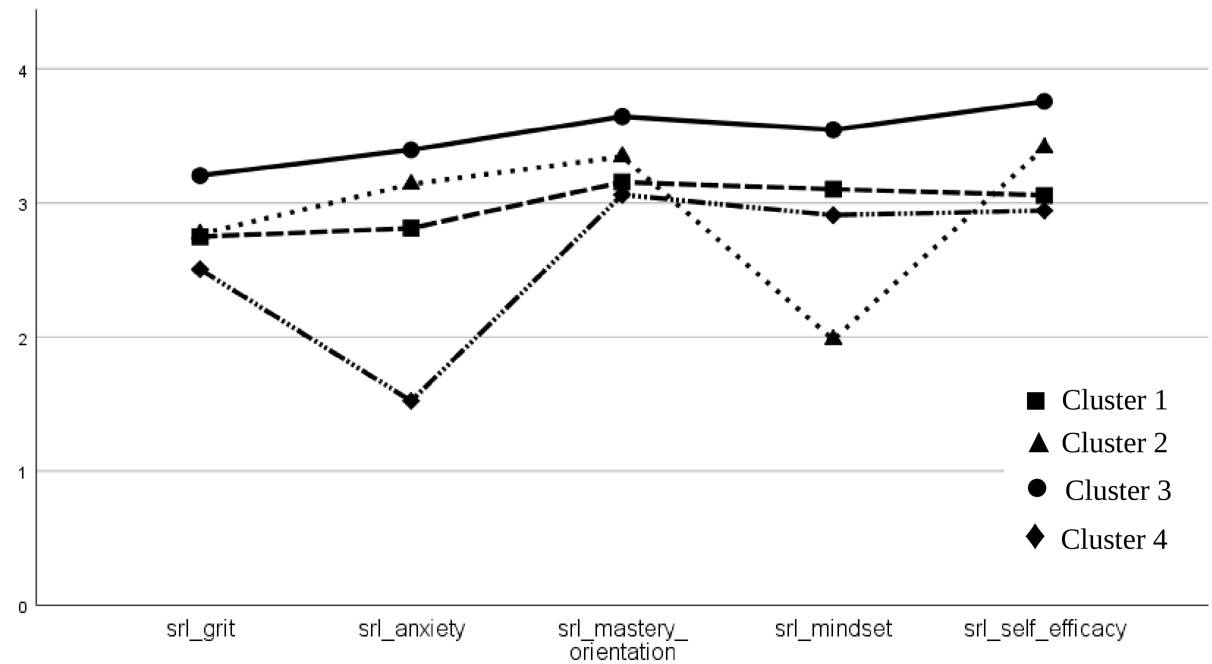


Figure 2. Cluster means for the cluster analysis with the primary subsample.

Table 4

Cluster Analysis Cluster Means for Primary Subsample (n = 4,771)

Variable	Cluster 1 (*n* = 1880; 39.41%)	Cluster 2 (*n* = 574; 12.03%)	Cluster 3 (*n* = 1576; 33.03%)	Cluster 4 (*n* = 741; 15.53%)
Grit	2.75	2.77	3.20	2.50
	(0.37)	(0.44)	(0.33)	(0.44)
Test	2.81	3.14	3.40	1.52
Anxiety	(0.37)	(0.52)	(0.46)	(0.55)
Mastery	3.16	3.35	3.64	3.06
Orientation	(0.38)	(0.48)	(0.31)	(0.49)
Mindset	3.10	1.98	3.55	2.91
	(0.38)	(0.48)	(0.42)	(0.55)
Self-	3.06	3.41	3.76	2.94
Efficacy	(0.40)	(0.47)	(0.31)	(0.53)

Note. Scores for each motivation variable could range from 0 to 4. Standard deviations are presented in parentheses.

Cluster analysis with validation subsample. For the validation subsample, a k-means cluster analysis was conducted for only the four-profile solution, as the results from the primary subsample indicated that the four-profile solution was the most meaningful fit for the data. The cluster analysis with the validation subsample (20% of total sample) suggested that the four-profile solution was a meaningful and interpretable solution for the data (Table 5; Figure 3). ANOVAs indicated that all clusters significantly ($p < .05$) differed from each other across the five motivation variables with the exception of similar mean scores on grit between a pair of clusters and self-efficacy for online learning on another pair.

Table 5

Cluster Analysis Cluster Means for Validation Subsample (n = 1,178)

Variable	Cluster 1 (*n* = 458; 38.88%)	Cluster 2 (*n* = 146; 12.39%)	Cluster 3 (*n* = 399; 33.87%)	Cluster 4 (*n* = 175; 14.86%)
Grit	2.70	2.74	3.20	2.51
	(0.38)	(0.46)	(0.34)	(0.45)
Test Anxiety	2.77	3.01	3.41	1.38
	(0.38)	(0.56)	(0.47)	(0.56)
Mastery	3.13	3.39	3.62	2.97
Orientation	(0.39)	(0.40)	(0.32)	(0.47)
Mindset	3.12	2.10	3.47	2.92
	(0.37)	(0.50)	(0.44)	(0.53)
Self-Efficacy	3.06	3.30	3.74	2.93
	(0.39)	(0.45)	(0.31)	(0.54)

Note. Scores for each motivation variable could range from 0 to 4. Standard deviations are presented in parentheses.

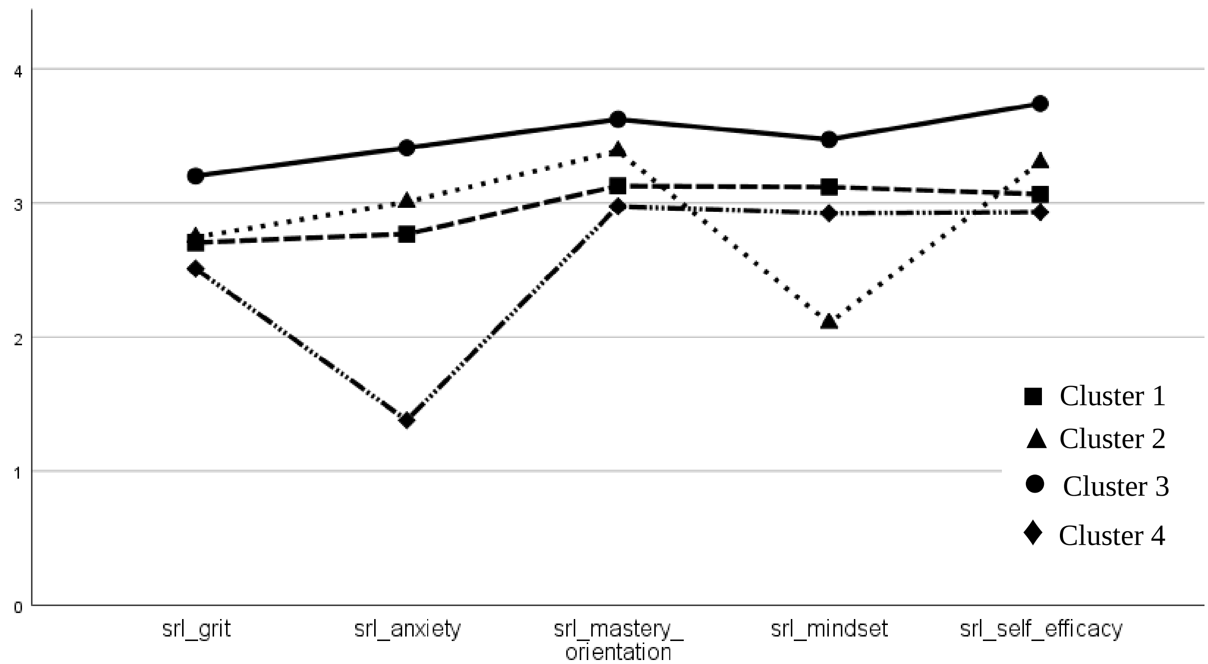


Figure 3. Cluster means for the cluster analysis with the validation subsample.

The results from the validation sample were highly consistent with the results from the cluster analysis with the primary subsample. The descriptive and visual pattern of motivational processes was highly similar across the two subsamples. Additionally, ANOVAs indicated that the mean motivation scores for each corresponding cluster did not significantly differ between the primary and validation results. This finding suggests that the pattern of motivational processes uncovered by the primary cluster analysis converges across multiple random samples, supporting the validity the patterns of motivational processes identified in the current study.

Final cluster analysis with the entire sample. Due to the highly similar nature of the motivation profiles produced by the cluster analyses across the two subsamples, data were merged and the results of a final cluster analysis on the entire sample (N = 5,949) are presented in Table 6 and Figure 4.

Table 6

Final Cluster Descriptive Statistics for the Cluster Analysis with the Entire Sample

Variable	Cluster 1 (*n* = 2346; 39.44%)	Cluster 2 (*n* = 722; 12.14%)	Cluster 3 (*n* = 1958; 32.91%)	Cluster 4 (*n* = 923; 15.51%)
Grit	2.744	2.76	3.20	2.50
	(0.37)	(0.45)	(0.33)	(0.44)
Test	2.81	3.11	3.40	1.50
Anxiety	(0.37)	(0.53)	(0.47)	(0.55)
Mastery	3.15	3.35	3.64	3.04
Orientation	(0.38)	(0.47)	(0.31)	(0.49)
Mindset	3.11	2.00	3.54	2.92
	(0.37)	(0.49)	(0.42)	(0.55)
Self-	3.06	3.38	3.76	2.94
Efficacy	(0.39)	(0.46)	(0.31)	(0.54)

Note. Scores for each motivation variable could range from 0 to 4. Standard deviations are presented in parentheses.

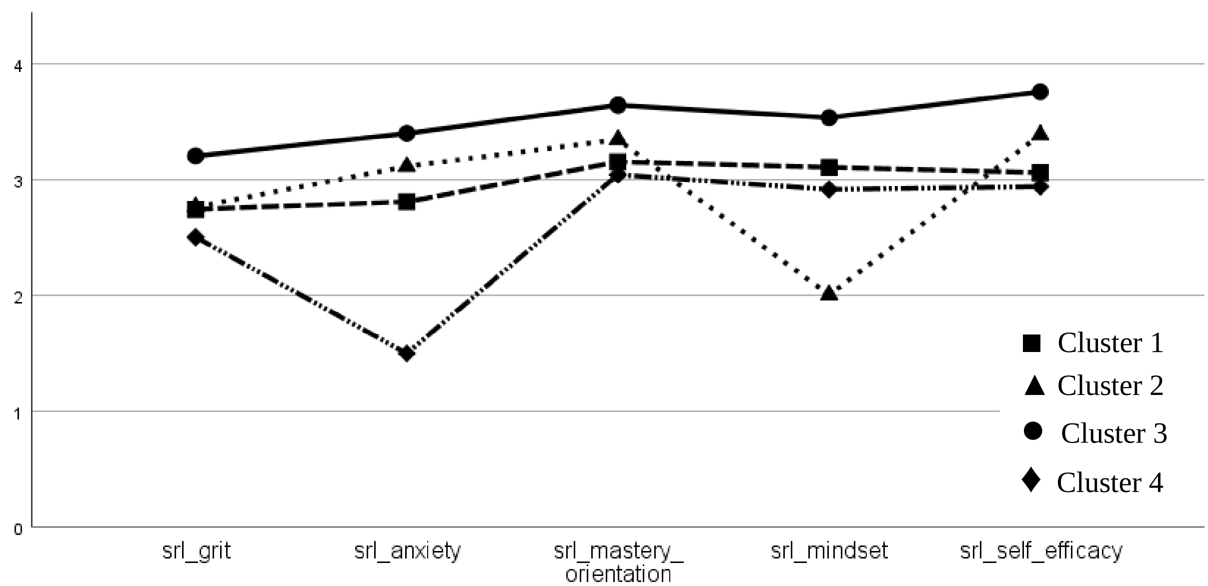


Figure 4. Cluster means for the cluster analysis with the entire sample

Research Question 2: Validating Motivation Profiles through Latent Profile Analysis

To validate the CA results, secondary latent profile analyses (LPA) were also conducted on the two subsamples. The LPA results were not as consistent and clear cut as those of the CA; they are presented in the following sections separated by subsample. Then, a comparison of the best fit solution between the CA and LPA will then be examined.

Latent profile analysis (LPA) with the primary subsample. Similar to the CA, the LPA yielded a four-profile solution as the best fit for the data, based on the fit statistics (i.e., BIC, entropy, BLRT), sample size of each profile, and interpretability of the profiles from each solution. In summary, the following fit statistics or criteria were observed: (a) adequate BIC (i.e., the second-lowest of the solutions examined) and entropy (i.e., greater than 0.80; see Table 7), (b) adequately large sample sizes, ranging from 11.02% to 46.05%, and (c) each pattern of motivational processes was meaningfully distinct (i.e., the level of each motivation variable is meaningfully different between profiles) and distinguished by a key characteristic (e.g., a profile with considerably lower mindset scores than other motivational processes; Figure 5; Table 8). For this LPA, the BLRT was unable to be computed and was therefore not considered in selecting the solution that best fit the data for the LPA with the primary subsample. For the four-profile solution, ANOVAs indicated that all clusters significantly ($p < .05$) differed from each other across the five motivation variables with the exception of similar mean scores on grit between two clusters.

In selecting whether another solution fit the data better than the four-profile solution, solutions for three, five, and six profiles were considered. The three-profile solution did not produce fit statistics (i.e., BIC, entropy) that were superior to those of the four-profile solution. Additionally, the pattern of motivational processes did not capture more distinct, meaningful patterns of motivation variables than the four-profile solution. The five-profile solution produced a marginally superior BIC value, but lower entropy, and contained three profiles with approximately 10% of the sample in each profile. Additionally, the pattern of motivational processes across the five- and six-profile solutions did not descriptively appear to add additional meaningfulness to the interpretation of each profile. The ability of each profile to be meaningfully different from the others, from a descriptive standpoint, decreased from the four-profile solution to the five- and six-profile solutions. Based on the fit statistics, interpretability of the pattern of motivation variables, and the minimum cluster size for each solution, the solution with four profiles provided the best fit for the data from the primary 80% subsample.

Table 7

Fit Statistics and Sample Sizes within Clusters for Primary LPA

Model	# of Clusters	BIC	BLRT	Entropy	Cluster Sample Sizes
Varying variances and covariances	3	32703.182	N/A	.863	1186, 2225, 1360
Varying variances and covariances	**4**	**32540.610**	**N/A**	**.836**	**2197, 1289, 759, 526**
Varying variances and covariances	5	32535.676	N/A	.798	603, 2068, 1208, 419, 473

Note. BIC = Bayesian information criteria; lower numbers indicate better fit. Entropy = aggregate classification uncertainty; higher values (e.g., over 0.8) indicate higher classification utility. BLRT = Bootstrap Likelihood Ratio Test; indicates if K-1 cluster, where K is a cluster solution, is a better fit than K cluster. Bolded numbers indicate the solution with the best overall fit.

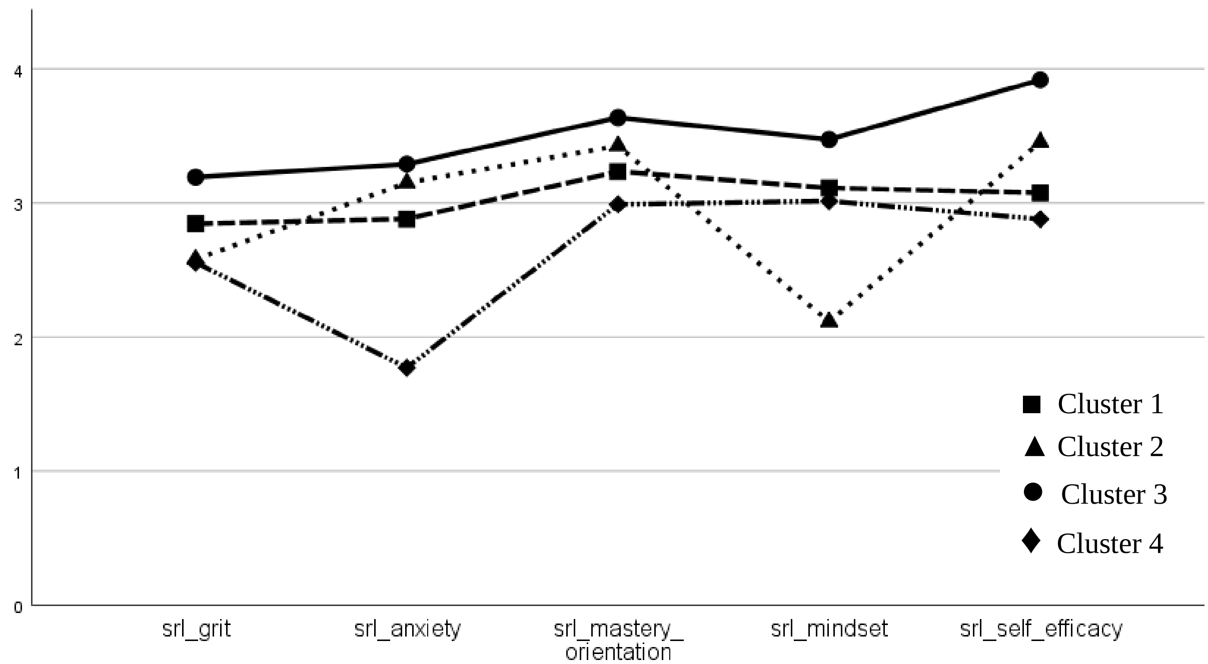


Figure 5. Cluster means for the latent profile analysis with the primary subsample.

Table 8

LPA Cluster Means and Standard Deviations for the Primary Subsample

Variable	Cluster 1 (*n* = 2197; 46.05%)	Cluster 2 (*n* = 526; 11.02%)	Cluster 3 (*n* = 1289; 27.02%)	Cluster 4 (*n* = 759; 15.91%)
Grit	2.84	2.58	3.19	2.56
	(0.35)	(0.52)	(0.33)	(0.49)
Test	2.88	3.15	3.29	1.77
Anxiety	(0.48)	(0.59)	(0.53)	(0.86)
Mastery	3.23	3.43	3.64	2.99
Orientation	(0.36)	(0.42)	(0.33)	(0.58)
Mindset	3.11	2.11	3.47	3.01
	(0.43)	(0.73)	(0.47)	(0.61)
Self-	3.08	3.45	3.92	2.88
Efficacy	(0.26)	(0.41)	(0.12)	(0.65)

Note. Scores for each motivation variable could range from 0 to 4. Standard deviations are presented in parentheses.

Latent profile analysis with validation subsample. Consistent with the LPA from the original subsample, results from the LPA with the validation subsample suggested that a four-profile solution was a good fit for the data. The four-profile solution demonstrated the following fit statistics and criteria: (a) cluster sample sizes above 5% of the sample, (b) adequate fit statistics (Table 9), and (c) a pattern of motivation variables across the four profiles that meaningfully distinguished each profile from another (see Table 10; Figure 6). Similar to the LPA with the primary subsample, the BLRT could not be estimated and was therefore not considered for the validation subsample. For the four-profile solution, ANOVAs indicated that all clusters significantly ($p < .05$) differed from each other across the five motivation variables with the exception of similar mean scores on mastery orientation between two clusters.

Table 9

Fit Statistics and Sample Sizes within Clusters for Validation LPA Solutions

Model	# of Clusters	BIC	BLRT	Entropy	Cluster Sample Sizes
Varying variances and covariances	4	8383.960	N/A	.844	330, 347, 440, 61

Note. BIC = Bayesian information criteria; lower numbers indicate better fit. Entropy = aggregate classification uncertainty; higher values (e.g., over 0.8) indicate higher classification utility. BLRT = Bootstrap Likelihood Ratio Test; indicates if K-1 cluster, where K is a cluster solution, is a better fit than K cluster.

Table 10

LPA Cluster Means and Standard Deviations for the Validation Subsample

Variable	Cluster 1 (*n* = 347; 29.46%)	Cluster 2 (*n* = 61; 5.18%)	Cluster 3 (*n* = 330; 28.01%)	Cluster 4 (*n* = 440; 37.35%)
Grit	2.78	3.50	3.15	2.58
	(0.37)	(0.17)	(0.28)	(0.46)
Test Anxiety	2.89	3.80	3.23	2.29
	(0.47)	(0.23)	(0.48)	(0.92)
Mastery	3.16	3.88	3.58	3.13
Orientation	(0.32)	(0.17)	(0.29)	(0.52)
Mindset	3.07	3.98	3.26	2.84
	(0.34)	(0.06)	(0.47)	(0.73)
Self-Efficacy	2.99	3.89	3.79	3.10
	(0.15)	(0.17)	(0.21)	(0.56)

Note. Scores for each motivation variable could range from 0 to 4. Standard deviations are presented in parentheses.

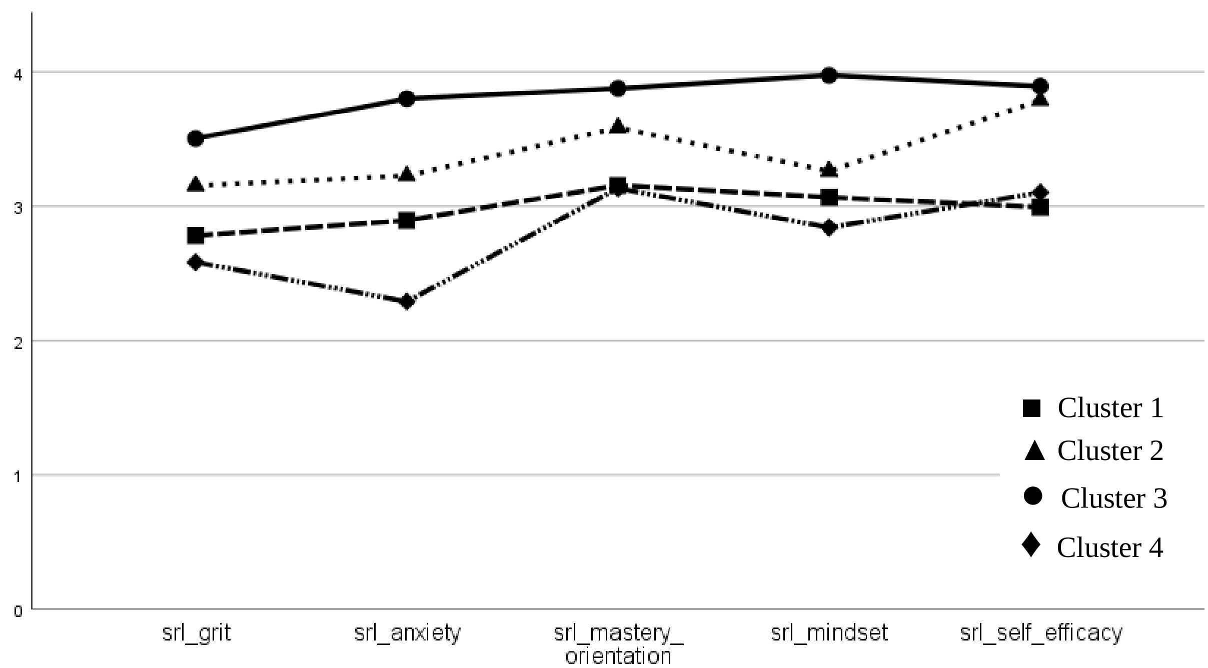
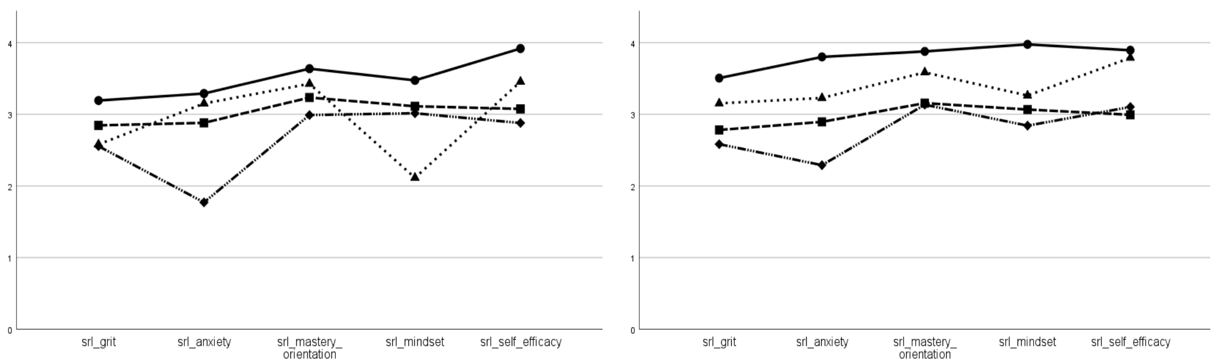


Figure 6. Cluster means for the latent profile analysis with the validation subsample.

However, the pattern of motivation variables in the four-profile solution from the validation subsample diverged in meaningful ways from that of the primary subsample. That is, although three of the profiles from each subsample descriptively appeared to be highly similar, the last profile (i.e., the profile with the lowest mindset scores in the primary sample) did not demonstrate the same level across all five motivation variables across samples (Figure 7). Due to the differences in the pattern of motivation processes across the LPA results produced by the two subsamples, the data were not merged to conduct an LPA on the entire sample.



Primary Subsample Validation Subsample

Figure 7. Comparing LPA results across the primary and validation LPA samples.

Comparing results of the CA and LPA. Overall, results of the CA and LPA indicated that the four-profile solution was a meaningful (i.e., produced distinct patterns of motivational processes) and valid solution that converged across multiple random samples. That is, the primary CA results were replicated with the validation CA both descriptively and statistically. Additionally, the four-profile CA solution was further supported by the descriptive similarities between the primary CA results and the primary LPA results. That is, the patterns of motivation between the primary CA and primary LPA results were visually very similar. The corresponding clusters between the CA and LPA also included similar percentages of students (e.g., the highest cluster contained approximately 33% of students in the CA and 27% of students in the LPA).

It is relevant to note, however, that the patterns of motivation from the primary CA and primary LPA differed statistically on some motivation variables. ANOVAs indicated that each corresponding cluster between the primary CA and primary LPA significantly differed ($p > .05$) on at least one variable, despite as many as four motivation variables emerging as non-significantly different. These results indicate that the four-profile solution from the CA and LPA produced patterns of motivation variables that were somewhat different. Because the CA results could be replicated across the primary and validation subsamples, while the LPA solution could not be replicated, and therefore may not be the most stable solution, cluster membership from the CA results was selected for use in comparing multiple indicators of academic success across profiles.

Research Question 3: Motivation Profile Descriptions

The motivation profiles identified from the CA of the entire sample are described below. The first cluster (n = 2,346; 39.44%) called *Moderately Motivated Learners*, included students who reported fairly similar and moderately high (i.e., near the three-point mark on the zero-to-four scale) motivational processes across all five variables. Students in this cluster reported feeling moderately confident in their online academic abilities (i.e., self-efficacy for online learning), moderately able to persevere over time (i.e., grit), moderately interested in mastering learning materials (i.e., mastery orientation), moderately sure that they could change their mindset with time and effort (i.e., growth mindset), and did not feel much anxiety in regards to evaluative situations (i.e., test anxiety). The distinguishing feature of this cluster was the consistency of motivation level across all five motivational processes.

The second cluster (*n* = 722; 12.14%), called *Uncommitted Mindset Learners*, contained students who reported moderately high levels of mastery orientation, grit, test anxiety, and self-efficacy for online learning, but a considerably lower level of mindset than students in any other cluster. Due to the fact that the lower mindset scores indicate more of a fixed mindset, whereas higher mindset scores reflect a growth mindset, and the overall mean score for this cluster aligned with the mid-point for the scale (*M* = 2.0), students in this cluster appeared to endorse both fixed and growth mindset beliefs, suggesting they were uncommitted to either a fixed or growth mindset (i.e., whether or not their intelligence can change). In addition to the uncommitted mindset, students in this cluster engaged in learning with the intent to master the material, felt confident in their abilities to learn online, felt interested in and able to persevere through their learning long-term, and did not feel very anxious in the face of evaluative situations. Compared to the other clusters, the second cluster contained the smallest percentage of students, indicating that roughly one in 10 students may feel uncommitted to their mindset, even if they exhibit other adaptive motivational beliefs.

The third cluster (*n* = 1,958; 32.91%) was labeled *Highly Motivated Learners* given that participants in this cluster demonstrated a pattern of objectively (i.e., scores relative to the five-point Likert scale) and relatively (i.e., compared to other clusters) high motivation levels across all five motivational processes. Thus, students in this cluster reported the highest level of each motivational process compared to students in any other cluster. Students reported feeling extremely confident in their ability to learn online, having a strong desire to master their learning, strongly believing their intelligence could change with time (i.e., growth mindset), believing they can persevere over time (i.e., gritty), and not feeling much anxiety in evaluative situations. Within this cluster, the lowest reported motivational process was grit, and the highest was self-efficacy, which was nearly at the top of the possible range of scores for the scale used in the current study. Therefore, the students in this cluster could be considered both highly motivated and confident.

Lastly, the fourth cluster (n = 923; 15.51%), called *Anxious Learners,* demonstrated a more variable pattern of scores across motivation variables, with test anxiety scores that suggested significantly higher test anxiety relative to students in the other clusters. Students in this cluster also reported moderate scores (i.e., between 2.5 and three on the zero-to-four scale) across grit, mastery orientation, mindset, and self-efficacy for online learning. Students in this cluster reported feeling somewhat anxious regarding evaluative situations, feeling moderately able to persevere over time (i.e., grit) and improve their intelligence with effort (i.e., growth mindset), having a moderate desire to master their learning, and feeling moderately confident in their ability to learn online. Students in this cluster also reported the greatest test anxiety, on average, than students in any cluster. The students in this cluster felt moderately confident in their abilities to approach and persevere through learning tasks, but also experienced some anxiety in regards to evaluative situations.

Research Questions 4, 5, and 6: Cluster Group Differences in Academic Success

To examine differences among the four clusters in terms of academic success, several one-way ANOVA's were conducted. The results revealed statistically significant differences among clusters across two of the three academic success indicators. Cluster group differences emerged across *credits earned to attempted ratio* ($F(3, 5945) = 7.767$; $p < .001$; $\eta^2 = .004$) and *engagement with online SRL resources* in terms of students' log-transformed feedback views ($F(3, 5942) = 7.138$; $p < .001$; $\eta^2 = .004$). No cluster differences emerged for *term-to-term retention* ($F(3, 5929) = 1.063$; $p = .363$).

Table 11

Academic Success Indicators by Motivation Profile

Variable	Credit Ratio		Feedback Views		Retention	
	M	*SD*	*M*	*SD*	*M*	*SD*
Moderately Motivated Learners	0.81_a***	0.30	1.09_a***	0.39	0.77	0.42
Uncommitted Mindset Learners	0.82_a***	0.28	1.06	0.41	0.77	0.42
Highly Motivated Leaners	0.79_a*	0.31	1.04_b	0.42	0.76	0.43
Anxious Learners	0.76_b	0.32	1.07	0.39	0.74	0.44

Note. Means that are subscripted by a different letter are statistically different. Values presented for feedback views have been log(10) transformed.
* p<.05. ** p< .01. *** p<.001

To determine specific cluster differences in terms of credit ratio Tamhane's post-hoc tests were conducted. Results indicated that that the *Anxious Learners* exhibited a statistically lower credit ratio (i.e., completed a lower percentage of credits out of the number of credits attempted) than all other clusters. That is, the *Anxious Learners* had a lower credit ratio (*M* = 0.76; *SD* = 0.32) than the *Moderately Motivated Learners* (*M* = 0.81; *SD* = 0.30; *d* = 0.16), *Uncommitted Mindset Learners* (*M* = 0.82; *SD* = 0.28; *d* = 0.21), and the *Highly Motivated Leaners* (*M* = 0.79; *SD* = 0.31; *d* = 0.12). However, the differences in credit ratio between these clusters were small (*d* = 0.12-0.21). No other cluster group differences emerged across credit ratio.

In terms of engagement with the online SRL feedback system, Tamhane's post hoc tests showed that only two clusters significantly differed from each other. The *Moderately Motivated Learners* (*M* = 1.09; *SD* = 0.39) viewed online SRL resources more frequently than the *Highly Motivated Learners* (*M* = 1.04; *SD* = 0.42). Similar to credit ratio, the effect sizes for these cluster differences were small (*d* = 0.14). No other cluster group differences in feedback views emerged.

In regards to term-to-term retention, results indicated that there were no significant differences between clusters in the amount of students who continued for a second term after enrolling in a first term.

Discussion

The current study aimed to identify motivation profiles in a large sample of non-traditional students at an online college who are more likely to encounter barriers to their learning as a result of the challenging learning context. The findings from the current study are important because motivational processes are essential for helping students overcome challenges, and it is critical to understand which patterns of motivational strengths and weaknesses relate to academic success in students who experiences challenges. The goals of this study were to (a) identify clusters representing patterns of motivational processes (i.e., self-efficacy for online learning, mindset, mastery goal orientation, test anxiety, and grit) across a sample of non-traditional college students enrolled in an online college, and (b) identify how these clusters differentially related to indicators of academic success, engagement, and persistence. Findings from this study yielded distinct patterns of motivational processes that were validated across multiple random samples of a unique population of college students. Additionally, the results indicated that some patterns of motivational processes are related to slightly better success in attaining key academic outcomes in an online college.

Motivation Profiles

The results of this study showed that a cluster solution with four profiles of motivational processes provided the best fit for the data generated from a group of non-traditional college students shortly after they enrolled in an online college. The results are robust and fairly compelling because the number and pattern of motivational processes was replicated and validated across multiple statistical techniques and two random samples of non-traditional college students. That is, both the CA and LPA analyses suggested that a four-profile solution emerged as the best fit for the data. Additionally, despite the statistically significant differences between the primary CA and LPA, the patterns of motivation variables across clusters were virtually identical from a descriptive analysis standpoint. That is, the clusters across both the primary CA and primary LPA exhibited means that were highly similar and conveyed the same overall pattern of motivation variables between the two statistical approaches. This pattern of motivation variables was also statistically similar across the two CA subsamples. These similarities support the validity and robustness of a four-profile solution.

It is important to note that the profiles that emerged in the current study are from a large, yet unique sample of college students. These students are non-traditional in the sense that they are older, may be returning to college after failing to complete a prior degree, and may be working full-time or have to manage the responsibilities of a family in addition to their school work. Students also completed the DAACS-SRL survey shortly after enrolling in an online college. Although the online learning context presents with demands that amplify the importance of adequate motivational beliefs, the students in the current sample had only just begun their online education at the time of completing the DAACS-SRL survey. Their prior educational experiences may have influenced their current motivation beliefs to a similar or greater degree than their perceptions of their abilities in relation to their current educational experiences.

Two of the motivation profiles that emerged demonstrated fairly consistent levels of motivation across the five processes. That is, students in these two clusters endorsed a similar pattern of motivational process, with the distinction involving the level (i.e., quality) of those processes. Interestingly, these two clusters, *Moderately Motivated Learners* and *Highly Motivated Learners*, included more than 70% (n = 4,304) of the entire sample. Since students in both clusters demonstrated moderate or high levels across all five motivational processes, both clusters can be considered adaptive from a descriptive standpoint, with the *Highly Motivated*

Learners being conceptually more adaptive than the *Moderately Motivated Learners*. This finding is encouraging, given that more than 70% of non-traditional students in the current study reported adaptive motivational beliefs, which is essential for these students who will likely encounter challenges as a result of their personal responsibilities (e.g., a full-time job) and contextual challenges (e.g., learning online without the support of an in-person instructor).

Interestingly, prior studies with different samples and contexts have also revealed motivation clusters with highly consistent scores at a moderate or high level across multiple motivation beliefs (Bråten & Olaussen, 2005; Dörrenbächer & Perels, 2016). Bråten & Olaussen (2005) measured the interest, mastery goal orientation, task value, and self-efficacy across two samples of 105 business Master's and 99 undergraduate nursing students. Using a CA, the authors identified three clusters (i.e., positive/high, moderate, and low), with students in each cluster exhibiting a consistently high, moderate, or low level across all motivation beliefs, respectively. Similarly, Dörrenbächer and Perels (2016) examined the motivation (i.e., self-efficacy, goal orientation, and intrinsic motivation) and SRL skills (e.g., goal setting, planning, elaboration, self-monitoring) of 337 college students. Using a LPA, the authors and identified four clusters: low SRL with moderate motivation, moderate SRL and motivation, conflicting SRL with high motivation, and high SRL and motivation. Regardless of the level of SRL skills, which were lower than students' reported motivation in two of the four clusters, Dörrenbächer and Perels results yielded two clusters with consistently moderate motivation and two with consistently high motivation.

The remaining two clusters from the current study, the *Uncommitted Mindset* and *Anxious Learners*, included approximately 30% (n = 1,645) of the sample. These two clusters exhibited a more variable pattern of motivational processes than the previous two consistent clusters. The *Uncommitted Mindset Learners* reported an uncommitted mindset (i.e., endorsed both fixed and growth mindset items), along with moderate, adaptive levels across the other four motivational beliefs. Interestingly, students in this cluster reported the second most adaptive (i.e., highest) levels of grit, self-efficacy for online learning, mastery orientation, and test anxiety out of students in all four profiles. The distinguishing characteristic of this cluster, however, was that they were neither committed to either a growth mindset nor fixed mindset. This pattern of motivational processes is somewhat inconsistent with some theories of motivation, which suggest that students who exhibit a mastery orientation and are self-efficacious also tend to report a growth mindset, not an uncommitted or fixed mindset (Schunk et al., 2014). For example, Chen (2012) examined the mindset and epistemic beliefs about science in 1,225 middle and high school students, and then compared clusters to goal orientation, self-efficacy, and achievement. Chen (2012) found one cluster of students who reported an uncommitted mindset, but also reported low mastery orientation goals and self-efficacy. However, the *Uncommitted Mindset Learners* in the current study may simply believe that they possess an adequate level of knowledge or skills and do not need to further improve their intelligence. Given that the current sample consists of students who are non-traditional and may be returning to college to complete a degree they previously started, these students may be interested in mastering material to achieve a degree, but are less interested in improving their overall knowledge and skills. Although prior research has also combined the growth and fixed mindset items from the mindset scale into one overall mindset score (e.g., Blackwell et al., 2007), it is also possible that if the growth and fixed mindsets were measured as separate constructs, they may have exhibited distinct patterns across the observed clusters, or may have led to the production of entirely different clusters.

Students in the last cluster, the *Anxious Learners,* also endorsed one motivation process at a considerably different level than the other four motivation beliefs. The students in this cluster reported higher test anxiety than students in any other cluster, while also reporting moderate levels across the other four motivation beliefs. Although the level of grit, self-efficacy, and mastery orientation of students in this cluster was the lowest of any other cluster, on average, the scores still fell in the moderate range of the scale (i.e., two to three on the zero-to-four scale). Due to the nature of the current sample, which was comprised primarily of non-traditional college students who may have previously attempted to start a degree at another institution, this pattern of considerably higher test anxiety may provide some insight into why students are re-enrolling at an online college at an older age. That is, these students may have previously experienced significant anxiety surrounding exams and evaluations that interfered with their ability to successfully complete coursework and attain a degree at a prior institution. Prior research has also identified clusters characterized by a high level of test or evaluation anxiety relative to the other clusters. For example, Liu et al. (2014) examined the self-efficacy, test anxiety, task value, and SRL skills (i.e., metacognition, elaboration, rehearsal) of 238 junior college students. The authors observed four clusters, two with relatively low test anxiety, one with moderate test anxiety, and one with moderate-to-high test anxiety. Liu et al. (2014) reported that students in the cluster with moderate test anxiety reported adaptive SRL skills and motivation, which is consistent with the pattern of motivational processes of the *Anxious Learners* in the current study.

Overall, the motivation profiles indicate that most non-traditional, newly-enrolled online college students viewed themselves as moderately motivated across most, if not all, motivational processes. This conclusion is based upon the absolute level of each motivational process in relation to the mid-point of the zero-to-four scale, rather than the relative level at which clusters are compared to each other. In general, these students may have felt optimistic about their new college experience and felt capable of persisting through obstacles to learning online that they could encounter in the future. In regards to relative comparisons between clusters, the two clusters with consistent levels across all five motivational processes, the *Moderately Motivated Learners* and *Highly Motivated Learners*, appeared to be more adaptive in terms of the absolute level of motivational processes than the other two clusters. Subsequently, the *Uncommitted Mindset Learners* and the *Anxious Learners* cannot be considered as adaptive based on the levels across each motivational belief, because both a growth mindset and less test anxiety are associated with achievement (e.g., Dweck, 2006; Hayes et al., 2009).

Comparing Results of the Cluster Analysis and Latent Profile Analysis

Although CA was the primary statistical analysis emphasized in this study, the LPA was also used to further examine the validity of the cluster solution. Despite the primary focus of the current study on the resulting motivation profiles and how these profiles relate to academic success, there are a few notable issues when examining the correspondence between the CA and LPA that warrant further discussion. In the CA, results between the two subsamples were largely similar, both descriptively and statistically. However, different results were produced between the two subsamples of the LPA. One explanation for the inconsistency in results produced by the two LPAs is that the four-profile solution with varying means and variances is not, in fact, the best fit for the data, because the solution is not stable across multiple random samples. That is, when the LPA was asked to identify profiles with the assumptions for variances and covariances relaxed, it created a latent structure as an artifact of the analysis, rather than identifying the true underlying latent structure of the data, as is possible with clustering techniques (Marsh et al., 2009). This may have resulted in the largely different percentages of students in the most similar clusters between the two LPA subsamples. For example, approximately 16% of students fell in the cluster of students with the lowest anxiety scores in the primary LPA; however, about 37% of students fell in the cluster with the lowest anxiety scores in the validation LPA. This may be due, in part, to the fact that the LPA model was not stable and, therefore, students ended up in different clusters between the primary and validation LPA. If additional LPA models were examined, such as if the covariances were constrained to be equal across clusters, a more stable LPA solution may have been produced where students were more similarly dispersed across clusters and the solution could then be replicated across multiple random samples.

In regards to comparing the CA and LPA, results suggested that three of the four sets of analyses—the two CA analyses and the primary LPA results—were descriptively similar, but that the results of the primary CA and primary LPA (i.e., both utilized the 80% subsample), did not statistically converge. That is, only two-to-four of the five motivational processes were statistically similar across comparable clusters between the CA and LPA. Two possible hypotheses for this difference are discussed. First, the CA and LPA make different assumptions. A k-means cluster analysis attempts to find homogenous clusters where within-cluster variation from the mean is minimized, and between-cluster differences are maximized; no assumptions are made regarding the underlying probability distribution for this type of analysis (Pastor et al., 2007). An LPA, on the other hand, assumes that there is an underlying probability distribution that is pre-determined (i.e., by constraining or relaxing assumptions for variances and covariances) and dictates how the clusters are formed (Magidson & Vermunt, 2002; Pastor et al., 2007; Vermunt & Magidson, 2002). This difference in the fundamental assumptions made by each statistical technique, and the corresponding mathematics, could impact the way in which participants are grouped together (i.e., by looking for homogenous clusters or the underlying probability distributions), which could yield different groups of students and thus account for the statistical differences in the patterns of motivation produced by each statistical technique.

Second, the results of the CA produce definitive cluster membership assignments for all participants; while the LPA results provide probabilities for the likelihood that a participant belongs in a given cluster (Magidson & Vermunt, 2002). Since the LPA accounts for this error and potential overlap between clusters, students may have been grouped into different clusters between the CA and LPA, which, again, could have resulted in slightly different cluster means between the LPA and CA results, even though the overall pattern of motivation variables appeared to be visually similar.

Due to the differences between the results of the best fit solution from the CA and LPA, and the inability to replicate the results of the LPA between two random subsamples, results from the CA were selected for use in additional analyses; however, there are both pros and cons to this decision. It is important to note that the decision to select the CA results over the LPA results is inconsistent with prior research that has compared CAs and LPAs (DiStefano & Kamphaus, 2006; Magidson & Vermunt, 2002; Pastor et al., 2007). In most cases, these researchers elected to use the LPA results because of the availability of fit statistics to decrease subjectivity, option to relax model assumptions, and ability to use posterior cluster probabilities rather than definitive cluster membership in subsequent analyses. In the current study, results of the CA are still subjective, but this subjectivity can be superseded by successful replication of profiles across the two randomly selected samples (Pastor et al., 2007). That is, the CA results were descriptively and statistically similar across two subsamples, and were descriptively similar to the initial LPA results, which suggests that this four-profile solution is stable and reliable and provides more objective evidence for the validity of the CA results. Additionally, prior CA and LPA comparison studies do not always replicate results of the LPA across multiple samples (DiStefano & Kamphaus, 2006). If I had only elected to run the initial LPA in the current study, I may have viewed the initial LPA results to be a more accurate depiction of the underlying latent clusters in the data, as many other researchers have done. However, because the LPA did not replicate across samples, this additional information calls into question the validity of using the LPA results over the CA, and supports my decision to select the CA results as the best fit for the data.

Motivation Profiles Differences in Academic Success

Motivation profile differences across indicators of academic achievement, engagement, and persistence were also examined in the study. Overall, the key finding was that significant, yet small, profile differences were found in terms of both credit attainment and engagement with online SRL resources, but not with term-to-term retention. These cluster differences in academic outcomes suggest that prior motivational beliefs (i.e., the beliefs of students who had recently enrolled in an online college) may impact the future academic achievement of non-traditional online college students, although a causal relationship cannot be concluded, as other factors that may have occurred between the two time points (i.e., shortly after enrollment and after one or two academic terms) were not measured.

Regarding credit attainment, the *Anxious Learners* completed significantly fewer credits per credit attempted relative to students in all other clusters. That is, those who reported significantly higher test anxiety than the other motivational processes shortly after enrollment completed a lower percentage of credits during the first academic term than students with less test anxiety. These results support the notion that the *Anxious Learners* cluster can be considered less adaptive than the other clusters. One potential reason why the *Anxious Learners* exhibited a lower credit ratio than the other clusters is because of the higher test anxiety of students in this cluster relative to students in other clusters. Previous research supports the notion that higher test anxiety is related to slightly poorer performance on exams, quizzes, and students' overall GPA (Chapell et al., 2015; Pintrich & De Groot, 1990). Person-centered studies targeting SRL have also underscored the critical role played by test anxiety in academic performance. For example, some researchers have found that clusters of students with the highest test anxiety and low to moderate SRL skills attained less desirable academic outcomes (e.g., GPA) than clusters of students with less test anxiety (Liu et al., 2014; Ning & Downing, 2015). Therefore, it is possible that the higher test anxiety of students in the *Anxious Learners* cluster is responsible for the lower credit completion percentage in the current study. Notably, students' reported level of test anxiety may have been based on their prior academic experiences, as students completed the DAACS-SRL survey shortly after enrolling in the online college, and their actual level of test anxiety during the first academic term may have differed from the level they originally self-reported.

In regards to students' use of online SRL resources through the DAACS intervention, the *Moderately Motivated Learners* viewed available online resources more times than the *Highly Motivated Learners*. That is, non-traditional college students who reported moderate, but not high, levels of all five motivational processes shortly after enrolling in the online college were more likely to log-on and view available resources designed to improve students' SRL skills during the first academic term to a greater extent than students who felt highly motivated. One potential explanation for this difference in clusters' use of the online resources is that the *Moderately Motivated Learners* may have identified some areas of weakness, such as a specific area of motivation or SRL skill, and simultaneously been motivated enough to access the online resources. On the other hand, the *Highly Motivated Learners* may have viewed their motivational beliefs and SRL skills as adaptive enough, and therefore chose to view the online resources less. Although one might expect the less adaptive motivation clusters to use the online resources more often, since they have the greatest need to improve their motivation and SRL skills, prior research has found that groups of students who were more highly motivated and self-regulated accessed available online academic resources to a greater extent than students who reported less adaptive SRL skills (Abar & Loken, 2010). Although the study by Abar and Loken (2010) substantiates the finding that motivated groups of students may use online resources more than less motivated groups, it is also somewhat inconsistent with the findings of the current study. Specifically, Abar and Loken (2010) found that students in their highly motivated cluster used online resources more than students in their low cluster; whereas the findings from the current study indicate that the *Highly Motivated Learners* viewed online resources less frequently than the *Moderately Motivated Learners*.

Regarding retention from the first term to the second term, no significant cluster differences emerged. In the current study, the sample size was large enough to detect small effects in term-to-term retention, which suggests that there is likely not a significant effect of students' motivation profile shortly after enrolling in an online college on their retention after the first academic term. Since there is very limited research that examines how motivation or self-regulation profiles relate to retention, it is difficult to draw conclusions as to why no effects of cluster membership on retention were found. However, one possible reason for the lack of findings is that another variable that relates to students' success in overcoming academic challenges accounted for the difference in retention rates to a greater degree than motivation beliefs. For instance, there may be differential patterns of self-regulation skills (e.g., time management) across profiles that counterbalanced any effect that the motivational processes would have had on persistence. In fact, Dörrenbächer and Perels (2016) found that students could be moderately or highly motivated and also exhibit poor self-regulation skills, which could provide insight into the broader patterns of motivation and self-regulation that were not measured in the current study.

Overall, there is no clear or discernable pattern illustrating the advantage of one profile relative to others based on the outcome measures used in this study, as no single cluster consistently outperformed the others in key indicators of academic success. However, despite the limited number of observed cluster group differences, the results of the current study highlight two potentially maladaptive patterns of motivational processes that exist in a unique sample of college students, due to the overall level of motivational beliefs: (1) when students exhibit an uncommitted mindset (i.e., *Uncommitted Mindset Learners*) and (2) when students report moderate to high levels of test anxiety (i.e., *Anxious Learners*). Additionally, the few cluster group differences further support the notion that some motivation profiles, such as the *Anxious Learners*, are linked to worse academic outcomes than other, more adaptive patterns of motivation. In terms of non-traditional, online college students, who may also exhibit poor academic or self-regulation skills, this means that students with higher anxiety or an uncommitted mindset need to address their motivational weaknesses in order to increase their chances to succeed in their new online educational experience. Since many students may have experienced difficulties completing a degree at a prior institution, these two potentially maladaptive patterns of motivation may be key to enhancing students' future academic success. Additionally, despite the literature that suggests that students who encounter challenges (e.g., students who are non-traditional, exhibit poor skills, or attend college online) are more likely to achieve less (e.g., complete fewer course credits; Grimes & David, 1999) than students who do not encounter challenges, these findings suggest that many non-traditional students who have recently enrolled in an online college did self-report mostly moderate to high levels of motivational beliefs that may have help them persist from one term to the next.

Implications

The results of this study have implications for both research and educational practices. From a research standpoint, the findings from the current study provide initial evidence regarding the utility of motivation profiles based on patterns across several motivational processes for understanding students' credit completion at an online college. That is, person-centered statistical approaches may bring insight and importance to the motivation field, in addition to the more traditional variable-centered research approaches, in examining how motivation relates to academic success. Furthermore, these findings highlight the importance of considering the particular motivational processes addressed in this study when examining the link between motivation and academic outcomes in non-traditional students at an online college. Additionally, the clusters produced from this study could enhance the predictive validity of models linking motivation and academic success (e.g., credit attainment), beyond what researchers already know based on existing variable-centered research. That is, although the cluster group differences on academic success variables were small, these few statistically significantly associations between motivation profiles and academic outcomes could slightly enhance researchers' prediction models when examining how motivation relates to achievement.

The findings are also important from a practical viewpoint, particularly for educators and practitioners (e.g., school psychologists) within the education field. Most notably, the results of this study highlight the importance of identifying students according to their motivation profiles, particularly those students who may be at risk of lesser academic achievement in an online learning environment, rather than focusing on just one or two individual traits or motivational processes. That is, practitioners can view a student's motivation profile as if it were a screening tool and use the results to identify students in need of additional assessment and potential intervention. Practitioners can then have more intensive conversations with and assessments of students motivational and self-regulatory skill strengths and weaknesses, and can discuss plans to target skill deficits. Even though the research has yet to sufficiently support a direct link between identifying students using their cluster membership and eventual improvements in motivational processes due to interventions, there is the potential for practitioners to use the information to develop an intervention plan to help improve motivational weaknesses and improve a student's chance at success. However, it is important to note that the motivation profile results should not be used to provide the same intervention to all students in a particular profile; practitioners should consider each student's needs separately and create an individualized intervention plan.

Another practical implication of the results is that practitioners can use a student's motivation profile to highlight and build off of motivational strengths through the process of improving the student's weaknesses. Rather than simply discussing motivational weaknesses, practitioners can also discuss where a student excels and use those strengths to improve weaknesses. For example, if a student exhibits moderate to high levels of mastery goal orientation, but struggles with their self-regulatory skills, test anxiety, and/or basic academic skills, a practitioner can use that student's desire to master their learning to motivate them to learn better time management, anxiety management, and basic academic skills that will help them master their learning over time.

Also of importance are the practical implications for institutions that provide students with access to online skill-building resources. When colleges or universities encounter students who exhibit poor academic or self-regulation skills, the institutions may provide students with additional resources to help remediate skill weaknesses. However, a key assumption in this link between providing resources and eventual skill improvement is that students will be motivated to access and use the available resources. As the current study found that students who were already moderately motivated (i.e., *Moderately Motivated Learners*) accessed online SRL resources more than students who were highly motivated (i.e., *Highly Motivated Learners*), and because no significant differences emerged between either of the two less adaptive clusters (i.e., *Uncommitted Mindset Learners* and *Anxious Learners*) and the moderate or highly motivated students, it is plausible to hypothesize that the students who would have benefitted most from the online SRL resources did not, in fact, access these resources as frequently as they should have. Therefore, when institutions prescribe online interventions to improve motivation and self-regulation skills, such as the online DAACS SRL resources, the educators and practitioners should consider the types of students that are more or less likely to access these available resources, and provide additional support to students who are less likely to independently engage with the online resources.

Limitations and Future Directions

In considering the findings of the current study, there are a handful of important limitations to note. Regarding the measures used for the current study, there are four limitations. First, although the study included a broad range of motivational processes, there are additional motivation variables (e.g., task interest, value, performance goal orientation) that were not assessed as part of the current study. These additional variables have been shown to impact achievement and the behaviors that relate to achievement (Ainley, Hidi, & Berndorff, 2002; Liem et al., 2008), and, if included in this study, may have both changed the pattern exhibited across the measured motivation variables as well as their relation to achievement. Future research should aim to include an even wider array of motivation variables in analyses, or determine the most salient motivation variables for a given population prior to selecting the variables to include in person-centered analyses.

Second, students self-reported their motivational processes and may have over- or under-estimated their skills and beliefs. Prior research suggests that students may not be able to reliably perceive and report on their SRL skills, and that there may be discrepancies between students' self-reported motivation or regulation skills and the actual level of skills demonstrated during an academic task (Cleary, Callan, Malatesta, & Adams, 2015; Winne & Jamieson-Noel, 2002). However, this is not always the case (Cleary & Callan, 2014). Future research should include teacher reports and/or in-person observations of the motivated behaviors that students engage in as well as the levels of underlying motivational processes.

Third, data regarding students' motivational processes were gathered shortly after students enrolled in the online college, whereas achievement data were collected throughout the course of the students' first and second six-month terms. It is possible that other factors, such as the passage of time or the impact of using online resources to improve their motivational processes, influenced students' later achievement. Additionally, because data were collected shortly after students enrolled in the online college, their self-reported motivational beliefs may be based on their prior academic experiences or reflect their hopes and intentions for their future academic career. Future research should concurrently examine students' motivation and achievement when students are further along in their online learning program and should account for potential confounding variables, such as the use of online resources, when examining how motivation profiles relate to achievement.

Fourth, there was a discrepancy between some measures that were domain-specific and the DAACS-SRL survey instructions, which were presented in a more course/college-general way. That is, some measures, such as self-efficacy for online learning, referred to a specific domain (e.g., online learning), while others were more general (e.g., grit). When students completed the DAACS-SRL survey, they were not directed to consider a specific domain, and it is unclear whether students responded to items with a particular domain in mind, or in a more general manner. Future research should more explicitly target only course/college-general measures and assessments, or dive into how students' motivation profiles in relation to a particular domain or subject relate to achievement in that same area.

In addition to limitations due to the nature of the measures, there are two notable limitations regarding the sample and data analysis procedures utilized for the current study. Regarding the sample, the students included in the current study were often returning to school as an older adult and/or while managing the demands of a full-time job or family (i.e., non-traditional students), may have exhibited poor academic and/or self-regulation skills that contributed to their potential for success, and were enrolled in an online institution. Due to the unique nature of the sample in the current study, the findings may not be generalizable to more typical college populations. Additional research is needed to extend the results of this study to other populations, including more traditional college students who are younger and/or attend college at an in-person institution. Lastly, in order to run the LPA using the statistical program R, the tidyLPA package provided the code to run analyses. However, this package only allowed for four variations of cluster variances and covariances (i.e., to relax the assumptions), and the results from only one model (i.e., varying variances and covariances) were examined as part of the current study, based on prior assumptions about the nature of the data. Additionally, the tidyLPA package included some fit statistics that were unhelpful for interpreting the results of the current study. Specifically, the entropy statistic may not have been the most valid measure of fit due to the differences in cluster sizes across solutions. Similarly, since the BLRT could only be conducted for some solutions, it did not provide adequate information to evaluate whether a model with more or less clusters was a better fit for the data. Together, these limitations of the LPA software constricted the ability to further estimate models or consider additional fit statistics to evaluate the solution that best fit the data.

Conclusions

The purpose of the current study was to identify clusters of students enrolled in an online college who exhibited similar patterns across multiple motivational processes (i.e., self-efficacy for online learning, mindset, mastery goal orientation, test anxiety, and grit). Overall, the results of this study provide some insight into the patterns of motivation that exist in a unique sample of students, and suggest that these patterns are marginally, yet significantly, associated with various indicators of academic success, engagement, and persistence. These findings are consistent with prior person-centered studies that have identified similar patterns of motivational variables, including consistently moderate or high motivational processes (Bråten & Olaussen, 2005; Dörrenbächer & Perels, 2016), as well as clusters with notably different levels of mindset or test anxiety (Chen, 2012; Liu et al., 2014). However, the findings deviate from prior literature in that previous studies often find more differences between clusters on measures of academic achievement (e.g., Chen, 2012; Hsieh, 2016; Liu et al., 2014; Ng, Liu, & Wang, 2015). Regardless of the cluster differences, the distinct patterns of motivational beliefs across clusters have important implications for both researchers and practitioners. Specifically, these findings could enhance both predictive models of academic success in research and could help practitioners identify students who may be in need of additional support. Future research should examine how motivational profiles change when additional motivation variables are included, multiple measures of students' motivation are collected, and confounding variables between motivation and achievement are accounted for, as well as replicating analyses with more traditional samples of college students to expand the generalizability of results.

References

Abar, B., & Loken, E. (2010). Self-regulated learning and self-directed study in a pre-college sample. *Learning and Individual Differences*, *20*, 25-29.

Ainley, M., Hidi, S., & Berndorff, D. (2002). Interest, learning, and the psychological processes that mediate their relationship. *Journal of Educational Psychology, 94*(3), 545-561. doi: 10.1037//0022-0663.94.3.545

Allen, I. E., Seaman, J., Poulin, R., & Straut, T. T. (2016). *Online report card: Tracking online education in the United States.* Retrieved from https://onlinelearningsurvey.com/reports/onlinereportcard.pdf

Ames, C. (1992). Classrooms: Goals, structures, and student motivation. *Journal of Educational Psychology*, *84*(3), 261-271. doi: 10.1037/0022-0663.84.3.261

Ames, C., & Archer, J. (1988). Achievement goals in the classroom: Students' learning strategies and motivation processes. *Journal of Educational Psychology*, *80*(3), 260-267. doi: 10.1037/0022-0663.80.3.260

Artino, A. R., & McCoach, D. B. (2008). Development and initial validation of the Online Learning Value and Self-Efficacy Scale. *Journal of Educational Computing Research*, *38*(3), 279-303. doi: 10.2190/EC.38.3.c

Artino, A. R., Jr., & Stephens, J. M. (2009). Beyond grades in online learning: Adaptive profiles of academic self-regulation among naval academy undergraduates. *Journal of Advanced Academics*, *20*, 568-601.

Bailey, T., & Cho, S. W. (2010). *Developmental education in community colleges.* Issue brief prepared for the White House Summit on Community Colleges. New York, NY: Teachers College, Columbia University.

Bandura, A. (1977). Self-efficacy: Toward a unifying theory of behavioral change. *Psychological Review*, *84*(2), 191-215. doi: 10.1037/0033-295X.84.2.191

Barnard-Brak, L., Lan, W. Y., & Paton, V. O. (2010). Profiles in self-regulated learning in the online learning environment. *International Review of Research in Open and Distance Learning, 11*(1), 62-79. Retrieved from http://www.irrodl.org/index.php/irrodl/article/view/769

Barron, K. E., & Harackiewicz, J. M. (2001). Achievement goals and optimal motivation: Testing multiple goal models. *Journal of Personality and Social Psychology, 80*, 702-722. doi: 10.1037//0022-3514.80.5.706

Barrows, J., Dunn, S., & Lloyd, C. A. (2013). Anxiety, self-efficacy, and college exam grades. *Universal Journal of Education Research*, *1*(3), 204-208. doi: 10.13189/ujer.2013.010310

Blackwell, L. S., Trzesniewski, K. H., & Dweck, C. S. (2007). Implicit theories of intelligence predict achievement across an adolescent transition: A longitudinal study and an intervention. *Child Development, 78*, 246-263. doi: 10.1111/j.1467-8624.2007.00995.x

Bråten, I., & Olaussen, B. S. (2005). Profiling individual differences in student motivation: A longitudinal cluster-analytic study in different academic contexts. *Contemporary Educational Psychology*, *30*, 359-396. doi: 10.1016/j.cedpsych.2005.01.003

Brewer, S. A., & Yucedag-Ozcan, A. (2013). Educational persistence: Self-efficacy and topics in a college orientation course. *Journal of College Student Retention*, *14*(4), 451-465. doi: 10.2190/CS.14.4.b

Bryer, J., Cleary, T. J., & Andrade, H. L. (2015). *Diagnostic assessment and achievement of college skills: Personalized feedback and targeted student supports.* Fund for the

Improvement of Postsecondary Education (FIPSE) First In The World (FITW) grant proposal.

Butler, D.L., Schnellert, L., & Perry, N.E. (2017). *Developing self-regulated learners.* Toronto: Pearson Education Canada.

Chapell, M. S., Blanding, B., Silverstein, M. E., Takahashi, M., Newman, B., Gubi, A., & McCann, N. (2005). Test anxiety and academic performance in undergraduate and graduate students. *Journal of Educational Psychology*, *97*(2), 268-274. doi: 10.1037/0022-0663.97.2.268

Chen, J. A. (2012). Implicit theories, epistemic beliefs, and science motivation: A person-centered approach. *Learning and Individual Differences*, *22*, 724-735. doi: 10.1016/j.lindif.2012.07.013

Chen, J. A., & Usher, E. L. (2013). Profiles of the sources of science self-efficacy. *Learning and Individual Differences*, *24*, 11-21. doi: 10.1016/j.lindif.2012.11.002

Chen, W. W., & Wong, Y. L. (2014). Chinese mindset: Theories of intelligence, goal orientation and academic achievement in Hong Kong students. *Educational Psychology*, *35*(6), 1-12. doi: 10.1080/01443410.2014.893559

Cleary, T. J., & Callan, G. L. (2014). Student self-regulated learning in an urban high school: Predictive validity and relations between teacher ratings and student self-reports. *Journal of Psychoeducational Assessment*, *32*(4), 295-305. doi: 10.1177/0734282913507653

Cleary, T. J., Callan, G. L., Malatesta, J., & Adams, T. (2015). Examining the level of convergence among self-regulated learning microanalytic processes, achievement, and a self-report questionnaire. *Journal of Psychoeducational Assessment*, *33*(5), 439-450. doi: 10.1177/0734282915594739

Cleary, T. J., & Kitsantas, A. (2017). Motivation and self-regulated learning influences on middle school mathematics achievement. *School Psychology Review*, *46*(1), 88-107. doi: 10.17105/SPR46-1.88-107

Cohen, J. (1992). A power primer. *Psychological Bulletin*, *112*(1), 155-159. doi: 10.1037/0033-2909.112.1.155

Credé, M., Tynan, M. C., & Harms, P. D. (2017). Much ado about grit: A meta-analytic synthesis of the grit literature. *Journal of Personality and Social Psychology*, *113*, 492-511. doi: 10.1037/pspp0000102

Davis, H. A., DiStefano, C., & Schutz, P. A. (2008). Identifying patterns of appraising tests in first-year college students: Implications for anxiety and emotion regulation during test taking. *Journal of Education Psychology*, *100*(4), 942-960. doi: 10.1037/a0013096

DiStefano, C., & Kamphaus, R. W. (2006). Investigating subtypes of child development: A comparison of cluster analysis and latent class cluster analysis in typology creation. *Educational and Psychological Measurement*, *66*(5), 778-794. doi: 10.1177/0013164405284033

Dörrenbächer, L., & Perels, F. (2016). Self-regulated learning profiles in college students: Their relationship to achievement, personality, and the effectiveness of an intervention to foster self-regulated learning. *Learning and Individual Differences*, *51*, 229-241. doi: 10.1016/j.lindif.2016.09.015

Driscoll, R. (2007). *Westside test anxiety scale validation.* ERIC Digest, ED495968. Retrieved from https://eric.ed.gov/?id=ED495968

Duckworth, A. L., Peterson, C., Matthews, M. D., & Kelly, D. R. (2007). Grit: Perseverance and passion for long-term goals. *Journal of Personality and Social Psychology, 9*, 1087-1101. doi: 10.1037/0022-3514.92.6.1087

Dugan, R. F., & Andrade, H. L. (2011). Exploring the construct validity of academic self-regulation using a new self-report questionnaire – the Survey of Academic Self-Regulation. *The International Journal of Educational and Psychology Assessment, 7*(1), 45-63.

Dupeyrat, C., & Mariné, C. (2005). Implicit theories of intelligence, goal orientation, cognitive engagement, and achievement: A test of Dweck's model with returning to school adults. *Contemporary Educational Psychology*, *30*, 43-59. doi: 10.1016/j.cedpsych.2004.01.007

Dweck, C. S. (2006). *Mindset*. New York, NY: Random House.

Elliot, A. J., Dweck, C. S., & Yeager, D. S. (2017). Competence and motivation: Theory and application. In Elliot, A. J., Dweck, C. S., & Yeager D. S. (Eds.), *Handbook of Competence and Motivation, Second Edition: Theory and Application*. New York, NY: The Guilford Press.

Grimes, S. K., & David, K. C. (1999). Underprepared community college students: Implications of attitudinal and experiential differences. *Community College Review*, *27*(2), 73-92. doi: 10.1177/009155219902700204

Guay, F., Ratelle, C. F., Roy, A., & Litalien, D. (2010). Academic self-concept, autonomous academic motivation, and academic achievement: Mediating and additive effects. *Learning and Individual Differences*, *20*, 644-653. doi: 10.1016/j.lindif.2010.08.001

Hartley, K., & Bendixen, L. D. (2001). Educational research in the internet age: Examining the role of individual characteristics. *Educational Researcher*, *30*(9), 22-26. doi: 10.3102/0013189X030009022

Hawley, T. H., & Harris, T. A. (2005-2006). Student characteristics related to persistence for first-year community college students. *J. College Student Retention*, *7*(1-2), 117-142. doi: 10.2190/E99D-V4NT-71VF-83DC

Hayes, S., MacLeod, C., & Hammond, G. (2009). Anxiety-linked task performance: Dissociating the influence of restricted working memory capacity and increased investment of effort. *Cognition and Emotion*, *23*(4), 753-781. doi: 10.1080/02699930802131078

Hembree, R. (1988). Correlates, causes, effects, and treatment of test anxiety. *Review of Educational Research*, *58*(1), 47-77.

Hsieh, T. L. (2016). Motivation categories in college students' learning engagement behaviors and outcomes in Taiwan: An application of cluster analysis. *International Journal of Research Studies in Education*, *5*(4), 19-30. doi: 10.5861/ijrse.2016.1222

Jokić, B., & Purić, D. (2019). Relating relational and experiential thinking styles with trait emotional intelligence in broader personality space. *Europe's Journal of Psychology*, *15*(1), 140-158. doi: 10.5964/ejop.v15i1.1692

Korpershoek, H., Kuyper, H., & van der Werf, G. (2015). Differences in students' school motivation: A latent class modeling approach. *Social Psychology of Education*, *18*, 137-163. doi: 10.1007/s11218-014-9274-6

Kuh, G. D., Kinzie, J., Buckley, J. A., Bridges, B. K., & Hayek, J. C. (2006). *What matters to student success: A review of the literature.* Commissioned report for the National Symposium on Postsecondary Student Success: Spearheading a Dialog on Student Success. Washington, DC: National Postsecondary Education Cooperative.

Langley, S., Wambach, C., Brothen, T., & Madyun, N. (2004). Academic achievement motivation: Differences among underprepared students taking a PSI general psychology course. *Research and Teaching in Developmental Education*, *21*(1), 40-48. Retrieved from http://www.jstor.org/stable/42802567

Liem, A. D., Lau, S., & Nie, Y. (2008). The role of self-efficacy, task value, and achievement goals in predicting learning strategies, task disengagement, peer relationship, and achievement outcome. *Contemporary Educational Psychology*, *33*, 486-512. doi: 10.1016/j.cedpsych.2007.08.001

Liu, W. C., Wang, J. C. K., Kee, Y. H., Koh, C., Lim, B. S. C., & Chua, L. (2014). College students' motivation and learning strategies profiles and academic achievement: a self-determination theory approach. *Educational Psychology*, *34*(3), 338-353. doi: 10.1080/01443410.2013.785067

Lubke, G. H., & Muthén, B. (2005). Investigating population heterogeneity with factor mixture models. *Psychological Methods*, *10*(1), 21-39. doi: 10.1037/1082-989X.10.1.21

Lui, A. M., Franklin Jr., D., Akhmedjanova, D., Gorgun, G., Bryer, J., Andrade, H. L., & Cleary, T. J. (2018). Validity evidence of the internal structure of the DAACS Self-Regulated Learning Survey. *Future Review: International Journal of Transition, College, and Career Success*, *1*(1), 1-18.

Lynch, R., & Dembo, M. (2004). The relationship between self-regulation and online learning in a blended learning context. *International Review of Research in Open and Distance Learning*, *5*(2), 1-16. doi: 10.19173/irrodl.v5i2.189

Machimbarrena, J. M., Calvete, E., Fernández-González, L., Álvarez-Bardón, A., Álvarez-Fernández, L., & González-Cabrera, J. (2018). Internet risks: An overview of victimization in cyberbullying, cyber dating abuse, sexting, online grooming and problematic internet use. *International Journal of Environmental Research and Public Health*, *15*. doi: 10.3390/ijerph15112471

Magidson, J., & Vermunt, J. K. (2002). Latent class models for clustering: A comparison with K-means. *Canadian Journal of Marketing Research*, *20*, 37-44. Retrieved from https://www.researchgate.net/publication/303215946_Latent_class_models_for_clustering_A_comparison_with_K-means_Canadian_J_Mark_Res

Magno, C. (2012). Implicit theories of intelligence, achievement goal orientation, and academic achievement of engineering students. *The International Journal of Research and Review*, *9*, 32-43.

Marsh, H. W., Lüdtke, O., Trautwein, U., & Morin, A. J. S. (2009). Classical latent profile analysis of academic self-concept dimensions: Synergy of person- and variable-centered approaches to theoretical models of self-concept. *Structural Equation Modeling*, *16*, 191-225. doi: 10.1080/10705510902751010

McMahon, M., & Oliver, R. (2001). Promoting self-regulated learning in an on-line environment. In C. Montgomerie & J. Viteli (Eds.), Proceedings of World Conference on Educational Multimedia, Hypermedia and Telecommunications 2001 (pp. 1299-1305). Chesapeake, VA: AACE.

Mindset Works Inc. (2015). *Mindset assessment profile tool.* Retrieved from https://www.mindsetworks.com/assess/

Moore, R. (2007). Course performance, locus of control, and academic motivation among developmental education students. *Research and Teaching in Developmental Education*, *24*(1), 46-62. Retrieved from http://www.jstor.org/stable/42802615

Moylan. A. (2013). Cyclical feedback approaches for enhancing academic self-regulation in postsecondary mathematics classrooms. In Bembenutty, H., Cleary, T. J., & Kitsantas, A. (Eds.), *Applications of Self-Regulated Learning across Diverse Disciplines* (125-152). Charlotte, NC: Information Age Publishing Inc.

Muenks, K., Yang, J. S., & Wigfield, A. (2018). Associations between grit, motivation, and achievement in high school students. *Motivation Science*, *4*(2), 158-176. doi: 10.1016/j.lindif.2011.09.005

National Association for Developmental Education (n.d.). *Mission, vision, and goals.* Retrieved from https://thenade.org/Mission-Vision-and-Goals

Neuville, S., Frenay, M., Bourgeois, E. (2007). Task value, self-efficacy and goal orientations: Impact on self-regulated learning, choice and performance among university students. *Psychologica Belgica*, *47*(1), 95-117. doi: 10.5334/pb-47-1-95

Ng, B. L. L., Liu, W. C., & Wang, J. C. K. (2015). Student motivation and learning in mathematics and science: A cluster analysis. *International Journal of Science and Math Education*, *14* (7), 1359-1376. doi: 10.1007/s10763-015-9654-1

Nie, Y., Lau, S., & Liau, A. K. (2011). Role of academic self-efficacy in moderating the relationship between task importance and test anxiety. *Learning and Individual Differences*, *21*, 736-741. doi: 10.1016/j.lindif.2011.09.005

Ning, H. K., & Downing, K. (2015). A latent profile analysis of university students' self-regulated learning strategies. *Studies in Higher Education*, *40*(7), 1328-1346. doi: 10.1080/03075079.2014.880832

Pastor, D. A., Barron, K. E., Miller, B. J., & Davis, S. L. (2007). A latent profile analysis of college students' achievement goal orientation. *Contemporary Educational Psychology*, *32*, 8-47. doi: 10.1016/j.cedpsych.2006.10.003

Pawlo, E. P., Cleary, T. J., Slemp, J., Waire, J., Bryer, J., & Gambino., T. (2019). *Academic success in online colleges: The role of self-regulated learning profiles.* Paper to be presented at the American Educational Research Association annual meeting in Toronto, Canada.

Pintrich, P. R., & De Groot, E. V. (1990). Motivational and self-regulated learning components of classroom academic performance. *Journal of Educational Psychology*, *82*(1), 33-40. doi: 10.1037/0022-0663.82.1.33

Puente-Diaz, R., & Cavazos-Arroyo, J. (2017). Creative mindsets and their affective and social consequences: A latent class approach. *The Journal of Creative Behavior*, 0(0), 1-12. doi: 10.1002/jocb.217

Putwain, D. W., & Daly, A. L. (2013). Do clusters of test anxiety and academic buoyancy differentially predict academic performance? *Learning and Individual Differences*, *27*, 157-162. doi: 10.1016/j.lindif.2013.07.010

Putwain, D. W., & Sander, P. (2016). Does the confidence of first-year undergraduate students change over time according to achievement goal profile? *Studies in Higher Education*, *41*(2), 381-398. doi: 10.1080/03075079.2014.934803

Puzziferro, M. (2008). Online technologies self-efficacy and self-regulated learning as predictors of final grade and satisfaction in college-level online courses. *The American Journal of Distance Education*, *22*(2), 72-89. doi: 10.1080/08923640802039024

R Core Team. (2018). *R: A language and environment for statistical computing*. Vienna, Austria: R Foundation for Statistical Computing. Retrieved from https://www.R-project.org

Ratelle, C. F., Guay, F., Vallerand, R. J., Larose, S., & Senécal, C. (2007). Autonomous, controlled, and amotivated types of academic motivation: A person-oriented analysis. *Journal of Educational Psychology, 99*(4), 734-746. doi: 10.1037/0022-0663.99.4.734

Rosenberg, J. M. (2018). *Introduction to tidyLPA*. Retrieved from https://jrosen48.github.io/tidyLPA/articles/Introduction_to_tidyLPA.html

Schunk, D. H., Meece, J. L., & Pintrich, P. R. (2014). *Motivation in education: Theory, research, and applications* (4th ed.). New York, NY: Pearson Education, Inc.

Senko, C. (2016). Achievement goal theory: A story of early promises, eventual discords, and future possibilities. In Wentzel, K. R., & Miele, D. B. (Eds.), *Handbook of motivation at school* (2nd ed.). New York, NY: Routledge.

Shell, D. F., & Soh, L. K. (2013). Profiles of motivated self-regulation in college computer science courses: Differences in major versus required non-major courses. *Journal of Science Education and Technology, 22*, 899-913. doi: 10.1007/s10956-013-9437-9

Shih, S. (2008). The relation of self-determination and achievement goals to Taiwanese eighth graders' behavioral and emotional engagement in schoolwork. *The Elementary School Journal, 108*(4), 313-334. Retrieved from https://www.jstor.org/stable/10.1086/528974

Smith, J. L., Deemer, E. D., Thoman, D. B., & Zazworsky, L. (2014). Motivation under the microscope: Understanding undergraduate science students' multiple motivations for research. *Motivation and Emotion, 38*, 496-512. doi: 10.1007/s11031-013-9388-8

Vermunt & Magidson (2002). Latent class cluster analysis. In J. A Hagenaars & A. L McCutcheon (Eds.) *Applied Latent Class Analysis*. New York, NY: Cambridge University Press.

Walker, C. O., Greene, B. A., & Mansell, R. A. (2006). Identification with academics, intrinsic/extrinsic motivation, and self-efficacy as predictors of cognitive engagement. *Learning and Individual Differences*, *16*, 1-12. doi: 10.1016/j.lindif.2005.06.004

Wang, C., Shannon, D. M., & Ross, M. E. (2013). Students' characteristics, self-regulated learning, technology self-efficacy, and course outcomes in online learning. *Distance Education, 34*(3), 302-323. doi: 10.1080/01587919.2013.835779

Winne, P. H., & Jamieson-Noel, D. (2002). Exploring students' calibration of self reports about study tactics and achievement. *Contemporary Educational Psychology, 27*, 551-572.

Wolters, C. A., & Hussain, M. (2015). Investigating grit and its relations with college students' self-regulated learning and academic achievement. *Metacognition Learning*, *10*, 293-311. doi: 10.1007/s11409-014-9128-9

York, T. T., Gibson, C., & Rankin. S. (2015). Defining and measuring academic success. *Practical Assessment, Research, and Evaluation*, *20*(5), 1-21. Retrieved from https://eric.ed.gov/?id=EJ1059739

Zeidner, M. (1998). *Test anxiety: The state of the art.* New York: Plenum Press.

Zimmerman, B. (1986). Becoming a self-regulated learner: Which are the key subprocesses? *Contemporary Educational Psychology*, 11(4), 307–313. doi:10.1016/0361-476X(86)90027-5

Zimmerman, B. J. (2000). Self-efficacy: An essential motive to learn. *Contemporary Educational Psychology*, *25*, 82-91. doi: 10.1006/ceps.1999.1016

Zimmerman, B. J. (2008). Investigating self-regulation and motivation: Historical background, methodological developments, and future prospects. *American Educational Research Journal*, *45*(1), 166-183. doi: 10.3102/0002831207312909

Zimmerman, B. J., Bandura, A., & Martinez-Pons, M. (1992). Self-motivation for academic attainment: The role of self-efficacy beliefs and personal goal setting. *American Educational Research Journal*, *29*, 663-676. doi: 10.3102/00028312029003663

Appendix A: Literature Review

Overview

The following literature review explores students' motivation for learning and how previous studies have investigated the relationship between motivational processes and achievement using person-centered statistical approaches. Specifically, this literature review begins with definitions of self-regulation, motivation, and the cognitive processes underlying students' motivation for learning. Next, the relation between motivation and achievement, as well as how motivation plays a role in achievement for students who encounter challenges are discussed. The majority of the literature review then turns to reviewing the current motivation literature, beginning with an overview of some variable-centered studies before an in-depth exploration of much of the existing person-centered motivation literature. Lastly, gaps in the current literature are emphasized.

Overview of Self-Regulated Learning

SRL refers to the processes students engage in to monitor and control their thoughts and actions in the pursuit of learning and understanding (Zimmerman, 2008). It involves interconnected processes that students use to think about their thinking (i.e., metacognition), engage in and persist through learning (i.e., motivation), and manage how well they set the stage for learning and gain understanding about new material (i.e., learning strategies). Broadly, SRL includes these three dimensions—metacognition, motivation, and learning strategies—that influence learning (Butler, Schnelert, & Perry, 2017; Zimmerman, 1986). Metacognition refers to how students plan, monitor, and evaluate their cognitive processes over the course of a learning activity. Learning strategies refers to a variety of tactics learners use to control their learning environment, organize their time and study materials, enhance how well they remember and retain information, and check their understanding of learned materials, amongst other strategies (Butler et al., 2017; Zimmerman, 1986). Motivation refers to students' desire to initiate and sustain efforts towards a predetermined goal; it is influenced by cognitive processes and personal beliefs such as a student's confidence, interest, goals, and affect (Elliot, Dweck, & Yeager, 2017; Schunk et al., 2014). The three dimensions of SRL can reciprocally influence each other throughout the learning process (Butler et al., 2017). For instance, metacognition can help build students' awareness of their motivation for learning, or of how well they use effective learning strategies. In order to use the metacognitive or learning strategies, students must have some desire to learn effectively. Subsequently, the successes or failures students experience with a variety of learning strategies can influence how students think about adapting their learning behaviors, and influence their level of motivation to learn in the future. The following sections focus on one dimension of SRL: motivation.

Overview of Motivation for Learning

Motivation for learning pertains to the desire to attain goals, and the effort and persistence students employ to reach those goals (Schunk et al., 2014). When we examine motivation, we often do not simply assess how motivated students are for a particular academic task, in general. This is because motivation is a process and cannot be directly observed; it is instead inferred through what students say and do. This motivation process is a combination of a variety of cognitive processes that influence students' motivated behavior, thoughts, and verbalizations (Schunk et al., 2014). That is, what students think, feel, and believe about their academic abilities contributes to their motivation to learn.

Motivation for learning and achievement is influenced by students' motives and goals for learning, perceptions of their competence and study-skills or other learning-related behaviors, values related to their academic competence, and anxiety about being incompetent (Elliot et al., 2017; Schunk et al., 2014). Some common motivational processes include students' goal orientation, mindset, self-efficacy, grit, or anxiety regarding a topic or learning activity. Goal orientation refers to the types of goals students set for their learning; the reasons students have for exerting effort toward their education. Students' goals may be mastery-oriented in that they aim to master learning materials, gain knowledge, and learn for the sake of learning. Alternatively, students' goals may be performance-oriented in that they aim to learn enough to outperform others or achieve a particular grade or benchmark (Senko, 2016). Mindset refers to students beliefs about the nature of their intelligence. That is, whether students believe their intelligence can change over time and improve with effort (i.e., growth mindset) or is fixed and unchangeable (i.e., fixed mindset; Dweck, 2006). Self-efficacy for learning refers to students' confidence in their academic abilities. It is specific to a single topic or learning activity; therefore, students can feel very self-efficacious for one task or topic and less confident for others (Bandura, 1977; Zimmerman, 2000). Grit refers to students' persistence of effort and their sustained interest in a task or topic over time in the pursuit of long-term goals. While grit partly reflects motivated behaviors (i.e., persistence), it also refers to the cognitive factors that contribute to students' interest in a task, desire to put forth effort to persist in the face of challenges, and resilience in working through challenges (Duckworth et al., 2007). Lastly, test anxiety refers to the apprehension or fear students' experience prior to or during tests or other academic evaluations. Test anxiety includes both the emotional reaction to evaluations (e.g., fear) and cognitive appraisals of anxiety-provoking situations (e.g., worry; Hembree, 1988; Zeidner, 1998). These key cognitive processes and beliefs can simultaneously influence and underlie students' motivation for learning.

How Motivation Influences Achievement

Motivation for learning plays a fundamental role in students' later achievement (Cleary & Kitsantas, 2017; Dweck, 2006). Many scholars have developed and tested theories about how key motivation processes create behavioral change that increases future academic success. Although researchers often agree that motivation for learning involves cognitive processes that influence students' behaviors in the pursuit of academic goals, there are a variety of influential processes and theories with differing opinions about which cognitive processes are most important for achievement (Schunk et al., 2014). However, at the heart of many of these theories lies the notion that students who are more motivated will engage in more adaptive activities that they believe will help them learn and achieve their goals. This means that students who are more self-efficacious, aim to master material and concepts, and those with a growth mindset—along with other adaptive motivational processes—are more interested in seeking out academic experiences and challenges that will help them grow (Ames & Archer, 1988; Barron & Harackiewicz, 2001; Blackwell et al., 2007; Dweck, 2006; Zimmerman, 2000). These experiences could include enrolling in and focusing during classes, using strategies to manage their time and study environment, checking their comprehension of materials while studying, or seeking help from others when the challenges become too difficult. Because cognitive processes underlie motivation for learning, some theories regarding how five key processes influence achievement are discussed in the following sections.

Self-efficacy. Self-efficacy reflects a students' confidence in their abilities regarding a particular academic task or domain (Bandura, 1977; Zimmerman, 2000). For instance, students can feel very self-efficacious about solving mathematics problems, but less confident in their ability to write a research paper. According to social cognitive theory, self-efficacy is a core personal factor that reciprocally interacts with students' behavioral and environmental factors that can promote or hinder learning (Schunk et al., 2014). Self-efficacy can alter environmental events, such as how teachers' respond to a student's confidence in a task, as well as the student's behaviors, such as the extent to which they engage in a task. When students feel confident in their academic abilities, they are more likely to engage in and put effort toward learning activities, persist and persevere through learning challenges, and show an interest in and satisfaction with learning (Brewer & Yucedag-Ozcan, 2013; Walker et al., 2006; Zimmerman, 2000). As a result, these students can learn and retain more information and achieve greater in school. On the contrary, when students are not self-efficacious, they may avoid or give up in the face of setbacks and be hesitant to take on similar academic tasks in the future (Schunk et al., 2014).

Goal orientation. Goal orientation pertains to the reasons students have for engaging in learning activities in pursuit of their academic goals (Senko, 2016). Even though there are a variety of theories that capture different types of goal orientations, there are two widely agreed upon orientations: mastery and performance. Students who hold mastery goal orientations pursue learning in order to master material, develop competence, gain understanding, and learn for the sake of learning. On the other hand, students develop performance goals when they want to demonstrate their competence, perform better than others or than a set standard, or avoid being perceived as incompetent (Senko, 2016). Goal orientation theory denotes that a variety of factors contribute to the formation of different goal orientations, including students' mindset, classroom and school settings, and aspects of the topics or tasks they are learning (for more information, see Schunk et al., 2014). Mastery goals are often seen as more adaptive goals and can lead to better academic achievement than performance goals (e.g., Liem et al., 2008). The relationship between mastery goal orientation and achievement may occur because students with mastery goals are more likely to seek challenges and persist through setbacks, make adaptive attributions about their successes and failures, and use more adaptive self-regulation strategies (Ames & Archer, 1988; Liem et al., 2008; Shih, 2008). These behaviors subsequently improve achievement outcomes. On the contrary, students with performance goals may avoid challenges, make maladaptive attributions about their lack of innate ability, feel helpless or experience negative affect, and use less adaptive self-regulation strategies, which can hinder their achievement (Ames & Archer, 1988; Schunk et al., 2014; Shih, 2008).

Mindset. Mindset reflects students' views about the nature of their intelligence; that is, whether they view their intelligence as stable and unchangeable overtime (i.e., a fixed mindset) or malleable with time and effort (i.e. a growth mindset). A students' mindset can influence whether or not they persevere or give up after experiencing obstacles, approach or avoid challenges, how they view successes and failures, and the level of confidence they feel in their academic abilities (Dweck, 2006). Dweck's theory about mindset connects the concept of mindset to other motivational processes, including goal orientations, self-efficacy, and adaptive attributions. When students have a growth mindset, they also tend to display a stronger desire to learn (i.e., mastery goal orientation) and may feel more confident in their abilities, which contributes to their tendency to embrace challenges, put forth effort to learn, and learn from negative feedback (Dweck, 2006). These adaptive behaviors may ultimately increase students' opportunities to learn and achieve. On the other hand, students with a fixed mindset are more likely to learn in order to be perceived as intelligent (i.e., performance goal orientation) and may or may not feel confident in their ability to achieve this goal. Students with a fixed mindset may have the tendency to avoid challenges, give up easily when they encounter challenges, feel their effort is useless, and ultimately achieve less than students with a growth mindset (Dweck, 2006).

Test anxiety. Test anxiety pertains to the physiological, cognitive, and emotional experience students encounter during academic evaluations, such as tests. When students encounter evaluative situations, they may experience worry, fear, unease, and/or physiological arousal that can impact their educational performance (Hembree, 1988; Zeidner, 1998). Test anxiety theory suggests multiple pathways between this excessive worry and fear and later academic performance (Schunk et al., 2014). For example, students' cognitive capacity may be consumed with negative thoughts and worry when learning or during an evaluation, which may distract students from the learning task or impair their working memory capabilities, and may interfere with their ability to recall previously learned information or perform accurately on a task (Hayes et al., 2009). When students feel anxious before or during tests and other academic evaluations, they are more likely to be overwhelmed, avoid adaptive learning activities in preparation for the test (e.g., adequate studying), give up when they feel anxious, feel less confident in their abilities, and/or become defensive or fear they will do poorly on evaluations. On the contrary, when students experience a lower level of anxiety that may facilitate work productivity, they can remain focused, engage in more adaptive self-regulation strategies, and may feel more confident in their ability to succeed (Hembree, 1988).

Grit. Grit refers to students' perseverance for and interest in long-term goals (Duckworth et al., 2007). Students who are grittier (i.e., display more grit) are more likely to engage in and sustain effort toward a consistent academic task over time, despite challenges or failures. Researchers who believe grit is most important for academic success describe how students who are grittier work harder and longer on academic tasks and intentionally direct their efforts towards these tasks. Grittier students may also be more focused and less distracted by new projects or activities, which can increase their likelihood of producing high-quality, finished school work and, subsequently, perform better in school (Duckworth et al., 2007). However, there are two important caveats to the notion of grit. First, grit is focused on long-term goals, and may not be as applicable for short-term goals that students develop. Second, some opponents of grit suggest that grit does not account for academic achievement beyond other, existing measures of personality traits, such as conscientiousness (Credé, Tynan, & Harms, 2017). Despite these cautionary statements, grit may still play a key role in the academic success for college students looking to attain a long-term goal of completing a college course or degree, particularly in settings where there is a strong need for internal, long-term drive and persistence.

Integrating multiple motivational processes in relation to achievement. Although each motivational process reviewed here independently and uniquely influences achievement, the motivational beliefs can also relate to each other, and the intersection of these beliefs can influence achievement. For example, path analyses have showed that students who report more growth mindset are more likely to also report mastery approach goals, particularly to a greater degree than students who reported a fixed mindset (Magno, 2012), and that the extent to which students report a growth mindset and mastery goals can predict achievement (Chen & Wong, 2014). Similarly, some research uncovered the relationship between one factor of grit, perseverance of effort, and self-efficacy, which then predicted some SRL strategy use (Wolters & Hussain, 2015). Self-efficacy has also been found to mediate the relationship between test anxiety and academic achievement (Barrows, Dunn, & Lloyd, 2013; Nie et al., 2011), which further supports the interconnected nature of these motivational processes.

When multiple motivation processes intersect, such as is illustrated here, positive academic outcomes can result. However, students may exhibit more variable patterns of motivation beliefs, with a higher level of one motivation variable and other motivational processes that students endorse to a lesser degree. Therefore, it is important to consider how each motivation variable relates to achievement, as well as how the integration of varying levels of motivational processes, or patterns across multiple motivation beliefs, relates to academic success.

Motivation for Achievement during Challenges

Motivational beliefs play a key role in students' success—differentiating between high- and low-achieving students—particularly when students encounter many challenges in their learning. When students come across challenging situations, they may put in additional effort to overcome the challenge and experience success, or they may succumb to the obstacle and experience failure. With multiple challenges accumulating in some difficult learning situations—such as when students lack necessary basic skills, have difficulties accessing or learning materials, and/or experience personal hardships—there are more opportunities for failure. As students experience these failures repeatedly, they may feel less confident in their abilities and intelligence, set fewer goals to master material, and/or persevere less—key processes that underlie students' motivation to learn (Grimes & David, 1999; Hawley & Harris, 2005-06; Moore, 2007). Those students who exhibit less adaptive motivational processes may need more support to improve their motivation and self-regulation in order to overcome the challenges they encounter.

College students may experience a variety of challenges to academic success due to personal or contextual barriers that interfere with their learning. First, college students may lack the necessary self-regulation and/or basic academic skills to pass placement exams and enroll in typical academic courses. When students enroll in college, they are expected to display basic academic competencies in reading, writing, and mathematics. Colleges also expect students to be autonomous and self-directed learners. Some students, however, may be unprepared to meet these challenges due to a lack of self-regulation (e.g., time management, mastery goal orientation) or the academic skills (e.g., reading comprehension, introductory algebra) needed to succeed. These students may need to utilize additional resources to build their skills or successfully pass "gateway" or remedial academic courses before they are permitted to enroll in degree-relevant courses (Bailey & Cho, 2010). Some research suggests that more than a third of first-year college students enroll in a remedial English or mathematics course (National Association for Developmental Education, n.d.), which may be due to poor academic or self-regulation skills. Second, some college students may stray from the typical young adult, full-time student and instead may have taken time off from school and are returning to start or finish a degree. These non-traditional students may work full time or have a family in addition to their coursework, and the accompanying personal demands can lead to an increased amount of challenges throughout their education. Third, when students enroll in online courses or degree programs, they are challenged with independently accessing and learning course material without the structure of an in-person classroom or frequent interactions with a teacher. Online learning environments are designed so that students act relatively independently, without much help of a teacher (Hartley & Bendixen, 2001; McMahon & Oliver, 2001); this means that students are largely responsible for deciding where and when to access course materials. In 2014, 14% of all higher education students were taking all of their courses online and another 14% took some, but not all, of their courses online (Allen, Seaman, Poulin, & Straut, 2016). Although online education may increase the accessibility for students who would otherwise proceed without higher education, some researchers caution about considering how individual characteristics of students may intersect with the demands of online learning (Hartley & Bendixen, 2001). When college students encounter these personal and/or contextual challenges, they must exhibit adaptive motivation beliefs and/or need increased support to overcome the barriers to their learning.

Research shows considerable differences in achievement between students who encounter repeated personal or contextual challenges and those who do not. Compared to typical college students (i.e., those beginning college full-time as a young adult with adequate academic and self-regulation skills), college students who are non-traditional or exhibit inadequate academic or self-regulation skills are more likely to enroll in fewer semesters and complete fewer course/credit hours, have a lower grade point average (GPA), and are more likely to drop out of college before completing their degree (Grimes & David, 1999). This poor level of academic performance may be due, in part, to less adaptive motivational beliefs. That is, these non-traditional college students who achieve less are also less likely to exhibit positive cognitive processes that underlie motivation for learning. As an example, Langley, Wambach, Brothe, and Madyun (2004) studied students’ self-efficacy, effort regulation, and control over time and environmental management in a sample of college students who exhibited poor academic and/or self-regulation skills that are needed to succeed in college. The authors divided the sample into 47 high- and 28 low-achieving students and found that the motivation and self-regulation characteristics varied within the sample, depending on their achievement level. The authors also found that higher achieving students reported more adaptive motivation for learning and self-regulation than lower achieving students (Langley et al., 2004).

Other studies have explored how goals, personal beliefs, and self-regulation skills differ between traditional college students who have or do not have the skills needed to succeed in college. Moore (2007) compared levels of time management, effort regulation, and self-efficacy between typical college students and college students who exhibited poor academic skills, and found that students who exhibited poor basic academic skills also exhibited less adaptive self-efficacy and time and effort regulation than traditional college students. Similarly, Grimes and David (1999) explored differences between traditional college students and those with poor academic skills using a sample of 500 first year students at a community college, with 48% of the sample considered to have poor academic skills due to low placement test scores. More college students who lacked basic skills reported attending college in order to attain a vocational or associates degree, to improve their academic skills, or because they could not find a job than typical college students. Additionally, the authors found that college students who exhibited poor basic skills were more likely than typical college students to believe they were less able to achieve, less able to understand others, less confident in their abilities, and less driven to succeed, as well as believe they were more likely to fail one or more classes and need extra time to complete a degree (Grimes & David, 1999).

Researchers have also examined how motivational processes related to achievement in non-traditional college students (i.e., those who are older and/or have a full-time job or family). Dupeyrat and Mariné (2005) assessed the motivational beliefs (i.e., goal orientation, mindset), effort expenditure, cognitive strategy use, and achievement (i.e., final course grade) in a sample of 76 adult learners who chose to return to school later in life to complete a high school degree equivalent. Correlation results indicated that mastery goals were positively related to achievement, although mindset was not. Similarly, path analyses suggested that students who reported more mastery goals also reported putting forth more effort toward learning and, subsequently, achieved more (Dupeyrat & Mariné, 2005).

Similar patterns of motivational beliefs and achievement emerge in studies of college students enrolled in online courses. Puzziferro (2008) examined the self-efficacy for using online technology and SRL processes (e.g., planning, time management, environment management, and effort regulation) of 815 community college students enrolled in online courses. The researcher found that students who achieved more in online learning environments were more likely to plan, schedule, manage their time, and manage their environment than students who achieved less. Additionally, students who reported more time and environment management and effort regulation attained higher grades. However, Puzziferro (2008) did not find that final grades varied based on students' self-reported online technology self-efficacy. On the contrary, Lynch and Dembo (2004) found that self-efficacy for learning accounted for 7% of the variance in course grades for 94 students in a blended online learning environment (i.e., 75% of course time online, 25% in-person meetings). Similarly, Wang et al. (2013) examined self-regulation, motivation, course satisfaction, and technology self-efficacy in 256 undergraduate and graduate students enrolled in online courses. Results indicated that students who used more self-regulation strategies were more motivated to learn, which subsequently increased their course satisfaction and technology self-efficacy and finally their course grades (Wang et al., 2013). Together, these studies suggest that motivation often plays a key role in academic success for students who experience a variety of challenges, including those who lack basic academic or self-regulation skills, return to college with a family or full-time job, and/or complete coursework autonomously online. Students who encounter these challenges may exhibit less adaptive motivational processes and need more support throughout their education to remediate their skills and build their motivation to overcome learning challenges.

Variable-Centered Approaches to Understanding Motivation for Learning

Traditionally, researchers have utilized variable-centered research techniques to understand *how* motivation relates to learning and achievement. Variable-centered research approaches (e.g., correlations, regressions, path analyses) examine how multiple variables relate to or predict each other and influence dependent variables; they treat each variable separately and as the individual unit of analyses (Marsh et al., 2009). Researchers have employed these variable-centered techniques to explore the relationship between many key motivation constructs, including goal orientation, mindset, and self-efficacy, and the relation between these motivation variables and a variety of academic achievement outcomes. In the following section, I review a sample of the current motivation literature to illustrate the nature of these types of studies and to provide some insight into how motivation variables relate to each other and varying types of achievement outcomes.

For instance, Barron and Harackiewicz (2001) examined how mastery and performance goals related to each other and to mathematics problem solving in a study of 166 undergraduate students. The author found that students who endorsed more mastery goals also reported more interest and enjoyment in the academic task, whereas students who endorsed more performance goals solved more easy-difficulty, but not hard-difficulty, math problems. The researchers concluded that both types of goals were important because they were linked to different academic outcomes and other motivational processes (Barron & Harackiewicz, 2001). Blackwell and colleagues (2007) also explored how motivation relates to achievement in terms of students' mindset and their grades over time. Researchers measured the growth and fixed mindset of 373 seventh graders and tracked their grades over two years. Results indicated that students with a growth mindset had a higher rate of improvement in grades over two years compared to students with a fixed mindset, and that four motivation beliefs (i.e., learning goals, beliefs about effort, causal attributions, and beliefs about strategy use) mediated the relationship between mindset and achievement (Blackwell et al., 2007). In these studies, student goals and mindsets influenced other aspects of motivation as well as achievement.

Researchers have taken similar methodological approaches to understand the unique contribution of self-efficacy on achievement. Pintrich and De Groot (1990) explored the self-efficacy, intrinsic value, and test anxiety of 173 seventh graders in relation to self-regulation strategy use and various types of achievement (e.g., classwork completed, grades). The researchers found that self-efficacy and value related to achievement, but that this relationship was mediated by cognitive strategy use (Pintrich & De Groot, 1990). Zimmerman et al. (1992) also examined self-efficacy and achievement, but utilized path analyses to understand the path between self-efficacy and later achievement. The researchers measured parents' goals for learning, students' goals for learning, self-efficacy for both self-regulation and achievement, and past and present grades in 102 high school students. The path analyses indicated that self-efficacy for self-regulation influenced self-efficacy for achievement, which directly related to achievement as well as influenced achievement through student goals; this model accounted for 31% of the variance in academic achievement (Zimmerman et al., 1992). Together, these studies, which place primary importance on motivational variables and how they influence other motivational processes and academic outcomes, are representative of a large chunk of the existing motivation literature.

Comparing Variable-Centered to Person-Centered Statistical Approaches

Although variable-centered studies are essential to our current understanding of how motivation relates to achievement, they cannot provide the same understanding about how multiple motivation constructs relate within an individual as person-centered analyses can. Person-centered statistical approaches, such as a cluster analysis or latent profile analysis, aim to categorize individuals into groups where each individual exhibits a similar set of characteristics to others within a given group, yet distinct from the individuals in other groups. More specifically, individuals within each cluster demonstrate a similar pattern of scores across multiple variables (i.e., similar levels of each variable). Person-centered analyses focus on an individual and their pattern of scores across multiple variables as the unit of analysis. The goal of person-centered approaches is to identify clusters of students with similar patterns across multiple variables. These clusters can then be compared to other variables of interest using additional variable-centered approaches to determine if cluster membership predicts or differentially relates to these other variables (Lubke & Muthén, 2005). On the contrary, variable-centered approaches focus on individual variables as the unit of analysis and aim to produce aggregate results about the amount of a variable in one sample, in comparison to other samples or variables. That is, variable-centered approaches allow researchers to understand how variable A relates to variable B, or if group X reports more of a variable than group Y.

From a research perspective, the two statistical approaches offer unique limits and benefits. Variable-centered approaches often test the significance of comparisons between variables or across groups. These approaches can answer questions such as “Does group X report more of this variable than group Y?” and get a relatively definitive “Yes” or “No” answer. Because variable-centered analyses aggregate data across a sample, rather than focusing on individuals within that sample, the results of variable-centered studies are often generalizable to large populations. On the other hand, person-centered approaches primarily produce clusters or categories of individuals. Even though person-centered approaches aim to create clusters that differ from each other on key elements (i.e., the variables being examined), they do not necessarily determine if one cluster is significantly different than others, but instead determine that the pattern of variables within each cluster differs from the other clusters in meaningful ways. Because these clusters are dependent upon the sample in each study, it may be harder to generalize the results of person-centered studies to larger populations.

Although variable-centered approaches can help researchers test hypotheses about group differences, person-centered approaches may be more advantageous when applying research to practice, because person-centered approaches focus on the individuals rather than variables. That is, variable-centered approaches can tell practitioners to look for key factors that may make students at risk, such as students who are not self-efficacious. However, variable-centered approaches do not always provide guidance on how to integrate across multiple factors within a student, particularly when that student demonstrates varying levels of key factors. For example, if a student is highly self-efficacious but demonstrates poor goals and mindset, person-centered analyses may better equip practitioners with the knowledge to understand if that pattern is more concerning for the students' achievement, or if students in that motivation cluster will perform adequately. In particular, researchers need to better understand how key motivational processes—including students' mindset, mastery orientation, self-efficacy, test anxiety, and grit—relate to adaptive or maladaptive academic outcomes. In practical situations, person-centered approaches inform how multi-component factors, such as motivation, can influence these outcomes, and produce clusters that can be used to classify individuals in order to identify their needs and intervene appropriately.

Person-Centered Approaches to Understanding Motivation for Learning

Although most literature within the self-regulation and motivation fields has focused on variable-centered statistical approaches, some research has turned toward a person-centered approach. The majority of person-centered studies utilize one of two common statistical techniques: cluster analysis and latent profile analysis (LPA). Both cluster analyses and LPAs aim to group individuals in a given sample based on homogeneity of variables within each group. Cluster analyses can be used with small (<50) to moderate (>150) sample sizes, can be completed using common statistical software (e.g., SPSS), and provide definitive cluster membership results for each participant in a sample (Neuville, Frenay, & Bourgeois, 2007). Because of these benefits, cluster analyses are commonly used in the person-centered literature. However, when researchers prefer to cluster participants based on models that reflect the unique population parameters (i.e., means, variances, covariances) of a given sample—or when they assume that each cluster represents a separate subsample that may have different population parameters—researchers may elect to use a more complex statistical approach such as a LPA. Instead of definitive cluster membership, LPAs will yield the probability that an individual belongs to a cluster, since clusters are allowed to overlap to some extent, rather than the definitive cluster membership, which may yield a more accurate classification of participants than a cluster analysis. LPAs also offer other benefits above cluster analyses including the availability of fit statistics to evaluation how well the final cluster result fits the data, which helps researchers make an informed, objective decision about the appropriate amount of clusters for a given sample (Magidson & Vermunt, 2002).

In the following sections, I provide an overview of the person-centered literature that includes motivation variables. Based on a review of this literature, it appears that over 100 person-centered studies have been conducted that involve motivation variables as the core focus for the study. Of these studies, three broad categories emerge that I will review. The first category consists of studies that included both motivation and SRL variables to establish distinct clusters. Approximately half of the available person-centered motivation studies that were examined for this dissertation fall under this first category. The remaining half of the existing literature focuses solely on motivation variables, as evidenced by the second and third categories. The second category includes studies that focus specifically on motivation variables to establish the clusters. The studies within this sub-section tend to include multiple motivational processes, such as clusters that emerge from patterns of self-efficacy, test anxiety, and goal orientation, for example. The final category of studies also only focuses on motivation variables, but explores studies where the researchers chose to examine only a single motivation process and include different types of that particular process, such as variations in types of mindset.

Clusters based on motivation and SRL variables. A considerable amount of the person-centered studies have included both motivation and SRL variables. Within these studies, many researchers have concentrated on common motivation and self-regulation variables such as self-efficacy, task value, rehearsal, elaboration, and/or metacognition (e.g., Ng et al., 2015). When researchers identified clusters of self-regulation, some focused on the extent to which a cluster was adaptive, whereas others focused on the specific regulatory processes that were emphasized in a given group.

Liu et al. (2014) identified self-regulation clusters that were defined by the extent to which students' reported motivation and self-regulation was adaptive. The authors examined the self-regulation and motivation of 238 junior college students using the Motivated Strategies for Learning Questionnaire (MSLQ); an established measure of self-regulation skills including self-efficacy, task-value, test anxiety, rehearsal strategies, elaboration strategies, and metacognition. Together, the MSLQ addresses the motivation, metacognition, and learning strategies dimensions of SRL to some extent. The authors conducted a hierarchical cluster analysis and identified four clusters according to students' motivated strategies for learning (i.e., their self-regulation): two adaptive clusters (i.e., positive and average) and two maladaptive clusters (i.e., negative and low). Students in the positive (24% of the sample) cluster endorsed moderate to high motivation (i.e., value, self-efficacy) and self-regulation (i.e., elaboration, rehearsal) with low levels of test anxiety. Students in the average cluster (38.4%) also reported adaptive levels of motivation and most self-regulation strategies, although to a lesser degree than students in the positive cluster. Additionally, these students did not endorse using elaboration strategies frequently, but also reported significantly lower test anxiety than students in the positive cluster. Both students in the positive and average clusters performed better academically (i.e., grades) and reported more enjoyment and effort than students in the two maladaptive clusters. In both the negative (13%) and low (24.5%) clusters, students reported being unmotivated and infrequently using self-regulation strategies. However, students in the negative cluster reported low levels of test anxiety, whereas those in the low cluster reported moderately high levels of test anxiety (Liu et al., 2014). Ng et al. (2015) conducted a very similar study with 782 eighth and ninth graders and similarly identified four clusters according to how adaptive or maladaptive students' reported motivation and self-regulation were. In both studies, students in the more adaptive clusters reported more positive academic outcomes. When researchers include a variety of motivation and self-regulation constructs in a single person-centered analysis, they can identify profiles of students based on how adaptive or maladaptive the students' self-regulation skills are, and connect these adaptive profiles to academic success.

From an alternative perspective, researchers have also identified patterns of students' self-regulation and motivation according to the specific regulatory skills emphasized in each cluster. For instance, Shell and Soh (2013) found groups of students who primarily used self-regulation and motivation skills prior to beginning an academic task and others who primarily utilized these skills while learning or after completing an assignment. The researchers examined goal orientation, future time perspective, instrumentality, emotions, metacognition, approach to learning, engagement in class, and self-regulation strategies in a sample of 233 college students enrolled in computer science classes. Together, these constructs reflect some aspects of motivation, metacognition, and learning strategies. Researchers then compared the clusters to gender, computer knowledge and skills, and college major. Five clusters emerged from the data that were labeled based on the type of self-regulation skills that students in the cluster reported. The clusters and some defining characteristics were: strategic (22.3%; high self-regulation, knowledge building, approach goals, instrumentality, and engagement), learned helplessness (18.9%; high self-regulation and engagement, but high avoidance goals and low instrumentality), knowledge-building (25.8%; high approach goals and instrumentality, low avoidance goals and somewhat low engagement and metacognition, but high knowledge-building strategies), apathetic (6%; low approach and high avoidance goals, low engagement and positive affect, negative affect, and lack of self-regulation), and surface-learning (27%; high avoidance goals, negative affect, moderate approach goals and engagement, but low knowledge-building strategies). Researchers found that men were more likely to be in the knowledge-building profile, while women were more likely to be in the surface-learning profile. Additionally, students in the strategic and knowledge-building clusters had more long-term retention of course knowledge (i.e., computer knowledge and skills) and were more likely to be computer science majors than students in the other clusters (Shell & Soh, 2013).

Similarly, Ning and Downing (2015) identified self-regulation clusters based on the specific patterns of skills, but focused on whether or not students' strategy use was more cognitive or behavioral in nature. That is, Ning and Downing (2015) used the Learning and Study Strategies Inventory (LASSI) to examine a variety of cognitive (i.e., use of self-testing, study aids, and information processing) and behavioral (i.e., concentration, time management, selecting main ideas, and test strategies) self-regulation skills in 828 final-year university students in Hong Kong using a latent profile analysis. The LASSI scales address some metacognitive and learning strategies dimensions of self-regulation. The researchers identified four clusters of self-regulated learners: competent, cognitive-oriented, behavioral-oriented, and minimal. As expected, students in the competent cluster reported the highest SRL, while those in the minimal cluster reported the lowest. Additionally, students in the cognitive-oriented cluster reported engaging in more cognitive/metacognitive strategies than behavioral strategies, which was the opposite of students in the behavioral-oriented cluster. Ning and Downing (2015) also found that the clusters differed significantly in academic achievement (i.e., GPA), with students in the competent cluster reporting the highest GPA.

These studies offer a sample of the existing person-centered literature that examines motivation in addition to other self-regulation constructs. Across these studies, a variety of motivation (e.g., self-efficacy, test anxiety) and self-regulation (e.g., time management, self-monitoring) variables are included. However, when researchers expand their study across two or three self-regulation dimensions as these authors did, they may not be able to adequately address any single SRL dimension. That is, only a limited number of variables can be measured in any individual study, and these studies measure some constructs across multiple SRL dimensions rather than more thoroughly exploring a single dimension. To address this concern, researchers have focused their attention and person-centered analyses on only one dimension at a time, in order to capture more nuanced patterns of metacognition, learning strategies, or motivation. This alternate approach to understanding SRL and motivation affords researchers the opportunity to gain a more thorough picture of students' motivation. On the other hand, researchers must acknowledge that they are only examining one SRL dimension, even though each dimension reciprocally influences each other throughout the learning process.

Clusters based only on multiple motivation variables. Many of the other motivation-related person-centered studies have focused exclusively on a series of motivation variables as the source of the clusters. For instance, researchers have examined the clusters of motivation that emerge from students' mindset and epistemic beliefs (e.g., Chen, 2012), or their interest, value, and confidence in their abilities regarding a specific subject (e.g., Bråten & Olaussen). The variables that researchers have elected to include were often based in motivation theory or prior research, such as Dweck's theory of growth and fixed mindsets, and the relation between mindset and other motivation variables (Chen, 2012; Dweck, 2006). In general, these types of studies have identified distinct patterns or clusters of motivational processes that are related to achievement. As an example, researchers have found clusters of students who are highly motivated to learn, somewhat motivated to learn, or barely motivated to learn, and found that these clusters were differentially related to academic outcomes (e.g., persistence over multiple courses and years of college), with highly motivated students reporting better academic experiences (Ratelle et al., 2007; Smith et al., 2014). The following studies illustrate some of the ways in which researchers have conducted person-centered analyses with multiple motivation variables. Of the three studies explored in-depth in this section, the first two only include two motivation variables in their person-centered analyses, whereas the researchers of the third study elected to include a broader series of motivation variables.

One study of 1,225 middle and high school students utilized a latent profile analysis of students' mindset and epistemological beliefs in order to capture part of students' motivation for learning (Chen, 2012). The author found four profiles of students' mindset and epistemological beliefs about science: thriving (47%; growth mindset with adaptive epistemic beliefs), fixed/sophisticated (15.8%; fixed mindset with adaptive epistemic beliefs), growth/passive (31.2% growth mindset with passive epistemic beliefs), and uncommitted (6%; uncommitted to a specific mindset or type of epistemic beliefs). When the clusters were compared to additional motivation variables (i.e., goal orientation, self-efficacy), achievement (i.e., grades), and demographic factors, Chen (2012) found that clusters of students with a growth mindset also had more adaptive goal orientations, students with adaptive epistemic beliefs were more likely to be Asian or White than Hispanic or Black, and students who were uncommitted to mindset or science beliefs also had lower self-efficacy. Additionally, students who displayed adaptive science beliefs (i.e., those in the thriving and fixed/sophisticated cluster) attained higher grades on average than those with passive or uncommitted science beliefs (i.e., students in the growth/passive and uncommitted clusters, respectively).

Putwain and Daly (2013) took an alternative approach to understanding students' motivation by examining the profiles of test anxiety and academic buoyancy (i.e., resilience) of 469 secondary school students in England. Their cluster analysis revealed five groups of students with varying levels of test anxiety and academic buoyancy, with the majority of students exhibiting moderate levels of both anxiety and buoyancy. Putwain and Daly (2013) concluded that students' academic performance is worse when they are anxious and not buoyant, and that buoyancy levels were more important for academic performance than differing levels of test anxiety, as some amount of anxiety may not be maladaptive for academic achievement.

Other researchers have included more comprehensive measures of motivation, albeit selecting only a handful of the possible motivation variables that can contribute to learning. Bråten and Olaussen (2005) examined students' interest, value, mastery goals, and self-efficacy in their cluster analyses of nursing college students and business graduate students. For both samples of students, researchers found three profiles of positive, moderate, and low motivation for learning. For nursing students, students in the positive cluster used more elaboration, rehearsal, and metacognition than students in the moderate or low clusters, and students in the moderate cluster also used significantly more elaboration and metacognition than students in the low cluster. Epistemological beliefs also significantly differed across all three clusters of nursing students, with the positive cluster reporting the most adaptive beliefs, followed by the moderate cluster. For business students, students in the positive cluster endorsed using more elaboration and metacognitive strategies than students in the other two clusters, and students in the moderate cluster also endorsed more elaboration and metacognition than students in the low cluster. For rehearsal, the positive and moderate clusters of business students only reported more strategy use than students in the low cluster. Regarding epistemological beliefs, the only group difference was for construction of knowledge, where business students in the positive cluster reported more adaptive epistemological beliefs than students in the other clusters.

These studies provide a glimpse of the existing person-centered literature regarding motivation for learning; they indicate that person-centered approaches can help to identify groups of students with varying levels of motivation for learning that relate to academic outcomes. However, the results and practical significance of a given study may depend on the specific motivation variables that are included. To better understand the nuances of an individual motivation variable, researchers may alternatively choose to conduct a more in-depth exploration of the patterns that emerge within a single aspect of motivation.

Clusters based on a single aspect of motivation. In order to attain a more nuanced look at a specific aspect of students' motivation for learning, some researchers have examined profiles of different types of mindsets, goal orientations, or factors that contribute to a students' self-efficacy. Some researchers have used person-centered analyses to explore factors that contribute to students' motivation, such as the cognitive appraisals that influence test anxiety or the experiences that help to build students' self-efficacy (e.g., Chen & Usher, 2013; Davis, DiStefano, & Schutz, 2008). Others have examined the various types of mindset or goal orientations. For instance, Putwain and Sander (2016) conducted an in-depth exploration of the various types of students' goal orientations. Even though many person-centered studies, such as those reviewed here, treat goal orientations as a single measure of mastery or performance goals, or include two separate measures of mastery and performance goals, some goal orientation theorists suggest the concept of goal orientations is more nuanced than this basic dichotomy (Senko, 2016). Putwain and Sander (2016) embraced this theoretical shift and included four types of goal orientations in their cluster analysis of 434 first year honors college students: mastery-approach (MP) goals, mastery-avoidance (MV) goals, performance-approach (PP) goals, and performance-avoidance (PV) goals. The authors found three profiles of the four goal orientations including (1) moderate MV, PP, PV and high MP, (2) low MV, moderate PP and PV, and high MP, and (3) moderate MV and high MP, PP, and PV. Although the authors did not compare these clusters to academic achievement, they hypothesized that the second cluster would be the most adaptive, as students endorsed both mastery and performance goals and endorsed both types of approach goals more than avoidance goals (Putwain & Sander, 2016).

Puente-Diaz and Cavazos-Arroyo (2017) used latent profile analysis on 618 college students to determine if distinct profiles of mindset for creativity would emerge. Based on the hypothesis that students could exhibit a mixture of both fixed and growth mindsets, the authors decided to independently measure students' fixed and growth mindsets, rather than administering one assessment that categorized students into a primarily fixed or growth mindset. Four clusters of students' mindset emerged including a high fixed and growth, high growth and low fixed, medium growth and high fixed, and low growth and fixed. Since only one of these clusters, the high growth and low fixed, followed the notion that students primarily exhibit a growth or fixed mindset only, this research highlights the importance of capturing the more nuanced aspects of motivation in person-centered analyses. These person-centered analyses that focus on specific motivation variables allow researchers to understand subtle differences in motivation patterns between students that may not be captured by typical variable-centered approaches.

Gaps in the Motivation Literature

The current research base of person-centered approaches to understanding motivation for learning touches on a wide range of motivation constructs; however, there are multiple areas for further research that have not yet been adequately addressed. First, the existing literature includes a variety of motivation variables such as self-efficacy, test anxiety, and task value simultaneously (e.g., Liu et al., 2014), and also studies that have examined one aspect of motivation in-depth (e.g., goal orientation; Korpershoek et al., 2015). Despite the array of variables included in some studies, there is a need for more research that comprehensively addresses many of the essential cognitive processes that influence motivation for achievement. Second, most studies use traditional students, rather than populations who encounter many challenges to their learning due to the nature of complex learning contexts. College students who exhibit poor academic or self-regulation skills, are non-traditional, and attend college online encounter many challenges that yield a need for strong motivational beliefs. Third, most of the previously identified person-centered studies of motivation and achievement rely on a single measure of success, such as course grades of GPA (e.g., Artino & Stephens, 2009; Chen, 2012; Putwain & Daly, 2013). Since academic achievement is a complex concept that can be represented by a multitude of outcomes, there is a need for person-centered studies to include multiple indicators of students' success, including students' engagement and achievement outcomes. The following sections further explore these three gaps in the current literature.

Comprehensive studies of motivational processes. The existing person-centered literature surrounding motivation spans across a variety of motivation variables, ranging from broad studies of motivation constructs intertwined with additional aspects of self-regulation, to more nuanced conceptualizations of a single motivation construct. These studies demonstrate how a variety of motivation levels and patterns can emerge, depending upon the variables included in each study. Although many studies aim to measure students' motivation for learning, most person-centered studies only include two to three motivation variables. For instance, Chen (2012) examined mindset and epistemological beliefs, whereas Liu et al. (2014) included self-efficacy, task value, and test anxiety in their study. Even with studies that include some of the most comprehensive measures of motivation, such as Bråten and Olaussen's (2005) study of students' interest, value, mastery goals, and self-efficacy, there is a need for more research that includes more extensive, comprehensive measures of a variety of motivation constructs that can influence learning and achievement. Future research should address key motivational processes including self-efficacy, mindset, goal orientation, test anxiety, and grit—five cognitive processes that can greatly influence motivation for learning and achievement—within the same person-centered analysis.

Students exposed to disproportionate challenges. When students experience repeated challenges (e.g., repeatedly failing basic college courses), they are less likely to exhibit adaptive motivational processes and can have difficulties overcome obstacles and achieving success (Moylan, 2013). In the college student population, students may be more likely to experience challenges and exhibit less adaptive motivational processes if they encounter certain personal and/or contextual barriers to their learning. These barriers include (a) students who lack self-regulation or basic academic skills, (b) non-traditional students who are returning to college at an older age, possibly with the additional responsibilities of a family and/or full-time job, and (c) students who are enrolled in some or all of their college courses online and must be independent and self-directed in their learning. While it is important for motivation literature to explore the patterns and profiles of motivation with students who encounter personal and/or contextual barriers to their learning, the majority of the current person-centered studies utilize typical students from the general population. A few notable exceptions have included such populations in their person-centered studies.

Artino and Stephens (2009) descriptively divided their sample of 481 college students enrolled in a short, self-paced online course into the top, bottom, and middle third based on students' scores for motivation (i.e., self-efficacy and task value), and academic emotions (i.e., boredom and frustration). The authors retained the top and bottom group for both motivation and academic emotions and found that students in the most adaptive group (i.e., high motivation, low affect) reported better SRL skills (e.g., elaboration) and achievement (i.e., final course grade) than students with less adaptive motivation and emotions.

Barnard-Brak, Lan, and Paton (2010) also conducted a person-centered analysis of students enrolled in online degree programs and evaluated their SRL skills (i.e., environmental structuring, goal setting, time management, help seeking, task strategies, self-evaluation). A latent class analysis revealed five clusters of self-regulators: super (i.e., endorsed consistently high SRL skills), competent (i.e., endorsed moderate to high SRL skills), forethought-endorsing (i.e., endorsed more goal setting and environmental management than other SRL skills, which are typically used before engaging in a task), performance/reflection-endorsing (i.e., endorsed more task strategies, time management, help seeking, and self-evaluation, which are typical used during or after a task), and non/minimal (i.e., endorsed low SRL skills). As expected, Barnard-Brak et al. (2010) found that students in the more adaptive clusters (i.e., super and competent self-regulators) had significantly higher GPAs than students in the other clusters. While this second study addresses SRL, it does not explicitly include motivation, even though motivation may play a critical role in students' success in online learning environments.

In a third study, Pawlo et al. (2019) conducted a cluster analysis of 6,176 students' SRL skills (i.e., metacognition, motivation, learning strategies) from an online college who are also typically considered to be non-traditional students. Four clusters of SRL skills emerged; two with variable patterns of SRL, where metacognition was significantly lower than learning strategies or motivation, and two with more consistent levels—either moderate or high—across all three areas of SRL. The authors found that students in the most adaptive cluster (i.e., consistently high SRL) attempted and earned more credits than students with consistently moderate SRL skills or variable but lower SRL skills. Although each of these three studies utilizes a sample of students who may experience personal and/or contextual barriers to their learning, these studies do not adequately address the construct of motivation and how motivation to learn impacts students' achievement in online learning environments. Additional research is needed to fill this gap.

Multiple indicators of success. As noted in many studies reviewed here, the person-centered motivation research that compares clusters to a measure of academic achievement only includes a limited range of achievement outcomes. That is, most studies examine if clusters differentially associate with students' grades or GPA, instead of including other outcomes that may indicate success. However, academic success could refer to students' knowledge or skill acquisition, satisfaction with learning, retention and persistence over time, engagement in learning-related activities, and attainment of learning objectives (Kuh et al., 2006; York et al., 2015). For college students, two indicators of success may be particularly important when students are tasked with learning independently: persistence (e.g., completing courses or progress toward a degree) and engagement (e.g., engagement in class or skill-development programs and learning-related activities). For instance, students who are motivated may attempt more course credits or engage in classes differently than students who are less motivated, and these behaviors may relate to eventual improvements in grades or GPA, even if those improvements are not reflected immediately. Therefore, in addition to traditional measures of academic achievement, behavioral indicators of success (e.g., credit attainment), measures of engagement in learning-related activities, and persistence over time should be examined in relation to clusters of motivational processes.

To my knowledge, only a few studies have included non-traditional measures of academic success in their person-centered approaches. Hsieh (2016) conceptualized success as engagement in class and compared three motivation clusters (i.e., high intrinsic, high extrinsic, high intrinsic and extrinsic) of 231 college students in Taiwan to classroom engagement (i.e., active participation, interactions with instructors, cognitive effort toward class) and GPA. Hsieh found that students with high intrinsic and extrinsic motivation actively participated in class more than students in the other two clusters and exerted more cognitive effort and achieved a higher GPA than students with only high intrinsic motivation. Hsieh's research highlighted the importance of including engagement as an alternative indicator of academic success. Dörrenbächer and Perels (2016) and Abar and Loken (2010) both conceptualized academic success as student use of or success with intervention programs. For example, Abar and Loken (2010) examined the SRL (i.e., metacognition, effort management, time and study environment, and test anxiety) and academic beliefs (i.e., academic efficacy, academic self-handicapping, and academic skepticism) of 205 high school students through a latent profile analysis, and then compared clusters to goal orientation and use of an online study-tool website. The authors found three SRL clusters: high SRL (15%; high adaptive SRL skills and low maladaptive skills), low SRL (37%; high maladaptive SRL skills and low adaptive skills), and average SRL (48%; all SRL skills close to the population average). Students in the high SRL cluster reported the highest levels of mastery goal orientation and studied materials on the website for a longer time and attempted more online tutorials and practice questions than students in the other clusters. These studies suggest that there is some benefit to exploring alternative forms of academic success indicators beyond traditional grades and GPA. Because there are few studies that explore these alternative indicators, and a limited scope of alternative success indicators, additional research is needed to expand the current knowledge base regarding how motivation profiles relate to various types of academic success, including engagement and persistence.