SMOOTH SAILING OR CHOPPY WATERS? PATTERNS AND PREDICTORS OF MOTIVATION IN ON-LINE MATHEMATICS COURSES

By

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A DISSERTATION

Submitted to
Michigan State University
in partial fulfillment of the requirements
for the degree of

Educational Psychology and Educational Technology - Doctor of Philosophy

2016

ABSTRACT

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The current study investigated high school students' patterns of motivation in mathematics, and their relation to academic outcomes in on-line mathematics courses. Participants reported their motivation (value, competency beliefs, and achievement goal orientations) at the beginning (n = 206) and middle (n = 83) of a single semester. Students also reported their reactions to exam feedback after the first two exams. Four motivational profiles—characterized as *Highly Motivated by Any Means, Intrinsically Motivated and Confident, Average All Motivation, and Amotivated*—were identified. Over 50% of participants remained in the same profile from the beginning to middle of the semester, with the Intrinsically Motivated and Confident profile most stable and the Highly Motivated by Any Means and Amotivated profiles least stable. Profiles differed with respect to achievement trajectories, dropout rates, regulation, and engagement; students in the Highly Motivated by Any Means and Intrinsically Motivated and Confident profiles were higher achieving and more engaged than students in the Amotivated profile. Amotivated students also responded differently to exam feedback than students in the other three profiles; even when controlling for objective achievement, Amotivated students were unlikely to perceive themselves as successful, make internal attributions, or experience positive emotions. The current study refines ongoing theoretical debates by examining profile membership and academic outcomes longitudinally. This study also guides educational practice by identifying an at-risk group of students and exploring underlying psychological mechanisms that may highlight promising avenues for intervention efforts.

To Mom, Dad, and Mike, who never lost hope.

ACKNOWLEDGMENTS

In the words of Virginia Woolf, "some people go to priests; others to poetry; I to my friends." Over the past five years, I have been surrounded by the most amazing friends within and outside of academia. Without their support, this journey would not have been nearly as fulfilling or enjoyable.

Outside of work, three people deserve my utmost appreciation. First, my parents Gaye and Steve have been unwavering sources of support. You've always encouraged me to work towards my dreams, no matter the circumstances. Thank you for teaching me through example the value of hard work, and patiently listening while I nerded out about statistics. I am also indebted to my husband Mike. True to your nature, you entered the picture late but made a substantial impact. You've brought a sense of calm and contentment to my life, but more importantly you've made the world a brighter and better place. Let's never stop adventuring.

I've also received support from many friends and family members, who deserve much more acknowledgement than I can give here. I will reserve my expressions of gratitude for another day. However, I will thank my friends Erin and Lex in particular. Your weekly check in's kept me going through even the toughest times. I also want to acknowledge my Aunt Sue, whose kindness is a true inspiration, and Mamaw, who I wish was still here to see this.

Within the academic realm, I have been fortunate to receive support from professors throughout my brief academic career. I am eternally grateful to Kris, Kathy, and Jennifer for unending (and, at times, unwarranted) encouragement and enthusiasm. The fact that you still support me five years after I left Reed speaks volumes about your character. Thank you for instilling in me the passion for learning I now can't imagine myself without. I am also indebted to my professors at Duke, who share their formidable knowledge and insights of the field so generously with their students. Through classwork and conversations, I have come to appreciate the importance of designing future research while keeping an eye on the past. I am also grateful to my committee members at Michigan State University. Hearing feedback from such great thinkers was invigorating (and only the slightest bit intimidating). In particular, I would like to thank Cary Roseth. I aspire to your level of caring as a teacher, mentor, and scholar.

I have also been lucky enough to work alongside fantastic labmates both at Duke and Michigan State University. Special thanks go to my academic older sibling Kate, who is still willing to room with me at AERA and provide massive amounts of support over gchat, and Tony, who is one of the kindest people I've ever met. I would also like to thank Michael, whose work ethic and determination is inspirational. There's no one with whom I would have rather gone through this crazy process. I am also grateful for the opportunity to work with fantastic graduate students at Michigan State. Transferring in the middle of graduate school was harrowing, but the process was much more enjoyable with such welcoming labmates. Thank you to You-kyung for pushing my thinking, Emily for your infectious happiness, Kristy for your truly impressive generosity and grace, and John for your Canadian kindness and long talks (even if rarely agreed on anything research-related). I will miss you all so much next year.

Finally, I am beyond grateful to my advisor Lisa. There is no doubt that you've fundamentally changed the way I think about research and education. More than that, you've inspired me as a person. Striving to live up to your example is certainly a challenge, but one that I look forward to tackling. Thank you for your patience, guidance, and wisdom in helping me discover my voice as an academic.

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CHAPTER 1:

Introduction

Students' motivational beliefs—or reasons for engaging in school—are critical determinants of their academic success (Linnenbrink-Garcia & Patall, 2016; Weiner, 1990; Wigfield & Cambria, 2010). Motivation has been linked to outcomes such as achievement, engagement, study habits, and career choices (Eccles et al., 1993; Maehr & Zusho, 2009). However, students tend to lose motivation during adolescence (Archambault, Eccles, & Vida, 2010; Martin, 2009; Otis, Grouzet, & Pelletier, 2005). These declines can have enduring consequences for later educational and job-related outcomes, including career and scholarly attainment (Maehr & Zusho, 2009; Wigfield & Cambria, 2010). Motivational declines may be particularly alarming in mathematics. Early interest in mathematics promotes later pursuit of science, technology, engineering, and mathematics (i.e., STEM) careers (Watt, Eccles, & Durik, 2006). Moreover, mathematics skills support learning within and beyond STEM fields (Cross, Woods, & Schweingruber, 2009; Middleton & Spanias, 1999). Despite the critical role of mathematics education, motivational declines are more pronounced in mathematics than other subjects such as social studies (Gottfried, Fleming, & Gottfried, 2001) or English (Wigfield & Eccles, 1994). Motivational declines may be even more substantial in on-line courses, which often exhibit higher dropout rates than face-to-face clarrooms (Patterson & McFadden, 2009). Thus, it is important to investigate and bolster students' motivation in mathematics and on-line learning contexts.

Educational psychologists have devoted significant attention to motivation, with researchers offering recommendations on fostering motivationally supportive educational environments (Maehr & Midgley, 1991; Stipek, Salmon, Givvin, & Kazemi, 1998). The research to date provides valuable insights into socialization factors such as peer or parent influences (Pomerantz, Grolnick, & Price, 2005; Rodkin & Ryan, 2012) and school climate (Maehr & Midgley, 1991). However, students' actual motivation is rarely as straightforward as conceptualized in studies. Often, motivation researchers use variable-centered analyses (e.g., regression analyses) to document general associations between one specific type of motivation and outcomes such as poor academic achievement, school truancy, and dropout (Ianni & Orr, 1996; Yonezawa, Jones, & Joselowsky, 2009). However, theory suggests that students endorse distinct combinations of motivation and these combinations have important consequences for academic success (Pintrich, 2000). With a focus on general trends, variable-centered analyses are limited in their ability to describe how different types of motivation combine and which students maintain adaptive combinations of motivational beliefs. As a result, researchers face a set of unique challenges in translating findings from motivation research into recommendations for classroom practices (Covington, 2000; Hulleman & Barron, 2016; Paris & Paris, 2001).

A person-oriented approach (Magnusson, 2003) can extend upon variable-centered work by identifying groups of students who endorse distinct combinations of motivation (i.e., profiles) and comparing groups on academic outcomes. Person-oriented research has gained popularity in achievement motivation, but is mostly limited to single time point designs and exclusively to face-to-face learning contexts (e.g., Conley, 2012; Daniels et al., 2008). To understand which profiles are most adaptive in the long term, researchers should consider the extent to which motivation changes across time. A longitudinal approach also allows researchers to identify psychological processes that may be associated with changing motivational beliefs. Similarly, research would benefit from examining achievement motivation in the burgeoning arena of on-line learning contexts (Allen & Seaman, 2013).

In the current study, I sought to extend person-oriented motivation research by documenting high school students' short-term motivational stability in on-line mathematics courses. Rather than drawing from a single motivational framework, I integrated across theoretical perspectives to broadly describe students' reasons for engaging in school. I also assessed students' motivation over time to describe students' changing motivational beliefs, and investigated exam achievement and reactions to exam feedback as potential correlates of motivational change. In the next chapter (Chapter 2: Literature Review), I specify my operationalization of achievement motivation. After providing a theoretical overview of motivation, I describe person-oriented methodology and review relevant motivational studies. I then outline the benefits of considering motivational profiles longitudinally to understand their relative stability or change, and draw on attribution theory (Weiner, 1986) to suggest how perceptions of success, attributions, and emotions might relate to profile stability. Finally, I discuss the potential influence of the high school and on-line learning contexts on processes of interest.

CHAPTER 2:

Literature Review

Operationalizing Motivation: An Integrative Perspective

Because motivation is an established predictor of achievement-related behaviors, researchers have developed several theories to characterize distinct aspects of students' motivation. With so many potential motivational beliefs linked to students' success, investigators face a challenge in selecting which factors to study. Studies should aim to provide a broad enough conceptualization of motivation to capture students' reasons for trying in school. Given considerable overlap among motivational beliefs, however, researchers must also seek to avoid unnecessary redundancy in the constructs measured (Murphy & Alexander, 2000).

Some scholars have advocated for an integrative perspective, in which researchers reference several theories to provide a broad picture of student motivation (e.g., Conley, 2012; Hulleman, Durik, Schweigert, & Harackiewicz, 2008; Shell & Husman, 2008; see Linnenbrink-Garcia & Patall, 2016). In the current study, I draw from achievement goal theory (Ames, 1992), expectancy-value theory (Barron & Hulleman, 2015; Eccles et al., 1983; Wigfield, Tonks, & Klauda, 2009), and social cognitive theory (Bandura, 1977) to conceptualize motivation.[1] Constructs described in these theories address two fundamental questions integral to students' motivation: "can I do this task?" (i.e., competency beliefs) and "do I want to do this task?" (i.e., task value and achievement goals). Each type of motivation also relates to different academic outcomes (Schiefele, 2001, 2009; Wigfield, Eccles, Schiefele, Roeser, & Davis-Kean, 2006). As such, assessing them in tandem increases predictive power while avoiding unnecessary

[1] I chose not to incorporate additional motivational constructs either due to significant overlap with the constructs already identified (e.g., interest; Hidi & Renninger, 2006; Schiefele, 2001, 2009) or because they do not ascribe to a social cognitive perspective of motivation (e.g., self-determination theory; Deci & Ryan, 1985; Ryan & Deci, 2000).

redundancy (Conley, 2012). Constructs from these theories are also interrelated (Hulleman et al., 2008; Plante, O' Keefe, & Theoret, 2013). For example, students' feelings of competence are associated with the academic goals they adopt (Elliot & Harackiewicz, 1994). Omitting any of these constructs, then, could provide an incomplete picture of students' motivation.

Achievement Goal Theory

In achievement goal theory, students' task-specific goals (i.e., goal standards) or general inclinations (i.e., goal orientations) shape their affect, cognition, and achievement-related behavior (Ames, 1992; Elliott & Dweck, 1988; Kaplan & Maehr, 2007; Maehr & Zusho, 2009). Students may endorse mastery (i.e., concern with developing competence) or performance goals (i.e., concern with demonstrating competence, often relative to others). Performance goals are further differentiated along an approach-avoidance dimension in most current conceptualizations, with individuals striving to demonstrate competence (performance-approach) or avoid demonstrating incompetence (performance-avoidance; Elliot, 1999; Elliot & Harackiewicz, 1996; Middleton & Midgley, 1997).[2] Mastery goals are positively associated with engagement and interest, with mixed findings concerning achievement (Maehr & Zusho, 2009; Midgley, Kaplan, & Middleton, 2001). Conversely, performance-avoidance goals are negatively associated with engagement and achievement (Hulleman, Schrager, Bodmann, & Harackiewicz, 2010; Linnenbrink-Garcia, Tyson, & Patall, 2008; Middleton & Midgley, 1997). The consequences of performance-approach goals are less straightforward, as they display positive (Barron & Harackiewicz, 2001; Hulleman et al., 2010), negative (Linnenbrink, 2005; Skaalvik,

[2] Some models of achievement goals also assess mastery-avoidance goals, in which individuals are driven to avoid not learning as much as possible or are concerned with losing skills they once possessed (Cury, Elliot, Da Fonseca, & Moller, 1996; Elliot, 1999; Elliot & McGregor, 1999). I did not consider mastery-avoidance goals in the current study due to concerns raised regarding multiple potential definitions (i.e., avoiding not learning as much as possible versus losing previously developed skills) and low internal reliability (Madjar, Kaplan, & Weinstock, 2011).

1997), and null associations (Gonida, Voulala, & Kiosseoglou, 2009; Walker & Greene, 2009) with outcomes such as achievement, test anxiety, and engagement.

Expectancy-Value Theory

Adapted from Atkinson's (1957) experimental work, modern expectancy-value theory highlights two aspects of motivation: expectancies for success (i.e., subjective judgments about the likelihood for completing a task successfully) and task value (i.e., perceived worth associated with a domain or task; Eccles et al., 1983). Task value is further separated into dimensions of interest (i.e., engaging in a task due to interest or enjoyment), attainment (i.e., engaging in a task to support one's identity), utility (i.e., engaging in a task due to usefulness), and cost (i.e., considering sacrifices associated with a task; Wigfield & Eccles, 2000). Expectancies for success are associated primarily with academic achievement, while value correlates with achievement-related choices (e.g., course enrollment; career intentions) and task persistence (Wigfield et al., 2009). Expectancies and values are also related to one another; according to theory, students express greater interest for a domain in which they also feel competent (Wigfield et al., 2009).

Social Cognitive Theory

Social cognitive theory is the foundation for modern social-cognitive motivation frameworks, including achievement goal theory and expectancy-value theory (Bandura, 1977; Weiner, 1990). A cornerstone of social cognitive theory is its discussion of self-efficacy, or students' beliefs that they can effectively organize and execute a given task (Bandura, 1977; Zimmerman, 2000). Because self-efficacy and expectancies for success both concern students' feelings of competency, I refer to both in the current study as competency beliefs. Experimental and survey-based evidence identify self-efficacy as a key predictor of achievement and task persistence (Bandura, 1977; Bandura, Barbaranelli, Caprara, & Pastorelli, 1996; Guay, Marsh & Boivin, 2003; Schunk, 1991). Critical to the current study, self-efficacy also moderates the impact of other motivational constructs. For example, Dweck and Elliott (1983) posited that the adaptive nature of performance goal endorsement depends on students' competency beliefs. Competency beliefs are considered within current conceptualizations of achievement goal theory, as low competency beliefs are posited to give rise to performance-avoidance goals and high competency to performance-approach goals (Elliot, 1999). However, competency beliefs are rarely measured alongside achievement goals. As such, there is little evidence examining which achievement goals are likely to accompany high competency beliefs. Similarly, it remains unclear whether students who feel highly competent but also endorse performance-approach and performance-avoidance goals are likely to be successful. Given its foundational role in both achievement goal theory and expectancy-value theory, it is important to consider competency beliefs alongside achievement goals and value.

Person-Oriented Approach

Motivation research often focuses on unique associations between motivational beliefs and outcomes (Linnenbrink-Garcia & Patall, 2016). For instance, Eccles' work has examined the relation between competency beliefs and early achievement or course selection (Archambault et al., 2010; Durik, Vida, & Eccles, 2006). These results provide useful information about the average association between motivational constructs and academic outcomes. In reality, however, students enter the classroom with a variety of motivations to succeed (Pintrich, 2000). A student, for example, may try hard in algebra because she perceives herself as both interested in and good at math (e.g., Trautwein et al., 2012). Students may also hold different motivational beliefs from one another, even within the same learning context; while some individuals are focused on outperforming classmates, others may be focused solely on mastering the material presented in class. Thus, average associations may not be sufficient to characterize any given student's motivation (Walls & Schafer, 2006).

A person-oriented approach can provide valuable insights into students' multiple reasons for engaging in school (Magnusson, 2003). Variable-centered analyses, which characterize the majority of motivation research, examine general associations between variables across a sample (Bergman & Trost, 2006; Tabachnick & Fidell, 2013). By contrast, person-oriented analyses examine how predictors combine at the level of the individual, identify common combinations of predictors (i.e., profiles), and compare profiles on outcomes of interest (Bergman, Magnusson, & El-Khouri, 2003; Laursen & Hoff, 2006; Marsh & Hao, 2007). A medical analogy from Magnusson (2000) illustrates the difference between the two approaches. Imagine that a patient suffering from a sore throat seeks treatment from a physician. If the physician were to use a variable-centered approach, she would consider which illnesses were most often associated with a sore throat without considering the patient's other symptoms. If she were to employ a person-oriented approach, the physician would consider the constellation of the patient's symptoms (e.g., fever, runny nose) and be able to distinguish between different illnesses such as a cold or flu. Similar logic may be applied to motivation research. A variable-centered approach provides information on the unique, general relations between types of motivation and academic outcomes. By contrast, a person-oriented approach sheds light on which combinations of motivation are most common and adaptive. With its unique focus, a person-oriented approach has the potential to contribute to motivation research, theory, and practice.

Research Implications

Two important assumptions underlie variable-centered analyses, both of which may present issues when investigating simultaneously endorsed forms of motivation. First, the relation between predictor and outcome variables is considered constant across an entire sample. Within motivation theory, however, the effect of one form of motivation may depend on other motivational beliefs (Midgley et al., 2001; Pintrich, 2000). To assess interrelations among predictor variables, researchers must include interaction terms in their analyses. More complex interaction terms require large samples for sufficient power and may be difficult to interpret; even two-way interactions may require large sample sizes to detect a significant effect (Trautwein et al., 2012). Researchers also run the risk of interpreting interactions terms at levels that are not frequently endorsed within their samples. Finally, interaction terms rely on the assumption that two variables are linearly related to one another. Person-oriented analyses, by contrast, identify naturally occurring combinations of motivation, require smaller sample sizes than higher-level interaction terms, and do not assume that constructs are linearly related.

Second, variable-centered analyses assess the variance explained by each construct above and beyond other predictor variables. Because variable-centered analyses assess the unique variance accounted for by independent variables, highly correlated constructs compete to predict outcomes and may give rise to multicollinearity. Multicollinearity is of concern within motivation research, as theoretically distinct constructs can be highly interrelated; for instance, it is not uncommon for performance-approach and performance-avoidance goals to be correlated as high as .60-.90 (Law, Elliot, & Murayama, 2012). Person-oriented analyses, by contrast, identify distinct profiles and compare profiles with respect to outcomes of interest. Since these analyses do not involve holding levels of other predictor variables constant, multicollinearity is not a concern.

Theoretical Implications

Several key motivational debates concern the most adaptive combination of motivation. However, variable-centered studies either overlook or cannot fully represent the interrelations among motivation constructs. For instance, the interaction between competency beliefs and task value is central to both current and classic models of expectancy-value theory (Atkinson, 1957; Wigfield, 1994). Despite its significance, disproportionately few studies examine interaction terms between competency beliefs and value (but see Trautwein et al., 2012). Person-oriented research can reintroduce the theoretically-relevant interaction between competency and task value.

Within achievement goal theory, one of the most sustained theoretical debates involves performance-approach goals. Recall that performance-approach goals are associated with both adaptive and maladaptive outcomes (Hulleman et al., 2010; Linnenbrink, 2005). One explanation for inconsistent findings concerns which other goals are simultaneously endorsed (Pintrich, 2000). For instance, studies demonstrate a substantial positive correlation between performance-approach and performance-avoidance goals (Law et al., 2012; Linnenbrink-Garcia et al., 2008; Murayama & Elliot, 2009). Some advocates of the *mastery goal perspective* highlight this high correlation as an argument against promoting performance-approach goals, suggesting that it may be difficult or rare for students to endorse performance-approach goals without also adopting performance-avoidance goals (Midgley et al., 2001). Proponents of the *multiple goal perspective*, conversely, assert that performance-approach goals are adaptive when endorsed alongside mastery goals (Barron & Harackiewicz, 2001; Harackiewicz, Barron, &

Elliot, 1998; Harackiewicz, Barron, Pintrich, Elliot, & Thrash, 2002; Senko, Hulleman, & Harackiewicz, 2011).[3] While goal theorists occasionally include two-way interactions between mastery and performance-approach goals in analyses (e.g., Barron & Harackiewicz, 2001), they rarely assess higher order interactions (but see Durik & Harackiewicz, 2003; Harackiewicz, Barron, Carter, Lehto, & Elliot, 1997). More importantly, including interaction terms does not speak to the frequency with which students endorse different combinations of motivation. By identifying and comparing achievement goal profiles to one another, person-oriented analyses are well suited to inform the mastery versus multiple goal debate (Wormington & Linnenbrink-Garcia, 2016).

Practical Implications

Critically, person-oriented research may facilitate the translation of motivation findings to classroom practices. Ultimately, educators and policy makers are concerned with helping individual students succeed in school. Person-oriented analyses may more accurately approximate students' real world motivation by acknowledging that students may be driven to try hard in school for multiple reasons. Researchers employing a person-oriented approach can describe different types of students with discrepant patterns of motivational beliefs; by doing so, researchers may provide insights for teachers on what drives their students. Moreover, researchers can use person-oriented analyses to identify groups of students prone to academic difficulty and describe groups of students who experience more favorable academic outcomes. Identifying profiles that are associated with more or less adaptive outcomes can guide

[3] The mastery versus multiple goals debate extends beyond issues of simultaneous goal endorsement. Supporters of the mastery goal perspective argue that performance-approach goals are either maladaptive, because they draw attention away from the task and learning by focusing on the self, or do not contribute to students' success for most individuals (Midgley et al., 2001). Some researchers supporting a multiple goal perspective also suggest that performance-approach goals are associated with unique benefits above and beyond mastery-approach goals, particularly concerning academic achievement (Barron & Harackiewicz, 2001).

recommendations for classroom practices. For instance, students with high competency beliefs and mastery goals may be most successful, regardless of how much they value a subject area. If that were the case, researchers could direct teachers towards practices that support high competency and mastery-focused learning environments rather than value-based interventions.

Prior Person-Oriented Studies

Although still less common than variable-centered research, person-oriented studies within the motivation field have become more pervasive over the past decade. Person-oriented work has been conducted across a variety of motivational frameworks, with fewer studies integrating across motivational perspectives or examining profiles longitudinally. In this section, I review person-oriented research conducted within a single motivational theory and integrating across motivational perspectives. As the current study draws from expectancy-value theory and achievement goal theory, I focus exclusively in this section on studies based within the same frameworks.

In the following section, I summarize person-oriented studies that have examined profile membership longitudinally. This subsumes a notably smaller number of studies, half of which have been conducted using a self-determination theory framework (Deci & Ryan, 1985; Ryan & Deci, 2000). To fully represent the corpus of literature, I review self-determination studies when describing longitudinal person-oriented research.

Person-oriented studies within a single motivational framework. Within expectancy-value theory, few published studies have examined profiles of competency beliefs and value (Baker & Wigfield, 1999; Guthrie, Coddington, & Wigfield, 2009; Simpkins & Davis-Kean, 2005). Of note, these studies created a-priori groups of students with high and low levels of motivation, rather than identifying naturally occurring combinations of variables. In addition, some of the studies included constructs introduced in later conceptualizations of expectancy-value theory, but not considered within the original framework. Guthrie and colleagues (2009), for instance, assessed avoidance and perceived difficulty alongside intrinsic motivation (value) and self-efficacy (competency beliefs). Thus, the question remains as to how competency beliefs and value might co-occur and the most adaptive combinations of beliefs.

The majority of person-oriented motivation studies are based within an achievement goal framework, with over thirty studies to date (e.g., Bembenutty, 1999; Cano & Berbén, 2009; Daniels et al., 2008; Jang & Liu, 2012; Liu, Wang, Tan, Ee, & Koh, 2009; Luo, Paris, Hogan, & Luo, 2011; Meece & Holt, 1993; Ng, 2009; Pastor, Barron, Miller, & Davis, 2007; Pulkka & Niemivirta, 2013a, 2013b). Even for studies based in a single motivational framework, there is little consensus among findings (Pastor et al., 2007). While some researchers provide evidence supporting the mastery goal perspective (e.g., Bembenutty, 1999), others interpret their findings as support for the multiple goal perspective (e.g., Daniels et al., 2008).

A recent synthesis by Wormington and Linnenbrink-Garcia (2016) identified ten profile types characterized by high (i.e., Mastery High, Approach High, High All Goals, Performance-Approach High, Work-Avoidance High), average (i.e., Average All Goals) or low goal endorsement (i.e., Performance Low, Performance-Approach Low, Performance-Avoidance Low, and Low All Goals).[4] Three profiles represented combinations of motivation consistent with mastery (Mastery High, 13.02%) or multiple goal pursuit (Approach High, 14.29%; High All Goals, 10.07%). Students in the Mastery High and Approach High profiles reported the

[4] High goals were characterized as an average endorsement greater than 4 on a 5-point scale, while low goals were characterized as an average endorsement less than 2 on a 5-point scale. I employed an analogous approach to naming profiles in the current study. This labeling approach not only represents meaningfully high and low endorsement of motivational constructs, but also facilitates comparison of results from the current study with past findings. For additional information on naming rules, see Wormington and Linnenbrink-Garcia (2016).

greatest motivation, well-being, engagement, and achievement; the two profiles did not differ significantly from one another on any outcomes. Students in the High All Goals profile, however, reported lower motivation than participants in the Mastery High profile. A fourth profile, labeled as Average All Goals, included 37% of the sample and was the least adaptive across all four categories of outcomes. Results suggested that both mastery and multiple goal pursuit are common, and that both orientations are equally adaptive when performance-avoidance goal endorsement is low.

Integrative person-oriented studies. A smaller proportion of person-oriented studies have integrated across motivational theories and related constructs (e.g., Dina & Efklides, 2009; Nelson, Shell, Husman, Fishman, & Soh, 2015; Seifert & O'Keefe, 2001; Valle et al., 2003). There is considerable heterogeneity in the constructs assessed and statistical techniques used to identify profiles, which makes any attempt to synthesize findings even more challenging than work within a single motivational theory.

Some researchers formed profiles using motivational and non-motivational constructs (e.g., goals, ability beliefs, and test anxiety; Dina & Efklides, 2009; goals, externality, and perceived meaning; Seifert & O'Keefe, 2001; goals and social reinforcement goals; Valle et al., 2003). Turner and colleagues (1998), for instance, used cluster analysis to identify profiles of achievement goals, competency beliefs, cognitive strategy use, and emotional well-being among adolescents. They identified four profiles, labeled as uncommitted (low goal endorsement, competency beliefs, and self-regulation), avoidant (high performance goals and negative affect with low mastery goals, competency beliefs, and self-regulation), success oriented (high competency beliefs and performance goals with moderate mastery goals, self-regulation, and negative affect), and learning oriented (high mastery goals, competency beliefs, and self-regulation with low performance goals and negative affect). Shell and Husman (2008) also identified college students' combinations of various motivational (i.e., self-efficacy, success expectancy, outcome expectancies, causal attributions, personal goal orientations, affect) and self-regulatory indicators (i.e., planning, monitoring, goal setting, strategy use, knowledge building strategies, question asking, lack of regulation behaviors, study time, and study effort). Using canonical correlations, the authors identified three canonical dimensions: highly motivated to apathetic, intrinsically motivated/highly competent to extrinsically motivated/utility-focused, and highly self-regulated to learned helplessness. These canonical dimensions were then used to characterize five distinct profiles of students. Though they provide intriguing results, findings from these studies obscure the relation between motivation constructs and their proposed correlates because they used both to create profiles. In this study, I constructed profiles based on motivation alone to explore the temporal relations between motivation and academic correlates.

Other integrative person-oriented studies have only used motivational variables to create profiles. Two relevant studies formed profiles using constructs drawn from achievement goal theory and expectancy-value theory, as in the current study. Bräten and Olaussen (2005) created profiles based on professional students' interest, mastery goals, task value, and self-efficacy. The researchers identified three profiles characterized by high, moderate, and low levels of motivation. Students with high levels of motivation reported the highest self-regulation and most sophisticated epistemological beliefs. Conley (2012) also examined profiles of achievement goals, value, cost, and competency beliefs among seventh-grade students. She identified seven distinct profiles with low (n = 1), average (n = 3), or high (n = 4) motivation. More importantly, Conley empirically evaluated whether integrative motivational profiles better predicted academic outcomes than achievement goal profiles. Integrative profiles accounted for more variance in achievement and affect than goal profiles. Conley's (2012) findings provide support for examining goals, value, and competency beliefs together rather than achievement goals alone. Important to note is that the goal profiles in her study were formed using median splits, while the integrative profiles were defined using cluster analysis. Using two discrepant techniques—particularly since cluster analysis is considered more methodologically rigorous than median splits—may represent an unfair comparison of achievement goal and integrative profiles.

Profiles of goals, value, and competency beliefs. Most relevant to the current research, Linnenbrink-Garcia, Wormington, and colleagues identified profiles of achievement goals, value, and competency beliefs in several studies (Linnenbrink-Garcia, Riggsbee, Hill, Snyder, & Ben-Eliyahu, 2012; Linnenbrink-Garcia, Perez, & Wormington, 2014; Wormington, Barger, & Linnenbrink-Garcia, 2014; Wormington et al., 2016). In several studies, the researchers measured fifth grade students' general school motivation (Linnenbrink-Garcia et al., 2012), middle school (6^{th}-8^{th} grade) students' motivation in mathematics and social studies (Wormington et al., 2014), college students' (1^{st} and 2^{nd} year) science motivation (Linnenbrink-Garcia et al., 2014), and college students' anatomy motivation (Wormington et al., 2016). Given parallels with the current study, I relied most heavily on this body of work in formulating hypotheses.

Four strikingly similar profiles were identified across the studies, labeled as *Highly Motivated by Any Means* (high on all achievement goals, value, and competency beliefs), *Intrinsically Motivated and Confident* (high mastery goals, value, and competency beliefs with low performance goals), *Performance Focused* (high performance goals with low mastery goals, competency beliefs, and value), and *Amotivated* (low overall motivation). Several of the identified profiles align with motivation theory. For instance, the Highly Motivated by Any

Means profile aligns with multiple goal pursuit and the Intrinsically Motivated and Confident profile aligns with mastery goal pursuit within achievement goal theory, with the additional caveat that students felt competent and valued the subject. The Amotivated profile, while not discussed by achievement goal theory or expectancy-value theory, parallels amotivation as described in self-determination theory (Deci & Ryan, 1985; Ryan & Deci, 2000). In fact, the majority of person-oriented studies within self-determination theory have identified a profile with low levels of all types of motivation (Corpus, Wormington, & Haimovitz, 2016; Hayenga & Corpus, 2010; Ratelle, Guay, Vallerand, Larose, & Senecal, 2007; Vansteenkiste, Soenens, Sierens, Luyckx, & Lens, 2009; Wormington, Corpus, & Anderson, 2012).

Findings from Linnenbrink-Garcia, Wormington, and their colleagues also provided converging evidence for profile adaptiveness, particularly for engagement (Linnenbrink-Garcia et al., 2012, 2014; Wormington et al., 2014, 2016). Across studies, students in the Highly Motivated by Any Means and Intrinsically Motivated and Confident profiles reported greater engagement than students in the Performance Focused and Amotivated profiles. Students in the Amotivated profile sometimes reported lower engagement than those in the Performance Focused profile; these additional detriments included lower metacognitive strategy use in college science, behavioral and cognitive engagement in middle school social studies, and behavioral engagement in elementary school. Achievement-related findings were less consistent. For the elementary and college science samples, profiles did not differ on achievement (Linnenbrink-Garcia et al., 2012, 2014). In the college anatomy sample, students in the Highly Motivated and Intrinsically Motivated and Confident profiles received higher final course grades than their classmates in the Performance Focused and Amotivated profiles (Wormington et al., 2016). Among the middle school samples, the Highly Motivated by Any Means and Intrinsically

Motivated and Confident profiles did not differ from one another in terms of achievement. However, the least adaptive profile varied by subject area; while students in the Amotivated profile received the lowest grades in mathematics, students in the Performance Focused profile received the lowest grades in social studies (Wormington et al., 2014).

Findings suggested a relatively straightforward message regarding profile adaptiveness. It appears that endorsing performance goals may be adaptive as long as students also endorse high level of competency beliefs, value, and mastery goals; endorsing performance goals alone, however, is just as maladaptive as being completely unmotivated. In addition, Intrinsically Motivated and Confident students appear to be consistently successful and engaged while Amotivated students suffer a myriad of academic difficulties relative to their classmates.

Short-Term Longitudinal Perspective

Most person-oriented motivation studies use profiles at one time point to predict outcomes at the same or later time points (but see Tuominen-Soini, Salmela-Aro, & Niemivirta, 2011, 2012). However, decades of variable-centered work suggest meaningful changes in motivation, particularly across adolescence (Archambault et al., 2010; Eccles et al., 1993). Cross-sectional research only provides a snapshot of motivation, rather than capturing meaningful fluctuations in students' motivational beliefs. Relating profiles to later outcomes may lead to inaccurate conclusions about profile adaptiveness if students' motivation changes across time.

Person-oriented studies are well equipped to document patterns of change (Bergman & El-Khouri, 1999). By measuring motivation at multiple time points, researchers can assess how often students shift between distinct profiles and characterize the nature of those shifts. Assessing outcomes such as achievement or engagement longitudinally also allows researchers to explore the relation between profile membership and academic outcomes over time. A short-term longitudinal design may be particularly beneficial for person-oriented motivation research, which has examined profile shifts between semesters or school years if at all (Pulkka & Niemivirta, 2013a; Schwinger & Wild, 2012). Short-term longitudinal data provide a more fine-grained analysis of motivational stability, which has rarely been assessed from either a variable-centered or person-oriented perspective (but see Fryer & Elliot, 2007; Muis & Edwards, 2009). Just as commonly measured classroom behaviors (e.g., engagement) fluctuate throughout the semester, so too may motivation shift over brief time periods.

Research Implications

A short-term longitudinal design contributes to the person-oriented literature by addressing issues of measurement. Assessing profile membership within a semester can guide researchers' decisions regarding how often motivation should be measured to predict outcomes; if, for instance, profile stability between the beginning and middle of the semester is nearly 100%, researchers can conclude with greater confidence that profile membership at the beginning of the semester will represent mid-semester engagement and be associated with mid-term engagement or achievement.

Moreover, longitudinal data provide additional information on which profiles are adaptive or maladaptive. For instance, past integrative studies suggest that students in the Intrinsically Motivated and Confident and Highly Motivated by Any Means profiles are equally engaged (Linnenbrink-Garcia et al., 2012, 2014; Wormington et al., 2014, 2016). If one of these profiles were more stable across time, however, it could be considered more adaptive than the less stable profile. However, this assessment would depend on whether students in the less stable profile shift into less adaptive or equally adaptive profiles. Similarly, assessing outcomes (e.g., achievement) longitudinally could distinguish profiles that lead to short-term achievement from those associated with continued achievement. High performance-approach goals, for instance, could encourage a student to study for a midterm but may not be sufficient to sustain high grades through the end of the semester.

Theoretical Implications

Longitudinal person-oriented studies can also speak to open theoretical debates. In a controversial article, Middleton, Kaplan, and Midgley (2004) reported that performance-approach goals in sixth grade gave rise to performance-avoidance goals in seventh grade. Relevant to the current study, this pattern was most pronounced for highly efficacious students. Middleton and colleagues' (2004) results lend credence to their earlier claim that performance-approach goals spur performance-avoidance goals (Midgley et al., 2001). Unlike variable-centered correlational studies or cross-sectional person-oriented designs, longitudinal person-oriented analyses can quantify the number of students with high initial performance-approach goals but low performance-avoidance goals who eventually adopt high performance-avoidance goals. Short-term longitudinal studies can also assess how quickly performance-approach goals spur performance-avoidance goals, and whether this change is transient or enduring. Questions from other motivational theories may also be addressed using a longitudinal person-oriented approach, such as whether high competency beliefs give rise to high value or vice versa (Wigfield et al., 2009). More generally, longitudinal person-oriented research can elaborate upon variable-centered evidence suggesting motivational declines by quantifying the proportion of students who experience meaningful motivational loss (Eccles et al., 1993).

Prior Longitudinal Person-Oriented Studies

Only a handful of articles have examined profile shifts, mostly within self-determination theory (Corpus & Wormington, 2014; Hayenga & Corpus, 2010) and achievement goal theory (Pulkka & Niemivirta, 2013a; Schwinger & Wild, 2012; Tuominen-Soini et al., 2011, 2012). Those studies suggest considerable motivational change, with overall stability ranging from 35-60%. Stability rates did not systematically differ by sample age, time between measurements, or theoretical perspective. For instance, three studies reported approximately 35-40% of students remaining in the same profile across time. These studies examined high school students' goal profiles over four and twelve months (Tuominen-Soini et al., 2011), middle school students' patterns of intrinsic and extrinsic motivation from the fall to spring semester (Hayenga & Corpus, 2010), and achievement goal profiles from third to seventh grade (Schwinger & Wild, 2012). In the three remaining studies, around 60% of participants remained in the same profile when measured four months apart; these studies investigated elementary school students' intrinsic and extrinsic motivation (Corpus & Wormington, 2014), high school students' achievement goal profiles (Tuominen-Soini et al., 2012), and college students' achievement goal profiles (Pulkka & Niemivirta, 2013a).

Linnenbrink-Garcia and Wormington's integrative studies indicated similar levels of stability, with 40-50% of students shifting to a new profile between consecutive semesters (Linnenbrink-Garcia et al., 2012; Wormington et al., 2014) or from the first to fourth semester of college (Linnenbrink-Garcia et al., 2014). One study, which investigated profile stability at three points during a single semester, suggested higher stability (Wormington et al., 2016). As might be expected, profile shifts across shorter time spans were somewhat less common; approximately

50% of students remained in the same profile from the beginning to middle of the semester, and 60% remained in the same profile from the middle to end of the semester.

Beyond overall stability, findings suggested that some profiles are more stable than others. Pooling evidence from different theoretical perspectives suggests two general patterns. First, it may be difficult for students to maintain high levels of all forms of motivation, particularly when some beliefs are contradictory (e.g., competency beliefs and performance-avoidance goals). Within achievement goal theory, profiles with high mastery and performance-avoidance goals were less stable than profiles with high mastery goals alone (Pulkka & Niemivirta, 2013a; Schwinger & Wild, 2012; Tuominen-Soini et al., 2011, 2012). Within self-determination theory, profiles with high intrinsic and extrinsic motivation were substantially less stable than profiles with high intrinsic but low extrinsic motivation (Corpus & Wormington, 2014; Hayenga & Corpus, 2010). Within integrative motivational studies, stability rates for the Intrinsically Motivated and Confident profile were higher than those for the Highly Motivated by Any Means profile. In fact, the Highly Motivated by Any Means profile was the most precarious among all but the late elementary-aged sample (Linnenbrink-Garcia et al., 2012).

Second, students with low or average levels of motivation appeared unlikely to gain motivation over time. Studies within achievement goal theory all identified a profile representing average goal endorsement, which was equally (Pulkka & Niemivirta, 2013a; Tuominen-Soini et al., 2011, 2012) or more stable than profiles with high mastery goals (Schwinger & Wild, 2012). Integrative studies identified a similar group of Amotivated students, with low overall motivation. The Amotivated profile displayed high levels of stability, particularly over short time periods (Wormington et al., 2014, 2016). Compared to the Performance Focused profile, another maladaptive profile, the Amotivated profile was more stable across all but one sample. Since these low motivated students also reported less adaptive outcomes than their classmates, students in such profiles may be a particularly at-risk group.

Understanding Profile Shifts

Because most person-oriented studies have not assessed profile membership longitudinally, there has been little discussion of *why* students follow certain motivational trajectories. What differentiates a highly motivated student who experiences motivational loss from a similar student who maintains high motivation over time? Current person-oriented findings characterize students' motivation and identify most and least adaptive profiles. However, they do not shed light on why students adopt certain motivational beliefs and what predicts whether students will maintain or shift between profiles. Examining underlying psychological processes is key to identifying avenues through which to intervene with struggling students and best practices for supporting classroom motivation in general.

Theory and variable-centered evidence highlight numerous precursors of motivational change. One framework for understanding underlying psychological processes is Weiner's (1986) attribution theory. Attribution theory describes students' appraisal of achievement-related stimuli, focusing on both individual and contextual predictors. Considering individual mechanisms can account for why students in the same educational context or motivational profile follow distinct trajectories. The mechanisms discussed in attribution theory are promising to consider given research suggesting they are responsive to intervention efforts (e.g., attribution retraining; Butler & Winne, 1995; Chodkiewicz & Boyle, 2014; Försterling, 1985; Perry, Chipperfield, Hladkyj, Pekrun, & Hamm, 2014; emotion regulation coaching; Gross, 1998; Gross, Richards, & John, 2006).

The Attributional Process

The attributional process begins when students receive achievement-related feedback, such as exam grade (Weiner, 1986). When feedback is important, negative, or unexpected, students seek to explain their achievement. Students' *attributions* for success or failure vary along three dimensions: locus (internal versus external), control (controllable versus uncontrollable), and stability (stable versus unstable).[5] The most commonly assessed attributions in academic settings are effort (internal, controllable, unstable), ability (internal, uncontrollable, stable), luck (external, uncontrollable, unstable), test difficulty (external, uncontrollable, unstable), teacher quality (external, uncontrollable, stable), and strategy use (internal, controllable, unstable).

Attributions, in turn, give rise to expectancies for future success and emotions. Weiner (1986) differentiated between attribution independent emotions and attribution dependent emotions. Attribution independent emotions—such as happiness, sadness, and frustration—arise from the general positive or negative affect associated with success or failure. Attribution dependent emotions—such as surprise, pride, and anger—arise from specific attributions for success or failure (Graham & Taylor, 2014; Weiner, 1986). Guilt and shame, for example, both result from internal attributions but differ in controllability (guilt=controllable, shame=uncontrollable). Hopelessness also arises from internal attribution but, unlike guilt and shame, is stable. Finally, attributions and emotions give rise to achievement-related behavior such as achievement, engagement, or school dropout (Perry, Stupnisky, Daniels, & Haynes, 2008). Hopelessness, for instance, may decrease future task persistence (Weiner, 1986).

[5] While other dimensions such as globality have been hypothesized, a corpus of research identifies locus, control, and stability as the three main discriminating causal dimensions (Weiner, 1986, 2000).

Motivational Profiles and Reactions to Exam Feedback

Motivation shapes students' cognition and affect (Ames, 1992; Maehr & Zusho, 2009; Pekrun & Perry, 2014). As such, students' multiple motivational beliefs could lead to distinct attributions and emotions following success or failure.

Students' competency beliefs are determined by past achievement (Bandura, 1977, 1986). Highly competent students, then, will likely attribute success to internal causes. Conversely, students with low competency beliefs may be reluctant to attribute success to internal causes because it does not fit with their conceptualization of themselves as incompetent. Evidence from Pekrun and colleagues' (2006, 2014) control-value theory suggests that competency beliefs are associated with internal emotions such as pride, shame, and hopelessness.

Performance goals may also influence attributions because they represent a focus on appearing competent; indeed, early goal theorists referred to performance goals as ego goals (Dweck & Leggett, 1988). Performance oriented students may display an intensified form of the hedonic bias by attributing success to internal causes but failure to external factors (Miller & Ross, 1975). In support, research suggests a positive relation between performance-approach goals and pride (Linnenbrink-Garcia & Barger, 2014). Performance goals are also associated with entity beliefs, which assert that intelligence is predetermined (Dweck & Leggett, 1988). Consequently, performance oriented students may be likely to experience shame and hopelessness following failure, as the failure would be considered uncontrollable (Dweck & Leggett, 1988; Linnenbrink-Garcia & Barger, 2014; Middleton & Midgley, 1997). Mastery goals, by contrast, are positively associated with incremental theories of intelligence; an incremental theory of intelligence represents the belief that intelligence can be increased through effort (Dweck & Leggett, 1988). As such, mastery-oriented students are likely to attribute their achievement to internal, controllable sources such as effort or strategy use.

Reactions to Exam Feedback and Profile Shifts

Attributions and emotions may also influence whether students maintain or shift between profiles. Objective achievement provides information on students' progression toward a goal, and may in some instances cue students to shift their motivational focus (Fryer & Elliot, 2007; Muis & Edwards, 2009). For instance, a student who fails an exam may experience greater performance-avoidance goals because she wants to avoid failing the course and less competency because she views herself as less likely to succeed. Experimental and classroom-based evidence suggests that poor exam achievement predicts declines in mastery and performance-approach goals, and gains in performance-avoidance goals (Senko & Harackiewicz, 2005).

However, objective achievement alone may not account for profile stability. Integrative person-oriented studies suggest that the Intrinsically Motivated and Confident and Highly Motivated by Any Means profiles were equally high achieving; however, the former profile was substantially more stable than the latter profile. Perceptions of success may also be important, as perceived success or failure impacts students' attributions. For example, individuals are more likely to take credit for success than failure (Graham & Taylor, 2014; Miller & Ross, 1975). The same objective score may not indicate success for students with differing motivational beliefs; for instance, an Amotivated student may interpret a 70 as succeeding while a Performance Focused student would interpret a 70 as failing. Similarly, students with different motivational tendencies may differ in the extent to which they attribute success and failure to different causes. Performance oriented students may attribute success to internal causes but failure to external causes, for example, while mastery focused students would likely attribute both success and failure to internal and controllable causes.

Emotions may also relate to motivational change, particularly if they signal a misalignment between current motivational orientations and achievement outcomes. I focused on four such emotions: surprise, shame, hopelessness, and relaxation. Surprise should arise in response to an unexpected outcome, including failing when one expected success (Weiner, 1986). Surprise could signal a need to adjust motivational beliefs, such as recalibrating competency beliefs or shifting from performance-approach to avoidance goals (Senko & Harackiewicz, 2005). Shame and hopelessness may also lead to motivational change. They are expected to arise when students attribute failure to lack of ability, an internal and uncontrollable source. Shame is particularly likely to be experienced following feedback, as it is an outcome-dependent emotion (Pekrun & Perry, 2014). Experiencing shame or hopelessness could lead students to adjust both their goals and competency beliefs. Finally, relaxation may be associated with motivational change. Students who expected to fail but succeeded may experience relaxation, potentially spurring changes such as a dampened focus on performance-avoidance goals or increasing adoption of competency beliefs. Taken together, attribution theory provides a strong foundation for hypotheses on how students from different motivational profiles respond to academic success and failure, as well as a potential explanation for why past studies have found some motivational profiles to be consistently less stable than other profiles.

Contextualizing Motivation

Thus far, motivational profiles and profile stability have been discussed independent of context. However, motivation is highly contextualized. Research suggests that motivation differs across development (Corpus, McClintic-Gilbert, & Hayenga, 2009; Wigfield et al., 2009) and learning contexts (Bong, 2005; Stodolsky, 1988; Stodolsky & Grossman, 1995; Wolters, Yu, & Pintrich, 1996). Which combinations of motivation emerge and are adaptive across person-oriented studies may vary as a function of the sample, academic domain, or learning context. However, most person-oriented studies overlook context, either by assessing motivation at the general school level (Corpus & Wormington, 2014; Schwinger & Wild, 2012; Vansteenkiste et al., 2009) or failing to make context-specific hypotheses (for an exception, see Wormington et al., 2014).

By carefully considering characteristics of the sample and learning environment, researchers can develop empirically supported hypotheses for which profiles are likely to be most common and adaptive. Acknowledging context may also help account for discrepant findings across person-oriented studies. For instance, performance goal endorsement may be more adaptive in an otherwise uninteresting subject area because they encourage student engagement (e.g., social studies; Gehlbach, 2006). As evidence, middle school students in the Performance Focused profile reported greater engagement than students in the Amotivated profile in social studies but not mathematics (Wormington et al., 2014). Profile adaptiveness may also vary as a function of development. Variable-centered research has documented motivation changes across the school years, which may look different at particular points in development (Corpus et al., 2009; Wigfield et al., 2006). Developmental stage may provide an explanation for why certain profiles are common or adaptive among some samples but not others (Wormington & Linnenbrink-Garcia, 2016).

In the current study, I examined high school students' motivation in on-line mathematics courses. Hypothesized profiles were based on findings from past integrative person-oriented studies. However, how common and adaptive those profiles would be among the current sample depends on the sample's age (high school) and learning context (on-line mathematics courses).

High School

A substantial amount of attention has been paid to motivational changes across the middle school transition. Generally speaking, motivationally supportive, autonomous elementary school classrooms stand in sharp contrast to competitive, unsupportive middle school classrooms (Anderman & Anderman, 1999; Anderman & Maehr, 1994; Brookhart, 1994; Eccles & Midgley, 1989; Maehr & Midgley, 1991; McMillan, Myran, & Workman, 2002; Midgley & Edelin, 1998; Midgley, Anderman, & Hicks, 1995; Randall & Engelhard, 2009; Ruble & Frey, 1991; Stipek & MacIver, 1989). Structural changes in the educational environment, coupled with relevant cognitive developments (e.g., increased ability to socially compare to similar others; perceived inverse relation between effort and ability), interact to foster less adaptive motivation during adolescence (Covington & Omelich, 1979; Harter, 1999; Nicholls & Miller, 1984; Stipek & MacIver, 1989). Evidence suggests that adolescents report increased performance goal orientation (Ryan & Patrick, 2001; Urdan & Midgley, 2003) and decreased competency beliefs (Eccles & Roeser, 2008; Wigfield, Eccles, MacIver, Reuman, & Midgley, 1991) on average compared to elementary-aged students.

Motivational declines continue into high school, where school environments emphasize normative comparison and are generally unsupportive (Martin, 2009; Otis et al., 2005; Seidman & French, 1997). High school students also experience unique developmental tasks that may influence motivation (Eccles, Lord, & Buchanan, 1996). Notably, high school students are faced with impending entry into college or the job market. With this comes a heightened focus on academic achievement, as grades and standardized tests remain among the most important determinants of college or job acceptance (Westrick, Le, Robbins, Radunzel, & Schmidt, 2015). High school students may be likely to endorse or benefit from motivational factors that predict achievement, even more so than at other points of development. Performance goals in particular may be uniquely beneficial, since the most critical tasks in high school (e.g., being accepted to college) require students to demonstrate their competence.

Person-oriented studies in self-determination theory suggest that motivation may function differently in high school than at other developmental stages (Ratelle et al., 2007; Vansteenkiste et al., 2009; Wormington et al., 2012). Contrary to findings with younger and older students, few (if any) high school students endorsed high intrinsic but low extrinsic motivation. Notably, students in profiles with high intrinsic and extrinsic motivation were just as academically successful as their classmates in profiles characterized by high intrinsic but low extrinsic motivation (Wormington et al., 2012). To explain their theoretically inconsistent findings, several research teams suggested that extrinsic motivation is adaptive given the controlling, performance-focused nature of high schools (Ratelle et al., 2007; Wormington et al., 2012). Similar logic may be applied to performance goals; while performance goals are associated with either mixed (performance-approach) or negative outcomes (performance-avoidance) in most contexts, they may be uniquely adaptive within the high school context.

On-line Mathematics Courses

On-line courses are an increasingly popular educational venue, with over 1 million secondary students enrolled in on-line courses nationwide (Allen & Seaman, 2013; Horn & Staker, 2011; Journell, McFadyen, Miller, & Brown, 2014). Growing access to on-line learning holds promise for STEM retention; recent studies suggest that on-line mathematics and science courses augment both the number and diversity of students entering into STEM majors (Drew, 2015). However, on-line learning environments are not without their challenges. Evidence suggests that low achieving students may face increased difficulties in on-line courses (Dillon & Gabbard, 1998). Dropout rates are also higher in on-line courses compared to their face-to-face counterparts (Roseth, Saltarelli, & Glass, 2011). Given the increasing popularity and unique challenges associated with on-line courses, it is critical to understand what motivates on-line learners and who will maintain or lose motivation. Indeed, the school I partnered with for this survey identified motivation and self-regulation as one of the key foci in its Tool Kit for supporting on-line learners (*Michigan Virtual University,* 2014).

Characterizing motivation in a learning context plagued by high dropout and failure rates is critical. Beyond concerns about on-line students' success, examining profiles in on-line courses also provides an opportunity to better understand the generalizability of person-oriented motivation literature in its current state. All extant person-oriented motivation studies have been conducted within face-to-face learning contexts. As such, the profiles that emerge could be a function of both individual characteristics and social aspects of the classroom. In on-line courses, however, the social aspect of the classroom is largely absent. Thus, on-line classes provide a unique opportunity to control for social influences, to a certain extent, and examine non-contextual factors that may impact motivational beliefs. Whether profiles from past studies are also present and adaptive in on-line learning contexts will provide initial evidence regarding the extent to which profiles are dependent on the social environment of face-to-face classrooms.

When considering motivation in on-line courses, two distinctions from face-to-face contexts seem relevant. First, performance goals may function differently in on-line classes. Performance goals represent a desire to show competence or hide incompetence from others (Elliot, 1999). Students have myriad opportunities to do so in face-to-face learning contexts by answering questions in class or discussing grades on assignments. Opportunities to demonstrate competence—or even to compare oneself to classmates—are likely limited in on-line courses due to diminished social presence (e.g., Stodel, Thompson, & MacDonald, 2006) or perceived lack of community (Rovai, 2002). Opportunities that might arise (e.g., posting on forums) may either not be normative or require additional effort. Moreover, some types of classes (e.g., mathematics course) may provide limited opportunities for comparison even more so than other subject areas. Thus, students may endorse performance goals less in on-line learning contexts.

Second, on-line learners may report lower levels of overall motivation. In the relatively anonymous on-line setting, high school students may feel less accountability to pay attention or be motivated compared to face-to-face learning contexts where they share a physical space with instructors and classmates. Elevated dropout rates for on-line versus face-to-face courses provide some support for this assertion (Patterson & McFadden, 2009; Roseth et al., 2011). Among students enrolled in on-line mathematics courses in Michigan during the 2013-2014 school year, 3.9% withdrew from the course and 23.5% completed the course but received a failing grade (*Michigan Virtual University,* 2014); the fail rate for mathematics courses was higher than that of any other subject area for virtual classes, illustrating the need to conduct research in on-line mathematics courses. To compound the issue, on-line course completion is mandated for high school students in the state of Michigan. Students who complete on-line courses as a requirement, rather than through their own volition, may value the course less even if they remain enrolled throughout the semester.

A Contextualized Model of Profile Stability

Based on the literature outlined above, I constructed a model to conceptualize profile stability (Figure 1). Profile-specific hypotheses are outlined in Table 1. For the purposes of this study, I considered students' reactions to exam feedback in relation to motivational change. Upon receiving feedback on an exam, students would interpret their achievement as indicating success or failure and attribute their performance to different causes. Students' reactions to exam feedback were expected to differ as a function of their profile membership because motivation affects cognition (Ames, 1992). For example, highly competent students would likely take credit for success more so than low competent students (Bandura, 1986). Similarly, mastery-oriented students may attribute success to effort because they believe that intelligence is malleable; performance-oriented students, conversely, believe that intelligence is fixed and thus may attribute success or failure to ability (Dweck & Leggett, 1988).

Students' reactions to exam feedback, particularly emotions, were expected to predict subsequent motivational changes. This could manifest in an individual's likelihood to belong to a given motivational profile. In particular, students who experienced surprise, shame, hopelessness, and relaxation may be more likely to exhibit changes in profile membership. A student who experiences hopelessness, for example, might be increasingly likely to move to a profile characterized by low overall motivation. Students' new motivational orientations, along with their initial motivational tendencies, were expected to relate to academic achievement, engagement, and self-regulation. As a final consideration, the model is encompassed within a cylinder to acknowledge the critical role of development and learning context.

Current Study

Declining engagement and achievement is a major concern during high school, as both can limit job prospects or promote school dropout (Barber & Olsen, 2004; Seidman & French, 1997). While motivation is associated with student success, translating research findings into recommendations for practice can be challenging (Linnenbrink-Garcia & Patall, 2016;

Linnenbrink-Garcia, Patall, & Pekrun, in press; Schunk & Zimmerman, 2012; Weiner, 2013). The current study employed a person-oriented approach to examine the combinations, consequences, and precursors of high school students' motivation in mathematics. This study extended past person-oriented work by exploring short-term motivational stability, considering underlying psychological processes, and examining motivation within the on-line learning context.

RQ 1: What Motivates Students in On-line Mathematics Courses?

RQ 1a: Do students endorse different motivational profiles? The initial goal of the current study was to identify distinct, common motivational profiles. Based on past integrative person-oriented studies, I expected to identify four profiles of students: Highly Motivated by Any Means, Intrinsically Motivated and Confident, Performance Focused, and Amotivated (Linnenbrink-Garcia et al., 2012, 2014; Wormington et al., 2014, 2016). Prior person-oriented integrative studies, however, were conducted with students at different developmental stages and within face-to-face learning contexts. As such, a secondary goal was to consider whether motivational profiles were different among high school students in on-line mathematics classes. Given the strong emphasis on academic achievement in high school (Eccles et al., 1993; Ratelle et al., 2007), I hypothesized that profiles characterized by high performance goals would be the most common. This hypothesis was tentative given that social comparison processes may function differently in on-line learning contexts due to lower social presence (Stodel et al., 2006). I also hypothesized that an Amotivated profile would be more common than in past studies.

RQ 1b: How does profile membership shift across a semester? Using a short-term longitudinal design, I documented students' motivation at the beginning and middle of a single semester. In an analogous study with college anatomy students, 50% of students remained in the same profile from the beginning to middle of the semester, with profile-specific stability ranging from 33-74% (Wormington et al., 2016). Consistent with these findings, I predicted that approximately half of the sample would shift to a new profile by the middle of the semester. Further, I expected the Highly Motivated by Any Means profile would be the most precarious and Intrinsically Motivated and Confident or Amotivated profiles most stable. The Performance Focused profile was expected to display moderate levels of stability (see Table 1).

RQ 1c: Which motivational profiles are most adaptive? To characterize the adaptive nature of profiles, I compared profiles with respect to self-reported regulation and engagement, likelihood to drop the course, and achievement trajectories. Past integrative studies suggested that students in the Highly Motivated by Any Means and Intrinsically Motivated and Confident profiles were more engaged and higher achieving than students in the Performance Focused and Amotivated profiles (Linnenbrink-Garcia et al., 2012, 2014; Wormington et al., 2014, 2016). This study extended upon past research by (1) examining predictive and concurrent relations of profile membership with engagement and achievement, and (2) documenting achievement trajectories throughout the semester rather than simply focusing on final grade. Based on higher stability rates, I predicted that students who began the semester as Intrinsically Motivated and Confident would end the semester with higher achievement than students in the Highly Motivated by Any Means profile. Similarly, I hypothesized that students in the Amotivated profile would display less adaptive achievement trajectories than students in the Performance Focused profile, as the former is more stable.

RQ 2: Do Motivational Profiles Differ in Reactions to Exam Feedback?

I hypothesized that students' initial motivation in mathematics would influence their reactions to exam feedback. Table 1 details hypotheses at each step of the attributional process for the four hypothesized profiles. I formed these hypotheses based on the premise that students' combination of motivation—rather than any single component—shapes their interpretation of and explanation for exam feedback (Bergman et al., 2003; Laursen & Hoff, 2006).

Highly motivated by any means. These students are interested in and able to demonstrate their competency relative to others. Based on the hedonic bias, students in this profile were expected to attribute success to internal and stable causes (i.e., ability, strategy use) and failure to external causes (i.e., test difficulty, teacher quality; Miller & Ross, 1975; Graham & Taylor, 2014). Students in the Highly Motivated by Any Means profile are also concerned with avoiding appearing incompetent. Accordingly, they were expected to attribute failure to an internal, uncontrollable cause such as ability and experience relaxation in response to success. Given these attributions, students were hypothesized to experience pride and relaxation following success and shame, hopelessness, and anger following failure. Students who fail were also expected to experience surprise because they would be accustomed to succeeding.

Intrinsically motivated and confident. Unlike their peers in the Highly Motivated by Any Means profile, students in the Intrinsically Motivated and Confident profile are not concerned with demonstrating competence. Therefore, they were not expected to attribute success and failure to different causes as a result of the hedonic bias (Miller & Ross, 1975). Rather, students were expected to attribute achievement to internal, unstable causes like effort and strategy use because they can be changed. As a result, Intrinsically Motivated and Confident students were anticipated to experience joy and contentment as a result of success and guilt in the case of failure. Because students in this profile would most often be successful, they were also expected to experience surprise in reaction to failure.

Performance focused. Students in the Performance Focused profile are concerned with how competent they appear, but do not feel efficacious in their ability to perform well. As such, they were hypothesized to attribute failure to a lack of ability. Given a strong performance goal orientation, however, students in this profile were also expected to take credit for success when it was experienced and be relieved when they avoided failure. Low competency beliefs were also expected to lead these students to attribute success to external, uncontrollable sources like luck. As a result of these proposed attributions, Performance Focused students were hypothesized to experience pride, relaxation, and surprise when they succeeded but anger, shame, and hopelessness when they failed.

Amotivated. Amotivated students are not interested in the material, confident in their ability to succeed, or concerned with appearing competent. With such a pronounced lack of agency and investment, their attributions were expected to be external in nature. Amotivated students were also hypothesized to attribute success to luck and failure to either test difficulty or teacher quality. In turn, Amotivated students were expected to experience gratitude following success and anger following failure. Because students would be unlikely to succeed, they were also expected to experience surprise following success.

RQ 3: Are Exam Scores and Reactions to Exam Feedback Associated with Profile Shifts?

I also hypothesized that students' achievement or reactions to exam feedback could partially account for changes in motivational beliefs. Based on past variable-centered studies implicating achievement as a predictor of motivational change (Senko & Harackiewicz, 2005), I hypothesized that high achievement would be associated with an increased likelihood of membership in the Intrinsically Motivated and Confident profile. Students in this profile feel competent and are not concerned with hiding incompetence, both of which would be fostered by high achievement. Conversely, I expected low performance to be associated with a greater likelihood of membership in either the Performance Focused or Amotivated profiles. Low performance may increase performance-avoidance goal endorsement (Senko & Harackiewicz, 2005) and negatively impact competency beliefs (Bandura, 1977, 1986). Performance Focused students are characterized by both high performance-avoidance goals and low competency beliefs. Low competency beliefs may also negatively perceived value (Wigfield et al., 2009); as such, low performing students were expected to adopt an Amotivated stance towards mathematics. No hypotheses were made for to the Highly Motivated by Any Means profile; motivational beliefs within this profile could be fostered by either high (i.e., competency beliefs) or low achievement (i.e., performance-avoidance goals), and thus might cancel each other out.

Alongside objective achievement, emotional reactions to exam feedback were also anticipated to account for motivational changes. As emotions represent the most proximal step to subsequent change in attribution theory, I hypothesized that surprise, shame, hopelessness, and relaxation would predict a higher likelihood of profile shifts. More generally, I predicted that negative emotions would negatively predict likelihood of membership in the Highly Motivated and Intrinsically Motivated and Confident profiles. Conversely, I anticipated that positive emotions would correspond to a greater likelihood of membership in either profile. The opposite pattern was expected for membership in the Performance Focused and Amotivated profiles.

CHAPTER 3:

Method

Participants

Recruitment and Eligibility

Participants were 9^{th}-12^{th} grade students (114 girls, 97 boys) enrolled in on-line mathematics courses at a virtual university in the Midwestern United States[6]. Participants were recruited from one of 17 courses focused on Algebra I (4 sections), Algebra II (4 sections), Geometry (4 sections), and Precalculus (5 sections). The majority of participants were recruited from semester-long courses, though 23 students enrolled in one of six trimester courses were also invited to participate. Students reported enrolling in the course because the course was unavailable at their school (17.5%), for credit recovery purposes (10.4%), learning preference (32.2%), scheduling conflict (18.5%) or another unspecified reason (21.4%).

All students across the selected mathematics courses were invited to take an on-line, anonymous survey regarding their thoughts and feelings about mathematics. Electronic letters briefly describing the study to parents and guardians were posted to the course information page. Parents were informed that all data would be kept confidential and that there was no penalty for their child choosing not to participate. They were also invited to contact the primary researcher in the event that they did not wish for their child to participate in the study, but none did so.

Students were required to provide electronic assent to participate prior to the first data collection. They were made aware that their responses would be confidential, and that neither their teachers nor the researchers would know whether or not they chose to participate in the study. Students were also told that they could choose to skip any questions or stop taking the

[6] Information on student race and ethnicity were not available from the participating school.

survey at any time. Participants were offered financial compensation (a $10 Amazon gift code) for completing all three primary surveys (Time 1, Time 2, and Time 3) across the semester. They also received one entry into a drawing for an iPad per completed survey. Only students who provided electronic assent were allowed to participate in the current study.

Measures

All measures referenced students' current mathematics course (see Appendix).[7] All self-reported variables were assessed using a five point Likert-type scale (*1 = not at all true, 3 = somewhat true, 5 = very true*). Because each attribution and emotion was measured using a single item, no data are available concerning internal reliability.

Academic Motivation

Academic motivation was assessed in surveys at the beginning and middle of the semester.

Achievement goal orientations. Achievement goal orientations were assessed using the trichotomous model of achievement goals (PALS; Midgley et al., 2000). Students reported on their mastery-approach (5 items; e.g., "One of my goals in math is to learn as much as I can"), performance-approach (5 items; e.g., "It's important to me that other students in my math class think I am good at my classwork"), and performance-avoidance goal orientations (4 items; e.g., "It's important to me that my teacher doesn't think that I know less than others in math class").

Task value. Task value was assessed using an abbreviated version of the task value utilized by Linnenbrink-Garcia and colleagues (2010) and Conley (2012). This scale included 9

[7] As a control variable, participants also reported on their self-efficacy related to technology (Venkatesh, Morris, Davis, & Davis, 2003). The internal reliability for the measure was unacceptably low ($\alpha = .58$). As such, technology self-efficacy was not considered as a covariate in subsequent analyses.

items assessing interest value, attainment value, and utility value (e.g., “I enjoy what I am learning in math”; “I think the things I learn in math are useful”).

Competency beliefs. Competency beliefs were assessed using perceived competence items from PALS (Midgley et al., 2000; 5 items; e.g., “Even if the work in math is hard, I can learn it”).

Academic Correlates

Self-reported regulation. In the middle of the semester, participants reported on their regulation in their mathematics course. Items assessing behavioral regulation were drawn from a measure developed by Pintrich (1991; 6 items; e.g., “I made good use of my study time for this course”). Items assessing effort regulation were derived from Linnenbrink (2005), and queried about students’ likelihood to put forth effort on tasks for the course (4 items; e.g., “I forced myself to finish my coursework even when there were other things I’d rather be doing”).

Self-reported cognitive engagement. In the middle of the semester, participants also reported on their cognitive engagement in mathematics. Cognitive engagement was measured using eight items from Linnenbrink (2005; e.g., “when I make a mistake in math, I try to figure out which things I don’t really understand”).

Academic record data. School personnel provided information regarding participants’ demographic and academic record data. Demographic data included participants’ gender, final enrollment status (i.e., dropped, withdrawn, or enrolled), and reasons for enrolling in the course (i.e., credit recovery, course unavailable at local school, scheduling conflict, learning preference of the student, and other). Evidence from past data at Michigan Virtual University indicates that reason for enrollment is associated with pass/fail rates (*Michigan Virtual University,* 2014); as such, reason for enrollment and gender were included as control variables in subsequent analyses. Participants' achievement on each exam, as well as final course grade, was also obtained from school records. Time stamps were also obtained for each exam in the course.

Response to Exam Feedback

Following each exam, students reported their reactions to exam feedback.

Perceptions of success. Perceptions of success were measured using a single item on a ten point Likert-type scale: "To what extent did you *succeed* on this exam?"

Attributions. Participants also reported on their attributions for success or failure. Participants responded to the stem, "To what extent did the following contribute to your performance?" Six attributions were assessed: effort, test difficulty, strategy use, teacher quality, ability, and luck (Perry et al., 2008; van Overwalle, 1989).

Emotions. Finally, participants reported on the emotions experienced in response to receiving exam feedback using the stem, "After receiving this grade on my exam, I feel…" (Watson & Clark, 1999; Watson, Clark, & Tellegen, 1988). Ten attribution-dependent emotions—anger, gratitude, guilt, shame, relaxation, surprise, pride, joy, contentment, and hopelessness—were assessed with a single item each. While not the focus of the current study, attribution independent emotions (i.e., happiness, frustration, sadness) were also measured.

Procedure

Data Collection Schedule

Data for the current study were collected during the Fall 2015 academic semester, which began in early September 2015 and concluded in late January 2016. Critical to note is that all courses were self-paced. Students received a pacing guide with suggestions on when to complete assignments during the 18-week semester. However, students were permitted to complete assignments at their leisure, and received credit for any assignments completed before the final day of classes. Survey placement, described below, was based on course pacing guides. To account for the varied timing of survey completion, as well as the fact that participants could complete surveys at any time given the self-paced nature of courses, I controlled for timing between surveys in relevant analyses.

Surveys assessing motivation and academic correlates were collected at two time points: once at the beginning of the semester (Time 1) and once in the middle of the semester (Time 2).[8] All Time 1 surveys, which were intended to assess participants' initial beliefs about mathematics, were administered at the very beginning of the semester before the first unit. The exact timing of Time 2 surveys varied by course, as different classes followed different pacing schedules. As a rule, Time 2 surveys were placed as close to the middle of the semester as possible. Given hypotheses concerning the relation of achievement and motivation, survey administrations were scheduled such that they occurred at least two units after a graded assignment. For semester courses, Time 2 survey administration ranged from the beginning of Week 8 to the middle of Week 9, as indicated in course pacing guides. For trimester courses, surveys administration ranged from the middle of Week 6 to the middle of Week 7, as indicated in course pacing guides. Time stamps indicated that participants completed the Time 1 and Time 2 surveys eight weeks apart on average, with substantial variation among the sample (M = 56.20 days; SD = 24.07 days).

[8] I also collected survey data on motivation, regulation, and engagement at the end of the semester (Time 3). Administration of this survey ranged from the beginning of Week 15 to the end of Week 17 by class for semester courses, and the middle of Week 9 to the end of Week 11 for trimester courses. Placement of the Time 3 survey followed the same guidelines as those for the Time 2 survey to avoid proximity to graded class assignments. Only 46 (21.80%) participants who completed the Time 1 survey also completed the survey administered at the end of the semester (Time 3). An even smaller percentage of students (n = 37; 17.54%) completed the Time 1, Time 2, and Time 3 surveys. While the original intention of this dissertation was to document profile shifts between the beginning, middle, and end of a semester, low response rates for the Time 3 survey precluded me from doing so. Analyses in the current study, then, focused exclusively on profile shifts from the beginning to the middle of a single semester (i.e., Time 1 to Time 2). More detailed information about participant flow is reported in the results section.

Measures collected at each time point are presented in Table 2. At Time 1, students reported on their motivation in mathematics (i.e., achievement goal orientations, value, and competency beliefs). These measures were meant to capture students' initial attitudes towards mathematics, and were collected as close to the beginning of the semester as possible. Participants also reported on their motivation in mathematics during the Time 2 survey, along with self-reported behavior regulation, effort regulation, and cognitive engagement.

For post-exam surveys, students completed surveys after receiving exam feedback. Participants reported on their perceptions of success on the exam, attributions for success or failure, and emotions. Finally, academic record data were collected from designated school personnel after the semester ended.

Data Collection Procedure

Permission to conduct this study was obtained from Michigan State University's Internal Review Boards and Michigan Virtual University, who deferred to Michigan State University's review process. Surveys were administered electronically using Opinio, an on-line survey program. All survey data were linked via a unique identifier, and an IRB-trained employee at the partnering virtual school deidentified all survey and academic record data. Besides data regarding student assent, I had no knowledge of participants' identity. I also did not have access to course pages once the semester had begun. Instructors were unaware of which students chose to participate in the current study.

Participants were alerted to each survey via an electronic announcement on the class page, a reminder announcement, and a link in the class folder. To accommodate the self-paced nature of the course, initial announcements were posted two weeks prior to the scheduled date according to each course's pacing guides. A reminder announcement was posted one week following the scheduled date for the assessment according to pacing guides.

Important to note is that survey links were available throughout the semester. When processing data, I examined the date and time participants completed surveys to ensure they were completed within the intended interval. Participants who completed surveys at times other than what was intended (e.g., completing the Time 1 survey on the last day of class) or completed the surveys out of order (e.g., completing the Time 1 survey after the Time 2 survey) were excluded from subsequent analyses; additional detail is provided in the participant flow section. Time 1 and Time 2 surveys took less than 15 minutes to complete (M_{T1} = 9.37 minutes; SD_{T1} = 4.83 minutes; M_{T2} = 4.46 minutes; SD_{T2} = 4.52 minutes). Post-exam surveys took most students less than one minute to complete; mean values are unavailable because Opinio records start and end times in minute increments.

Analytic Plan

Data analyses for primary and ancillary research questions are outlined in Table 3. Given the sizable number of analyses being conducted, I employed Bonferroni corrections to protect against Type I error (Abdi, 2007).

Preliminary Analyses

Before testing specific research questions, I first ensured that the proposed analyses were appropriate. To do so, I (1) examined response distributions on outcome variables via histograms, skew, and kurtosis; (2) assessed internal reliability for multi-item self-report measures via Cronbach's alpha; and (3) inspected interrelations among variables via bivariate correlations.

For motivation measures, which were assessed at two time points, I conducted longitudinal confirmatory factor analyses. Such analyses are critical to establish measurement invariance, and consequently rule out the possibility that changes in profile membership arose as a function of measurement invariance rather than meaningful changes in participants' motivational beliefs (Little, 2013; Vandenberg & Lance, 2000; see Pulkka & Niemivirta, 2013a; Tuominen-Soini et al., 2011, 2012). I assessed three separate models as increasingly strong evidence of measurement invariance: configural invariance (equal factor parameters), weak invariance (equal factor loadings), and strong invariance (equal item intercepts)[9]. To assess model fit, I examined changes in fit indices between subsequent models. Specifically, I considered changes in the Comparative Fit Index (CFI; values ≥ .95 indicating good fit; Bentler, 1990; Hu & Bentler, 1995) and root mean square error of approximation (RMSEA; values ≤ .08 considered acceptable; Hu & Bentler, 1995). Generally, models were considered equally well fitting if the CFI changed less than .01 and RMSEA changed less than .015 (Chen, 2007; Cheung & Rensvold, 2002; see Lee, Wormington, Linnenbrink-Garcia, & Roseth, under review).

RQ 1a: Do Students Endorse Different Motivational Profiles?

One of the primary goals of the present study was to investigate short-term changes in students' motivational beliefs. Based on the processes described in Figure 1, as well as evidence from past person-oriented motivation studies, I hypothesized that the constellation of students' motivational beliefs (i.e., motivational profiles) may change from the beginning to middle of a single semester. Given the brief time frame of the study, however, I did not expect the motivational profiles identified to change between the beginning and middle of the semester.

[9] The three models described assess factor invariance (i.e., that items are assessing the same underlying constructs). As part of measurement invariance, researchers also suggest testing for structural invariance to ensure that variables are related to one another in same fashion across time (Vandenberg & Lance, 2000). However, I did not necessarily anticipate that types of motivation would be related to one another in the same manner across time; in fact, I hypothesized that the combinations of motivational beliefs students endorsed would change. As such, I did not test for structural invariance in the present study.

The profiles that characterized students' motivation in mathematics from the beginning to middle of the semester were assumed to be the same, though any individual student was not necessarily expected to be characterized by the same profile at both time points.

With these assumptions in mind, I employed an I-States as Objects Analysis (ISOA; Bergman & El-Khouri, 1999) approach to identify motivational profiles. In ISOA analyses, a participant's response at each time point is treated as a discrete unit (i.e., i-state). Responses from 200 participants at two time points, then, would result in 400 i-states. I-states are subsequently used as the input to identify a final profile solution (Bergman & El-Khouri, 1999). ISOA, which is based on dynamic systems models, is well suited to the present study because it assumes a time-invariant profile solution and allows for examining individual's shifts between profiles (Bergman & El-Khouri, 1999; Nurmi & Aunola, 2005).

Using participants' i-states as input, I employed latent profile analysis as the analytic technique to identify the most appropriate profile solution. Latent profile analysis is based within a structural equation modeling framework, and thus is considered a model-based approach to identifying profiles (as opposed to non-model based person-oriented approaches such as cluster analysis). Latent profile analysis allows researchers to compare models specifying different numbers of latent profiles and determine which profile solution best characterizes the data (Collins & Lanza, 2010; Lanza & Cooper, 2016; Muthén & Muthén, 2010). Since the models are not nested, researchers use a variety of fit indices (i.e., entropy, AIC, BIC, adjusted BIC) as well as profile size to identify the most appropriate profile solution (Collins & Lanza, 2010). Typically, improved model fit is characterized by higher values of entropy, lower values of AIC and BIC (which adjusts for sample size), and solutions without empty or disproportionately small profiles.

Once an optimal solution has been identified, the model provides two pieces of information on each i-state: (1) which profile the i-state is most likely to belong to, and (2) the likelihood (i.e., post-probability) of membership in each of the profiles identified. The former information was used to address questions of profile membership (RQ 1a), shifts (RQ 1b), and adaptiveness (RQ 1c). Students' most likely profile was also used to examine how students from different profiles reacted to exam feedback (RQ 2). Post-probabilities were used examine how exam achievement and reactions to exam feedback related to changes in profile membership (RQ 3).

RQ 1b: How Does Profile Membership Shift Across a Semester?

A second goal of this study was to document the extent to which students' motivational beliefs changed from the beginning to middle of the semester. Once the final profile solution was identified, I reorganized the data by participant rather than i-state, with each participant who completed Time 1 and Time 2 surveys assigned to a profile at both time points. This reorganization allowed me to examine profile shifts from the beginning to middle of the semester.

I conducted several analyses to assess profile stability. First, I calculated the overall stability of profiles based on the number of students who remained in the same profile versus shifted to a new profile. I also assessed stability rates for each profile by calculating the number of students who remained in the same profile across time. Comparing relative stability of each profile allowed me to consider my research question regarding which profiles are likely to be most durable or changing. Second, I calculated the gain to loss ratio for each profile by comparing the number of students who shifted into a given profile to students who shifted out of that same profile. This analysis allowed me to consider the relative growth rate of each profile, characterizing the extent to which profiles became more or less common across the semester.

Finally, I examined whether particular profile shifts were more or less likely than chance. To do so, I conducted a configural frequency analysis (von Eye, Spiel, & Wood, 1996). Using standardized scores, configural frequency analysis compares observed frequencies for each profile shift to expected values to identify types (i.e., profile shifts that are more common than chance) and antitypes (i.e., profile shifts that are less likely than chance). Findings from configural frequency analysis allowed me to consider specific patterns of change and characterize the movement of students who shifted to a different motivational profile.

RQ 1c: Which Motivational Profiles are Most Adaptive?

After identifying a profile solution, I compared profiles with respect to several academic correlates. The following analyses were conducted within a multilevel modeling framework to account for the nesting of students within classrooms (Heck & Thomas, 2015; Hox, 1998; O'Connell & McCoach, 2008). Observations from students enrolled in the same course are likely to be correlated with one another, which violates the assumption of the General Linear Model that residuals are independent and identically distributed (Raudenbush & Bryk, 2002). Similarly, observations from the same individual are likely to be related to one another. Multilevel modeling takes into account nesting within the data, allowing for an examination of how highly correlated scores are for students within the same course or exam scores for the same student.

The models outlined below included profile membership as a fixed effect, with the Amotivated profile serving as the reference category. Aside from profile membership, student gender and reason for enrollment in the course were included as fixed effects at the student level. Males served as the reference category for gender, while credit retention served as the reference category for reason for enrollment. For analyses examining achievement trajectories, the model included the fixed effects outlined above as well as (1) time of completion of each exam (i.e., days since beginning) and (2) interaction terms between profile membership and growth trends. The former accounted for the self-paced nature of the on-line courses, while the latter allowed for a consideration of whether students from different profiles displayed different growth trajectories in exam scores across the semester. Interaction effects were probed when significant (Preacher, Curran, & Bauer, 2006). Two-level models were evaluated using the SPSS MIXED procedure. Three-level models were assessed using MPlus, as the models failed to run in SPSS. Random intercepts and linear slope terms were included at the classroom level to reflect the possibility that there could be course-level differences in the overall endorsement of outcome variables and the association between predictor and outcome variables.[10]

The first set of models compared profiles with respect to self-reported engagement and regulation outcomes (i.e., behavioral regulation, effort regulation, and cognitive engagement). I conducted separate multilevel model analyses with students nested within courses. First, I examined predictive relations, with Time 1 profile predicting Time 2 correlates. Next, I examined concurrent relations, with Time 2 profile predicting Time 2 correlates. I was interested in comparing results from predictive and concurrent relations in part to address a measurement question—specifically, whether analyses using Time 1 profile as a predictor variable would yield the same pattern of findings as analyses using Time 2 profile as a predictor variable. Post-hoc Tukey HSD tests were conducted to determine which profiles differed from one another.

[10] Before conducting analyses, I tested assumptions to ensure that the data were appropriate for multilevel modeling. No outliers were detected across studies, nor were there issues with the distribution of residuals across individuals (for longitudinal data) or courses. Several outcome variables were negatively skewed, but transforming the variables did not substantively impact the results. Consequently, I retained untransformed variables for analyses. Sample size was a concern for the current models, though all models converged.

Adopting notation from Raudenbush and Bryk (2002), reduced form equation for a representative model would be depicted as:

$Eng_{ij} = (\gamma_{00} + \gamma_{10}gender_{ij} + \gamma_{20}profiled1_{ij} + \gamma_{30}profiled2_{ij} + \gamma_{40}profiled3_{ij} + \gamma_{50}reasond1_{ij} + \gamma_{60}reasond2_{ij} + \gamma_{70}reasond3_{ij} + \gamma_{80}reasond4_{ij}) + (u_{0j} + r_{ij})$

In this example equation, cognitive engagement served as the outcome variable. The segment $[\gamma_{00} + \gamma_{10}gender_{ij} + \gamma_{20}profiled1_{ij} + \gamma_{30}profiled2_{ij} + \gamma_{40}profiled3_{ij} + \gamma_{50}reasond1_{ij} + \gamma_{60}reasond2_{ij} + \gamma_{70}reasond3_{ij} + \gamma_{80}reasond4_{ij}]$ represents the fixed coefficients. The segment $[u_{0j} + r_{ij}]$ contains the random effects portion of the model. The term γ_{10} is the regression coefficient for gender. The terms $[\gamma_{20}profiled1_{ij} + \gamma_{30}profiled2_{ij} + \gamma_{40}profiled3_{ij}]$ represent the regression coefficients for profile membership. This categorical variable was dummy coded, with the Amotivated profile serving as the reference category and the first, second, and third dummy codes representing membership in the Highly Motivated by Any Means, Intrinsically Motivated and Confident, and Average All Motivation profiles respectively. Reason for enrolling in the course was similarly dummy coded, and represented by the regression coefficients $[\gamma_{50}reasond1_{ij} + \gamma_{60}reasond2_{ij} + \gamma_{70}reasond3_{ij} + \gamma_{80}reasond4_{ij}]$. The $[u_{0j} + r_{ij}]$ terms represent residual errors at Level 2 and Level 1, respectively. The u_{0j} are assumed $N(0,\tau)$ and the (r_{ij}) are assumed $N(0,\sigma^2)$.

The second model compared profiles with respect to their likelihood to drop or withdraw from the course. Because the dropout outcome is binary (i.e., dropped versus not), a logistic regression analysis was employed. Remaining enrolled in the course served as the reference category for the outcome variable; as such, larger odds ratios indicated a greater likelihood to drop the course. The reduced form equation is the following:

$Dropout_{ij} = (\gamma_{00} + \gamma_{10}gender_{ij} + \gamma_{20}profiled1_{ij} + \gamma_{30}profiled2_{ij} + \gamma_{40}profiled3_{ij} + \gamma_{50}reasond1_{ij} + \gamma_{60}reasond2_{ij} + \gamma_{70}reasond3_{ij} + \gamma_{80}reasond4_{ij}) + (u_{0j} + r_{ij})$

Link Function: $\eta_{ij} = \log(\mu_i/1\text{-}\mu_i)$

The term μ_i refers to the expected value—or, in this case, probability. This model differed from the multilevel models for engagement and regulation only with respect to the response distribution (logistic) and the specification of an appropriate link function (logit). The logit function bounds the range of the response distribution between 0 and 1, which is appropriate for the dichotomous outcome variable in this analysis. The logit function is defined as the log of the odds. All other assumptions and predictor variables remained the same.

The third model involved examining profile differences in achievement trajectories. For the purposes of this study, I operationalized achievement as exam scores across the semester. This analysis involved a three-level growth curve model, with exam scores nested within individuals nested within courses. Each course included 4-5 exams throughout the course of the semester. Because I was interested in students' final achievement in the course, I set the intercept to the last exam and coded time points backwards (i.e., Exam 1 = -4, Exam 2 = -3, Exam 3 = -2, Exam 4 = -1, Exam 5 = 0); as such, the intercept can be interpreted as students' score on the final exam. I used a top-down approach for building the random effects model (West, Welch, & Galecki, 2007). The process involved first testing a fully loaded model with all potential random effects included. At the classroom level, I included a random effect for both the intercept and linear slope term. I also included random effects of the intercept and growth terms for exam scores nested within students; because achievement trajectories were not expected to be exclusively linear, I included linear, quadratic, cubic, and quartic growth trends.

Once the random effects model had been established, I employed a bottom-up approach to build the fixed model (Bauer & Curran, 2015; Tabachnick & Fidell, 2013). Gender, reason for enrollment, profile membership, growth trends (linear, quadratic, cubic, quartic), and interactions between profiles and growth trends were all hypothesized to be potential predictors of student achievement. As such, I examined each predictor variable individually to determine whether its inclusion improved the model fit.

For model building, I relied on likelihood ratio tests to determine whether it was appropriate to include predictor variables in the model. Likelihood ratio tests serve as a way to compare nested models to one another. Specifically, likelihood ratio tests involve comparing the deviance (-2 log likelihood) of a more restricted model to a less constricted model. Based on the change in degrees of freedom, the test indicates whether the change in deviance suggests that a predictor variable should be included in the model (Bauer & Curran, 2015). I began by first including main effects (i.e., gender, reason for enrollment, profile, growth terns), then interaction terms (i.e., profile x growth terms) at the fixed level. Likelihood ratio tests were also employed to determine the appropriate random effects to retain in the model. REML-based likelihood ratio tests were conducted to determine whether to retain random effects, while FIML-based tests were conducted to determine whether to retain fixed effects.[11] The full model was substantially more complicated than the final model, which included only the fixed and random effects that significantly contributed to the prediction of achievement trajectories as determined by model building and reduction techniques. I describe the final model and factors retained for analyses in Chapter 4 (Results).

RQ 2: Do Motivational Profiles Differ in Reactions to Exam Feedback?

I also compared profiles with respect to their reactions to exam feedback: in other words, was students' initial profile membership associated with their perceptions of success,

[11] The difference between nested-model deviances, as assessed with the Likelihood Ratio Test, is asymptotically distributed along a chi-square distribution, and requires a sufficient sample size to obtain the appropriate distribution. Although no universal rules dictate what a sufficient sample size entails, caution should be taken given sample size of the current study.

attributions, and emotions following an exam? A series of MANCOVAs were conducted, comparing profiles with respect to (1) perceptions of success, (2) attributions for success or failure, and (3) emotions following exam feedback. I hypothesized that students within different profiles would respond differently to exam feedback, but also that attributions and emotions would differ in response to success and failure. However, profiles were expected to differ in terms of academic achievement (see Table 1). As such, I controlled for exam achievement in these analyses. When omnibus MANCOVAs were significant, I conducted follow-up ANOVAs for each individual outcome and post-hoc Tukey HSD tests to determine which profiles differed significantly from one another.

RQ 3: Are Exam Scores and Reactions to Exam Feedback Associated with Profile Shifts?

The final goal of this study was to assess whether students' reactions to exam achievement were associated with their likelihood to shift between profiles. My analytic plan initially involved conducting multilevel regression analyses, with reactions to exam feedback (i.e., perceptions of success, attributions, and emotions) predicting changes in the probability of membership in each of the four motivational profiles from Time 1 to Time 2. However, this analytic plan was inappropriate given an insufficient sample size. As an alternative, I conducted bivariate correlation analyses as a preliminary examination of the relations among reactions to exam achievement and changes in profile membership. I used information regarding post-probabilities to operationalize change in profile membership. Recall that latent profile analysis assigns each case a probability of being categorized in each of the four profiles (i.e., post-probabilities). To assess change, I calculated the difference in post-probability membership at Time 1 and Time 2 for each profile. Positive values indicated an increased likelihood to be categorized in a given profile at Time 2 compared to Time 1; negative values indicated a decreased likelihood to be categorized in a given profile at Time 2 compared to Time 1.

Ancillary Analysis: Do Person-Oriented Analyses Contribute Unique Information?

A central premise of this paper is that person-oriented techniques afford unique information that may be of practical and theoretical benefit to motivation research. However, the majority of person-oriented studies do not explicitly test this assertion. As ancillary analyses in the current study, I compared the findings based on motivational profiles to information that could be gleaned by employing variable-centered analyses.

One possible approach might be to conduct parallel analyses to examine how the five motivational variables (i.e., mastery-approach goals, performance-approach goals, performance-avoidance goals, task value, and competency beliefs) were associated with outcomes of interest (i.e., behavior regulation, effort regulation, cognitive engagement, academic achievement, and course dropout). To do so, one would need to calculate all 2-way, 3-way, 4-way, and 5-way interactions among motivational variables and include them as predictors in analyses alongside centered main effect variables. To represent all five motivation variables and the interrelations between types of motivation, a total of 28 main effect and interaction terms would be required. Even with the total sample, there was insufficient power to consider all main effect and interaction terms simultaneously; this was one of the arguments made in favor of person-oriented approaches, which allow researchers to examine interactions between multiple variables of interest using smaller sample sizes.

An alternative approach would be to reduce the data using principal components analysis, and use the resulting factors as predictors of outcomes of interest (Bryant & Yarnold, 1995; Dunteman, 1989). Principal components analysis is a data reduction method, and thus may circumvent power issues that were likely to arise with the first proposed variable-centered approach. Conducting a principal components analysis in the current study allowed me to examine the unique contributions of a person-oriented approach in two ways. First, I evaluated whether motivational profiles contributed any unique information that could not be captured by dimensions identified via principal components analysis. To consider this possibility, I plotted profile membership by the primary two dimensions identified using principal components analysis. One possible outcome is that profile membership would map linearly on to these dimensions, such that all individuals from the same profile were plotted at similar points on the graph, and profiles would differ only in overall values on the two components. In that scenario, the information gleaned from person-oriented analyses would appear to be adequately captured with a principal components analysis approach. Second, I conducted analogous analyses to those described in Research Question 1c to determine how principal component factors were associated with engagement, regulation, dropout rates, and achievement trajectories. As the most stringent test of the additive value of profiles over variable-centered findings, I included both variable-centered factors and profiles as predictor variables in the same analysis. I focus in particular on results from the analysis examining exam score trajectories.

CHAPTER 4:

Results

Participant Flow

Total Sample

Of the 347 students enrolled in targeted mathematics courses, 211 (60.8%) completed the survey at the beginning of the semester (Time 1). Participation rates per class ranged from 30-100%, with an average participation rate of 63.39% across courses. Participating students (M = 247.56, SD = 363.49) did not differ in terms of their unstandardized final course grade from those who did not choose to participate (M = 187.58, SD = 307.66), t(df=409) = 1.81, p = .07. Participating and non-participating students also did not differ by gender distribution (χ^2[df=1] = .24, p = .63), reason for enrolling in course (χ^2[df=4] = 3.21, p = .52), or likelihood to have dropped the course (χ^2[df=1] = 3.17, p = .08). Valid *n*s for each set of analyses are listed in Table 3.

Profile Shift Analyses

Of the 211 participants who completed the Time 1 survey, 88 (41.71%) also completed the survey distributed in the middle of the semester (Time 2). Five participants were excluded from subsequent analyses because they completed the Time 1 and Time 2 surveys within less than 2 weeks of one another or completed the Time 2 survey before the Time 1 survey; this left a total sample of 83 students for analyses examining profile shifts (RQ 1b). Participants who completed the Time 2 survey differed in several ways from participants who did not complete the Time 2 survey. Specifically, students who completed the Time 2 survey reported higher overall course grades (M = 82.91, SD = 16.97) than students who did not complete the survey (M = 62.67, SD = 31.42), t(df=181) = 5.49, p < .0001. Students who did not fill out the Time 2 survey were also more likely to have dropped the course than students who completed the Time 2 survey, χ^2[df=1] = 21.18, $p < .0001$. In addition, non-participating students were more likely to have enrolled in the course for credit recovery reasons and less likely because the course was unavailable at their local school, when compared to students who did complete the Time 2 survey, χ^2[df=4] = 12.21, $p = .02$. Students who did and did not complete the Time 2 survey did not differ by gender, χ^2[df=1] = 1.70, $p = .19$. Of greatest concern, students from different Time 1 profiles were differentially likely to complete the Time 2 survey, χ^2[df=3] = 8.45, $p = .04$; Amotivated students were less likely than chance to complete the Time 2 survey. I consider the issue of selective attrition in the discussion.

Reactions to Exam Feedback Analyses

Participants were also invited to complete brief surveys following each exam in the course. Post-exam survey data were used in two sets of analyses: one examining how students from different profiles reacted to exam feedback (RQ 2), and the other considering whether reactions to exam feedback predicted profile shifts (RQ 3). The number of participants considered for each set of analyses differed, as described below.

For Research Question 2, students were required to have completed at least one of the first two post-exam surveys along with the Time 1 survey. Of those participants who completed the Time 1 survey, 108 students completed one or both of the first two post-exam surveys (post-exam survey 1 only: $n = 45$; post-exam survey 2 only: $n = 11$; both post-exam 1 and 2: $n = 52$). Of this subsample, 30 students completed the post-exam surveys before completing the exam (as indicated by time stamps) and were excluded from analyses. Eight students who completed the post-exam surveys more than ten days after completing the exam were also excluded from analyses, as the intent of these surveys was to assess students' immediate reactions to exam feedback. The remaining 68 students varied in the time between completing the exam and filling out the post-exam survey: 51 students took the survey within a day of completing the exam, ten students took the survey 1-5 days after the exam, and eight students within 6-10 days.

For Research Question 3, participants were required to meet several additional criteria along with those required for Research Question 2. First, participants needed to have completed the Time 2 survey and at least one of the first two post-exam surveys; 67 students responded to the necessary surveys. Second, students were required to have completed the Time 2 survey after taking one of the first two exams, as reactions to exam achievement were hypothesized to predict motivational changes from Time 1 to Time 2; three students were excluded based on this stipulation. Finally, students were required to complete post-exam surveys after completing the exam and within a reasonable amount of time after completing the exam. Participants who completed post-exam surveys before taking the exam (n = 12) or more than ten days after taking the exam (n = 5) were excluded from analyses. This left a final sample of 47 students for analyses examining predictors of profile shifts.

Preliminary Analyses and Descriptive Statistics

Descriptive statistics, internal reliabilities (α), and bivariate correlations among multi-item self-report variables are presented in Table 4. Mastery-approach goals and competency beliefs were endorsed at higher levels than performance-approach and performance-avoidance goals across the sample, with task value endorsed at moderate levels. At the sample level, motivational constructs were highly stable from Time 1 to Time 2 (rs = .51-.72). Motivation variables at the beginning of the semester were all positively correlated with one another (rs = .21-.61), except that competency beliefs were not significantly associated with performance-avoidance goals. Motivational variables displayed a similar pattern of interrelations at Time 2, except that mastery-approach goals and competency beliefs were no longer significantly correlated with performance-approach and performance-avoidance goals. As expected, performance-approach and performance-avoidance goals were highly correlated with one another ($r_{T1} = .67$; $r_{T2} = .85$; see Law et al., 2012). Mastery-approach goals and task value were also highly correlated with one another at both time points ($r_{T1} = .70$, $r_{T2} = .70$).

With respect to academic correlates, self-reported regulation and engagement variables were positively correlated with one another (*r*s = .48-.71). At both Time 1 and Time 2, mastery-approach goals and competency beliefs were positively associated with all three outcomes (*r*s = .25-.71); in addition, task value was associated with all outcomes except for Time 1 value with effort regulation (*r*s = .23-.56). Performance goals, conversely, were not correlated with outcomes except for positive concurrent correlations with behavioral regulation (*r*s = -.01-.29).

I also attempted to conduct longitudinal confirmatory factor analyses on motivational constructs. However, the model for configural invariance was not identified because there was not enough information in the data to estimate all of the specified parameters. This occurred even when I attempted to assess measurement invariance for each motivational construct separately. Consequently, I could not use the chi-square from the non-identified model to compare subsequent models and could not conduct the planned analyses. A non-identified model is almost certainly a function of a small sample size ($n = 83$). This should be considered a limitation of the study and considered when interpreting findings involving profile shifts.

RQ 1a: Do Students Endorse Different Motivational Profiles?

Fit indices indicated that either a four-profile or five-profile solution best fit the data (see Table 5). A four-profile solution displayed higher entropy and more equal profile sizes, but a five-profile solution exhibited slightly lower or comparable AIC, BIC, and adjusted BIC indices.

I selected a four-profile as most appropriate after examining the overall pattern of fit indices and the fact that the five-profile solution included a disproportionately small profile characterizing only fourteen cases.[12]

Standardized and raw scores for the four profiles are presented in Figures 2 and 3. Raw cluster centroids at each time point are listed in Table 6. An examination of *Z* scores and raw scores at Time 1 and Time 2 separately suggested that the identified profile solution adequately represented the data at both time points. Three of the four profiles were consistent with prior integrative studies. Profile membership did not differ by gender (χ^2[df=6] = 7.10, p = .31) nor reason for enrollment in course (χ^2[df=15] = 24.97, p = .06).

Highly Motivated by Any Means

The first identified profile represented students who were Highly Motivated by Any Means. Students in the Highly Motivated by Any Means profile reported meaningfully high levels of all achievement goals, value, and competency beliefs in mathematics, with average values greater than four on a five-point scale and higher endorsement relative to the sample. Among these students, all forms of motivation were endorsed at similar rates to one another; in other words, Highly Motivated by Any Means students appeared to value mathematics and strove to develop their competence as much as they sought to demonstrate competence to others. The Highly Motivated by Any Means profile was the second smallest group identified in the sample, representing approximately one fifth of participants at each time point (n_{T1} = 54,

[12] There has been controversy over whether a model-based (e.g., latent profile analysis) or non-model based approach (i.e., cluster analysis) is optimal for identifying profiles (Pastor et al., 2007; Steinley & Brusco, 2011). In the current study, I formed profiles using a model-based approach. However, past integrative studies employed a non-model based approach to identify profiles. As such, any differences in profiles that emerged could have been a function of the statistical method employed. To empirically evaluate this possibility, I conducted both latent profile analysis and cluster analysis separately on the sample to identify motivational profiles. Findings from cluster analysis closely mirrored those presented in the current study: an analogous four-profile solution was identified, and only three i-states were categorized into a different profile compared to results from latent profile analysis. Thus, it seems unlikely that the profile solution for this sample arose as a function of the analytic technique.

26.21%; n_{T2} = 13, 15.66%).

Intrinsically Motivated and Confident

A second, more sizable group of students were labeled as Intrinsically Motivated and Confident. These students reported equally high levels of mastery goals and competency beliefs (though lower value) as their counterparts in the Highly Motivated by Any Means profile. However, Intrinsically Motivated and Confident students reported notably low performance goal endorsement, with average values lower than two on a five-point scale. The Intrinsically Motivated and Confident profile represented one of the largest groups of students in the sample, particularly at Time 2 (n_{T1} = 60, 29.13%; n_{T2} = 39, 46.99%).

Average All Motivation

A third group of students were labeled as Average All Motivation. As the name suggests, students in the Average All Motivation profile reported moderate levels of all five motivational beliefs (i.e., between 2.8 and 3.8 on a five-point scale). Students in the Average All Motivation profile reported significantly lower levels of mastery goals, competency beliefs, and task value than students in the Highly Motivated by Any Means and Intrinsically Motivated and Confident profiles. Similar to the Highly Motivated by Any Means profile, students in the Average All Motivation profile reported equivalent levels of all forms of motivation relative to one another. The Average All Motivation profile was the largest group identified at the beginning of the semester and the second largest by mid-semester (n_{T1} = 71, 34.47%; n_{T2} = 24, 28.92%).

Amotivated

The final identified profile represented students who were Amotivated. Students in the Amotivated profile reported low levels of achievement goals, competency beliefs, and task value relative to the sample; all forms of motivation were endorsed lower than three on a five-point scale, with performance-approach goals, performance avoidance goals, and task value lower than two. The Amotivated profile was by far the smallest profile identified at both time points (n_{T1} = 21, 10.19%; n_{T2} = 7, 8.43%).

RQ 1b: How Does Profile Membership Shift Across a Semester?

Stability Rates

Of the 83 participants with survey data at both Time 1 and Time 2, 55.42% (n = 46) remained in the same profile over time. Overall rates of stability differed considerably among the profiles (Figure 4). Consistent with past findings, the Intrinsically Motivated and Confident profile was the most stable; nearly 75% of students who began the semester as Intrinsically Motivated and Confident remained in the same profile by the middle of the semester. Also consistent with past results, the Highly Motivated by Any Means profile displayed among the lowest rates of stability; fewer than 40% of students who were categorized as Highly Motivated by Any Means at the beginning of the semester remained highly motivated by the mid-semester assessment. The Amotivated profile was also surprisingly unstable, with only one of three students remaining in the profile from the beginning to the middle of the semester. The Average All Motivation profile displayed moderate rates of stability, with close to half of participants remaining in the profile across time and half shifting to a different profile.

Gain to Loss Ratio

Considering the gain to loss ratio for each profile also provides useful information. Over the first half of the semester, both the Highly Motivated by Any Means and Average All Motivation profiles lost more participants than they gained. This loss was most pronounced for the Highly Motivated by Any Means profile, which displayed nearly a 1:2 gain to loss ratio (6 students shifted into profile, 11 students shifted out of profile). The gain to loss ratio was less striking for the Average All Motivation profile, with 11 students shifting into the profile from Time 1 to Time 2 and 15 students shifting to a new profile. By contrast, the Intrinsically Motivated and Confident and Amotivated profiles both gained more students than they lost from Time 1 to Time 2. The gain to loss ratio was most notable for the Amotivated profile, which experienced a 3:1 gain to loss ratio (6 students shifted in, 2 students shifted). Meanwhile, fourteen students shifted in to the Intrinsically Motivated and Confident profile; nine students shifted from the Intrinsically Motivated and Confident profile into a different profile.

Profile Shifts

With close to 50% of students changing profiles between time points, it is important to characterize likely and unlikely profile movement among the sample. Results from configural frequency analysis are reported in Table 7 and visually represented in Figure 5. Configural frequency analysis identifies types (i.e., shifts that are more likely than chance) and antitypes (i.e., shifts that are less likely than chance). Only two significant types were identified, with one marginally significant type also detected. Consistent with past research, each type involved students remaining in the same profile across time. Students were more likely than chance to remain in the Highly Motivated by Any Means and Intrinsically Motivated and Confident profiles, and marginally more likely than chance to remain in the Average All Motivation profile. Only one marginally significant antitype was identified. Students were marginally less likely than chance to shift from the Intrinsically Motivated and Confident profile at the beginning of the semester to the Average All Motivation profile by mid-semester. These findings should be interpreted cautiously, as the expected cell sizes were less than 5 for a number of shifts.

On a more descriptive level, students who shifted from each profile into a new profile displayed somewhat distinct patterns of movement. Highly Motivated by Any Means students who shifted to a new profile moved into the Intrinsically Motivated and Confident or Average All Motivation profile, but not into the Amotivated profile. Of those who shifted out of the Intrinsically Motivated and Confident profile, students moved equally into the other three profiles but were slightly less likely than chance to shift into the Average All Motivation profile. Average All Motivation students who shifted moved into all three profiles, but least so into the Intrinsically Motivated and Confident profile. Finally, the two students who shifted out of the Amotivated profile moved into the Average All Motivation profile.

RQ 1c: Which Motivational Profiles are Most Adaptive?

As a reminder, gender and reason for enrollment were included as control variables in all analyses. Neither of the variables were significant predictors of students' regulation and engagement, likelihood to drop out, or achievement trajectories.

Regulation and Engagement

I conducted analyses to examine both predictive and concurrent associations between profiles and outcomes by considering Time 1 and Time 2 profile membership as the predictor variable, respectively. Analyses with Time 1 profile as the predictor variable assessed predictive associations between profile membership and regulation or engagement. Analyses with Time 2 profile as the predictor variable captured concurrent associations between profile membership and regulation or engagement. Differences by profile with respect to self-reported outcomes are presented in Table 8.

In terms of predictive associations, students in different profiles at Time 1 reported differing levels of behavioral regulation and cognitive engagement. Post-hoc analyses indicated that students who began the semester in the Highly Motivated by Any Means profile reported significantly greater behavioral regulation than students in the Average All Motivation and

Amotivated profiles; students in the Intrinsically Motivated and Confident profile did not differ significantly from any other profile. A similar pattern emerged with respect to cognitive engagement. Students in the Highly Motivated by Any Means and Intrinsically Motivated and Confident profiles reported greater cognitive engagement than students in the Amotivated profile; students in the Average All Motivation profile did not differ from any other profile. Profile membership was only a marginally significant predictor of effort regulation, but the pattern of results mirrored that of behavioral regulation and cognitive engagement.

For concurrent associations, profiles differed with respect to all three self-reported outcomes. For all outcomes, students in the Highly Motivated by Any Means and Intrinsically Motivated and Confident profiles reported significantly higher values than students in the Amotivated profile. The Average All Motivation profile did not differ from either the Intrinsically Motivated and Confident or Amotivated profiles with respect to behavioral or effort regulation; however, Average All Motivation students reported significantly lower cognitive engagement than Intrinsically Motivated and Confident students but higher cognitive engagement than Amotivated students. Together, results suggest that students in the Highly Motivated by Any Means and Intrinsically Motivated and Confident profiles consistently reported more regulation and engagement than students in the Amotivated profile, with mixed findings for students in the Average All Motivation profile.

Dropout Rates

I also examined whether students' initial profile membership was associated with their likelihood to drop or withdraw from the course. A test of the model with gender, profile membership, and reason for enrollment compared to an intercept-only model was significant, χ^2[df=8] = 15.81, p = .04. This indicates that the set of predictor variables distinguished between students who dropped versus remained enrolled in the course. The overall percentage of students correctly classified was 87.6%, although a small proportion of variance was accounted for (Nagelkerke $R^2 = .14$).

Table 9 reports results from the logistic regression analysis. The only significant predictor identified among the set was the dummy code for the Intrinsically Motivated and Confident profile; the odds of a student who began the semester as Intrinsically Motivated and Confident to remain enrolled in the course were 6.57 times greater than a student who began the semester in the Amotivated profile. Neither gender, reason for enrollment, nor any of the other profile dummy variables was associated with students' likelihood to drop the course.

Achievement Trajectories

I also examined whether students' Time 1 profile membership was associated with their exam scores throughout the semester. For this analysis, Time 1 profiles were dummy coded and the Amotivated profile served as the reference group.

Random effects and intraclass correlations. Parameter estimates and fit indices for the final retained model are listed in Table 10. Intraclass correlations indicated that, of the total variance, 54% was due to between-person differences; in other words, exam scores for a given individual were correlated approximately 0.54. Conversely, a small proportion of the variance was accounted for at the course level; only 3% of the total variance was due to between-course variance. Stated another way, exam scores for students within the same course were correlated at only .03. Random effects for slope and linear intercept were significant at the student level, and retained in the final model. A random intercept at the course level was also significant and retained in the model (see Table 10).

Fixed main effects. Neither gender nor reason for enrollment was a significant fixed effects of exam scores; thus, neither predictor was retained in the final model. Since courses were self-paced, it was also important to control for the days on which students completed exams in analyses. Timing of exams, labeled as days since beginning in Table 10, was a significant predictor of exam scores. On average, there was a 0.10 drop in exam scores for every day since the beginning of the course that students completed an exam. Because it was a significant predictor, timing of exam was retained in the final model. The intercept was also significantly different from zero, and indicated that students in the Amotivated profile (the reference group) received an average of 70.35 on their final exam. With respect to growth terms, there was a marginally significant linear trend and a significant quadratic trend detected. On average, students' exam achievement followed a decreasing, concave pattern across the semester.

Interaction effects with profile membership. The primary predictors of interest involved profile membership. I was interested in whether Time 1 profile membership was associated with final exam scores, as well as whether students in different profiles at Time 1 followed distinct exam score trajectories. Results identified significant interactions of profile membership with the intercept and linear trend, as well as a marginally significant interaction for the quadratic trend term. The model-implied achievement trajectories are displayed in Figure 6.

A significant intercept by profile interaction indicated that students from the Highly Motivated by Any Means, Intrinsically Motivated and Confident, and Average All Motivation profiles received significantly higher final exam scores than students in the Amotivated profile. Post-hoc analyses revealed that last exam scores did not differ among students in the Highly Motivated by Any Means, Intrinsically Motivated and Confident, and Average All Motivation profiles.

Students in the Highly Motivated by Any Means and Intrinsically Motivated and Confident profiles also displayed different linear achievement trajectories compared to students in the Amotivated profile. Highly Motivated and Intrinsically Motivated and Confident students' average exam scores increased across the semester; Amotivated students, conversely, displayed decreasing exam scores over time (see Figure 6). Students in the Intrinsically Motivated and Confident profile also differed from Amotivated students with respect to the quadratic growth trend; while Amotivated students displayed a clearly concave achievement trajectory, Intrinsically Motivated and Confident students followed a straight line.

RQ 2: Do Motivational Profiles Differ in Reactions to Exam Feedback?

Three separate MANCOVAs were conducted, examining students' (1) perceptions of success, (2) attributions, and (3) emotions following the first two exams. Results are presented in Table 11. Means for each profile across the outcomes are listed in the table for descriptive purposes, even if profiles did not differ from one another (i.e., emotions).

Exam score was included as a covariate in all analyses. This meant that the effect of profile membership on reactions to exam feedback was assessed at a comparatively high level of achievement ($M = 79.06$). Accordingly, findings may be interpreted as differences in the case of relative success. Exam achievement was a significant predictor of both attributions (Wilk's $\lambda = 5.31$, $p < .001$, $\eta^2 = .43$) and emotions (Wilk's $\lambda = 4.35$, $p < .001$, $\eta^2 = .40$). However, exam achievement did not predict perceptions of success ($F = 1.93$, $p = .17$, $\eta^2 = .02$).

Controlling for exam achievement, Time 1 profile membership was a significant predictor of perceptions of success. Post-hoc analyses suggested that students in the Amotivated profile reported lower perceptions of success than students in the Highly Motivated by Any

Means, Intrinsically Motivated and Confident, and Average All Motivation profiles. Students in the latter three profiles did not significantly differ from one another.

Profile membership was also a significant predictor of students' attributions (Wilk's λ = 1.79, p = .03, η^2 = .18). Follow-up ANOVAs indicated that profiles differed with respect to ability and strategy use attributions; profiles also differed with respect to effort attributions, though this difference was only marginally significant when employing Bonferroni corrections. Interestingly, effort, ability, and strategy use all represent internal attributions for success or failure. The pattern of differences for all three attributions was analogous, and mirrored that found for perceptions of success; students in the Amotivated profile reported lower attributions due to effort, ability, and strategy use than students in the other three profiles, who did not differ significantly from one another. Students in the Intrinsically Motivated and Confident profile also did not differ significantly from students in the Amotivated profile in their likelihood to attribute achievement to strategy use. Time 1 profile membership was not a significant predictor of attributions related to luck, test difficulty, or teacher quality.

Finally, profile membership was not a significant predictor of students' post-exam emotions (Wilk's λ = 1.13, p = .23, η^2 = .30). From a purely descriptive perspective, the pattern of emotions endorsed by students in each profile was somewhat aligned with hypothesized emotions following success (see Table 1). Students in the Highly Motivated by Any Means and Intrinsically Motivated and Confident profiles tended to experience positive emotions following success, while Amotivated students experienced negative emotions in general following success.

RQ 3: Are Exam Scores and Reactions to Exam Feedback Associated with Profile Shifts?

The final research question involved identifying predictors of profile shifts. In particular, I was interested in whether students' exam achievement or reactions to exam feedback were associated with changes in their likelihood to be categorized in different profiles. Table 12 lists relevant bivariate correlations. For the purposes of this research question, I examined whether exam achievement, perceptions of success, attributions, and emotions were correlated with changes in membership in each of the four profiles from Time 1 to Time 2. As a reminder, a positive change score indicated that a participant was more likely to be categorized in a given profile at Time 2 compared to Time 1. A negative change score, conversely, indicates that a participant was less likely to be categorized in a given profile at Time 2 than at Time 1. Likewise, a positive correlation between a change score and a variable would indicate that increased endorsement of that variable would be associated with an increased likelihood of belonging to a given profile. A negative correlation would suggest that increased endorsement of that variable would be associated with a decreased likelihood of belonging to a given profile.

First, I hypothesized that exam achievement may be associated with changes in the likelihood of profile membership from Time 1 to Time 2. Higher achievement was expected to be related to an increased likelihood of belonging to the Intrinsically Motivated and Confident profile from Time 1 to Time 2. Conversely, higher achievement was anticipated to be associated with a lesser likelihood of belonging to the Amotivated profile. Correlations did not support this hypothesis; achievement on the first two exams was not significantly associated with changes in post probabilities for any of the four profiles.

Second, I predicted that perceptions of success would be associated with changes in profile membership in the same way as predicted for objective exam achievement. Perceptions of success were positively associated with the Highly Motivated by Any Means variable. Higher perceptions of success were associated with an increased likelihood of being categorized in the

Highly Motivated by Any Means profile at Time 2 than Time 1. The opposite pattern emerged for the Average All Motivation profile.

Several attributions and emotions were also significantly correlated with changes in the probability of profile membership. For the Highly Motivated by Any Means profile, frustration, sadness, and anger were associated with a decreased likelihood to be categorized in the Highly Motivated by Any Means profile; as participants reported greater frustration, sadness, or anger following exam feedback, they were also less likely to be characterized as Highly Motivated by Any Means at Time 2 than they were at Time 1. The opposite pattern emerged for pride and relaxation; as participants reported greater pride and relaxation in response to exam feedback, they were increasingly likely to be categorized as Highly Motivated by Any Means at Time 2 than at Time 1.

For the Intrinsically Motivated and Confident profile, no emotions were significantly associated with changes in the likelihood to be categorized in the profile from Time 1 to Time 2. Effort and strategy use attributions, however, were positively associated with changes in the probability of profile membership; as students made more effort and strategy use attributions following exam achievement, their likelihood to be labeled as Intrinsically Motivated and Confident increased from Time 1 to Time 2.

Correlations for the Average All Motivation profile displayed the opposite pattern. Participants who made higher effort and strategy use attributions for the first two exams became less likely to be categorized as Average All Motivation from beginning to mid-semester. In addition, guilt, shame, and hopelessness were all positively associated with an increased likelihood to be characterized as Average All Motivation from Time 1 to Time 2.

Unlike the other three profiles, no attributions or emotions were significantly associated with changes in the likelihood of students to be categorized in the Amotivated profile.

Do Person-Oriented Analyses Contribute Unique Information?

Preliminary Analyses

When conducting principal components analysis, four assumptions must be met. First, variables must be continuous. Ordinal variables are frequently assessed, and as such the motivational variables in this study satisfy this assumption. Second, there must be a linear relationship between all motivational variables. Although this assumption is somewhat relaxed in practice, I examined correlation coefficients and assessed scatterplots between motivational variables prior to conducting analyses. The five motivational variables were continuous, there was a linear relation between all variables (see Table 4), and no significant outliers were detected. Third, principal components analysis requires a sufficient sample size. Recommendations for minimum sample size vary, with cutoffs ranging from at least 150 cases to 5-10 cases per item. With respect to the first cutoff, my data for the initial survey were sufficient. With respect to the second recommendation, data from the initial time point represent approximately 7-8 cases per item (i.e., 210 participants, with 27 motivational items total). However, the sample size of $n = 83$ for the second time point was insufficient to conduct analyses. As such, I only conducted principal components analysis using data at the beginning of the semester.

Finally, the variables in question must be suitable for data reduction. I conducted Bartlett's test of sphericity to determine whether this assumption was met (Bartlett, 1950). A Kaiser-Meyer-Olkin Measure of Sampling Adequacy value of 0.90 also indicated that the sample of students at Time 1 was adequate; this value ranges between 0 and 1, with values closer to one considered ideal. Finally, Bartlett's test of sphericity indicated that data were suitable for data reduction, $\chi^2(df=378) = 3946.12$, $p < .001$. Bartlett's test evaluates the null hypothesis that the correlation matrix is an identity matrix, so a researcher would want to reject the null hypothesis.

Principal Components Analysis

When conducting an unrestricted principal components analysis, two factors were identified above a clear elbow on the scree plot. As such, I conducted the analysis a second time and forced the analysis to identify two factors. When examining the rotated component matrix, it appeared that mastery goals, task value, and competency belief items loaded on to the first factor and performance-approach and performance-avoidance items loaded on to the second factor. There was no crossover in items between the two factors; all items tapping in to mastery goals, task value, and competency beliefs loaded on to the first factor, and all items tapping in to performance-approach and performance-avoidance goals loaded on to the second factor. Findings from principal components analysis indicate a clear separation of motivational variables in to two factors.

Individual cases were then examined via a scatter plot along the two principal component factors (see Figure 7). If individuals from the same profile clustered together, that would serve as evidence that the principal components factors were sufficient to represent information captured by profile membership. In general, students from the same profile appeared along the same points on the scatter plots. Students in the Highly Motivated by Any Means, Average All Motivation, and Amotivated profiles fell along the diagonal on the scatter plot at high, medium, and low values on each factor, respectively. Students in the Intrinsically Motivated and Confident profile were represented by high values on the factor representing mastery goals, value, and competency beliefs, but low values on the factor representing performance-approach and performance-avoidance goals. There was virtually no overlap in profiles on the scatter plot. It appeared that the factors identified using principal components analysis distinguished profiles from one another.

I then conducted analyses using the two principal component factors, as well as an interaction term between the two factors, as predictors of all outcomes (RQ 1c). The factors were significantly associated with the likelihood to drop the course and self-reported regulation and engagement. With respect to dropout rates, the factor associated with mastery goals, task value, and competency beliefs was a significant predictor of the likelihood to drop out, with higher values on that factor associated with a greater likelihood to remain enrolled in the course (B = 0.58, *SE* = .22, Odds ratio = 1.79, *p* = .01). Neither the factor associated with performance-approach and performance-avoidance goals (B = -0.39, *SE* = .26, Odds ratio = 0.67, *p* = .13) nor the interaction between the two factors (B = -.12, *SE* = .24, Odds ratio = 0.89, *p* = .63) was related to the likelihood of dropping the course. These analyses aligned with person-oriented findings, in that students in the Intrinsically Motivated and Confident profile were more likely to remain enrolled in the course and would generally be characterized by high values on the factor associated with mastery goals, value, and competency beliefs. However, students in the Highly Motivated by Any Means profile were also characterized by high values on the same factor, and were not more likely to remain enrolled in the course compared to students in the Amotivated profile. Thus, it appears that person-oriented and variable-centered analyses provide compatible but distinct information about the relation of motivation to dropout rates.

Principal components factors were also associated with regulation and engagement outcomes (see Table 13). The factor associated with mastery goals, value, and competency beliefs was positively related to behavioral regulation, effort regulation, and cognitive engagement. The factor associated with performance-approach and performance-avoidance goals, however, was not significantly related to regulation or engagement outcomes. Significant main effects were qualified by a significant interaction term between factors for behavioral regulation and effort regulation.

An interaction term between the two dimensions was significant for behavioral regulation and cognitive engagement only (see Table 13). Both interactions were probed by plotting values of behavioral regulation and cognitive engagement at one standard deviation below the mean, the mean, and one standard deviation above the mean on the two principal component dimensions. For behavioral regulation, the interaction appeared to be driven by students with higher than average endorsement of the performance-approach/performance-avoidance dimension; compared to those with lower than average values on the dimension, students with higher than average performance-approach/performance-avoidance goals reported more behavioral regulation at higher than average levels of mastery goals/value/competency beliefs but lower behavioral regulation at lower than average levels of mastery goals/value/competency beliefs (see Figure 8). For cognitive engagement, students with high values on the mastery/value/competency beliefs dimension were equally engaged regardless of values on the performance-approach/ performance-avoidance dimension; at low levels of mastery/value/competency beliefs, students with lower than average performance-approach/performance-avoidance goals were more engaged than students with higher than average performance goals (see Figure 9).

Finally, I examined the relation of principal component factors to achievement trajectories. I conducted this analysis including both principal component factors and profile dummy variables as predictors of exam trajectories; by doing so, I could empirically examine the extent to which profile membership predicted exam scores above and beyond principal component dimensions. A likelihood ratio test indicated the block of profile-related predictor variables was significant ($\chi^2 = 107.52$, $p < .001$), suggesting that information regarding profile membership contributed unique information to the model above and beyond information captured by principal component factors. Coefficients for the model are displayed in Table 14. Overall standard errors were slightly inflated compared to the model without principal component factors (see Table 10), but this increase was tolerable.

Importantly, the pattern of significance with respect to profile-related predictors did not change when principal component factors were included in the model. This analysis provides compelling evidence that information regarding profile membership provides unique information regarding achievement trajectories that are not captured by linear, variable-centered predictor variables.

CHAPTER 5:

Discussion

Decades of motivation research have operationalized, measured, and evaluated factors that drive students in the classroom (Maehr & Zusho, 2009; Wigfield & Cambria, 2010). However, researchers may face difficulty translating research into clear and concise recommendations for classrooms, where students endorse sundry motivational combinations and do not necessarily hold the same beliefs as their classmates. Person-oriented findings have the potential to bridge research to practice by more accurately describing students' motivation. Person-oriented research may also inform theory by refocusing theoretical debates on the combinations of motivation students most commonly endorse.

This study aimed to holistically describe students' motivation in mathematics, document motivational stability, and identify precursors to motivational change. Focusing on an academically at-risk age group could inform efforts to support students in pursuing STEM-related career pathways (Watt et al., 2006). Moreover, an integrative approach provides a more comprehensive and predictive consideration of students' motivation (Conley, 2012). The current study extended past person-oriented research, which is primarily descriptive, cross-sectional, and devoid of analyses examining mechanisms. This study also extended past person-oriented research, based exclusively in face-to-face learning contexts, by documenting motivation in on-line classrooms. Findings allow a more nuanced consideration of which profiles are adaptive, and provide some insight into factors associated with short-term motivational change.

What Motivates Students in On-line Mathematics Courses (RQ 1a-b)?

Profiles in the current study were largely consistent with findings from past integrative person-oriented research (Bräten & Olaussen, 2005; Conley, 2012). Consistent with findings from Linnenbrink-Garcia and colleagues (Linnenbrink-Garcia et al., 2012, 2014; Wormington et al., 2014, 2016), I identified groups of students who were Highly Motivated by Any Means, Intrinsically Motivated and Confident, and Amotivated. The Highly Motivated by Any Means profile characterized a small proportion of the overall sample. Students who began the course in the Highly Motivated profile were unlikely to maintain high motivation through the middle of the semester, which was in line with past research. Conversely, a sizable proportion of students began the semester as Intrinsically Motivated and Confident, and approximately 75% remained in the Intrinsically Motivated and Confident profile from beginning to mid-semester. The Intrinsically Motivated and Confident profile was even more stable in this sample compared to studies examining shifts between semesters (average stability = 57%; Linnenbrink-Garcia et al., 2012, 2014; Wormington et al., 2014) or within a single semester (stability = 50-60%; Wormington et al., 2016).

Also consistent with past studies, the Amotivated profile characterized a small group of students. Contrary to studies examining shifts across semesters (average stability = 57%; Linnenbrink-Garcia et al., 2012, 2014; Wormington et al., 2014) or within a semester (stability = 74-82%; Wormington et al., 2016), however, only 33% of students remained in the Amotivated profile from the beginning to middle of the semester. This particular finding should be interpreted with extreme caution given sample size and selective attrition. I return to these issues in the limitations section.

Absent and Unexpected Profiles

A fourth hypothesized profile, representing Performance Focused students, was not identified in the present study. The absence of a Performance Focused profile was surprising among a high school sample, as variable-centered evidence indicates mean-level increases in performance goals during adolescence (Ryan & Patrick, 2001; Urdan & Midgley, 2003). However, motivation was assessed in on-line mathematics courses. Both the subject area and on-line learning context could explain why students were not driven by performance goals alone.

Mathematics is categorized as a hard, pure domain (Biglan, 1973). There is often considered to be a single right answer in hard subjects, and pure domains focus on concepts rather than applications. In face-to-face classrooms, social comparison may be more prevalent in hard domains than in soft and applied subjects; for instance, students may be called to answer questions on the board more often in hard subject areas (e.g., Stodolsky & Grossman, 1995), and it may be easier to compare grades than in soft domains (i.e., comparing the number of questions correct on an exam versus comments on an essay). As a result, it is possible for some students to be driven by a sole desire to appear competent in hard, pure subjects. Indeed, past integrative studies in mathematics and science have identified groups of students characterized as Performance Focused (Linnenbrink-Garcia et al., 2014; Wormington et al, 2014, 2016).

However, opportunities for comparison in *on-line* mathematics courses may be limited. In Chapter 2, I argued that the way in which students demonstrate competence—and, consequently, pursue performance goals—would differ in face-to-face and on-line learning environments. Face-to-face classrooms afford students opportunities to appear competent by answering questions, comparing exam grades, or engaging in group discussions. Many of these behaviors do not translate to on-line learning contexts. Thus, it is important to consider how on-line learners might demonstrate their competence. Potential avenues could include reaching out to the instructor or to classmates, either to ask for help or demonstrate their understanding of the material. Such actions are likely to require additional effort. Similarly, courses may not provide the infrastructure necessary to do so (e.g., the ability to send private messages to classmates).

The added effort required to present oneself as competent may be too high to sustain performance goal orientations for some students. As evidence, performance-approach and performance-avoidance goals were endorsed at lower levels across the sample compared to mastery goals, task value, and competency beliefs (see Table 4).

Discussion boards, a key element of many on-line courses, may provide a more normative avenue for students to convey their competence to others. Both soft and applied subject areas lend themselves well to the use of discussion boards. In an applied subject area, such as marine biology, students might discuss the impact of global warming on rising sea levels. The same logic would apply to soft subject areas like English. In a course such as American Literature, students might discuss their different interpretations of *Tom Sawyer*. In both examples, discussion boards approximate behaviors within face-to-face classrooms that allow students to show others how smart they are—or, conversely, make salient the possibility of appearing incompetent to others. Such is less likely to be the case within on-line mathematics courses. When reviewing syllabi for the courses from which students were recruited in the present study, the only student-to-student interactions available appeared to be through group projects. Group projects were almost exclusively limited to once per course, indicating that students' opportunities to compare themselves to one another were limited.

That is not to suggest that it is impossible to pursue performance goals on-line. As evidenced by the Highly Motivated by Any Means profile, some students still sought to demonstrate their competence on-line. Students in the Average All Motivation profile also reported relatively substantive levels of performance goals. Importantly, students in both profiles reported value, competency, and mastery goals equal to their performance goals. The additional motivational push from mastery, value, and competency beliefs may have served as impetus to overcome additional barriers associated with demonstrating competence. Performance Focused students, conversely, would by definition not have valued the course, saw themselves as competent, or desired to develop their mathematics skills. The additional effort required to demonstrate competence, then, would likely be too high for students who saw little value in the content area. As such, on-line mathematics courses may not support a sole focus on performance goals. Future research should seek to test this hypothesis examining whether Performance Focused profiles were identified among on-line learners enrolled in soft or applied on-line courses.

In place of a Performance Focused profile, an Average All Motivation profile was identified. A group of students with average overall motivation was not originally hypothesized, as Linnenbrink-Garcia, Wormington, and colleagues did not identify an analogous profile in any of their past studies. However, studies by Conley (2012) and Bräten and Olaussen (2005), which also examined profiles of goals, value, and competency beliefs, identified profiles of moderately motivated students. Conley (2012) identified three groups of students reporting average overall motivation: average-traditional, average-high cost, and average-multiple goals. Only the average-multiple goals profile displayed a similar pattern as that in the current study, in which students endorsed achievement goals, value, and competency beliefs at relatively equal levels. The average-multiple goals profile was relatively uncommon in Conley's (2012) sample, representing only 14% of participants. Bräten and Olaussen (2005) also identified a group of students with average motivation, though the profile was also characterized by high task value. Their identified average profile was relatively common, representing nearly half of the sample. Finally, Wormington and Linnenbrink-Garcia (2016) identified an Average All Goals profile as the most common profile across person-oriented achievement goal studies. Consistent with all but Conley's findings, the Average All Motivation profile was one of the largest groups identified in the present study. The profile was relatively stable in the first half of the semester.

Theoretical Implications

The combinations of motivation that were observed or absent speak to theoretical issues. I limit my discussion in this section to the profiles identified and implications for theory. I consider the relation of profiles to outcomes in the following section on profile adaptiveness.

Achievement goal theory. Given associations with both positive and negative outcomes, performance-approach goals have been the topic of considerable debate (Senko et al., 2011). Goal theorists have posited that multiple goal pursuit (i.e., the extent to which performance-approach goals are endorsed alongside other achievement goals) can account for discrepant findings. Current findings suggested that mastery and performance-approach goals may be endorsed separately, as in the Intrinsically Motivated and Confident profile, or at equally high, average or low levels. Results also corroborated variable-centered findings regarding the high positive correlation between performance-approach and performance-avoidance goals (Law et al., 2012); these two goals were endorsed at equal levels among all four profiles. Most integrative person-oriented studies also failed to identify students with differential performance-approach and performance-avoidance endorsement (for exceptions, see Conley, 2012; Wormington et al., 2014; Wormington & Linnenbrink-Garcia, 2016).

Regardless of whether performance-approach and performance-avoidance goals can be endorsed separately, findings clearly suggest that they often co-occur. One concern raised regarding performance-approach goals is that they ultimately give rise to performance-avoidance goals (Midgley et al., 2001). In the current study, I was unable to evaluate this claim because there were no students who endorsed high performance-approach goals without high performance-avoidance goals. The fact that the two goal orientations almost always co-occurred in this study and many others may render the point moot. It is possible that, among younger samples, performance-approach goals may spur performance-avoidance goals. Within this sample of high school students, however, there was no evidence that one gave rise to the other.

Expectancy-value theory. Theory suggests that expectancies for success and value are reciprocally related, with high values of one fostering high endorsement of the other (Wigfield et al., 2009). Findings in the current study supported this assertion; students in each profile reported similar levels of competency beliefs and task value, though mean levels of value in each profile were lower than mean values of competency beliefs. As with achievement goals, the fact that competency beliefs and value were endorsed at equivalent levels precluded a consideration of whether high competency beliefs encourage high value, or vice versa. Experimental or intervention efforts targeting either competency or value may shed light on directional relations between the two constructs. Findings also bring into question the extent to which researchers should be concerned about students endorsing high competency without value, or high value without competency. Variable-centered studies have suggested that students with low competency beliefs but high value perform poorly (Trautwein et al., 2012). The infrequency with which this combination has been identified in person-oriented studies, however, suggests that the issue of high value but low competency may characterize few students in classrooms.

Integrative perspective. In line with past studies, I argued that integrating across profiles would be more informative and predictive than forming profiles based on achievement goals or value and competency alone (Conley, 2012). In considering the pattern of motivations across profiles, two conclusions may be drawn. First, competency beliefs and value were always endorsed at equal rates to mastery goals. Students who felt efficacious and valued mathematics also reported a desire to develop their competence; conversely, students with low competency beliefs and value did not aim to develop their skills in mathematics. Second, mastery goals, value, and competency sometimes but not always co-occurred with performance-approach and performance-avoidance goals. Returning to the mastery versus multiple goal debate, researchers have argued over whether students with high mastery goals or high mastery and performance-approach goals would be more successful (Midgley et al., 2001; Senko et al., 2011). Findings from the present study suggested that students representing both these patterns are also likely to feel competent in their abilities and value the subject area. These findings suggest that the debate is not as simple as whether performance-approach goals are endorsed alongside mastery goals. Similarly, whether mastery or performance-avoidance goals accompany performance-approach goals is not an either-or scenario; that is, individuals with high performance-approach goals may endorse both mastery and performance-avoidance goals. Beyond goal theory, integrative findings might suggest that performance-approach goals are adaptive when students feel competent and value the material, regardless of the other achievement goals adopted.

Multiple Pathways to Success: An In-Depth Consideration of Profile Adaptiveness (RQ 1c)

A central aim of person-oriented research is to identify the most and least adaptive combinations of motivation. This question holds theoretical importance across motivational frameworks, and is the topic of unresolved debates. Past person-oriented studies relied exclusively on concurrent relations between profiles and academic outcomes to evaluate success. The issue of adaptiveness, however, is multifaceted, and should be addressed using multiple indicators. Profile stability, patterns of shifts, and reactions to exam feedback may serve as additional barometers of profile adaptiveness. To gauge profile adaptiveness (RQ 1c), I draw from findings on profile stability (RQ 1b), reactions to exam feedback (RQ 2), and how reactions relate to motivational change (RQ 3).

Highly Motivated Students: Are Performance Goals a Help or Hindrance?

First, the relation of profile membership with academic outcomes speaks to profile adaptiveness. Past integrative studies found that the Highly Motivated by Any Means and Intrinsically Motivated and Confident profiles were equally adaptive (Linnenbrink-Garcia et al., 2012, 2014; Wormington et al., 2014, 2016). Students in both profiles were confident in their abilities, valued mathematics, and sought to develop their competence. The primary distinction between the Highly Motivated by Any Means and Intrinsically Motivated and Confident profiles, in both the current study and past studies, is that students in the former profile were focused on how competent they appear and students in the latter profile were not. The difference in performance goal endorsement for the two profiles in the current study was substantial, with a nearly two standard deviation discrepancy in performance orientation (Figure 3). With such a marked difference in performance goal focus, comparing students in the Highly Motivated by Any Means and Intrinsically Motivated and Confident profiles serves as an excellent test of whether performance goals contribute to or detract from academic success. The present study built upon past findings by examining more distal outcomes—in other words, whether students who began the semester as Highly Motivated by Any Means or Intrinsically Motivated and Confident would differ with respect to achievement trajectories, dropout rates, and mid-semester engagement and regulation. The inclusion of two objective measures of academic success (i.e., dropout rates, exam achievement) also contributed to person-oriented research, which has primarily examined self-report outcomes (Wormington & Linnenbrink-Garcia, 2016).

For the most part, students in the Highly Motivated by Any Means and Intrinsically Motivated and Confident profiles were equally successful; students in the profiles did not differ on exam trajectories or self-reported outcomes. For the few outcomes on which the two profiles significantly differed, neither the Highly Motivated nor Intrinsically Motivated profile displayed consistent advantages. Students in the Intrinsically Motivated and Confident profile were less likely to drop the course, compared to students in the Amotivated profile. Students who were Highly Motivated by Any Means at Time 2, however, reported higher behavioral regulation than students in the Intrinsically Motivated and Confident profile. Thus, evidence from longer-term and objective outcomes in the current study was consistent with findings from past person-oriented integrative research: neither the Highly Motivated by Any Means or Intrinsically Motivated and Confident profile appeared to be more adaptive than the other.

Stability and patterns of shifts (RQ 1b). Profile stability may serve as an alternative means to differentiate the two profiles. As postulated in the introduction, a stable adaptive profile would be preferable to an unstable adaptive profile because it indicates that the former combination of motivational beliefs is more likely to be maintained. The Intrinsically Motivated and Confident profile represented a larger group of individuals who were likely to remain in the same profile from the beginning to middle of the semester. The Highly Motivated by Any Means profile, by contrast, was relatively less common and nearly twice as unstable as the Intrinsically Motivated and Confident profile (see Figure 4). Smaller profile size and lower rates of stability could suggest that the Highly Motivated by Any Means profile was less adaptive than the Intrinsically Motivated and Confident profile.

However, it is important to consider whether students who shifted out of the Highly Motivated by Any Means profile moved to another adaptive profile (i.e., Intrinsically Motivated and Confident) or into a less adaptive profile (e.g., Amotivated profile). If Highly Motivated students shifted to another adaptive profile, low overall stability may not necessarily indicate that the Highly Motivated by Any Means profile was less adaptive. This appeared to be the case in the current study. Students who shifted out of the Highly Motivated by Any Means profile from Time 1 to Time 2 moved into the Intrinsically Motivated and Confident and Average All Motivation profiles at equal rates (see Table 7). The Intrinsically Motivated by Any Means profile was adaptive across all outcomes. Students in the Average All Motivation Profile performed relatively well on exams (though this analysis considered profile membership at Time 1 only), but exhibited a mixed pattern with respect to regulation and engagement. Importantly, no Highly Motivated students shifted into the Amotivated profile by mid-semester. Comparing students who shifted out of the Highly Motivated by Any Means and Intrinsically Motivated and Confident profiles, approximately equal numbers moved into relatively less adaptive profiles (i.e., Average All Motivation, Amotivated). Evidence from profile shifts again suggests that the two profiles were equally adaptive, though they are likely to follow distinct pathways.

Reactions to exam feedback (RQ 2). A final metric on which to compare students from the Highly Motivated by Any Means and Intrinsically Motivated and Confident profiles is their reaction to exam feedback. If students in one profile made more adaptive attributions or experienced more positive emotions than students in the other profile, that could suggest that one profile is likely to be associated with more beneficial outcomes than the other. Different reactions would be particularly relevant when considering students' responses to failure; students would be most likely to experience detrimental changes in motivation such as decreased competency beliefs or increased performance-avoidance goals following failure (Senko & Harackiewicz, 2005). Once again, results suggested no differences between students in the

Highly Motivated by Any Means and Intrinsically Motivated and Confident profiles; when exam achievement was held constant, students in the two profiles reported equally high perceptions of success and attributed success to internal sources (i.e., effort, ability, and strategy use).

A lack of differences between the two profiles is perhaps unsurprising when considering the circumstances under which reactions to exam achievement were assessed. Students in the Highly Motivated by Any Means and Intrinsically Motivated and Confident profiles reported equivalent achievement trajectories across the semester, and these profiles indicated moderately high and modestly increasing rates of success (see Figure 6). Similarly, analyses comparing profiles on reactions to exam feedback controlled for exam achievement; exam achievement was held constant at a value around 80, which would represent relatively high levels of success. With this in mind, a more accurate interpretation of findings is that students who began the semester in the Highly Motivated by Any Means and Intrinsically Motivated and Confident profiles reported equivalent perceptions of and attributions for success *under equal and relatively high levels of achievement*. Given their equally high mastery goals, competency beliefs, and task value, students from the Highly Motivated by Any Means and Intrinsically Motivated and Confident profiles would not necessarily be expected to differ in their reactions to success (see Table 1).

By contrast, students in the Highly Motivated by Any Means and Intrinsically Motivated and Confident profiles were hypothesized to respond differently to failure (see Table 1). Intrinsically Motivated and Confident students, who were confident in their abilities and primarily driven by intrinsic value and a desire to develop competence, were expected to attribute failure to the same causes as success—that is, internal, unstable, and controllable sources such as effort and strategy use. Highly Motivated by Any Means students, on the other hand, were expected to make external attributions in response to failure (i.e., strategy use for success, test difficulty and teacher quality for failure) as opposed to internal attributions in response to success. The discrepancy in how students would respond to success and failure was hypothesized to arise as a self-protective measure; students so highly focused on appearing competent may have been more invested in preserving competence in the face of failure. Based on this reasoning, I expected students in the Intrinsically Motivated and Confident profile to respond more favorably to failure than students in the Highly Motivated by Any Means profile. The extent to which I could investigate this hypothesis was limited in the current study; students from the Highly Motivated by Any Means profile were relatively successful overall and few performed poorly on exams. However, the question of how students from these two profiles respond to failure still warrants investigation. I return to this point later in the discussion when considering the contribution of attribution theory to understanding profile shifts.

Ability attributions. Returning to hypotheses from Table 1, students in the Highly Motivated by Any Means profile were also expected to attribute success to high ability more so than students in the Intrinsically Motivated and Confident profile. This hypothesis was based on the possibility that high endorsement of performance-approach goals would enhance effects of the hedonic bias (Graham & Taylor, 2014; Miller & Ross, 1975). Along the same lines, students in the Highly Motivated by Any Means profile were also hypothesized to attribute failure to ability, in light of high performance-avoidance goals. However, findings did not support this hypothesis; students in the Highly Motivated by Any Means profile made fairly high ability attributions, but not significantly higher than ability attributions among students in the Intrinsically Motivated and Confident or Average All Motivation profiles (Table 12). Findings might suggest that hypotheses from Table 1 were inaccurate. It is also possible that students in

Highly Motivated by Any Means and Intrinsically Motivated and Confident profiles attributed success to ability because students in both profiles perceived themselves as highly competent.

Two alternative explanations also merit consideration. First, students in the Highly Motivated by Any Means profile reported high endorsement of performance-avoidance goals alongside other forms of motivation. Despite high competency beliefs, Highly Motivated students' focus on hiding incompetence could reflect an underlying doubt in their capability, which could make them wary to attribute success to internal, uncontrollable causes like ability. Second, it is possible that students in the Highly Motivated by Any Means profile did not credit ability more than students in other profiles due to social desirability concerns. Students in the Highly Motivated by Any Means profile could be attributing success to high ability; however, they may be reluctant to report that on a survey because they are cognizant of societal pressures to attribute success to effort more so than ability. This alternative seems plausible, given that students in the Highly Motivated by Any Means profile agreed equally or more strongly on average to items regarding effort and strategy use (Table 12). Future studies might investigate the role of social desirability in students' attributions by changing item wording (i.e., using a less value-laden synonym for ability), measuring social desirability (Reynolds, 1982; Stöber, 2001), or utilizing non-survey methods such as cognitive interviewing to assess attributions.

Is Average Motivation Sufficient?

Past studies indicated that students in the Highly Motivated by Any Means and Intrinsically Motivated and Confident profiles were the highest achieving (Linnenbrink-Garcia et al., 2012, 2014; Wormington et al., 2014, 2016). In the current study, a sizable profile of students with Average All Motivation received equally high exam grades. Students who began the semester in the Average All Motivation profile did not differ in their end-of-semester exam scores from students in the Highly Motivated by Any Means and Intrinsically Motivated and Confident profiles, all of which were significantly higher than students in the Amotivated profile. That students in the Average All Motivation profile received equally high final exam scores as students in traditionally successful profiles (i.e., Highly Motivated by Any Means and Intrinsically Motivated and Confident) is surprising in light of past research. The Average All Goals profile in achievement goal research was consistently associated with the lowest achievement (Wormington & Linnenbrink-Garcia, 2016). Within integrative studies, students with average motivation received lower grades than students in profiles with higher overall motivation (Bräten & Olaussen, 2005; Conley, 2012).

The overall pattern of findings, however, suggests that average motivation may not give rise to wholly positive outcomes. Unlike participants in the Highly Motivated by Any Means and Intrinsically Motivated and Confident profiles, students in the Average All Motivation profile did not exhibit increasing exam scores across the semester. Rather, achievement for students in the Average All Motivation profile mirrored the concave trajectory of students in the Amotivated profile. Similarly, students in the Average All Motivation profile reported overall lower levels of regulation and engagement, particularly compared to students in the Highly Motivated by Any Means profile. The pattern of relation to self-reported outcomes was more adaptive for predictive analyses, in which Time 1 profile served as the predictor variable; the Average All Motivation profile did not differ from the Intrinsically Motivated and Confident profile on any outcomes, though they did report lower behavioral regulation than the Highly Motivated by Any Means profile. The pattern of regulation and engagement was less adaptive for concurrent analyses, in which Time 2 profile was used to predict Time 2 regulation and engagement outcomes; students in the Average All Motivation profile reported equally low behavioral and effort regulation as students in the Amotivated profile, and significantly lower cognitive engagement than students in the Highly Motivated by Any Means and Intrinsically Motivated and Confident profiles. When considering findings as a whole, students with average motivation were less successful than students with higher motivation overall.

One explanation for mixed findings involves the observed pattern of profile shifts (RQ 1b). Approximately half of the students who began the semester with Average All Motivation reporting average motivation by mid-semester. Students who shifted, however, moved primarily into either the Highly Motivated by Any Means or Intrinsically Motivated and Confident profiles. Recall that the most adaptive findings (i.e., achievement trajectories, predictive relations to regulation and engagement) utilized Time 1 profile as the predictor variable. The adaptive pattern of outcomes for students with average motivation could have arisen because more than half of those students shifted into more adaptive profiles. This possibility has implications for measurement; if motivation changes over time, measuring motivation at the beginning of the semester may occlude the true relation of profiles to outcomes. I return to this point in the limitations section.

A second explanation is that the unique pattern of findings is a result of measuring high school students' motivation in on-line mathematics courses. Conley (2012) and Bräten and Olaussen (2005) examined motivation among middle school and professional students, respectively, in face-to-face learning contexts. It is possible, then, that endorsing average levels of motivation may be as adaptive as endorsing high motivation exclusively among high school students or within on-line learning contexts, either because it is associated with high achievement in its own right or because it serves as a gateway to more adaptive patterns of motivation (i.e., Highly Motivated by Any Means, Intrinsically Motivated and Confident). Such a combination may not only be uniquely adaptive in high school or on-line courses, but also uniquely adopted by students within that specific developmental or learning context. The fact that the Average All Motivation profile was the only profile not identified in past integrative person-oriented studies might lend credence to this possibility (Linnenbrink-Garcia et al., 2012, 2014; Wormington et al., 2014, 2016). Whether findings were a function of developmental stage or the on-line learning context is unclear without additional research. The only literature that might shed light on this question comes from achievement goal theory. Wormington and Linnenbrink-Garcia (2016) examined whether school level (i.e., elementary, middle, high school, college) moderated the relation of goal profiles with outcomes; their findings did not suggest that school level was a significant moderator for the Average All Motivation profile. Future studies should consider both developmental stage and face-to-face versus on-line learning contexts as potential moderators of when average levels of motivation are endorsed and adaptive.

Amotivated and At-Risk

Examining the beliefs of successful students can inform both theory and practice. However, students in the Highly Motivated by Any Means and Intrinsically Motivated and Confident profiles appeared to be high achieving and engaged. Even students in the Average All Motivation profile ended the semester with relatively high grades, though they were somewhat less engaged by mid-semester. Researchers should be equally or more concerned with identifying students most at-risk for academic difficulties. By doing so, researchers can begin to investigate specific means through which to best support struggling students.

Perhaps the clearest, albeit unsurprising, conclusion from the current study was that students in the Amotivated profile were unsuccessful on average. Students in the Amotivated profile were, by definition, less motivated than any other group of participants in the sample;

they were neither efficacious in their mathematics course, a subject they did not value, nor did they express a desire to grow or show their competence. Across all indicators of academic success, students in the Amotivated profile displayed a consistently concerning pattern of engagement, achievement, and beliefs. Amotivated students had the lowest achievement, both beginning and concluding the semester with average exam scores barely above passing rates. Self-reported outcomes also indicated a maladaptive pattern of findings. Students who began the semester in the Amotivated profile reported lower rates of behavioral regulation, effort regulation, and cognitive engagement by mid-semester. Even when controlling for exam achievement, students in the Amotivated profile perceived lower rates of success compared to their classmates and were less likely to attribute success to internal causes.

Somewhat reassuring is the fact that only ten percent of students reported low overall motivation; indeed, the Amotivated profile was smaller than the Highly Motivated by Any Means, Intrinsically Motivated and Confident, and Average All Motivation profiles. Contrary to past findings, the Amotivated profile was also the least stable profile from Time 1 to Time 2 (Linnenbrink-Garcia et al., 2012, 2014; Wormington et al., 2014, 2016). Both findings present a more optimistic picture than past person-oriented studies; though students in the Amotivated profile were clearly at-risk for low achievement and engagement, the profile characterized a small proportion of students and was relatively unstable over short periods. The likely role of selective attrition and participation, however, qualifies these statements. In particular, Amotivated students were less likely than chance to participate in subsequent surveys. Regardless, available data identified a small but significant group of students in need of academic support. Documenting which reactions were associated with increased or decreased membership in the Amotivated profile would identify avenues for potential intervention; in other words, findings would help guide practice in identifying an at-risk group of individuals and suggesting means through which to best support them (RQ 3).

Because Amotivated students were low achieving across the semester, one potential means to increase motivation could be to provide Amotivated students with opportunities to succeed. As prior success is a key predictor of competency beliefs, Amotivated students who experienced success may have subsequently adopted higher competency beliefs and other forms of motivation (Bandura et al., 1996; Guay et al., 2003; Schunk, 1991). Contrary to expectations, exam achievement was not associated with changes in predicted membership in the Amotivated profile. The lack of a significant association could suggest that success experiences were not sufficient to motivate students with consistently low beginning motivation. Recall, however, that these processes were assessed at the beginning of the semester. Social cognitive theory suggests that competency beliefs are influenced by students' overall pattern of past performance (Bandura, 1977). To overcome a potentially long history of failure, students may require repeated success before they demonstrate any changes in competency beliefs. I consider this hypothesis and its implications for this study in the limitations section.

Beyond objective achievement, students in the Amotivated profile were hypothesized to react differently to exam feedback than students who reported higher overall motivation (RQ 2). Due to a lack of agency and investment in the course, Amotivated students were expected to make external rather than internal attributions to explain their success and failure. Results supported this expected pattern, to an extent; while students in different profiles did not differ in their external attributions for exam achievement, students in the Amotivated profile reported consistently lower endorsement of effort, ability, and strategy use attributions. Students also interpreted their exam scores as indicating success less than students in other profiles. Critically, this pattern emerged even when holding exam scores constant at 80. In other words, students in the Amotivated profile perceived lower rates of success and made fewer internal attributions for success at relatively high levels of achievement. Again, these perceptions must be considered in light of students' past history of success. A single high exam score may be dismissed as an anomaly if a student has consistently performed poorly in mathematics for years. In fact, it is possible that low achievement in the past may explain students' low overall motivation in mathematics at the beginning of the study. Exploring past achievement as a correlate of profile membership could be a promising direction for future person-oriented research.

Students in the Amotivated profile perceived lower overall success and were reluctant to attribute achievement to internal causes. Perhaps these differences in reactions to exam achievement could account for students' likelihood to remain in the Amotivated profile or shift to the Amotivated profile from another profile (RQ 3). Contrary to expectations, neither objective exam achievement nor reactions to exam feedback were significantly associated with changes in students' likelihood to be categorized in the Amotivated profile. A lack of significant correlations could be a result of low overall profile membership; only six new students shifted into the Amotivated profile, and three students who began the semester in the Amotivated profile completed the Time 2 survey.

Because Amotivated students are consistently identified as an academically at-risk group and findings from the current study were inconclusive, it may be fruitful to consider additional intervention targets. One possible means to support Amotivated students would be to utilize an empirically validated intervention focused on increasing a single motivational construct, with the hopes that increasing one form of motivation would precipitate increases in other forms of motivation. A utility-value intervention, for instance, could increase students' interest and subsequent achievement (Hulleman, Godes, Hendricks, & Harackiewicz, 2010). Increased achievement could, over time, lead students to perceive themselves as more competent and adopt goals to either develop or demonstrate their competence. Which motivational construct to intervene upon should be selected with care. Building from the example above, research suggests that high value could be detrimental when students do not hold high accompanying competency beliefs (Trautwein et al., 2012). As such, supporting value without also fostering competency could lead to less than ideal outcomes for some students. A second potential, then, would be to adopt a more universal intervention approach, with the goal of supporting several motivational beliefs simultaneously. For instance, a utility-value intervention could be coupled with repeated opportunities for success on small assignments to foster competency beliefs. The latter option aligns well with person-oriented approaches, which stress the importance of considering the constellation of motivational beliefs rather than a single belief in isolation (Bergman & Trost, 2006; Bergman et al., 2003).

On-line learning contexts may provide unique opportunities to engage Amotivated students in learning. Evidence suggests that discussion boards encourage greater participation among reticent individuals (Citera, 1988). More frequent participation in discussion boards is, in turn, positively associated with achievement (Davies & Graff, 2005). Discussion forums may provide low-stakes opportunities for Amotivated students to interact with class material and other students, when compared to analogous experiences in face-to-face courses (e.g., class discussions). Simply incorporating discussion boards or forums into course material, however, is not necessarily sufficient to foster motivation (e.g., Swan, 2002). Evidence also suggests that making discussion board assignments required can reduce both the quantity and quality of interactions (Weisskirch & Millburn, 2003). This may provide challenges for engaging

Amotivated students, who have already expressed little investment in the course. For students who are already Amotivated, making assignments mandatory—at least at first—may be necessary to spur initial engagement. Future research may wish to consider the extent to which discussion boards are useful tools for unmotivated students, how they might be incorporated into mathematics courses, and whether the mandatory nature of such assignments affects the quantity and quality of Amotivated students' interactions.

Is Attribution Theory Useful for Understanding Underlying Mechanisms (RQ 2-3)?

Past person-oriented studies are primarily cross-sectional (but see Schwinger & Wild, 2012; Tuominen-Soini et al., 2011, 2012). Among studies that have considered profile membership longitudinally, none have investigated the underlying psychological processes that may account for profile stability. Based on attribution theory, I hypothesized that students' reactions to exam feedback would be associated with changes in their profile membership (RQ 3; Weiner, 1990).

On the whole, the hypothesized associations were not present. Perceptions of success, attributions, and emotions were associated with some changes in profile membership, but haphazardly so. Given its proximity to outcomes, I expected emotions to be most consistently associated with changes in profile membership. Instead, different stages of the model (i.e., perceptions of success, attributions, emotions) emerged as important correlates of change for different profiles. Perceptions of success and emotions predicted changes in membership for the Highly Motivated by Any Means and Average All Motivation profiles. However, only attributions predicted changes in the likelihood to be a member of the Intrinsically Motivated and Confident profile. Neither perceptions of success, attributions, nor emotions were associated with changes in membership in the Amotivated profile. The lack of associations of reactions with Amotivated profile membership was disheartening, as students in the Amotivated profile were the least successful and most in need of academic support. In light of the disconnect between hypothesized and observed relations, one could conclude that attribution theory was not a useful lens through which to explain changes in profile membership.

Before abandoning attribution theory, however, three alternative explanations merit consideration. The most obvious explanation for null findings involves an insufficient sample size. I return to this point in the limitations section. A second explanation is that most students performed well on exams. Students in the Highly Motivated by Any Means, Intrinsically Motivated and Confident, and Average All Motivation profiles received average exam scores in the B- to B range and final exam scores in B+ to A range; most students in those profiles, then, reported reactions to relatively positive exam feedback. Conversely, Amotivated students performed poorly across the semester on average. Students in the Amotivated profile received exam grades ranging in the D+ to C+ range; Amotivated students' reactions to exam feedback, then, reflect responses following relatively negative performance.

It is possible that students in the Highly Motivated by Any Means, Intrinsically Motivated and Confident, and Average All Motivation profiles may have responded very differently from one another following failure (see Table 1). It is also possible that Amotivated students may not have been as reluctant to make internal attributions for their achievement when they succeeded. Future studies—in which failure is either experimentally manipulated or students experience authentic success and failure—should consider how individuals from each profile react to both success and failure. A within-subjects design would help to isolate the role of exam feedback on students' responses. It may also be informative to consider the number of exposures to success or failure required to spur motivational change for students from each profile. For instance, students from the Amotivated profile may only become more motivated after repeated exposures to success. This question could be assessed similarly to a *dosage effect* from pharmacology, in which a critical "dose" of success or failure experiences is needed to exhibit an effect on motivation. Understanding the number of success or failure experiences required for motivational change may serve as another means to assess profile adaptiveness. For example, students in the Highly Motivated by Any Means profile may shift to a less adaptive profile following one or two failed exams, while students in the Intrinsically Motivated and Confident profile may be more resilient to motivational loss after failure.

A third explanation for the lack of support for hypotheses could have arisen from the method for assessing Research Question 3. In analyses, I assessed whether students were more or less likely to be categorized in a given profile at the middle of the semester compared to the beginning of the semester. I then examined the association of changes in profile membership with perceptions of success, attributions, and emotions via bivariate correlations. This approach does not take students' initial profile membership into account. For example, I did not distinguish between students who moved into the Average All Motivation profile from the Amotivated or Intrinsically Motivated and Confident profiles. Students moving into the same profile could do so for different reasons, based on their initial motivational beliefs; it is possible, then, that groups of students shifting into the same profile from different initial profiles could cancel each other out when examining changes as a whole.

As an illustrative example, consider students moving into the Intrinsically Motivated and Confident profile at Time 2. Equal numbers of students who shifted into the profile began the semester in the Highly Motivated by Any Means and Average All Motivation profiles. Students from both initial profiles decreased in their performance goal endorsement, though this change was more pronounced for students from the Highly Motivated by Any Means profile. Students shifting from the Highly Motivated by Any Means profile also decreased in overall mastery goals, competency beliefs, and value. Students shifting from the Average All Motivation profile, conversely, increased on average in mastery goals, competency beliefs, and value. Attributing achievement to effort and strategy use might spur decreases in performance goals among students from both profiles, which is perhaps why both emerged as significant correlates of changing membership in the Intrinsically Motivated and Confident profile. However, the attributions and emotions associated with increasing and decreasing mastery, competency beliefs, and value for students from the Highly Motivated by Any Means and Average All Motivation profiles, respectively, likely cancelled one another out. Consequently, no other attributions or emotions were significantly correlated with increased membership in the Intrinsically Motivated and Confident profile.

Future studies with sufficient sample sizes should examine specific profile shifts and how they are associated with reactions to exam feedback. This alternative approach would better align with the stated research questions, which differentiate students who maintain adaptive combinations of motivation from those who shift into less adaptive profiles. Focusing on specific shifts, for instance, would allow researchers to distinguish between students who remained in the Highly Motivated by Any Means profile from Highly Motivated students who shifted to the Average All Motivation profile.

Comparing Person-Oriented and Variable-Centered Findings

Does a Person-Oriented Approach Contribute Unique Information?

A central premise of the current study was that person-oriented analyses would contribute unique information about the combination and correlates of motivation. When considering patterns of motivation among the four profiles, however, profiles varied along two dimensions: (1) mastery goals, value, and competency beliefs, and (2) performance-approach and performance-avoidance goals. Mastery goals, value, and competency beliefs were always endorsed at similar levels to one another, as were performance-approach and performance-avoidance goals. Moreover, three of the four profiles (i.e., Highly Motivated by Any Means, Average All Motivation, and Amotivated) displayed the same pattern of motivation but with different overall quantities. If profiles only differed along two motivational dimensions and with respect to quantity, could the same information gleaned from person-oriented analyses be captured using a variable-centered approach?

Prior variable-centered research has utilized two- or three-way interaction terms to capture the interrelations among motivational variables (e.g., Durik & Harackiewicz, 2003; Trautwein et al., 2012). Examining all possible interactions between goals, value, and competency beliefs would be difficult to interpret and require a prohibitively large sample size. Data reduction alternatives, such as principal components analysis, provide an alternative approach. Within the current sample, results from a principal component analysis suggested that motivational constructs could be represented along two dimensions capturing (1) mastery goals, value, and competency beliefs; and (2) performance-approach and performance-avoidance goals. The four profiles separated from one another almost perfectly when plotted along the two dimensions, suggesting that the dimensions adequately captured information regarding profile membership (see Figure 7). The fact that each group of constructs loaded onto a single factor was unsurprising, given the high correlations between variables within the same dimension (see Table 4) and the patterns of motivation among the identified motivational profiles.

The two principal component dimensions also significantly predicted self-reported outcomes and likelihood to drop the course, though they were not associated with achievement trajectories. Findings suggested that the dimension representing mastery goals, value, and competency beliefs was positively associated with mid-semester behavior regulation, effort regulation, cognitive engagement, and lower odds of dropping the course. The dimension representing performance-approach and performance-avoidance goals, conversely, was not a significant predictor of engagement, regulation, or dropping the course.

An interaction term between the two dimensions was significant for behavioral regulation and cognitive engagement only. Students with higher than average values on both dimensions reported the highest behavioral regulation. For cognitive engagement, students with high values of mastery/value/competency beliefs dimension but different endorsement of the performance-approach/performance-avoidance dimension were equally engaged. The pattern of findings using principal components dimensions was consistent with person-oriented results; students in the Highly Motivated by Any Means profile reported slightly higher behavioral regulation than students in the Intrinsically Motivated profile, but the two profiles did not differ on cognitive engagement. A variable-centered approach like principal components analysis, then, may serve as a viable alternative to person-oriented analyses *when researchers' goal is to understand the relation of motivation to some (but not all) academic outcomes*.

The most stringent comparison of variable-centered and person-oriented predictors was assessed in analyses when I included both profiles and principal component analyses together as predictors of achievement trajectories. Results suggested that profile membership predicted achievement trajectories above and beyond principal component factors, and that the inclusion of principal component factors did not change the overall pattern of significance for profile-related predictor variables. The fact that principal component dimensions did not relate to achievement trajectories speaks to the utility of motivational profiles for understanding the relation between motivation and achievement. In addition, results suggest that profiles represent unique information that cannot be captured by considering linear relations between motivational variables. Of course, conclusions should not be extrapolated beyond the current study. To my knowledge, this is the first time a researcher has compared person-oriented findings to those obtained from a variable-centered data reduction technique. It is unclear whether profiles from other studies would also fall along two dimensions or require additional dimensions.

Researchers, however, are not only concerned with how motivation relates to academic outcomes. A sustained focus within the motivation literature is documenting developmental changes in motivation across the short-term (Fryer & Elliot, 2007; Muis & Edwards, 2009; Senko & Harackiewicz, 2005) and long-term (Corpus et al., 2009; Eccles et al., 1993; Gottfried et al., 2001). In this respect, a person-oriented approach contributes unique information about the percentage of students who follow distinct motivational trajectories (Bergman & El-Khouri, 1999). A second but equally worthwhile goal is to characterize students' motivational beliefs in their own right, particularly as a means to communicate with teachers and policy makers. Discussing the relation between variables (e.g., value and achievement) may resonate less with educators than describing types of students who are likely to be successful or unsuccessful. Without accurately depicting classroom motivation and communicating effectively with educators, researchers' recommendations for practice may be limited. With this in mind, I contend that person-oriented analyses are appropriate *when researchers' goal is to characterize motivational change and translate research to practice.*

Do Variable-Centered Findings Suggest Changes to Person-Oriented Research?

Beyond comparing person-oriented and variable-centered findings, the results from principal components analysis suggest potential alterations to future integrative person-oriented studies. Recall that the goal of integrative person-oriented research is to represent motivation broadly while avoiding unnecessary overlap. Findings from this and other integrative studies suggest that mastery goals, value, and competency beliefs almost always co-occur and may not provide unique information. Similarly, performance-approach and performance-avoidance goals map on to the same underlying dimension. Whether to exclude any constructs when forming future integrative profiles is a decision that should be guided by both theory and research. On the one hand, each of the five constructs assessed in the current study are theoretically distinct from one another. On the other hand, motivational constructs overlap statistically and theoretically with one another (Murphy & Alexander, 2000). One of the arguments made for integrating across motivational perspectives is that doing so improves predictive validity (Conley, 2012). As such, each construct should contribute meaningfully to the profile.

A first step would be to empirically assess the contribution of each motivational belief; one could do so by creating profiles with and without each construct, then comparing each set of profiles on academic outcomes of interest. Final decisions, however, should always be theoretically justified. For instance, omitting mastery goals but including performance-approach and performance-avoidance goals may not be warranted because they are drawn from the same framework. Similarly, there may not be grounds for excluding competency beliefs because the construct addresses a distinct motivational question (i.e., “can I do this?”).

Researchers should also consider additional motivational beliefs to include in profiles. It may be useful to begin by examining additional variables within expectancy-value theory and achievement goal theory. Research based in expectancy-value theory has recently highlighted cost as an important but overlooked aspect of student motivation (Conley, 2012; Flake, Barron, Hulleman, McCoach, & Welsh, 2015). Other expectancy-value researchers discuss avoidance and perceived difficulty as negative indicators of student motivation (Guthrie et al., 2009; Wigfield, Cambria, & Ho, 2012). Within achievement goal theory, Nicholls' (1990) original conceptualization of goals included work-avoidance goals (Nicholls, 1990; Nicholls, Patashnick, & Nolen, 1985). Work-avoidance goals represent a desire to expend as little effort as possible in a given situation (Elliot & Harackiewicz, 1996; Skaalvik, 1997; Thorkildsen, 1988; Thorkildsen & Nicholls, 1998). In the context of mandatory, self-paced on-line classes, work-avoidance goals may be particularly likely to influence students' success. Considering additional motivational variables, such as the constructs mentioned above, could provide a more complete picture of student motivation. Again, researchers should take care to balance a complete picture of motivation with parsimony.

Limitations

Several limitations must be considered when interpreting findings from the current study. Some limitations arose as a function of the on-line learning context in which data were collected. I begin this section by describing four limitations associated with on-line learning contexts: participation rate, selective attrition, generalizability, and the self-paced nature of courses. Other limitations were due to my decisions regarding operationalization or analytic approach. I consider the repercussion of two such decisions: defining achievement as exam scores and predicting longitudinal outcomes based on students' initial motivational profile. Finally, I consider the potential drawback to recruiting participants from different mathematics courses.

Participation Rate and Selective Attrition

Perhaps the most obvious limitation concerned the percentage of eligible students who participated in the study, and the limited number of participants who completed the post-exam or mid-semester surveys. Approximately 61% of eligible students completed the Time 1 survey. It was not possible to assess whether participating and non-participating students differed in their motivation. However, there were no systematic differences between students who did and did not participate with respect to final course grade, gender distribution, reason for enrolling in the course, or likelihood to drop out of the course. Higher participation rates would be preferable to ensure accurate representation of the population (i.e., high school students in on-line mathematics courses). That students did not differ with respect to available demographic information or academic achievement may temper this concern to a degree.

Of greater concern were attrition rates. The current study suffered from substantially high attrition rates, to the point that it was necessary to alter the original research design by not analyzing surveys at the end of the semester. High attrition impacted analyses regarding profile stability and shifts, as well as analyses involving students' reactions to exam feedback. Of concern, participants who did and did not complete the Time 2 survey differed with respect to course grade, likelihood to drop the course, and likelihood to have enrolled in the course for credit recovery purposes. In addition, relatively few participants responded to post-exam surveys; in fact, I was forced to collapse data from the first two post-exam surveys to obtain a reasonable sample size. Selective differences and low participation rates have substantial implications for interpreting findings. Importantly, findings regarding the pattern of profile shifts do not include some of the students who would be likely to exhibit maladaptive patterns (i.e., students who performed poorly or dropped the course). As such, many findings in the current study should be interpreted with extreme caution. Findings least likely to be affected by low participation rates—and, therefore, most likely to be generalizable to other on-line mathematics learning contexts—include (1) the profiles identified, (2) the relation of profiles to achievement trajectories, and (3) the association of initial profiles to drop out rates.

Beyond concerns of accurate representation, low participation rates and substantial attrition also raise concerns regarding power. For several research questions, planned analyses were no longer deemed appropriate and required revision. For other analyses, it could be argued that sample sizes may have been too small. For instance, there is some disagreement regarding the ideal number of higher-order groups to conduct multilevel modeling (see Maas & Hox, 2005). An inappropriately small number of groups at the highest level (i.e., mathematics courses) can result in biased standard error estimates at the highest level. For the sake of this dissertation, course-level effects were not of central importance. Nevertheless, the potential for insufficient power and biased standard errors should be acknowledged and carefully considered.

The on-line nature of the courses could have attributed to low participation rates. Announcements and reminders were all posted to the course page to inform students of the survey and encourage participation. However, technical difficulties raised the possibility that announcements were not delivered as intended. For this study, announcements and surveys were erased from all courses several times before the semester began. I reentered all materials, but materials were erased once again after the semester began. To ensure anonymity, I was not granted access to course pages once classes had officially begun; as such, I was unable to validate that all announcements and surveys were reentered into the course pages. Additionally, some instructors expressed concern with the number of announcements; as a compromise, instructors were invited to integrate announcements with their weekly course announcements. Again, I was unable to validate whether announcements were included for all courses.

Insufficient incentive could have also precipitated low response rates. Students were offered $10 in exchange for completing all three main surveys at Times 1, 2, and 3. This incentive may not have been enough to encourage participation. Surveys were also optional, rather than mandatory. Offering more money or extra credit, or making surveys mandatory, would likely increase participation rates. However, there are motivational implications associated with all of these options. It may be preferable to encourage participation through non-extrinsic means, such as making a better case for the importance of the study to increase student buy in or appealing to instructors to encourage students to consider participating. Striking the appropriate balance between tangible rewards and non-extrinsic reasons for participating seems the most promising avenue to increase participation in future research.

On-line Learning Contexts and Generalizability

As a departure from past person-oriented studies, I assessed students' motivation in the context of on-line mathematics courses. On-line classes entail a very different type of learning experience than more traditional face-to-face classes. I interpreted discrepant findings between the current study and past research partially in light of the online nature of classes. However, the decision to investigate motivation in on-line courses limits the extent to which findings should be generalized to off-line learning experiences.

By the same token, surveying on-line learners extends upon prior person-oriented research. Similarly, varying the context provides preliminary evidence regarding the extent to which past findings might generalize beyond traditional face-to-face classroom contexts. Patterns of motivation and their relation to class achievement and engagement appeared fairly consistent between the current study, in an on-line learning context, and past studies in face-to-face courses. Findings alluded to some difference between on-line and in-person contexts, particularly with respect to students who focus on performance goals alone. Without corroborating evidence, any comparisons between the current and past research are tentative. However, findings suggest that studying on-line learners' motivation is a worthwhile endeavor.

Self-Paced Courses

A unique feature of on-line courses is that they are self-paced. Each course included a pacing guide, which provided recommendations for when material should be reviewed and assignments completed. However, students were free to complete course material at their leisure. A student who completed all assignments over the last two weeks of the semester would not be penalized for doing so. The self-paced nature of courses may place more responsibility on the student with respect to self-regulation, which was one of the reasons I assessed behavioral and effort regulation as outcome variables in the current study.

The self-paced structure of courses presented unique challenges with respect to research design. Given the nature of the research questions, survey placement was planned around graded assignments. However, students could—and did—take surveys at very different times. This presented a problem for numerous analyses, some of which could be addressed through statistical means and some of which represent true limitations in terms of interpreting findings.

The Time 2 survey was intended to assess students' motivational beliefs and academic behaviors in the middle of the semester. The data were used to examine profile shifts from the beginning to middle of the semester, as well as to examine the relation of motivational profiles at Time 1 and Time 2 to self-reported engagement and regulation. For each course, I placed the survey as close to the middle of the semester as possible based on the pacing guide. Time 1 and

Time 2 surveys were intended to be completed approximately 8-9 weeks apart. However, the time between survey completions ranged considerably for students. Differences in timing undoubtedly impact profile stability rates. To address this concern, I excluded students who completed surveys too close together, or completed the Time 1 survey after the Time 2 survey. Because graded assignments were hypothesized to influence motivation, I also ensured that the survey was at least two units removed from a graded assignment (e.g., exam, quiz) based on pacing guides. However, it is possible that students took the Time 2 survey in close proximity to a graded assignment, as assignments could be completed at any time. To address this concern, I examined time stamps for all quizzes and exams in each course, and controlled for time between surveys when appropriate. Controlling for time between surveys partially addresses the issue of self-pacing; however, survey administration was not as controlled as in face-to-face contexts.

Post-exam surveys were also purposely placed following exams, and intended to capture students' immediate reaction to exam feedback. However, few students completed the post-exam surveys as instructed. Instead, a sizable number of students completed the survey before taking the exam; I excluded these students from analyses. Several students also responded to the exam more than ten days after taking the exam. Attributions and emotions are likely to look very different ten days after receiving feedback, during which time one had an opportunity to reappraise feedback, than it would in the moment. Aside from excluding participants who took the survey more than ten days after the exam, I controlled for time between exams and post-exam surveys in appropriate analyses. However, data do not reflect the ideal case, in which students would have completed post-exam surveys within minutes of receiving feedback.

Finally, students completed exams at different times throughout the semester. In growth curve analyses examining achievement trajectories, I included the day on which each exam was completed as a time-varying covariate in analyses (i.e., days since beginning in Table 10). Still, the nature of the association between students' initial profile and exam trajectories is likely to differ for a student who followed the pacing guide and a student who took all exams in the last month of the semester. Future research should attempt to replicate these findings in a set-paced course, or determine a more sophisticated manner in which to account for self-paced courses.

Exam Scores as an Indicator of Academic Achievement

A primary outcome in the current study was achievement, which was operationalized as exam scores. Exam scores comprise a major portion of students' course grade, and are appropriate with respect to hypotheses regarding factors that might influence changes in student motivation. However, findings for exam trajectories may not generalize to other types of graded assignments like quizzes, projects, or homework assignments. These other assignments also contribute to final grades, but may be psychologically distinct from exams as exams are so much more high stakes. It is possible that students from certain profiles may perform well on exams, because they are so important, but neglect lower stakes assignments like homework. The Average All Motivation profile, for example, was higher achieving than expected. Average motivation may be enough to support high exam scores, but not quizzes or homework.

Initial Profile as a Predictor Variable

In several analyses, I examined the relation between students' Time 1 profile and outcomes later in the semester. However, findings suggested that motivation was not static across time. It could be argued, then, that it not meaningful to consider initial profile as a predictor without taking into account students' profile membership at later points in the semester. Not accounting for profile shifts in analyses could explain why some profiles were associated with more adaptive outcomes than anticipated. For instance, high final achievement for the

Average All Motivation profile could have been driven by the sizable proportion of students who shifted into the Highly Motivated by Any Means and Intrinsically Motivated and Confident profiles. At the same time, documenting long-term outcomes based on incoming motivation could provide useful information in its own right. Though attrition rates precluded me from taking profile shifts into account in the current study, I plan to do so in future studies.

Differences Between Types of Mathematics

Students were recruited from on-line mathematics courses in Algebra I, Algebra II, Geometry, and Precalculus. Although all of these subject areas are subsumed under the umbrella of mathematics, each class entails very different types of materials and tasks. For instance, Algebra courses cover topics such as the quadratic formula and task students with solving systems of linear equations by substitution. These foci are substantially different than the material covered in Geometry courses, which focus more on tasks such as solving two-column proofs. Motivation could look very different across different types of mathematics courses. ICCs from the present study were quite small, indicating that the relation between profiles and outcomes of interest did not vary substantially across courses. Even so, future studies should consider the implication of topic area on motivation; in other words, examining motivation in mathematics may not be as meaningful as at the level of Calculus.

Future Directions

Building from the justification for and limitations of the current study, I suggest several future directions as particularly promising for person-oriented motivation research. First, future research might focus on examining motivational stability at a more granular level. One goal of the current study was to assess whether students' multifaceted motivational beliefs were stable over the short-term. Such information holds implications not only for theory but also for guiding researchers' decision about when motivation should be measured. Current findings indicated that approximately 45% of the sample shifted profiles from Time 1 to Time 2, with certain profiles retaining only one-third of their original members. Findings from other short-term longitudinal person-oriented studies suggest higher stability rates, ranging from 50-75% (Lee et al., under review; Wormington et al., 2016). Nevertheless, students' motivation does not appear to remain constant from the beginning to middle of a single semester. Over what time frame, then, can researchers assume that students will hold the same motivational beliefs? Future research could employ an experience sampling methodological approach (Csikszentmihalyi & Larson, 2014; Hektner, Schmidt, & Csikszentmihalyi, 2007) to assess students' motivation on a daily or even more frequent basis (e.g., multiple times within a class period or school day). An experience sampling approach might also allow for a more careful consideration of the personal experiences (e.g., achievement emotions) and contextual factors (e.g., teacher messages) associated with motivational change.

Second, research may benefit from examining profile membership and shifts over a longer duration. Due to response rates, I was only able to examine profiles shifts between the beginning and middle of the semester. However, the nature of profile stability may differ as students near the end of the semester. Motivation may be more malleable as students enter a new course, particularly in the potentially less familiar context of on-line courses. As students become familiar with the course, however, their self-beliefs and goals may stabilize. Evidence from two short-term longitudinal person-oriented studies support this hypothesis, as overall profile stability was higher from the middle to end of the semester than the beginning to middle of the semester (Lee et al., under review; Wormington et al., 2016). Future studies should seek to replicate these findings. Future research might also extend these findings by comparing motivational change over the same time frame but comparing within-semester to between-semester changes; some variable-centered evidence suggests that students' within-year motivational changes differ from changes between school years (e.g., Corpus et al., 2009).

On a related note, the relation of profiles to exam achievement and reactions to exam feedback may also vary across the semester. Current findings provided limited evidence that exam achievement, perceptions of success, attributions, and emotions were associated with motivational change. These factors may play a more prominent role later in the semester, as final grades become more salient. Some of the motivational constructs assessed may also require multiple experiences of success or failure to change. For instance, highly competent students may not experience decreased competency beliefs after failing one exam because their beliefs are based on all past successes (Bandura, 1977); shifts between profiles with discrepant competency beliefs, then, may be rare during the first half of the semester. However, individuals' competency beliefs may decrease following repeated failure experiences. As such, it is possible that shifts between very different profiles may be more common in the latter half of the semester.

Finally, future work may benefit from differentiating between students who follow specific shifts rather than aggregating across students in the same profile at any given time point. Students who remained in the Intrinsically Motivated and Confident profile during the first half of the semester, for instance, likely differ from Intrinsically Motivated and Confident students who shifted to the Amotivated profile. What differentiates these two groups of students, and will they ultimately differ in how successful they are in this and future mathematics courses? Similarly, why did some students remain highly motivated across the semester while others who began with similarly high overall motivation shifted to the Average All Motivation profile? Future studies with more substantial sample sizes could investigate student or classroom characteristics that predict specific profile shifts. A mixed-methods approach, in which students following specific shifts were interviewed, could provide a richer understanding of students' experiences and what prompts specific motivational changes (for a similar approach, see Corpus et al., 2016). By better understanding the association between students' classroom experiences and constellation of motivational beliefs, researchers would be better equipped to identify and intervene with individuals prone to detrimental motivational changes.

Implications

This study suffered from several noteworthy limitations, and the future directions section made clear that questions remain to be answered. Nevertheless, the current study holds implications for theory and practice in its own right. I have discussed multiple specific implications throughout the chapter. In this section, I focus on three general implications for theory and practice: changing the dialogue around most adaptive profiles, acknowledging students with average or low motivation, and exploring underlying psychological processes.

Changing the Dialogue Around Most Adaptive Profiles

Across frameworks, researchers have sought to identify the ideal combination of motivation. Consistent with prior integrative studies, findings provided evidence of equifinality. Students in the Intrinsically Motivated and Confident and Highly Motivated by Any Means profiles held different motivational beliefs that likely changed in different ways across the semester; however, students in the two profiles were equally engaged, self-regulated, and high achieving. By employing a longitudinal approach and considering a wider array of outcome variables, this conclusion can be drawn with greater confidence. Students in the Average All Motivation profile were also high achieving by the end of the semester, potentially due to the likelihood of students from this profile to shift to a more adaptive profile.

These findings hold implications for both theory and practice. First, attempts to identify a single ideal combination of motivational beliefs may be misguided. Rather, evidence suggests there are multiple beneficial motivational pathways (Pintrich, 2000). Second, as argued earlier in the chapter, traditional debates regarding adaptive motivational combinations (e.g., mastery versus multiple goals debate) may be overly simplistic. Researchers should adopt an integrative perspective to better approximate students' various reasons for trying hard in school rather than be artificially restricted by theoretical silos. Finally, successful students all reported high levels of mastery goals, competency beliefs, and value; less successful students, conversely, reported lower levels of mastery, value, and competency. As such, findings indicate that all students would benefit from practices that foster students' value, feelings of competency, and mastery goal orientation. This advice aligns with recommendations that would be made based on variable-centered findings, pointing to methodological triangulation.

Acknowledging Students with Average and Low Motivation

More generally, findings highlight a need to move beyond an exclusive focus on students with high motivation. The debate over mastery versus multiple goal pursuit provides an excellent example of researchers' bias towards highly motivated students (Midgley et al., 2001; Senko et al., 2011); even discussions of at-risk groups have focused on students with high performance-avoidance goals (Brophy, 2005) or high value but low competence (Trautwein et al., 2012). By contrast, the current study found that average or low motivated students were both common and unsuccessful. These findings do not appear to be an anomaly, as prior person-oriented research also identified sizable groups of academically struggling students with average (Bräten & Olaussen, 2005; Conley, 2012; Wormington & Linnenbrink-Garcia, 2016) or low motivation (Bräten & Olaussen, 2005; Conley, 2012; Linnenbrink-Garcia et al., 2012, 2014;

Wormington & Linnenbrink-Garcia, 2016; Wormington et al., 2014, 2016). Arguably, students with low or average motivation should be of primary concern to educational researchers because they are most in need of academic support. Identifying specific groups of low-achieving students also holds practical implications for resource allocation. Rather than focusing attention on students who are likely to be successful, educators could identify students with low incoming motivation and ensure that they receive appropriate motivational supports early in the semester.

Exploring Underlying Psychological Processes

Finally, this study represented the first attempt to explain profile shifts by investigating underlying mechanisms. Findings provided only limited evidence that exam achievement, attributions, and emotions were both influenced by and associated with changes in motivation. Without replication, it is unclear whether these factors play a role in profile stability and aspects of the study (e.g., sample size) limited conclusions. Regardless, it is critical for researchers to move beyond documenting *how* students are motivated and consider *why* some students are driven by certain factors and follow distinct motivational trajectories. Beyond extending theory, exploring psychological mechanisms is a critical step in developing targeted motivational interventions. Researchers and educators cannot hope to support struggling students with any efficacy without identifying their challenges and needs. Person-oriented research, in particular, can illuminate particular factors that are most salient for particular groups of individuals.

Conclusion

Decades of research identify achievement motivation as a critical component of academic success (Weiner, 1990; Wigfield & Cambria, 2010). As such, motivation research holds great promise to inform educational practice (Berliner, 2006; Hulleman & Barron, 2016; Linnenbrink-Garcia et al., in press; Mayer, 2012). However, researchers may face challenges when making recommendations to teachers about how to support students in their classrooms. One challenge in translating research to practice may arise from the mismatch between motivation as it is commonly assessed in studies and motivation as it exists in the classroom. While researchers commonly examine motivational constructs in isolation and at a single time point, students' real-world motivation is multifaceted and malleable. Variable-centered analyses highlight general trends in students' motivation, but "the average may be highly atypical" of any given student (Bergman & Trost, 2006; Walls & Schafer, 2006, p. xiv).

The current study employed a longitudinal, person-oriented approach to address these concerns. Results suggested that students' motivation in on-line learning contexts generally mirrored that in face-to-face classrooms, with some notable exceptions. Consistent with past research, there was no one set of beliefs associated with the greatest academic success; rather, various combinations of motivational beliefs proved successful (Pintrich, 2000). Also consistent with past findings, results implicated a group of Amotivated students consistently at-risk for academic failure. Longitudinal analyses indicated that nearly half of the sample switched profiles from the beginning to middle of the semester, with some profiles more stable than others. This finding extends past research by indicating that motivation is not fixed, even over short periods of time. Finally, results suggested that exam achievement and reactions to exam feedback might play a role, albeit limited, in students' changing motivational beliefs. Current findings, coupled with prior person-oriented research, can complement evidence from the dominant variable-centered literature and inform motivation theory, research, and practice.

APPENDICES

APPENDIX A

Tables

Table 1:

Hypothesized profiles and relations to proposed attributional model

Hypothesized profile	Most likely to experience…	Attributions in case of success	Attributions in case of failure	Emotions in case of success	Emotions in case of failure	Profile stability
Highly Motivated by Any Means	Success	Ability Strategy use	Ability Test difficulty Teacher quality	Pride Relaxation	Anger Shame Hopelessness Surprise	Low
Intrinsically Motivated and Confident	Success	Effort Strategy use	Effort Strategy use	Joy Contentment	Guilt Surprise	Moderate to High
Performance Focused	Failure	Ability Strategy use Luck	Ability Test difficulty Teacher quality	Pride Relaxation Surprise	Anger Shame Hopelessness	Low to Moderate
Amotivated	Failure	Luck	Test difficulty Teacher quality	Gratitude Surprise	Anger	High

Table 2:

Study measures and data collection schedule

	Beginning of semester (Time 1)	Middle of semester (Time 2)	After each exam
Motivation (goals, value, competency beliefs)	X	X	
Behavior/effort regulation		X	
Cognitive engagement		X	
Exam achievement			X
Perceptions of success			X
Exam-related attributions			X
Exam-related emotions			X

Note: X represents each data collection at which construct was measured. Time 2 data collections were timed such that they were at least two units removed from a quiz or exam in the course (as indicated on the pacing guide).

Table 3:

Research questions and data analyses

Research Question	Data Analyses	Valid *n*
RQ1a: Do students endorse different motivational profiles?	I-states as objects analysis (ISOA) with latent profile analysis	289 (*i*-states)
RQ1b: How does profile membership shift across a semester?	Configural frequency analysis; gain-to-loss ratio; percent stability	83
RQ1c: Which motivational profiles are most adaptive?		
Self-report (regulation and engagement)	Multilevel MANCOVAs with follow-up ANOVAs and post-hoc Tukey HSD tests	83
Dropout	Multilevel logistic regression analysis	211
Achievement trajectories	Three-level growth curve model time, student, course)	211
RQ2: Do motivational profiles differ in reactions to exam feedback?	MANCOVAs with follow-up ANOVAs and post-hoc Tukey HSD tests	68
RQ3: Are exam scores and reactions to exam feedback associated with profile shifts?	Bivariate correlations	47
Ancillary analysis: Do person-oriented analyses contribute unique information?	Principal components analysis Repeat analyses from RQ 1c	83- 211

Note: T1=Time 1 survey (beginning of semester); T2=Time 2 survey (middle of semester).

Table 4:

Bivariate correlations and descriptive statistics for motivational variables and academic correlates

Measures	1	2	3	4	5	6	7	8	9	10	11	12	13
Time 1													
1. Mastery-Approach Goals	--												
2. Performance-Approach Goals	.23**	--											
3. Performance-Avoidance Goals	.23**	.67**	--										
4. Task Value	.70**	.35**	.22**	--									
5. Competency Beliefs	.47**	.21**	.07	.61**	--								
Time 2													
6. Mastery-Approach Goals	.53**	.02	-.03	.49**	.43**	--							
7. Performance-Approach Goals	.09	.72**	.42**	.22	.01	.14	--						
8. Performance-Avoidance Goals	-.01	.62**	.51**	.12	-.03	.07	.85**	--					
9. Task Value	.33**	.24*	.01	.59**	.39**	.70**	.43**	.34**	--				
10. Competency Beliefs	.38**	-.03	-.15	.43**	.59**	.74**	.07	-.01	.64**	--			
11. Behavioral Regulation	.35**	.17	.03	.38**	.30**	.58**	.29*	.28*	.55**	.60**	--		
12. Effort Regulation	.37**	.03	.09	.23	.25*	.48**	.02	.10	.28*	.48**	.63**	--	
13. Cognitive Engagement	.45**	.01	-.01	.36**	.43**	.75**	.06	.03	.56**	.71**	.65**	.57**	--
Mean	4.11	2.76	2.95	3.36	3.88	3.98	2.38	2.54	3.27	4.01	3.36	4.03	3.87
SD	0.82	1.18	1.17	0.84	0.84	0.89	0.89	1.24	0.89	0.82	0.59	0.86	0.85
α	.89	.93	.84	.91	.90	.90	.94	.92	.92	.94	.76	.86	.91

Note: All variables were assessed on a 5-point Likert-type scale.

Table 5:

Fit indices for latent profile solutions

Number of Profiles	AIC	BIC	Adjusted BIC	Entropy	Profile Sizes
2	3812.58	3816.28	3813.11	.69	186, 103
3	3688.03	3695.44	3689.09	.70	84, 99, 106
4	3536.45	3557.55	3558.04	.74	28, 99, 95, 67
5	3537.72	3552.52	3559.83	.70	14, 105, 59, 62, 49
6	3543.27	3561.77	3545.91	.70	12, 77, 55, 83, 20, 42

Note: AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion; Adjusted BIC = Adjusted Bayesian Information Criterion. Profile sizes refer to the total number of i-states included in each profile.

Table 6:

Clustering variables for motivational profiles

	Highly Motivated by Any Means	Intrinsically Motivated and Confident	Average All Motivation	Amotivated		
Time 1:	(n_{total} = 54; $n_{with T2}$ = 18)	(n_{total} = 60; $n_{with T2}$ = 34)	(n_{total} = 71; $n_{with T2}$ = 28)	(n_{total} = 21; $n_{with T2}$ = 3)	F (p-value)	Effect Size (η^2)
Mastery-Approach Goals	4.62_a (0.50)	4.39_a (0.62)	3.92_b (0.57)	2.66_c (0.73)	63.38 (p < .001)	.49
Performance-Approach Goals	3.99_a (0.71)	1.71_c (0.67)	3.08_b (0.78)	1.55_c (0.51)	122.85 (p < .001)	.65
Performance-Avoidance Goals	4.01_a (0.83)	1.82_c (0.66)	3.39_b (0.74)	2.11_c (0.83)	96.16 (p < .001)	.59
Task Value	4.13_a (0.56)	3.52_b (0.66)	3.08_c (0.60)	2.01_d (0.46)	72.32 (p < .001)	.52
Competency Beliefs	4.48_a (0.45)	4.18_a (0.56)	3.52_b (0.75)	2.72_c (0.74)	52.08 (p < .001)	.44
Time 2:	(n = 13)	(n = 39)	(n = 24)	(n = 7)		
Mastery-Approach Goals	4.61_a (0.46)	4.36_a (0.57)	3.56_b (0.61)	2.36_c (1.13)	28.20 (p < .001)	.52
Performance-Approach Goals	4.32_a (0.94)	1.59_c (0.54)	2.88_b (0.47)	1.51_c (0.43)	77.18 (p < .001)	.74
Performance-Avoidance Goals	4.31_a (0.84)	1.65_c (0.57)	3.32_b (0.69)	1.67_c (0.69)	66.86 (p < .001)	.72
Task Value	4.54_a (0.71)	3.38_b (0.66)	2.89_b (0.44)	1.85_c (0.52)	36.50 (p < .001)	.57
Competency Beliefs	4.71_a (0.51)	4.32_a (0.51)	3.49_b (0.56)	2.69_c (1.03)	28.26 (p < .001)	.53

Note: Values with different subscripts in same row represent significantly different values based on Tukey HSD post-hoc tests. Results represent follow-up ANOVA analyses to probe a significant MANOVA value. Effect size can be interpreted as percent of variance accounted for in each individual clustering variable.

Table 7:

Configural frequency analysis for shifts from Time 1 to Time 2

Type/ Antitype	Time 1 Profile	Time 2 Profile	Observed	Expected	χ^2	*Z* score	*p*-value
T	Highly Motivated by Any Means	Highly Motivated by Any Means	7	2.8	6.30	2.51	0.01
		Intrinsically Motivated & Confident	6	8.5	0.74	0.86	0.39
		Average All Motivation	5	5.2	0.01	0.09	0.93
		Amotivated	0	1.5	1.50	1.22	0.22
	Intrinsically Motivated & Confident	Highly Motivated by Any Means	2	5.3	2.05	1.43	0.15
T		Intrinsically Motivated & Confident	25	16	5.06	2.25	0.02
A†		Average All Motivation	4	9.8	3.43	1.85	0.06
		Amotivated	3	2.9	0.00	0.06	0.95
	Average All Motivation	Highly Motivated by Any Means	4	4.4	0.04	0.19	0.85
		Intrinsically Motivated & Confident	8	13.2	2.05	1.43	0.15
T†		Average All Motivation	13	8.1	2.96	1.72	0.09
		Amotivated	3	2.4	0.15	0.39	0.70
	Amotivated	Highly Motivated by Any Means	0	0.5	0.50	0.71	0.48
		Intrinsically Motivated & Confident	0	1.4	1.40	1.18	0.24
		Average All Motivation	2	0.9	1.34	1.16	0.25
		Amotivated	1	0.3	1.63	1.28	0.20

Note: T = type; A = antitype. † indicates a marginally significant type or antitype.

Table 8:

Self-reported regulation and engagement variables for motivational profiles

	Highly Motivated by Any Means	Intrinsically Motivated and Confident	Average All Motivation	Amotivated	*F* (*p*-value)	Effect Size (η^2)	Intercept	Model Fit (-2LL)
Time 1 profile:	(n= 18)	(n = 34)	(n = 28)	(n = 3)				
Behavioral Regulation	3.70_a (0.76)	3.38_{ab} (0.43)	3.19_b (0.64)	3.00_b (0.30)	3.02 (p = .04)	.11	3.00 (0.41)	145.89
Effort Regulation	4.15_a (0.77)	4.14_a (0.82)	3.93_a (0.93)	2.67_b (0.47)	2.19 (p = .09)	.08	2.67 (0.95)	200.74
Cognitive Engagement	4.21_a (0.76)	3.92_a (0.83)	3.66_{ab} (0.89)	2.75_b (0.17)	2.84 (p = .04)	.10	2.75 (0.59)	198.17
Time 2 profile:	(n = 13)	(n = 39)	(n = 24)	(n = 7)				
Behavioral Regulation	3.94_a (0.54)	3.40_b (0.45)	3.20_{bc} (0.42)	2.69_c (0.89)	10.09 (p < .01)	.30	2.69 (0.19)	124.96
Effort Regulation	4.38_a (0.69)	4.24_a (0.72)	3.72_{ab} (0.84)	3.39_b (1.28)	5.11 (p = .01)	.14	3.39 (0.30)	193.98
Cognitive Engagement	4.26_a (0.71)	4.18_a (0.65)	3.60_b (0.63)	2.49_c (0.98)	13.07 (p < .01)	.37	2.49 (0.27)	175.52

Note: Values with different subscripts in same row represent significantly different values based on Tukey HSD post-hoc tests. Intercept refers to random intercept term for the multilevel model; all intercept terms were significantly different than zero. -2LL indicates restricted log likelihood, which is an indication of model fit.

Table 9:

Logistic regression analysis for likelihood to drop course

	B (SE)	Wald (p-value)	Odds Ratio
Highly Motivated by Any Means (dummy)	-0.32 (0.68)	0.22 (p = .64)	0.71
Intrinsically Motivated and Confident (dummy)	-1.88 (0.92)	4.23 (p = .04)	0.15
Average All Motivation (dummy)	-0.12 (0.65)	0.03 (p = .86)	0.85
Enrollment Reason		5.67 (p = .23)	
Course Unavailable	-1.41 (1.15)	1.50 (p = .22)	0.24
Schedule Conflict	0.94 (0.74)	1.62 (p = .20)	2.55
Learner Preference	0.16 (0.66)	0.06 (p = .81)	1.17
Other	0.70 (0.69)	1.05 (p = .31)	2.02
Gender	0.03 (0.46)	0.01 (p = .95)	1.03

Note: For profile variables, the Amotivated profile served as the reference category. For enrollment reason, credit retention served as the reference category. For gender, males served as the reference category.

Table 10:

Growth curve model for achievement trajectories

	Parameter	Omnibus / Profiles	Estimate	SE
Fixed effects	Intercept		70.35^{***}	5.57
	Days Since Beginning		-0.10^{***}	0.03
	Intercept x Profile	$F(3, 542) = 7.25^{***}$		
		Highly Motivated vs. Amotivated	24.66^{***}	5.39
		Intrinsically Motivated vs. Amotivated	20.74^{***}	5.28
		Average All Motivation vs. Amotivated	17.67^{***}	5.28
	Linear trend		$-6.59^{\dagger}$	3.45
	Linear x Profile	$F(3, 542) = 2.19^{*}$		
		Highly Motivated vs. Amotivated	8.12^{*}	4.03
		Intrinsically Motivated vs. Amotivated	8.22^{*}	3.93
		Average All Motivation vs. Amotivated	3.99	3.93
	Quadratic trend		-1.74^{*}	0.80
	Quadratic x Profile	$F(3, 542) = 1.73^{\dagger}$		
		Highly Motivated vs. Amotivated	1.43	0.94
		Intrinsically Motivated vs. Amotivated	1.79*	0.91
		Average All Motivation vs. Amotivated	0.77	0.91
Random effects	Student Level			
	Intraclass Correlation		0.54	
	Intercept		175.26^{***}	31.65
	Intercept x Slope (Linear)		12.70^{*}	6.59
	Slope (Linear)		5.47^{**}	2.23
	Course Level			
	Intraclass Correlation		0.03	
	Intercept		78.41^{***}	1.55
	Residual		8.43	0.37
Model fit	-2LL		5619.07	

Note: -2LL = log likelihood ratio. Highly Motivated=Highly Motivated by Any Means profile. Intrinsically Motivated=Intrinsically Motivated and Confident profile. $^{\dagger}p < .10$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.

Table 11:

Reactions to exam feedback by motivational profiles

	Highly Motivated by Any Means	Intrinsically Motivated and Confident	Average All Motivation	Amotivated	*F* (p-value)	Effect Size (η^2)
	(n= 14)	(n= 25)	(n= 24)	(n= 5)		
Perceptions of Success	6.87_a (2.18)	7.06_a (1.51)	7.14_a (1.64)	4.17_b (1.58)	6.12 ($p < .001$)	.16
Effort	4.50_a (0.63)	4.57_a (0.48)	4.44_a (0.43)	3.00_b (0.89)	3.14 ($p = .03$)	.09
Ability	3.91_a (0.82)	4.02_a (0.85)	4.18_a (0.47)	2.50_b (0.71)	5.40 ($p = .002$)	.14
Luck	2.14 (0.92)	2.07 (0.98)	2.32 (1.10)	3.00 (1.41)	0.22 ($p = .88$)	.01
Test Difficulty	2.95 (1.11)	3.30 (0.65)	3.18 (0.66)	3.00 (2.12)	0.02 ($p = .88$)	.01
Strategy Use	3.91_a (0.92)	3.65_{ab} (0.83)	3.94_a (0.85)	2.00_b (0.71)	8.19 ($p = .005$)	.12
Teacher Quality	4.00 (1.20)	4.11 (0.94)	3.62 (1.02)	3.25 (0.35)	1.09 ($p = .36$)	.03
Happiness	3.55 (1.19)	3.74 (1.02)	3.32 (1.14)	2.25 (0.35)		
Frustration	2.45 (1.01)	2.13 (1.13)	2.65 (1.31)	3.00 (1.41)		
Sadness	2.14 (1.10)	1.63 (0.80)	2.09 (1.11)	3.00 (1.41)		
Anger	1.91 (0.97)	1.41 (0.63)	2.27 (1.24)	2.50 (0.71)		
Gratitude	3.18 (1.42)	3.33 (1.18)	2.79 (1.21)	1.75 (0.35)		

Table 11 (cont'd)

	Highly Motivated by Any Means	Intrinsically Motivated and Confident	Average All Motivation	Amotivated	*F* (p-value)	Effect Size (η^2)
Pride	3.00 (1.53)	3.37 (1.11)	3.00 (1.33)	2.00 (0.53)		
Guilt	1.36 (0.92)	1.56 (1.08)	1.50 (0.88)	1.25 (0.35)		
Shame	1.45 (0.96)	1.48 (0.98)	1.97 (1.17)	2.75 (0.35)		
Hopelessness	1.32 (0.90)	1.35 (0.75)	1.68 (1.03)	2.25 (1.06)		
Relaxation	2.64 (3.18)	3.17 (1.29)	2.74 (1.43)	1.75 (0.35)		
Surprise	2.50 (0.95)	2.70 (0.94)	2.38 (1.21)	2.50 (0.71)		
Joy	3.14 (1.34)	3.43 (1.04)	2.82 (1.22)	2.00 (0.71)		
Contentment	3.36 (1.27)	3.41 (1.29)	2.94 (1.25)	1.50 (0.85)		

Note: Analyses were conducted when controlling for exam scores on the first two exams (covariate assessed at 79.06). Values with different subscripts in same row represent significantly different values based on Tukey HSD post-hoc tests. Results from attributions represent follow-up ANOVA analyses to probe a significant MANOVA values; after Bonferroni corrections, *p*-values less than .005 were considered significant. The omnibus MANOVA for emotions was not significant.

Table 12:

Bivariate correlations between changes in profile membership from Time 1 to Time 2 (as assessed by changes in post-probabilities), exam achievement, and reactions to exam feedback

	Δ Highly Motivated	Δ Intrinsically Motivated	Δ Average All Motivation	Δ Amotivated	Mean (SD)
Exam Score	0.11	0.16	-0.22	-0.03	
Perceptions of Success	0.24*	-0.02	-0.24*	0.01	6.74 (1.67)
Effort	0.06	0.27*	-0.32*	-0.07	4.45 (0.57)
Ability	0.19	-0.11	-0.09	0.01	3.99 (0.80)
Luck	-0.09	0.05	0.13	-0.20	2.20 (1.01)
Test Difficulty	0.08	0.03	-0.05	-0.15	3.18 (0.83)
Strategy Use	0.08	0.32*	-0.43**	0.01	3.74 (0.91)
Teacher Quality	-0.10	0.23	-0.23	0.13	3.90 (1.02)
Happiness	0.17	0.03	-0.22	0.02	3.51 (1.10)
Frustration	-0.25*	0.12	0.17	-0.06	2.40 (1.17)
Sadness	-0.28*	0.15	0.20	-0.14	1.93 (1.01)
Anger	-0.24*	0.19	0.09	-0.06	1.83 (0.99)
Gratitude	0.10	-0.02	-0.09	0.01	3.07 (1.25)
Pride	0.30*	-0.20	-0.08	-0.07	3.12 (1.27)
Guilt	-0.04	-0.22	0.27*	-0.01	1.49 (0.95)
Shame	-0.01	-0.22	0.28*	-0.07	1.68 (1.05)
Hopelessness	-0.01	-0.20	0.30*	-0.16	1.48 (0.89)
Relaxation	0.31*	-0.11	-0.17	-0.09	2.87 (1.32)
Surprise	0.04	-0.15	0.01	0.22	2.55 (1.01)
Joy	0.18	-0.12	-0.07	0.02	3.12 (1.18)
Contentment	0.08	0.03	-0.07	0.02	3.18 (1.29)

Note: for these analyses, $n = 47$. Δ Highly Motivated=Change in the post-probability of membership in the Highly Motivated by Any Means profile. Δ Intrinsically Motivated = Change in the post-probability of membership in the Intrinsically Motivated and Confident profile. Exam score represents average score on first two exams, and was measured on a 100-point scale. Perceptions of success were measured on a 10-point scale. All other variables were measured on a 5-point Likert-type scale. $^{*}p < .05$; $^{**}p < .01$.

Table 13:

Predicting self-report variables by Principal Components Analysis factors

	Behavioral Regulation (β)	Effort Regulation (β)	Cognitive Engagement (β)
Step 1: Main Effects			
Factor 1	.35***	.40***	.50***
Factor 2	.04	.00	-.07
R^2	.22	.15	.19
Step 2: Interaction			
Factor 1 x Factor 2	.20*	.11	.23*
ΔR^2	.07	.01	.04

Note: Factor 1 represents items associated with mastery goals, task value, and competency beliefs. Factor 2 represents items associated with performance-approach and performance-avoidance goals. $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$. For all three models, R^2 for Step 1 was significant at $p < .01$. For behavioral regulation and cognitive engagement, ΔR^2 for Step 2 was significant at $p < .05$.

Table 14:

Growth curve model for achievement trajectories with Principal Components Analysis factors and profiles as predictor variables

	Parameter	Omnibus / Profiles	Estimate	SE
Fixed effects	Intercept		72.95***	5.21
	Days Since Beginning		-0.13***	0.03
	Intercept x Profile	$F(3, 542) = 7.35^{***}$		
		Highly Motivated vs. Amotivated	26.07***	4.61
		Intrinsically Motivated vs. Amotivated	23.86***	4.50
		Average All Motivation vs. Amotivated	19.02***	4.53
	Factor 1		-2.20†	1.16
	Factor 2		-0.44	1.15
	Factor 1 x Factor 2		0.10	1.15
	Linear trend		-6.78†	3.62
	Linear x Profile	$F(3, 542) = 2.57^{*}$		
		Highly Motivated vs. Amotivated	8.75*	4.16
		Intrinsically Motivated vs. Amotivated	10.22*	4.08
		Average All Motivation vs. Amotivated	6.05	4.07
	Linear x Factor 1		0.18	1.07
	Linear x Factor 2		-1.81	1.07†
	Linear x Factor 1 x Factor 2		2.12	1.08†
	Quadratic trend		-1.98**	0.70
	Quadratic x Profile	$F(3, 542) = 2.18^{\dagger}$		
		Highly Motivated vs. Amotivated	1.62*	0.81
		Intrinsically Motivated vs. Amotivated	2.24**	0.79
		Average All Motivation vs. Amotivated	1.21	0.79
	Quadratic x Factor 1		0.12	0.21
	Quadratic x Factor 2		-0.48*	0.22
	Quadratic x Factor 1 x Factor 2		0.57**	0.22

Note: Highly Motivated=Highly Motivated by Any Means profile. Intrinsically Motivated= Intrinsically Motivated and Confident profile. $^{\dagger}p < .10$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.

APPENDIX B

Figures

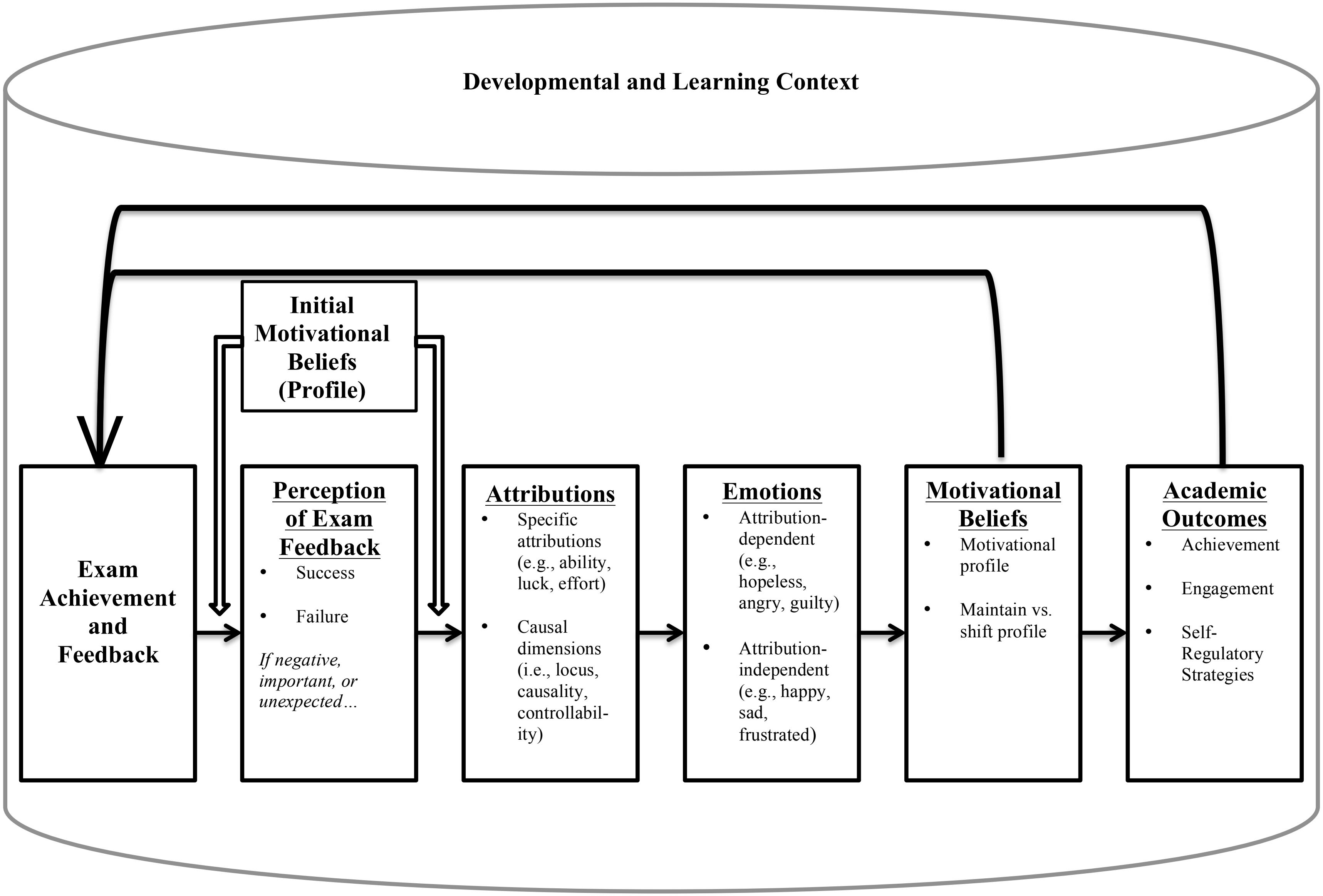

Figure 1: *A contextualized model of profile stability*. Block arrows represent hypothesized moderator effects (RQ 2).

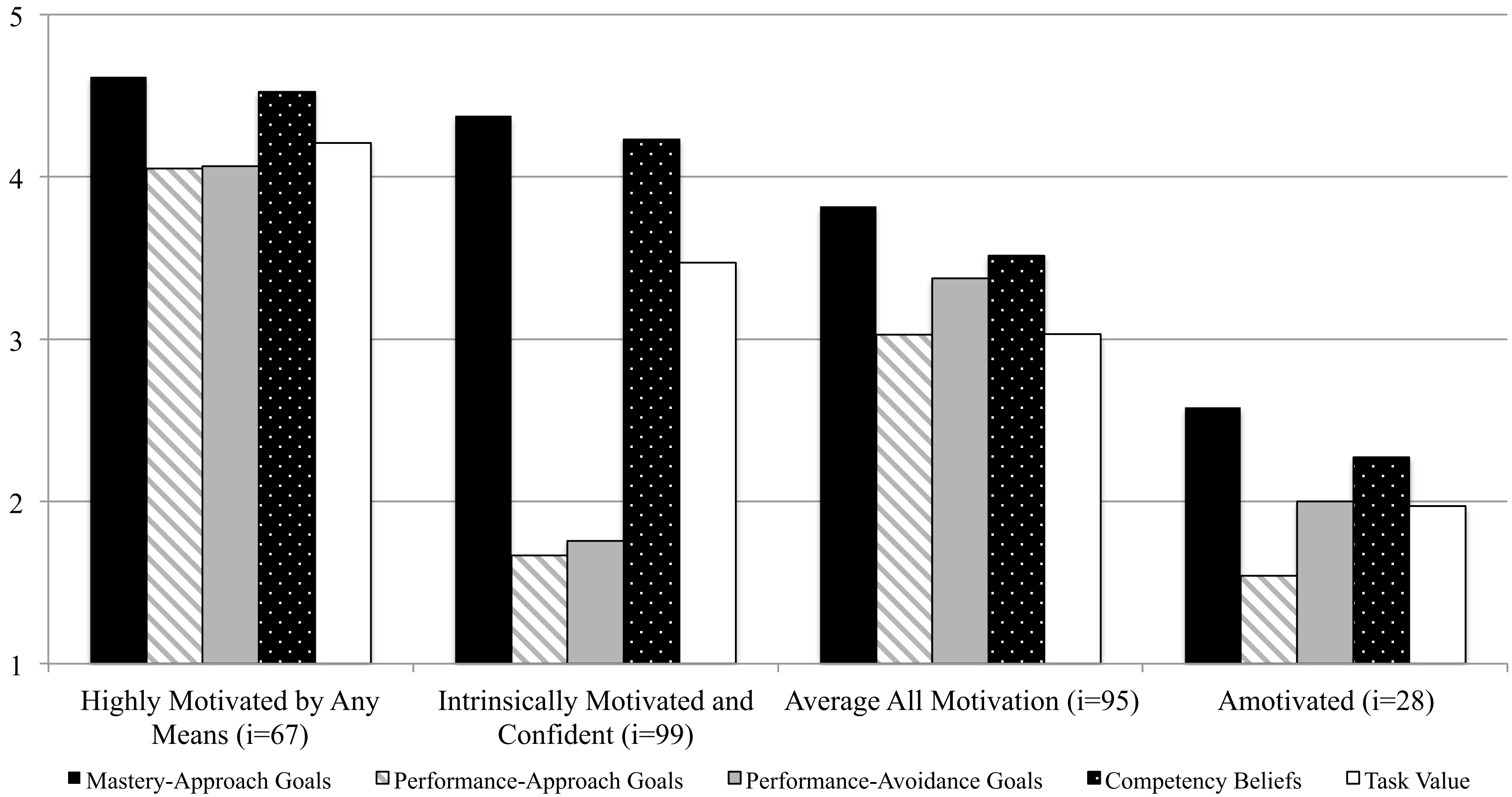

Figure 2: *Raw scores for time-invariant motivational profiles*. Motivational variables were measured on a 5-point Likert-type scale. *i* refers to i-states in each profile.

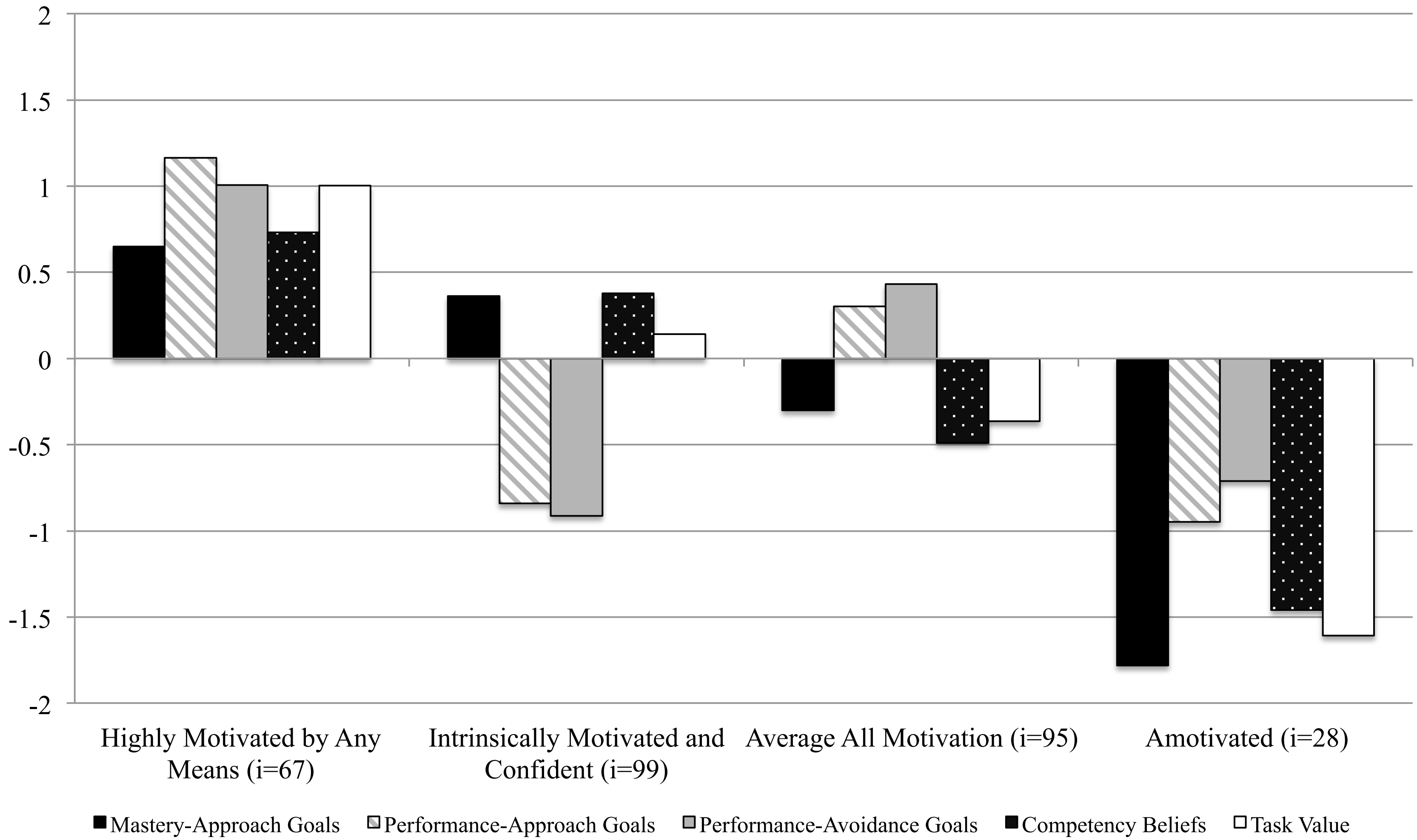

Figure 3: *Standardized Z scores for time-invariant motivational profiles*. *i* refers to i-states in each profile.

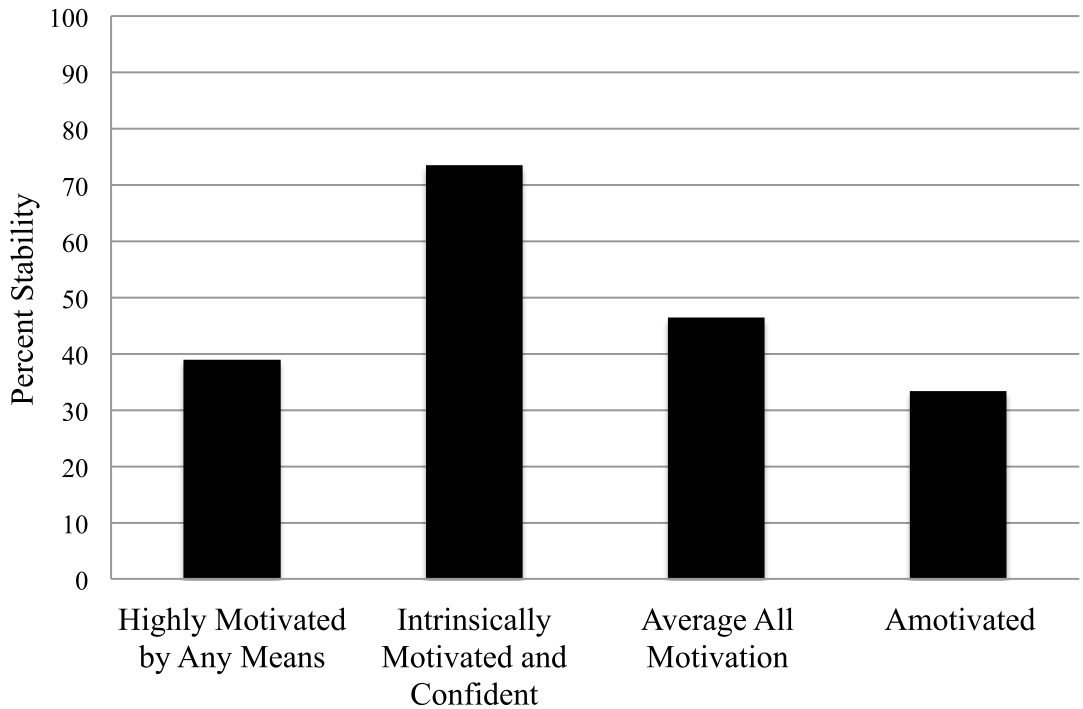

Figure 4*: Profile stability from Time 1 to Time 2.*

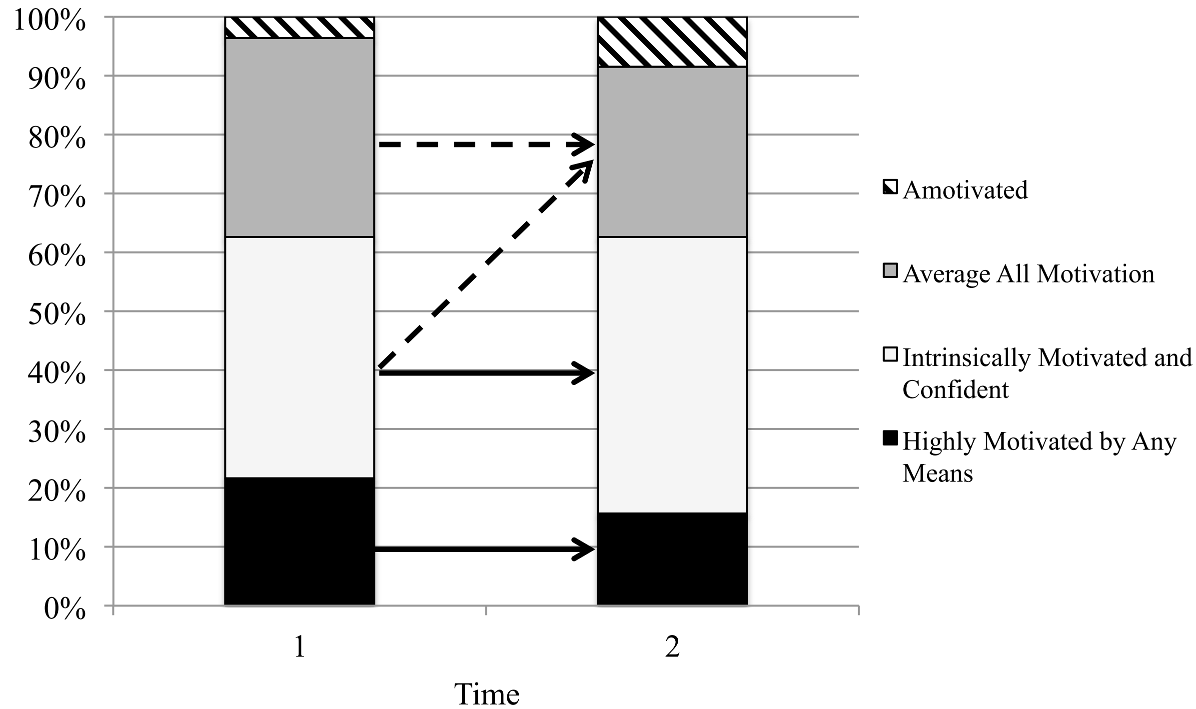

Figure 5: *Profile shifts from Time 1 to Time 2*. Solid arrows represent significant types. Dashed arrows represent marginally significant types and antitypes.

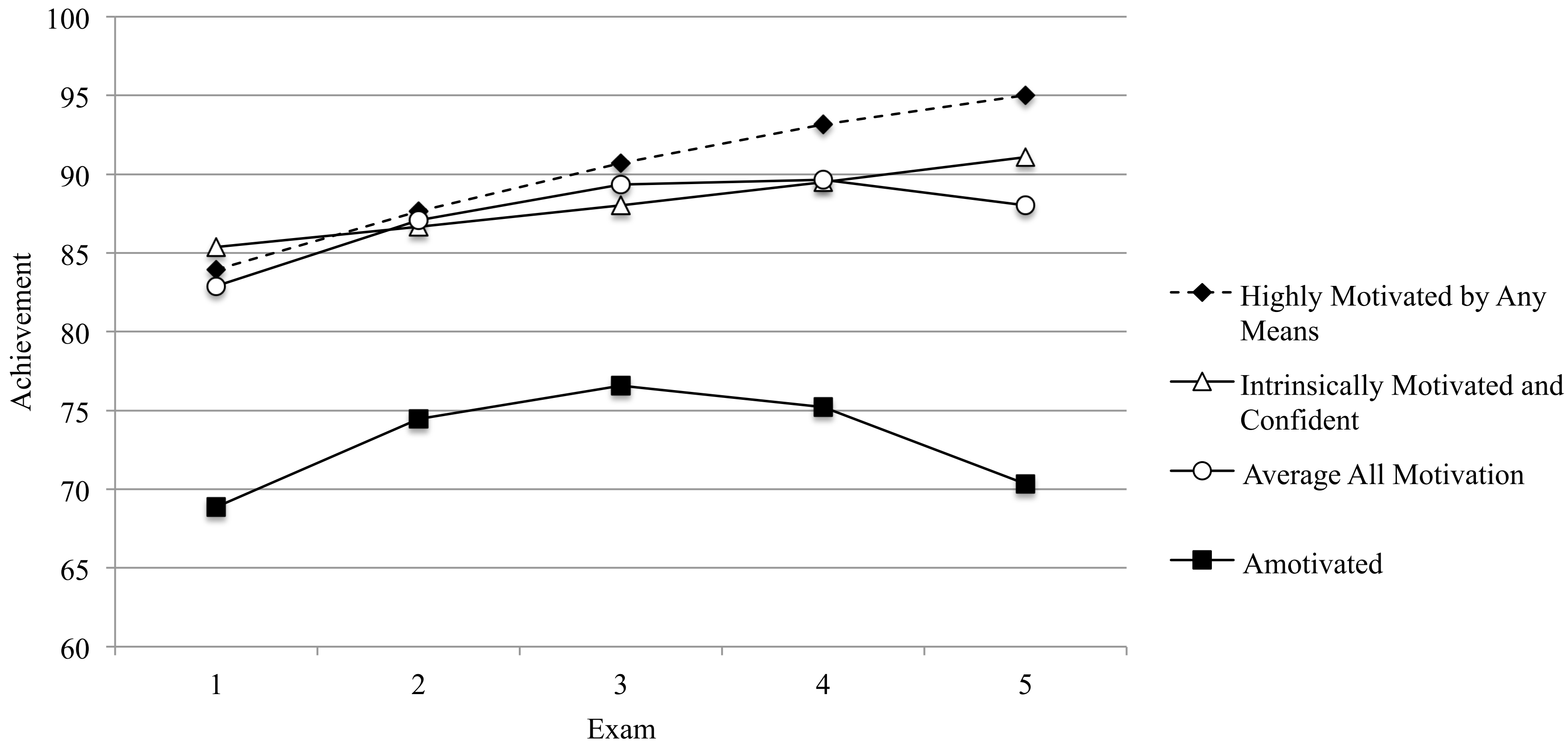

Figure 6: *Model-implied exam achievement trajectories by motivational profile*. Achievement was assessed on a 0-100 scale.

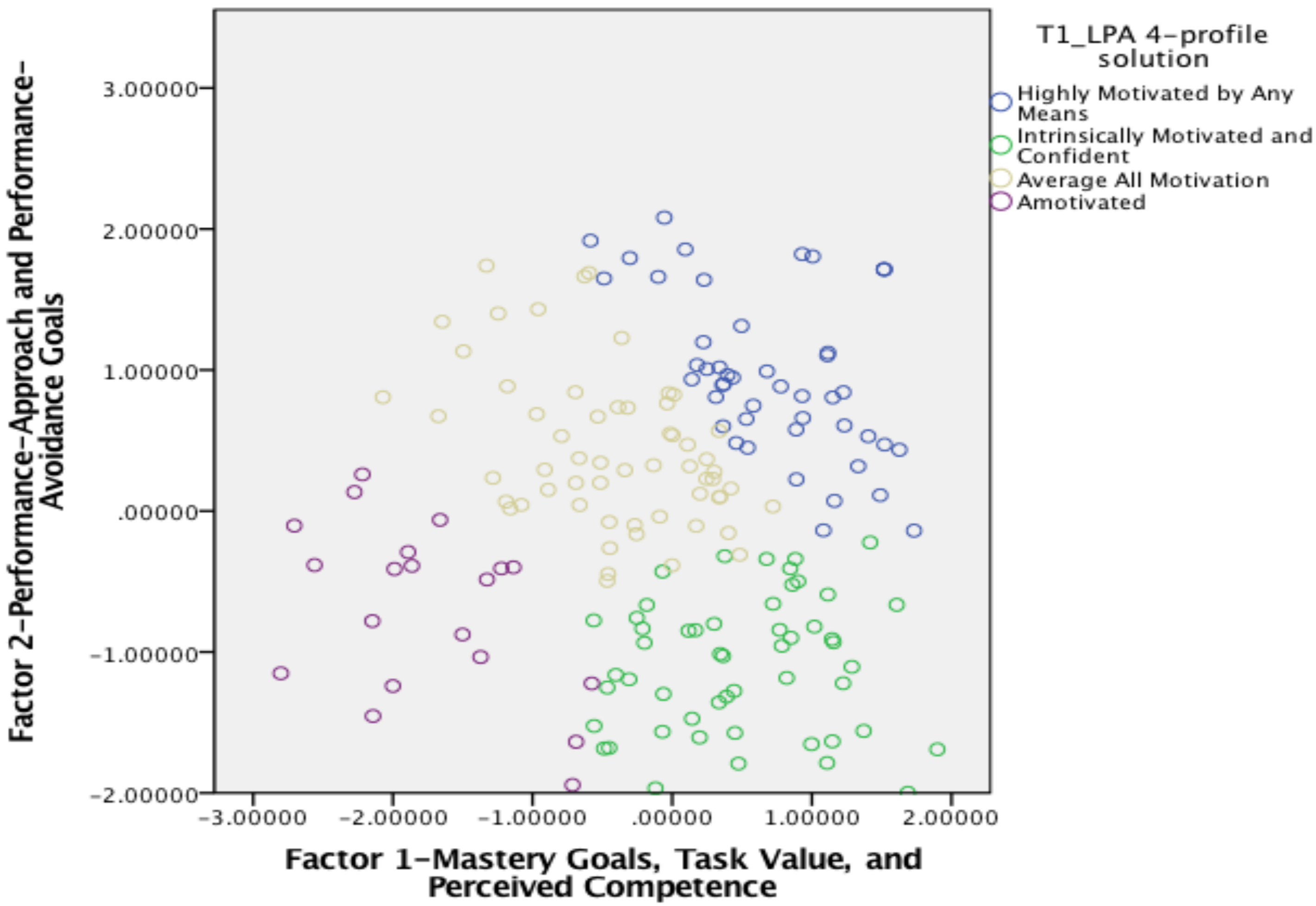

Figure 7: *Time 1 motivational profiles plotted by principal component factors*.

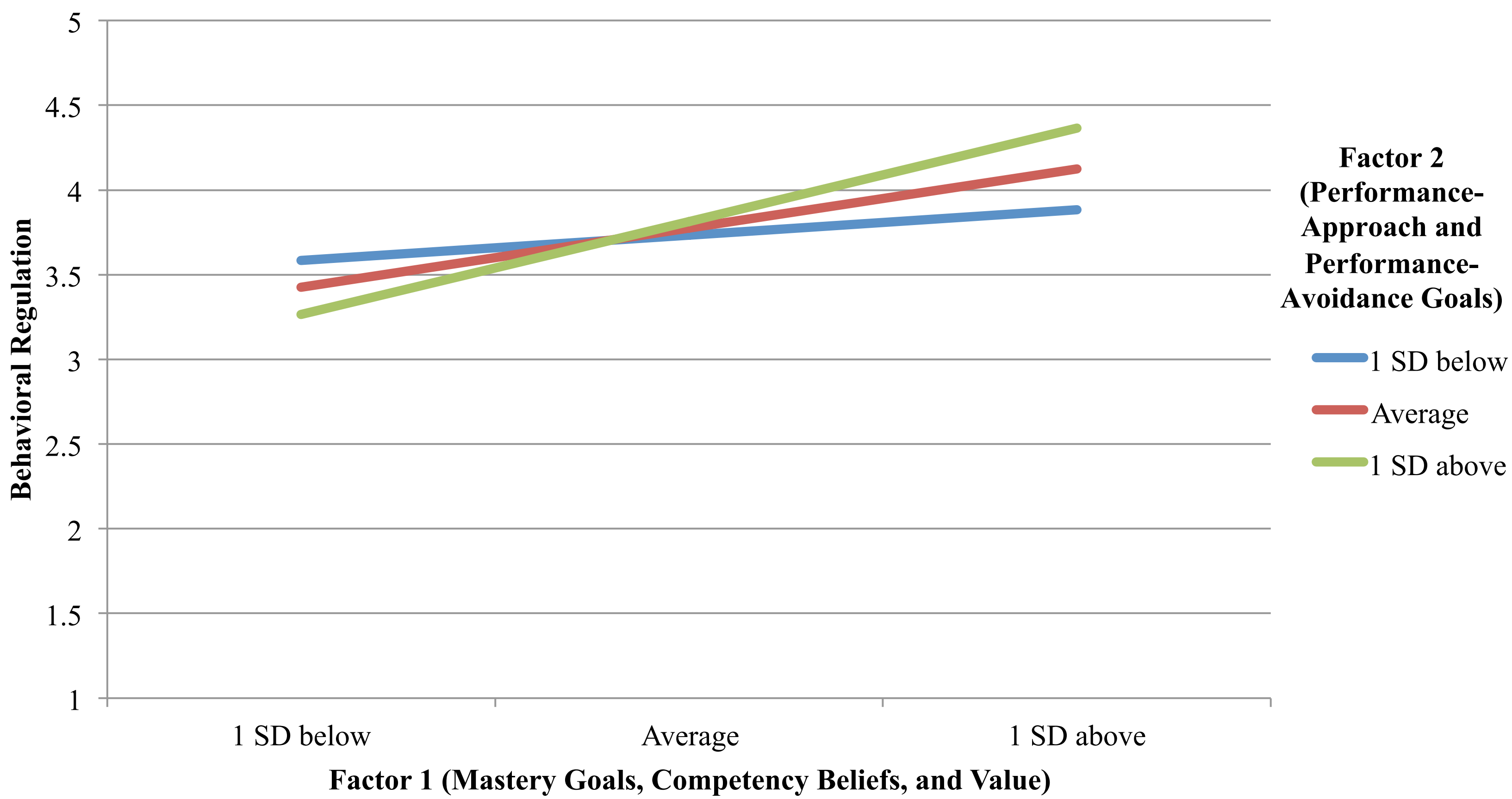

Figure 8: *Time 2 behavioral regulation plotted by principal component factors*. Behavioral regulation was assessed on a 5-point Likert-type scale.

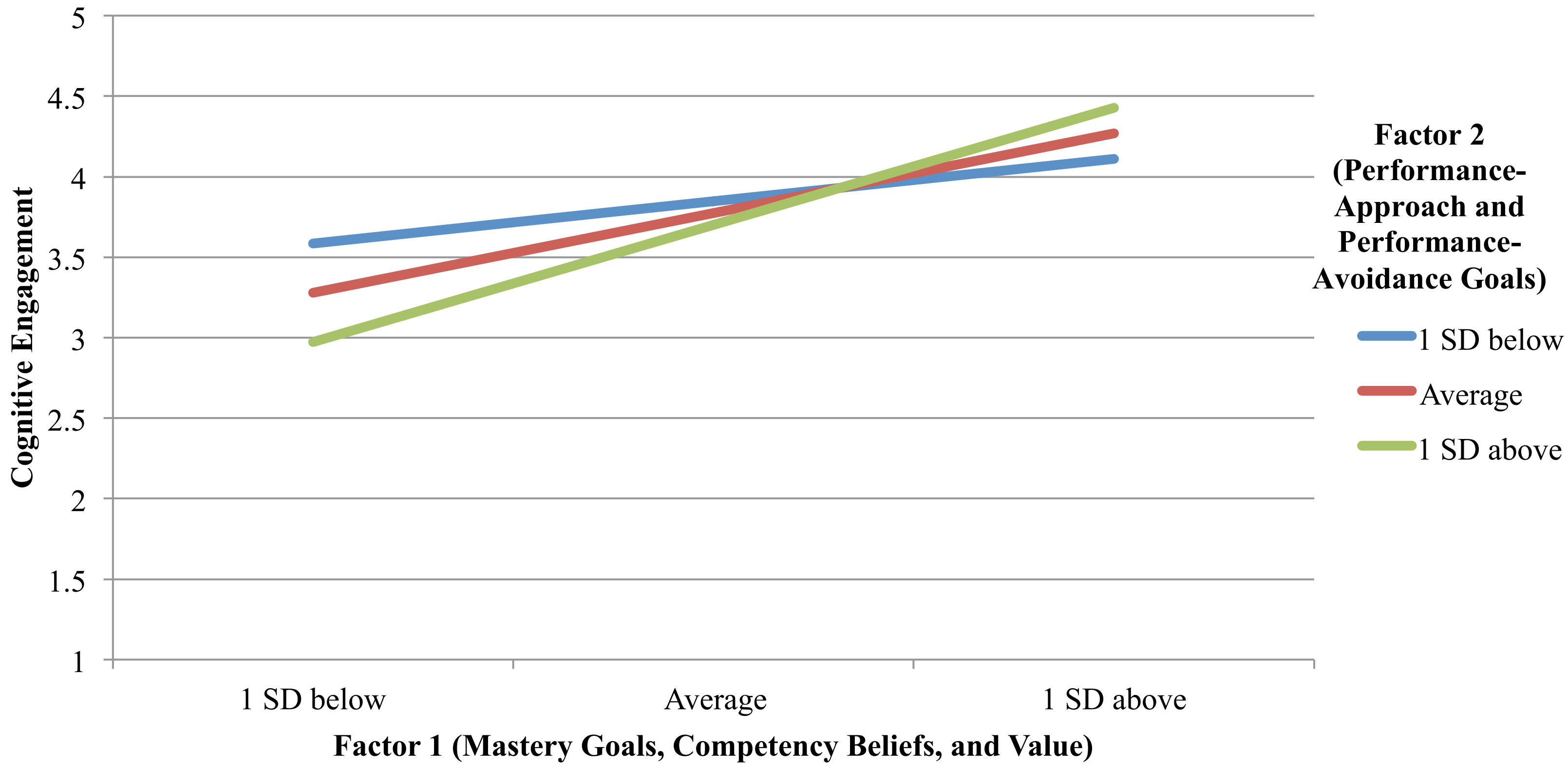

Figure 9: *Time 2 cognitive engagement plotted by principal component factors*. Cognitive engagement was assessed on a 5-point Likert-type scale.

APPENDIX C

Study Measures

Achievement Goal Orientations (Midgley et al., 2001)

Mastery Goals

1. It's important to me that I learn a lot of new concepts this semester in math.
2. One of my goals in math class is to learn as much as I can.
3. It's important to me that I improve my skills in math this year.
4. One of my goals is to master a lot of new skills in math this year.
5. It's important to me that I thoroughly understand my class work in math.

Performance-Approach Goals

1. One of my goals is to look smart in comparison to the other students in my math class.
2. It's important to me that other students in my math class think I am good at my classwork.
3. One of my goals is to show others that math class work is easy for me.
4. It's important to me that I look smart compared to others in my math class.
5. One of my goals is to show others that I'm good at my math class work.

Performance-Avoidance Goals

1. One of my goals in class is to avoid looking like I have trouble doing the work in math.
2. It's important to me that my teacher doesn't think that I know less than others in math class.
3. One of my goals is to keep others from thinking I'm not smart in math class.
4. One of my goals is to keep others from thinking I'm dumb in math class.

Task Value-Abbreviated Version (Linnenbrink-Garcia et al., 2010)

1. What I am learning in math is exciting to me.
2. Being good at math is an important part of who I am.
3. I like what I am learning in math.
4. It is important to me to do well in math.
5. For me, doing well in math is very important.
6. I enjoy what I am learning in math.
7. The things I learn in math are practical for me to know.
8. I think the things I learn in math are useful.
9. The things I learn in math help me in my daily life outside of school.

Perceived Competence (Midgley et al., 2001)

1. I'm certain I can figure out how to do the most difficult math class work.
2. Even if the work in math is hard, I can learn it.
3. I can do even the hardest work in math if I try.
4. I'm certain I can master the skills taught in math this semester.
5. I can do almost all the work in math if I don't give up.

Behavior Regulation (Pintrich et al., 1991)
1. I studied in a place where I could concentrate on course work.
2. I made good use of my study time for this course.
3. I found it hard to stick to a study schedule for this course.
4. I had a regular place set aside to study for this course.
5. I made sure I kept up with the weekly readings and assignments for this course.
6. I often found that I didn't spend very much time studying for this course because of other activities.

Effort Regulation (Linnenbrink, 2005)
1. Even when my coursework was dull and uninteresting, I kept working until I finished.
2. Even when I didn't want to do my course readings and assignments, I forced myself to do the work.
3. Even if I didn't see the importance of a particular course reading or assignment, I still completed it.
4. I forced myself to finish my coursework even when there were other things I'd rather be doing.

Cognitive Engagement (Linnenbrink, 2005)
1. When I do math work, I check over my work for mistakes.
2. If I don't understand what I read in math, I go back and read it over again.
3. Before I start my work in math, I look through the materials to see how I should organize my work.
4. When I do work in math, I ask myself questions to help me understand what to do.
5. When I become confused about something I'm learning in math, I go back and try to figure it out.
6. When I make a mistake in math, I try to figure out where I went wrong.
7. When I do work in math, I try to figure out which things I don't really understand.
8. I ask myself questions to make sure I understand the material I've been studying or reading in math.

Perceptions of Exam Achievement (Nicholls, 1976)
To what extent did you *succeed* on this exam?

Exam-Related Attributions (Perry et al., 2008; van Overwalle, 1989; Weiner, 1985)
To what extent did the following contribute to your performance?
- -Effort
- -Ability
- -Luck
- -Test Difficulty
- -Strategy Use
- -Teacher Quality

Exam-Related Emotions (Linnenbrink, 2005)
After receiving this grade on my exam, I feel:
-Happy (attribution independent)
-Frustrated (attribution independent)
-Sad (attribution independent)
-Angry
-Grateful
-Proud
-Guilty
-Ashamed
-Hopeless
-Relaxed
-Surprised
-Joyful
-Content

Lowest Possible Exam Score
What is the lowest possible grade you could have received on this exam and still considered it a success?

Technology Self-Efficacy (UTAUT; Venkatesh et al., 2003)
I could complete an assignment using this website if:
1. There was no one around to tell me what to do as I go.
2. I could call someone for help if I got stuck.
3. I had a lot of time to complete the assignment for which the website was provided.
4. I had just the built-in help facility for assistance.

Emotion Regulation (Gross & John, 2003)
Reappraisal
1. When I want to feel more positive emotion (such as joy or amusement), I change what I'm thinking about.
2. When I want to feel less negative emotion (such as sadness or anger), I change what I'm thinking about.
3. When I'm faced with a stressful situation, I make myself think about it in a way that helps me stay calm.
4. When I want to feel more positive emotion, I change the way I'm thinking about the situation.
5. I control my emotions by changing the way I think about the situation I'm in.
6. When I want to feel less negative emotion, I change the way I'm thinking about the situation.

Suppression
1. I keep my emotions to myself.
2. When I am feeling positive emotions, I am careful not to express them.
3. I control my emotions by not expressing them.
4. When I am feeling negative emotions, I make sure not to express them.

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