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UNIVERSITY OF CALIFORNIA,
IRVINE

Classification of Motivational Dispositions:
A Psychological Systems Perspective of Academic Behavior

DISSERTATION

submitted in partial satisfaction of the requirements
for the degree of

DOCTOR OF PHILOSOPHY

in Education

by

Osman Umarji

Dissertation Committee:
Distinguished Professor Jacquelynne Eccles, Chair
Professor Mark Warschauer
Associate Professor Drew Bailey

2019

DEDICATION

To

my wife, my children, and my parents

in recognition of their endless love and support

Behaviors are motivated and evaluated by their intentions, and every person will be rewarded to the extent of their intention.

Prophet Muhammad

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I would also like to thank my committee members, Professor Mark Warschauer and Professor Drew Bailey. Mark, you taught me think big about data and to consider the role of technology in education. Your frequent visits to my office to discuss the state of the NBA were always the perfect break from staring into covariance matrices and writing. Drew, you didn't discuss basketball as often as Mark, but you could play better than any professor I know. You regularly dropped academic wisdom on the court as often as your assists. You made me a better methodologist and causal thinker. I also would like to thank Distinguished Professor Greg Duncan for the advice and wisdom you would share on our walks around campus. Your research on poverty motivated me to further engage my religious community to address local poverty.

There were other scholars beyond UCI that I am thankful for. I am incredibly grateful to Stephen Peck for teaching me cluster analysis and person-centered research. I would also like to thank Katariina Salmela-Aro, for hosting me in Finland to learn experience sampling methods.

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Finally, and most importantly, I thank God for the circumstances He placed me in that allowed me to pursue and complete my doctorate. Nothing in this life happens except by His will and power.

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Osman Umarji

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Committee Members: Jacquelynne Eccles, Mark Warschauer, Drew Bailey
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Quantitative research methodology

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University of California, Irvine

Graduate Researcher, Next-Gen Undergraduate Success Measurement Project
2018-2019

PI: Dr. Richard Arum

Conduct literature reviews, create new measures, and lead the experience sampling component of the study to investigate the experiences of undergraduate students receiving a liberal arts education. Investigate methods to bring survey data, learning management systems data, and administrative data together to better understand the undergraduate experience.

Graduate Researcher, California Motivation Project (CAMP)
2018

PI: Dr. Jacquelynne Eccles, Dr. Stuart Karabenick

Use advanced statistical techniques to analyze longitudinal data from elementary school to high school of an ethnically diverse sample. Analysis include growth curve models, mixture models, and hierarchical models of student motivation and academic outcomes. Produce research on the effects of teacher and classroom context on student motivation.

Graduate Researcher, Reading for Understanding
2017-2018

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Umarji, O. (2016, October). The Diversity of Islam in America. Religious Studies. Irvine, CA.

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Umarji, O. (2013, July). Legal Taxonomies and the Objectives of Religious Law. Santa Ana, CA

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Umarji, O. (2011, November). Introduction to Islam. St. Mary's University, School of Religious Studies, San Antonio, TX.

Umarji, O. (2011, November). The Role of Women in Islam and Western Society. Trinity University, San Antonio, TX.

Umarji, O. (2011, November). The Power of Patience. Muslim Children Education and Civic Center, San Antonio, TX.

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ABSTRACT OF THE DISSERTATION

Classification of Motivational Dispositions:
A Psychological Systems Perspective of Academic Behavior

By

Osman Umarji

Doctor of Philosophy in Education

University of California, Irvine, 2019

Distinguished Professor Jacquelynne Eccles, Chair

Academic motivation is a complex psychological construct. It is multifaceted, hierarchical, dynamic, and developmental in nature. Students exhibit substantial heterogeneity in the ways in which academic motivation develops and manifests in short and long-term behavior. Much of the prior literature has considered motivated behavior in an academic subject like math to be the result of math motivation alone. This dissertation draws from the Eccles' expectancy-value theory of achievement motivation, which posits that academic behavior is the result of subjective psychological perceptions of competence and task-value, in order to investigate the hierarchical and dynamic nature of motivational dispositions and their associations with academic behavior. In Chapter 2, I use variable and person-centered approaches to investigate the development of math and English self-concept of ability throughout adolescence and their dual role in the process of selecting a college major. I demonstrate that the relationship between math and English self-concept changes over time, from being positively correlated to uncorrelated to negatively correlated between sixth and twelfth grade. Cluster analyses uncover heterogeneity in the patterns of math and English self-concept that students hold, and these clusters are predictive of the college major that students eventually select. The cluster also reveal

gender differences in self-concept hierarchies that ultimately relate to college major choice. In Chapter 3, I use longitudinal structural equation modeling to study the development of academic task-values in high school. I focus on the role of dimensional comparisons, which refer to cross-domain influences, across the domains of math, English, biology, and physical science. Results indicate that achievement relates to cross domain subjective task values (STV), and STV in 10th grade relates to cross domain STV in 12th grade. STVs in 12th grade relate to college major choice. In Chapter 4, I use cluster analysis and hierarchical logistic regression to investigate daily academic behavior in an undergraduate online course. I synthesize theories of motivated behavior and demonstrate that unique profiles of subjective task values and emotions relate to both expectations of task attainment and actual task attainment. In Chapter 5, I conclude with some critiques regarding the scientific study of motivation, such as problems with modeling latent constructs using linear models. I then present a dynamic systems approach from the physics to modeling human motivation.

CHAPTER 1

INTRODUCTION

Motivation is a strange thing. The concept is ubiquitous, its importance is well-known, but measuring and modeling it to explain behavior remain challenging and debated. In the lives of adolescents, who have numerous personal, family, social, academic, and extracurricular responsibilities, determining how to allocate their time and energy towards academics relates to their motivation towards these responsibilities. Every day, semester, and year, adolescents juggle minor and major questions such as *“How much energy do I want to spend on school work today? What classes do I want to take next semester? What should I take as an elective, creative writing or statistics? What major should I select in college?”* Motivation, in its most basic sense, is the study of action (Eccles & Wigfield, 2002), and can be considered the process by which goal-directed activity is instigated and sustained (Schunk, Pintrich, & Meece, 2012).

Motivation theorists attempt to explain people’s intentions, choices, and persistence in activities based on individual and social factors. Many prominent theories emphasize people’s perceptions of ability as key motivators of behavior (Bandura, 1977; Weiner, 1985), whereas other theories posit that people’s core values are more central motivators of action (Allport, 1961; Kluckhohn, 1951; Rokeach, 1973; Williams, 1979; Locke, 1991). Expectancy-value theory (Eccles et al., 1983; Feather, 1982) has considered both expectancies for success and subjective task-values as integral components of motivated academic behavior. Expectancies refer to feelings of competence towards an academic task, and values refer to the incentives and reasons for task engagement (Eccles & Wigfield, 2002). Both expectancies and subjective task values are posited to influence performance and task choice directly (Eccles & Wigfield, 2019). In this dissertation, I seek to investigate these psychological determinants of motivated academic

behavior, including the development of domain specific ability beliefs (i.e., expectancies) and subjective task-values through adolescence, their relation to college major selection, and the role of task-specific motivation and emotions on daily academic behavior in college.

Hierarchies and Dynamic Systems of Motivation

Psychological processes, including motivation, have been theorized as hierarchical and dynamic mental systems that unfold over time (Hamaker & Wichers, 2017). Seminal literature on ability beliefs (i.e., expectancies) and values have posited the existence of hierarchies that exist within a person. Self-concept of ability was theorized to be organized, multifaceted, and hierarchical (Shavelson, Hubner, & Stanton, 1976), and recent empirical work has demonstrated that domain-specific academic self-concepts influence one another (Möller & Marsh, 2013) in a dynamic fashion. Similarly, values have been posited to be hierarchical and coalesce into value systems (Rokeach, 1973), although most empirical work on academic values has substantially neglected this notion. The nature of hierarchical value development has received little attention since seminal work by Rokeach, and the role that value systems play in motivated academic behavior has also been sparse, as the vast majority of studies have considered single domain analyses. The incongruence between applied research and theory is problematic. Schwartz (2013) criticized this method of focusing on relations between single values and behavior, claiming that such research leads to a piecemeal accumulation of information that is not productive to the development of coherent theories. According to Schwartz, without a broad theory of the relations between values, it is possible that omitted values are just as important to understanding behavior as the single value included. Lastly, single-value approaches neglect the assumption that behavior is not guided by the priority given to a single value, rather through tradeoffs among competing values related to the behavior under consideration. Eccles (1994,

p.541) also criticized a narrow, single domain approach to understanding motivated behavior through the analysis of a single motivational construct as it pertained to motivation differences between men and women. “It is assumed that the decision to take advanced math is based primarily on variables related to math. We explicitly reject this assumption, arguing instead that it is essential to understand the psychological meaning of the roads taken, as well as the roads not taken, if we are to understand the dynamics leading to the differences in women’s and men’s achievement related choices.”

Dynamic systems theory may help conceptually explain the complex, dynamic nature of motivational processes. Dynamic systems theory considers modeling of complex multicomponent systems as they change over time. “The core premise is *self-organization*, which refers to the spontaneous emergence of coherent, higher order patterns resulting from recursive interactions among simpler components intrinsic to a complex, dynamic system” (Badcock, 2012, p. 14). An example of applying the conceptual aspect of dynamic systems theory to motivation would be to simultaneously consider the role of motivational constructs across multiple domains as influencing one another over time. In this case, consideration is not to a single domain such as math, but to interactions between constructs such as math and English motivation as mutually influencing the other, until the system stabilizes, and a coherent motivational disposition has been established. This dissertation seeks to contribute to the literature by bringing attention to these motivational hierarchies and dynamic motivational systems that change over time and influence behavior.

Heterogeneity and Individual Differences in Motivation

Another issue in conceptualizing the complex human behavior of motivation is the inherent heterogeneity of how, when, where, and under what circumstances motivation develops.

In the context of academic behavior, a young child may be single-minded from a young age about his or her desire to be a doctor or teacher, whereas other students may still be trying to figure out what to major in as they enter college. Motivational differences between genders have been consistently observed, where men have typically been more inclined than women to majors such as physics and engineering, whereas women have been more inclined than men towards language arts majors and biological sciences (Cheryan, Ziegler, Montoya, & Jiang, 2016). What explains these differences in when and for whom motivation develops? To address these types of questions, psychologists have suggested differences in socialization processes, actual ability, ability self-perceptions, and value differences, and a host of other systematic societal reasons (Eccles, 1994). Theories of motivation have considered developmental factors that influence academic motivation, such as the fit between the developmental stage that a student is at and the affordances of the environment (Eccles et al., 1993). While these perspectives consider the influences of motivation within a broad timeframe (e.g., semesters and years), motivational theories also need to consider factors that pertain to motivation in the moment or at the daily level. Although academic achievement is often measured by grades and degrees obtained, these outcomes are in fact the result of much finer grain behaviors that occur at the daily level. What motivates students on a day-to-day basis to engage with their schoolwork? Research on situational motivation has burgeoned over the past decade to explain the link from in the moment behavior to long term academic choices and persistence. For example, theories of interest have made a distinction between situation and personal interest, with the former being context-specific, whereas the latter is enduring and context-general (Hidi & Renninger, 2006; Schraw & Lehman, 2001). Similarly, research on emotions has considered the role of in-the-moment

academic emotions on academic behavior and outcomes, including the antecedents to these emotions (Ketonen & Lonka, 2012; Pekrun, 2006).

Heterogeneity has been observed in the development of academic motivation when measured over long intervals of time and in the moment. For example, over the early adolescent years, especially in middle school, average declines have been observed with respect to motivation for math, science, and literacy. Although such declines in self-concepts of ability and subjective task values are well-documented, these declines do not necessarily mean that all students are losing motivation at the same rate or experiencing homogeneous developmental changes (Gottfried, Marcoulides, Gottfried, & Oliver, 2009). In fact, focusing on average trends in student motivation may mask potential variability in these developmental processes (Wang, Cow, Degol, & Eccles, 2017). While many studies have shed light on heterogeneity in the development of motivation, most have focused on heterogeneity within a single domain, such as math (Musu-Gillette, Wigfield, Haring, & Eccles, 2015). In this dissertation, I give attention to heterogeneity in the development of motivation across multiple domains (e.g, math and English) and with respect to both long term and short term motivated behavior.

Ergodicity in Interindividual and Intraindividual Variation

The goal of psychological research is to accurately and parsimoniously explain human behavior, including feelings, beliefs, and dispositions. However, misspecification of conceptual models and incorrect application of statistical models threaten the validity of any inferences that are made. The field of psychology, including the study of motivation, has traditionally employed statistical methods that consider variation between people. The descriptive and inferential statistics derived from interindividual methods (e.g., means, correlations) explain the relations amongst variables in the sample population. A common assumption in research is that findings

from interindividual methods accurately apply to each person in the population, and thus also explain intraindividual variation. This assumption is tenable only under the strict assumption that the process under study is ergodic (Molenaar & Campbell, 2009). The assumption of ergodicity assumes that the structures of interindividual and intraindividual variation are asymptotically equivalent, and violations of this principle may lead to incorrect inferences, including the ecological fallacy. The ecological fallacy occurs when statistical inferences from groups are inappropriately generalized to individuals (Fisher, Medaglia, & Jeronimus, 2018). Some of the conditions for ergodicity to hold in psychological processes include homogeneity and stationarity. Homogeneity implies that each person in the population has to obey the exact same statistical model and stationarity implies that statistical parameters of the data, such as the mean and variance, should remain invariant over time (Molenaar & Campbell, 2009). If either of these conditions are not met, which they only are in exceptional cases, the inferences made are incorrect and we have to assume the underlying processes under study are nonergodic. Thus, in this dissertation, I utilize both variable-centered and person-centered methods to understand where these methods converge and diverge in explaining human behavior. As Molenaar (2004, p. 202) stated, “the study of scientific psychology should be focused on understanding the individual, prior to pooling across other people. Each person should be initially conceived of as a possibly unique system of interacting dynamic processes, the unfolding of which gives rise to an individual life trajectory in a high-dimensional psychological space.”

Goals of the Dissertation

The primary goal of this dissertation is to advance our understanding of academic motivation by considering motivation as dynamic and hierarchical in nature. As there are many theories and models of motivation present in the literature, I synthesize theories when

appropriate for explaining long-term and daily motivated behavior. In particular, I focus on three motivational constructs in the dissertation and their relationship with academic behavior: (1) self-concept of ability; (2) academic task-values; (3) academic emotions. In the final study, I present a model of task-specific academic motivation.

Overview of the Chapters

Chapter 2. Patterns of math and English self-concepts as motivation for college major selection

This chapter is a published study about the hierarchical development of academic self-concept and the relation between self-concept profiles and college major selection. People typically engage in tasks they believe they can succeed in, and many theories of motivation posit that ability beliefs (e.g., self-concept of ability, expectancy of success, self-efficacy) are key motivators of academic behavior. Self-concept of ability (SCA) in academic domains is known to develop throughout the formative years of schooling, yet the cooccurrence of self-concept of ability across domains, such as math and English, has been less studied. While recent literature has shown that SCA across domains may influence one another, understanding the development of SCA hierarchies that reside within students has not been studied extensively. Furthermore, the relationship between these SCA hierarchies and academic choices is also limited. This study considers both a variable- and person-centered approach to study SCA development across domains throughout adolescence.

Longitudinal data of 804 students from elementary school until college were analyzed to understand the development of math and English SCA over time and the patterns of SCA that occur at different developmental stages. Regression analysis identified a positive association of math self-concept throughout adolescence with math-related majors and a negative association of

English self-concept with math-related majors. Stereotypical gender differences were observed in cluster membership, with women overrepresented in high English clusters and males overrepresented in high math clusters. Cluster membership was predictive of the math-related college majors. Students who were higher in math self-concept of ability relative to English were overrepresented in math intensive majors. Findings support the importance of considering intraindividual hierarchies when studying the development of self-concept of ability and academic choices.

Chapter 3. Dimensional Comparisons of Academic Values in High School and College Major Choice

The selection of a college major is a pivotal life decision for students, as the major chosen will likely influence the types of occupations and career trajectories that one can attain in the future. However, majors are not selected haphazardly by students upon college entry or while in college, but rather are chosen based on various personal, social, and educational antecedents. Subjective task values are strong motivators of academic choices. Students typically select college majors based on not only what they believe they can succeed in, but also what they find interesting, useful for their careers and future, and that are important to their identity.

This study thus seeks to expand our understanding of the development of subjective task values across the domains of math, English, biology, and physical science by considering dimensional comparisons of subjective task values and their associations with college major choice. In order to answer these questions, I employ longitudinal structural equation modeling on a sample of high school students who reported their task values in 10th and 12th grade and their college major three years after high school. Results indicate that achievement in one

domain relates to some subjective task values in other domains and that subjective task values for multiple domains collectively influence college major choice.

Chapter 4. The Motivational System of Subjective Task Values and Anticipated Emotions in the Pursuit of Daily Academic Tasks

Relations between university students' domain specific motivation and their long-term academic choices and behaviors have been extensively studied. However, success in a particular course depends on students completing individual tasks and assignments on a daily and weekly basis, and little is known about how students' study intentions and motivation operate on a micro-level. As Ajzen (1993) pointed out, the principle of aggregation (i.e., the sum of a set of multiple measurements is a more stable and representative estimator than any single measurement) does not explain behavioral variability across situations, nor does it permit prediction of a specific behavior in a given situation. Therefore, relying on macro-models of motivation may not reflect micro-level motivation and behavior. As students approach academic tasks with varying levels of motivation, emotions, and priorities (Eccles et al., 1983; Pekrun, 2006), understanding the interplay of these constructs on a task-specific level is fundamentally important in developing motivational theories of achievement. Furthermore, as technology has created new learning environments, motivational theories need to consider the affordances and challenges of these contexts.

Chapter 4 investigates daily task motivation in an undergraduate online course. Whereas the previous two chapters used existing longitudinal data gathered over many years, chapter 4 utilized cutting edge methods of data collection to understand motivation at the task level over the course of one week. Intensive longitudinal data was collected using a daily diary method that involved personalized text messages with links to surveys about students' academic and non-

academic goals (e.g., tasks) for the day. Students task specific interest, opportunity cost, and anticipated emotions varied across tasks and were predictive of their expectations of task completion and actual task completion reported the following day.

Chapter 5. Final Reflections and Future Directions

The final chapter provides a summary of the findings in the dissertation and their implications for theory and practice. It also includes my final reflections on the scientific study of motivation and future research that may build on these ideas to further psychological research on motivated behavior. In particular, I critique common approaches to modeling latent variables as being inadequate to capture the true relations between latent variables and motivated behavior. Finally, I present a dynamic systems approach to modeling motivation.

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CHAPTER 2

Patterns of math and English self-concepts as motivation for college major selection

What influences students' decisions about whether to pursue a math intensive college major or a field of study requiring more language arts skills? Why do men and women have unequal representation in math intensive majors like engineering and technology? Researchers have offered many explanations to these questions that often focus on differences in academic abilities, academic self-concepts, and academic values. A large body of literature has found that math competence, by itself, is not the primary factor explaining college major choice and cannot explain gender disparities (Ceci, Williams, & Barnett, 2009; Lindberg, Hyde, Petersen, & Linn, 2010). Therefore, any sufficient explanation must include considerations beyond academic achievement. Researchers interested in academic motivation have identified ability beliefs and subjective task values as primary predictors of academic choices, above and beyond math competence and performance (Eccles & Wigfield, 2000; Guo, Marsh, Morin, Parker, & Kaur, 2015; Marsh & Yeung, 1997; Simpkins, Davis-Kean, & Eccles, 2006).

Expectancy-value theory (EVT) posits that individuals' ability beliefs and subjective task values related to various academic tasks predict academic choices, performance, and engagement across these tasks (Eccles et al., 1983; Eccles, 2009). Complementing EVT research, the internal-external frame of reference (I/E) model of academic self-concept and its newer extension, dimensional comparison theory (DCT), states that students compare their achievement between domains when making conclusions about their relative abilities (Marsh, 1986; Marsh, 1990; Möller & Marsh, 2013; Marsh et al., 2014). Therefore, higher math achievement can lead to lower verbal self-concept, and higher verbal achievement can lead to lower math self-concept

(Skaalvik & Skaalvik, 2002). Although this theory is well established, the effect of cross domain influences on future academic choices has not been studied extensively.

Most studies that have investigated the role of self-concept of ability (SCA) on academic choices have focused only on a single domain such as math or English (e.g., Archambault, Eccles, & Vida, 2010; Musu-Gillette, Wigfield, Harring, & Eccles, 2015). However, evidence from both expectancy-value theory and dimensional comparison theory suggests that cross subject area domain comparisons might influence the development of academic ability self-concepts in specific subject areas and thus also influence academic choices such as college major and occupation. When choosing which occupation to prepare for or which college major to take, one's relative SCA and subjective task values may be more important than the absolute values for the various options by themselves. Although at a between person level, the person with the highest math SCA may be more likely to major in math-intensive field than a person with a lower math SCA, at the individual level, it is likely to be relative SCA across different subject areas (e.g., math versus language) that most influences major choice.

To date, only a handful of studies have simultaneously considered multiple subject areas, and the results support the hypothesis that cross subject area comparisons help explain both individual and group differences in academic choices and gender differences (e.g., Wang, Eccles, & Kenny, 2013). However, most of these studies are not longitudinal, and the development of SCA over time across domains and its association with college major selection have not been studied to date. The present study builds on the existing literature by longitudinally investigating the development of academic ability beliefs of math and English in synchrony with each other throughout adolescence, and the extent to which these ability beliefs at various points of adolescence predict later college major selection. Additionally, we investigate gender differences

in the development of academic ability self-concepts and choices of college major. By studying underlying patterns of math and English self-concepts of ability and their relation to choice of college major, we combine expectancy-value theory and dimensional comparison theory to better understand how individual students may or may not come to identify as “math” people (meaning they identify as more of a math oriented person than an English oriented person).

Theoretical Framework

According to expectancy-value theory, achievement-related choices are directly influenced psychologically by relative expectations of succeeding in a task and the relative subjective task value associated with the task, compared to other options. Expectations for success reflect the perceived competence that an individual has in his or her ability to succeed in a domain in the near and distant future. Because expectancy for success and self-concept of ability within specific subject areas load highly on the same factor, we refer to these two highly related constructs with the term self-concept of ability when referring to perceived competence and personal efficacy. Self-concepts of ability are domain specific rather than global in nature (Wigfield et al., 1997; Marsh et al., 2015). For example, students may perceive themselves as competent in math, but not in English. Students assess their own skills by comparing their performances with those of other people and with their own performances across domains (Eccles, 2009). Furthermore, self-concepts are hierarchical in nature. For example, although a student may get high grades in multiple subjects, he or she may still feel more competent in one subject over another (e.g., math over English). Academic choices are made from a variety of options, and understanding the hierarchy of ability self-concepts is essential in understanding why a student would make one academic choice over another (Eccles, 2011).

Another theory focused on the development of self-concept of ability is the dimensional comparison theory, an extension of the internal-external frame of reference theory of self-concept (Möller & Marsh, 2013). According to the I/E model, self-concept of ability in a particular domain is informed in relation to internal and external frames of reference. The external frame of reference primarily reflects various types of social comparisons, such as when a student compares his or her perceived ability in a subject relative to the perceived ability of peers in the same subject. The internal frame of reference refers to how a student internally contrasts performance in one subject against his performance in another school subject. These internal, dimensional comparisons can result in a decreased SCA in one domain because of high achievement in another domain. For example, a student with high math achievement and low English achievement will likely develop a much higher math self-concept of ability than a student with high math achievement and even higher English achievement (Möller & Marsh, 2013). Generally, the better students perceive themselves at math, the less competent they perceive themselves at another subject like English, relative to their math SCA. DCT further adds that the farther apart two subjects are in content the larger the contrast effect will be. For example, math and English cross domain comparisons will likely be significantly more negative (contrasting) than nearer domains like math and physics, which will be less negative or possibly even positive (assimilation).

SCA, College Major, and Gender Differences

Many longitudinal studies have investigated SCA and subjective task value components in predicting academic choices such as math course taking behavior (Musu-Gillette et al., 2015; Simpkins et al., 2006). However, most studies that have investigated the role of SCA on academic choices have focused on analyzing a single domain, usually mathematics. Consistently,

math self-concept of ability predicts high school math course taking behavior (Meece, Wigfield, & Eccles, 1990; Simpkins et al., 2006; Updegraff, Eccles, Barber, & O'Brien, 1996).

Decisions about college major based on self-concepts of ability and task values likely begin to form years before entry into college, possibly as early as 6th grade (Eccles, Vida, & Barber, 2004). A few studies have investigated the extent to which high school ability self-concepts predict college major. In a recent study investigating growth trajectories of math self-concept of ability from fourth grade to college, students who maintained a high SCA in math had a 75% probability of being in a math intensive major (Musu-Gillette et al., 2015). This study did not consider the possible influence of other domains of self-concept such as English on college major.

A few recent studies have considered the dual roles of math and English ability and self-concepts of ability in determining academic choices. In an international study of American and German high school students, cross domain self-concepts in high school and gender were predictive of high school course selection, with the German sample having larger SCA and stereotypical gender differences (Nagy, Garrett, Trautwein, Cortina, Baumert, & Eccles, 2008). German students who were high in English self-concept were less likely to take advanced math courses and German students high in math self-concept were less likely to take advanced English courses. In another study looking at math and English ability and self-concepts in 12th grade and their associations with college major choice, students with high math and moderate verbal abilities were more likely to select a STEM career than students in the high math and high verbal ability group (Wang, Eccles, & Kenny, 2013). Women were more likely to be in the high math/high verbal group, possibly indicating that women had more choices based on their ability beliefs across multiple subjects. The authors suggested that frame of reference effects should be

further investigated in subsequent studies. Lauermann, Chow, and Eccles (2015) also investigated the cross-domain effects of self-concepts and values in math and English and found the combination of high perceived ability in both math and English led to a lower probability of math and science careers compared to students with high SCA in math and lower SCA in English. Although these studies looked at math and English self-concepts together, the analyses were cross-sectional and thus could not consider change over time in math and English self-concepts.

The Present Study

Researchers have recently expressed the need for more longitudinal analyses on self-concepts of ability across domains and concerns that analyses that only consider one domain such as math may be inadequate for understanding college major and occupation choices (Lauermann et al., 2015). This seems to be especially true when gender is considered, as prior research has found females to be consistently higher in English SCA than males (Jacobs, Lanza, Osgood, Eccles, & Wigfield, 2002), which may result in more females selecting majors requiring high verbal skills. Unfortunately, despite a significant amount of research stating the importance of understanding the interplay of domain specific self-concepts when studying academic choice, the literature on the subject has been sparse and limited by cross-sectional designs.

In the present study, we seek to expand upon and address these concerns by using a longitudinal study of math and English self-concept of ability from sixth to twelfth grade and then into college, using both a variable-centered and person/pattern-centered approach. Using these two different methods allows general associations to be made and individual differences to be highlighted. A person-centered approach provides a sophisticated method of investigating different clusters of math and English SCA, allowing for structural patterns of self-concepts

across subject areas to be revealed at multiple time points across adolescence. Furthermore, we examine the extent to which cluster membership is associated with college major selection. Finally, we investigate gender differences in these clusters across adolescence and in college major choice. This study allows us to determine the extent to which college major choice reflects both prior performance and SCA in the most directly related domain specific self-concept, in addition to the intraindividual hierarchy of self-concepts across different subject areas.

The three broad research questions we seek to answer are the following:

- 1) To what extent are math and English SCA generally associated with one another at different stages of adolescence, as well as with college major? Are there gender differences in math and English SCA throughout adolescence and in choice of college major?
- 2) What patterns of math and English self-concept beliefs co-occur within individual students at different stages of adolescence? Does cluster membership differ by gender at different stages of adolescence?
- 3) To what extent does self-concept cluster membership and gender relate to students' choices of a math-related college major, independent of math ability? To what extent does this relationship vary at different stages of adolescence for males and females?

We hypothesize that math and English SCA will be negatively correlated with each other at each wave (Marsh et al., 2014). Math SCA is expected to be positively associated with the level of math in college major, whereas English SCA is expected to be negatively associated with it. Females are expected to have higher English SCA than males throughout adolescence, whereas math SCA is anticipated to be higher for males throughout adolescence. Overall,

females are expected to pursue less math intensive majors than males (Lauermann, Chow, & Eccles, 2015)

For our second research question, we expect clusters to emerge with higher math self-concept relative to English, higher English self-concept relative to math, and clusters with equal self-concept in both domains. We anticipate these clusters to be quite stable throughout adolescence. We expect males to be overrepresented in clusters that are higher in math than English, and we expect females to be overrepresented in clusters that are higher in English than math (Wang, Eccles, and Kenny, 2013).

For our third research question, we hypothesize that students in clusters with higher math self-concept relative to English self-concept will pursue more math intensive majors than students who have lower math self-concept relative to English. Furthermore, we hypothesize that between clusters with equivalent math self-concept but differing English self-concept, the clusters with lower English concept will pursue more math intensive majors than clusters with higher English self-concept. For students possessing equal math and English self-concepts, females will pursue less math intensive majors. Finally, because we expect women to generally be in clusters with higher English SCA than math SCA, they will likely pursue less math intensive majors than males.

Method

Participants

The data used in this study come from the first seven waves of the Michigan Study of Adolescent and Adult Life Transitions (MSALT). MSALT is a longitudinal study that began in 1983, when participants were in the 6th grade. The data used in the analysis spans from 6th grade (approximately 11 years old) to three years after high school (approximately 21 years old). The

longitudinal sample included a total number of 2451 students in the first wave in the 6th grade, however, this study uses a subsample of 804 students who reported being in college at age 21. The subsample participants were predominantly White (91%) and 57% were female. The participants came from sixteen schools in twelve middle-class school districts in Michigan. The data used was obtained from students and school districts. Students initially completed surveys in school classrooms until the age of 18. Age 21 surveys were mailed to the participants. Grades and test scores were collected from school record data. Missing data and attrition are discussed below.

Measures

Self-concept of ability (SCA). SCA was measured for both math and English during the beginning of 6th grade, end of 7th grade, beginning of 10th grade, and the beginning of 12th grade. Three items were used to measure math SCA that assessed student perceptions about how good they were in math generally, how good they were at math compared to other subjects, and how good they were in math relative to classmates (sample items, “Compared to most of your other school subjects, how good are you at math?”, measured on a Likert scale from 1 = *not at all good* to 7 = *very good*). The three items were worded the same at every wave. Two items were used to measure English SCA (sample items, “How good are you at English”, measured on a Likert scale from 1 = *not at all good* to 7 = *very good*). The same two items were used in 6th and 7th grade (general English ability and comparison to classmates), whereas 10th and 12th grade used one different item (general English ability and comparison between domains). See Appendix I for a complete list of items.

College Major. Students filled in their major in an open-ended item asking, “What is your college major?” College major was coded from 1 to 4 for level of math required based on

an adapted version of Goldman and Hewitt’s (1976) scale for coding STEM-related majors. The adapted scale categorizes college majors based on the level of math required from (1) little to no math, (2) some math, (3) moderate math, and (4) intensive math. The level of math required per major was based on the average number of math courses required by each major. The adapted version was utilized and updated by Musu-Gillette et al. (2015). For college majors not existing in the scale, two coders independently categorized majors based on similarities with other majors. The coders initially agreed on 90% of the majors, and any discrepancies were discussed until 100% agreement was reached. 131 students had declared double majors, in which case the major with the highest level of math was considered in the analysis. Categories of college majors by level of math required are shown in Table 2.1.

Table 2.1

College majors classified based on the level of math intensiveness

Little to no math (1)	Some math (2)	Moderate math (3)	Intensive math (4)
Humanities	Psychology	Biology	Math
English/Literature	Sociology	Pharmacy	Engineering
Philosophy	Political Science	Economics	Computer Science
International Studies	Social Work	Science (other)	Chemistry
History	Nursing	Architecture	Physics
Music/Theater/Film	Health	Physiology	Finance
Foreign Languages	Anthropology	Astronomy	Accounting
Art	Counseling	Geology	Electronics

Moderators and Covariates. Gender moderation was dummy coded with males as the reference group. Math achievement was measured using the Michigan Educational Assessment Program (MEAP) scores that were reported by the school district in the 7th and 10th grade. A scale of the two math scores was created. The MEAP is a test of basic math proficiency measured from 1 to 28 ($M=25.28$, $SD=2.80$), and due to its function as a test of basic skills, the distribution is skewed to the left.

Attrition and Missing Data

The data from MSALT includes a complex pattern of complete and missing data. Of the 2451 participants from 6th grade (Wave 1), 1837 participants responded to questionnaires three years after high school (Wave 7). Of those 1837, 804 participants (44% of remaining sample) completed questionnaires indicating full-time enrollment in college with a major. Females were more likely to have remained in the study by Wave 7 than males. The participants who did not complete Wave 7 questionnaires tended to have lower levels of achievement and self-concepts of ability across multiple Waves. Of the 804 students who completed Wave 7 college questionnaires, there was significant missing data on self-concept measures (e.g., 5% in 7th grade and 45% in 12th grade). However, t-tests showed that there were no significant differences between those with missing data and complete data in SCA at other waves. Additionally, 62 students had more than 50% missing data on all SCA variables and were dropped from the analysis sample, as the imputation algorithm used required at least 50% available data. Therefore, the final sample for the profile analyses was 742. Ten students reported undecided/undeclared majors in the college survey, resulting in them being dropped from analyses regarding math intensiveness of college major.

Analysis Plan for Research Question 1

Multiple regression analyses were used to investigate the effect of self-concept of ability with the math level of college major. Gender was included as a key moderator variable and math achievement was included to isolate the predictive effect of self-concepts from actual math ability differences in predicting college major. Models were run for each of the four waves, using self-concept at each wave to predict college major. A variable-centered analysis allowed for understanding the general associations of SCA, gender, and math achievement with the outcome variable, yet it did not allow for analyzing possible individual differences in patterns of math and English self-concepts within students.

Analysis Plan for Research Question 2 and 3

To investigate self-concept of ability patterns, cluster analysis was used. Cluster analysis allowed for classifying individuals into homogeneous groups with respect to their patterns of values for dimensional self-concepts by maximizing within-cluster homogeneity and between-cluster heterogeneity (Magnusson & Törestad, 1993; Wormington, Corpus, & Anderson, 2012). Raw scores for self-concept of ability were used at each wave, as standardized estimates may eliminate the detection of developmental differences at different time points (Cairns, 1986). A multi-step analysis was carried out using ROPSTAT (Vargha, Torma, & Berman, 2015), a statistical package for pattern/person-centered analyses. The following steps were performed:

1. Preparatory steps of imputing missing data and removing outliers;
2. Hierarchical cluster analysis followed by K-means relocation clustering.
3. Random sample validation procedure to confirm cluster stability and reliability.

Missing data on self-concept variables was imputed using the twin/nearest neighbor method, which relies on the average squared Euclidean distance as a measure of proximity between cases. For cases missing a measure of self-concept of ability, data were imputed using the case of a twin, a student with complete data whose value for the variable of interest was used to impute the missing value of a neighbor. Proximity is determined based on all self-concept variables across the waves where imputation is not required (Bergman, Magnusson, & El-Khoury, 2003). This method of imputation is commonly used for handling missing data for cluster analysis (see Conley, 2012; Peck, Vida, & Eccles, 2008). After imputing the missing cases, we checked for multivariate outliers using the RESIDAN method (Bergman, 1988b), which identifies outliers prior to clustering. Hierarchical clustering methods are sensitive to outliers that may bias the hierarchical structure at any level of merging, and the cutoff point was a squared Euclidean distance greater than 0.7 (Berman et al., 2003). A small number of outliers were removed from the analysis sample.

After the preparatory steps were completed, cluster analysis was performed using Ward's method, a hierarchical agglomerative method that initially assigns each case to its own cluster and step-by-step the most similar clusters are joined together, eventually resulting in one cluster with all cases (Clatworthy, Buick, Hankins, Weinman, & Horne, 2005). Ward's method is based on squared Euclidian distances to create a similarity/dissimilarity matrix, aiming to minimize the within-cluster sum of squares (Wormington et al., 2012). Additionally, it makes no assumptions about the nature of the data being used. In order to determine the most suitable cluster solution, both a priori theorizing of clusters and statistical considerations based on the percent of variance explained were considered. The error sum of squares (ESS), a measure of cluster heterogeneity, and the explained error sum of squares (EESS) were calculated for all possible cluster solutions.

$$EES = 100 * ((\text{TotalESS} - \text{ESS of the given cluster solution}) / \text{TotalESS})$$

An EESS value of 100 implies perfect cluster homogeneity, whereas 0 implies the complete absence of cluster homogeneity (Bergman et al., 2003). ESS values were plotted against EESS values to display an array of possible cluster solutions based on how much additional error was included by reducing a cluster from the previous solution. This analysis was carried out at every wave independently, as it is possible that a different number of clusters would emerge at different developmental stages.

K-means clustering was performed to fine-tune cluster homogeneity by reassigning cases to the optimal cluster. In K-means clustering, the number of clusters is chosen before relocation using the initial hierarchical method. Centroids (i.e., profiles of means for the variables in the clusters) from the Ward's analysis were used as starting points, and all cases within a certain distance of the centroid became assigned to that cluster until all cases were assigned (Wormington et al., 2012). The K-means analysis reduced the homogeneity coefficient of the clusters at each wave, confirming that case relocation was appropriate. Cluster stability and reliability was tested by drawing a random split of the sample and confirming that similar clusters appeared. After all cluster solutions were completed, cross-tabulations were used to test for gender differences in cluster membership. Analyses of variance and covariance (ANCOVA) were used to test differences in level of math required by major depending on clusters, gender, and prior math achievement.

Results

There were several important descriptive findings to highlight. Reliabilities, means, and standard deviations are reported in Table 2.2. First, at the mean level for the sample, both math and English SCA decreased over time from 6th grade to 12th grade. Correlations between SCA

and analysis variables for all waves are displayed in Table 2.3. Although math SCA was positively correlated with English SCA in 6th grade ($r=.29, p<.001$) and 7th grade ($r=.12, p<.001$), there was a downward trend for the magnitude to diminish until math SCA was negatively correlated with English SCA by 12th grade ($r=-.26, p<.001$). Additionally, English SCA in 12th grade was negatively correlated with the level of math required by college major ($r=-.19, p<.001$).

Table 2.2

Means, standard deviations, and scale alphas for all variables.

	Mean	SD	Range	Scale α	Mean for Males	Mean for females	Difference (p-value)
Math SCA 6th	5.42	1.00	1-7	0.79	5.51	5.36	0.028
Math SCA 7th	5.23	1.09	1-7	0.85	5.39	5.11	0.001
Math SCA 10th	4.87	1.23	1-7	0.86	5.01	4.76	0.008
Math SCA 12th	4.43	1.36	1-7	0.87	4.54	4.34	0.051
English SCA 6th	5.38	0.98	2.5-7	0.76	5.32	5.43	0.121
English SCA 7th	5.35	1.13	1-7	0.84	5.21	5.45	0.004
English SCA 10th	5.25	1.20	1-7	0.89	5.06	5.40	0.000
English SCA 12th	5.05	1.42	1-7	0.87	4.80	5.24	0.000
Prior math achievement	25.28	2.80	11-28	0.76	25.32	25.25	0.903
Math level of major	2.59	1.02	1-4	-	2.82	2.41	0.000

Many gender differences also emerged. Some of these findings have been previously reported for 6th and 7th grade (Wigfield, Eccles, Mac Iver, Reuman, & Midgley, 1991) and high school (Nagy et al., 2008). Females had significantly lower mean math SCA than boys at every wave, although the 12th grade difference was only marginally significant ($t=1.95, p=0.051$). However, math achievement between genders did not differ. For English SCA, females had significantly higher SCA than males in grades 7, 10, and 12. There was a highly significant mean

difference in the math intensiveness of college majors between genders ($t=5.42, p<.001$), where males had a mean level of math required of 2.82 (i.e., close to moderate math) compared to 2.41 for girls. Being female was negatively correlated with the level of math required by major ($r=-.20, p<.001$).

Table 2.3*Correlations for all variables.*

	1	2	3	4	5	6	7	8	9	10
1. Math SCA 6th	1									
2. Math SCA 7th	0.38***	1								
3. Math SCA 10th	0.34***	0.37***	1							
4. Math SCA 12th	0.38***	0.39***	0.58***	1						
5. English SCA 6th	0.29***	0.13***	0.04	0.13***	1					
6. English SCA 7th	0.23***	0.12***	0.05	0.06	0.31***	1				
7. English SCA 10th	0.11**	0.08*	-0.04	-0.03	0.34***	0.37***	1			
8. English SCA 12th	0.01	-0.08*	-0.15***	-0.26***	0.21***	0.27***	0.50***	1		
9. Female	-0.08*	-0.13***	-0.10**	-0.07	0.06	0.11**	0.14***	0.15***	1	
10. Math of major	0.20***	0.16***	0.17***	0.26***	0.04	-0.06	-0.15***	-0.19***	-0.20***	1
11. Prior math achievement	0.27***	0.31***	0.27***	0.24***	0.13***	0.21***	0.09*	0.01	-0.01	0.11**

Note. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The results of the multiple regression analyses are presented in Table 2.4. Math SCA was positively associated with level of math by college major at every wave, although English SCA was not significantly associated with level of math until 7th grade. By 12th grade, a one standard deviation increase in English SCA was associated with a 0.12-unit decrease in math intensive college major ($p < .01$). Being female was associated with .36-unit decrease in math intensive majors at all waves ($p < .001$). Lastly, math achievement was not significantly associated with the outcome measure at any wave, likely due to our measure of math achievement being a test of competence exhibiting a ceiling effect. Interactions between math and English SCA were not significant, nor were interactions between gender and self-concepts. Ordered logistic regression analyses were run as a robustness check, and the results confirmed the previous findings. Although these results inform general trends of SCA and gender differences, cluster analyses reveal a more nuanced understanding.

Table 2.4*Coefficients for SCA, Gender, and Math Achievement as Predictors of Level of Math Required by College Major*

Predictor	Level of Math Required by College Major			
	6th Grade	7th Grade	10th Grade	12th Grade
Math SCA	0.18*** (0.04)	0.11** (0.04)	0.13*** (0.04)	0.21*** (0.04)
English SCA	-0.02 (0.04)	-0.08* (0.04)	-0.14*** (0.04)	-0.12** (0.04)
Female	-0.38*** (0.07)	-0.36*** (0.08)	-0.35*** (0.07)	-0.35*** (0.07)
Math Achievement	0.07 (0.04)	0.10* (0.04)	0.09* (0.04)	0.06 (0.04)
Intercept	2.81*** (0.06)	2.80*** (0.06)	2.79*** (0.06)	2.79*** (0.05)
R ²	0.08	0.07	0.09	0.12

Note. This table presents regression models predicting how math and English self-concept of ability, gender, and math achievement predict the level of math intensiveness of college major at each Wave. Interactions between gender and SCA variables and between math SCA and English SCA were not significant and not shown here. All independent variables are standardized. The dependent variable is unstandardized. Standard errors are in parentheses.

* $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$.

Cluster Analysis

To answer research question two, cluster analyses were conducted. After twin imputation, eight multivariate outliers were identified and removed. The initial results from Ward's hierarchical method revealed that a cluster solution between five and ten clusters could be considered by analyzing the ESS and EESS plots. After investigating the specific patterns in each cluster solution, we determined that a six-cluster solution best fit and explained the data in 6th grade. The five-cluster solution did not create enough meaningfully distinct clusters, and the seven-cluster solution began to break one distinct cluster into subgroups that was not theoretically meaningful. K-means clustering was used to relocate cases, correcting preliminary

classification and increasing cluster homogeneity. The final six-cluster solution in 6th grade accounted for 77% of the variance, above prior used thresholds of 50% or 67% (Hayenga & Corpus, 2010; Wormington et al., 2012). The same process was carried out at each subsequent wave, with seven-cluster solutions emerging during 7th, 10th, and 12th grade. However, the specific configuration of clusters differed from wave to wave. Complete EESS and ESS plots are available in the supplemental file.

We describe the clusters in terms of the extent to which the math and English SCA were high, medium, or low relative to other clusters at that wave. We understand that this operational definition of high, medium and low is unique to each wave. It would be more accurate to label these as high for wave, medium for wave and low for wave but this labeling is very cumbersome. We note this so the reader is aware of the operational meaning of the terms high, medium, and low in this paper. Cluster means and homogeneity coefficients are displayed in Table 2.5 and Figure 2.1 illustrates clusters visually.

Table 2.5*Cluster Centroids, Size, Homogeneity Coefficients, and Mean Math Level of College Major*

Name	MSCA	ESCA	Cluster Size	HC	Mean Math level
<i>6th Grade</i>					
Low math-low English	4.43	4.36	136	0.61	2.47
Low math-medium English	3.36	5.53	52	1.11	2.12
Medium math-low English	5.87	4.46	152	0.51	2.61
Medium math-high English	5.28	5.98	175	0.34	2.52
High math-medium English	6.35	5.73	125	0.22	2.88
High math-high English	6.39	6.72	92	0.21	2.7
<i>7th Grade</i>					
Low math-low English	3.65	3.99	59	0.6	2.45
Low math-medium English	3.26	5.71	66	0.81	2.34
Medium math-low English	5.03	4.51	104	0.34	2.56
Medium math-high English	4.89	6.17	147	0.42	2.43
High math-low English	6.11	3.65	79	1.15	2.86
High math-medium English	5.91	5.43	139	0.3	2.82
High math-high English	6.22	6.48	138	0.33	2.48
<i>10th Grade</i>					
Low math-low English	4.29	4.16	107	0.54	2.68
Low math-medium English	2.61	5.47	91	1.2	2.41
Low math-high English	4.26	6.62	85	0.47	2.19
Medium math-low English	5.36	2.28	30	1.06	2.7
Medium math-medium English	4.86	5.39	151	0.27	2.41
High math-low English	6.14	4.41	111	0.42	3.05
High math-high English	5.95	6.24	157	0.53	2.66
<i>12th Grade</i>					
Low math-medium English	2.48	4.92	65	0.84	2.33
Low math-high English	2.68	6.55	116	0.8	2.17
Medium math-low English	4.3	1.83	46	1.39	2.46
Medium math-medium English	4.34	4.81	178	0.43	2.53
Medium math-high English	5.07	6.42	132	0.74	2.45
High math-low English	5.58	3.3	84	0.82	3.14
High math-medium English	5.98	4.95	111	0.48	3.06

Note. MSCA stands for math self-concept of ability. ESCA = English self-concept of ability.
 HC = homogeneity coefficient.

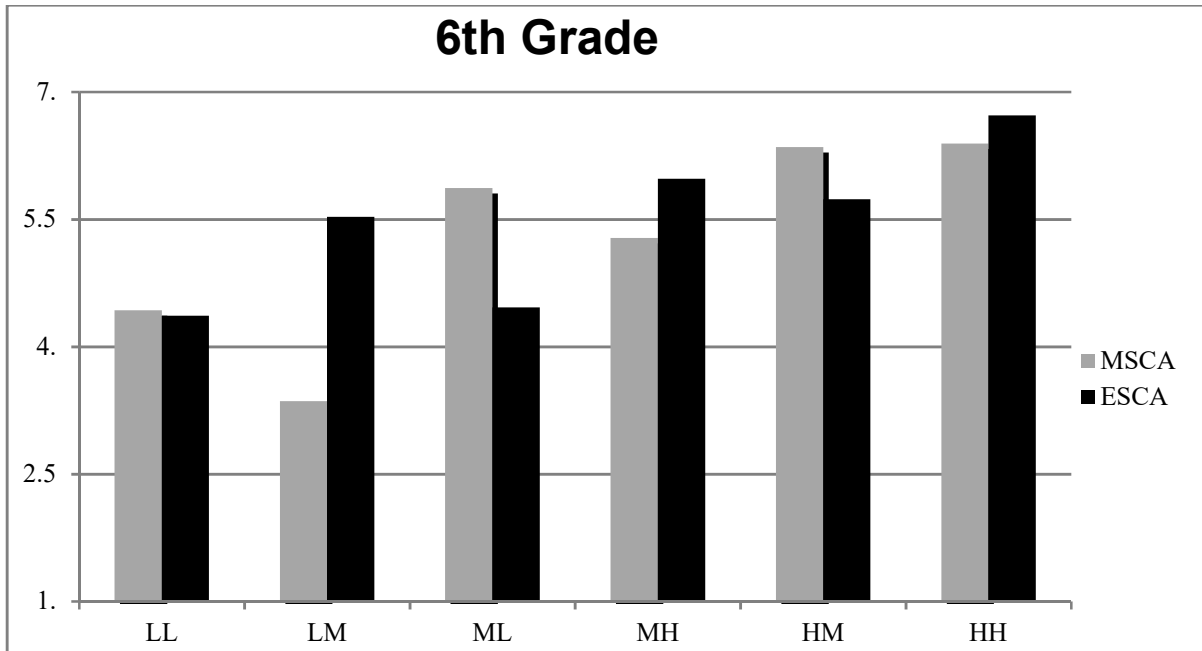


Figure 2.1a.

Six-cluster solution for 6th Grade. MSCA=math self-concept of ability. ESCA=English self-concept of ability. Scores are raw scores of SCA. LL=low math-low English. LM=low math-medium English. ML=medium math-low English. MH=medium math-high English. HM=high math-medium English. HH=high math-high English.

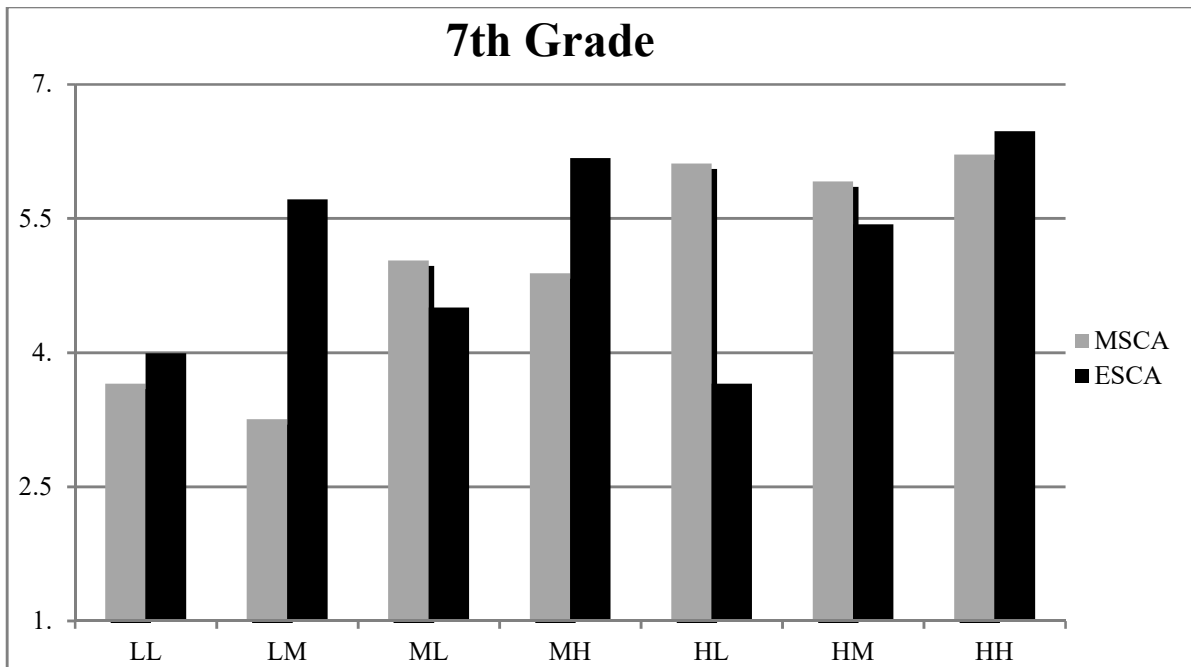


Figure 2.1b.

Seven-cluster solution for 7th Grade. MSCA=math self-concept of ability. ESCA= English self-concept of ability. Scores are raw scores of SCA. LL=low math-low English. LM= low math-medium English. ML=medium math-low English. MH=medium math-high English. HL=high math-low English. HM=high math-medium English. HH=high math-high English.

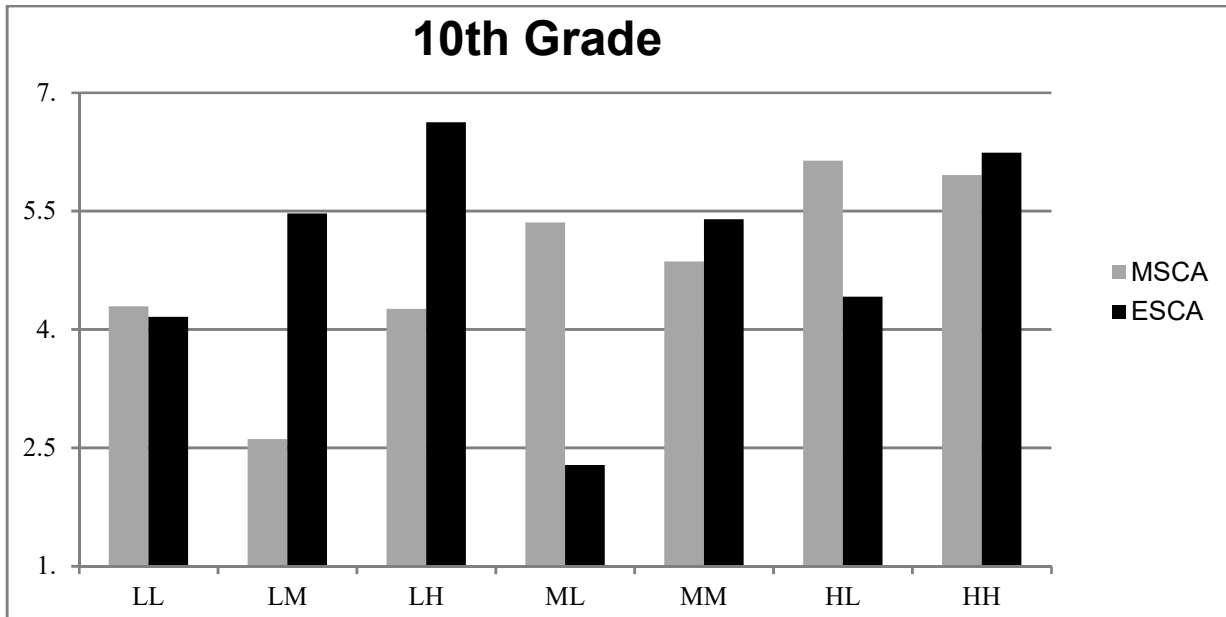


Figure 2.1c.

Seven-cluster solution for 10th Grade. MSCA=math self-concept of ability. ESCA= English self-concept of ability. Scores are raw scores of SCA. LL=low math-low English. LM= low math-medium English. LH=low math-high English. ML=medium math-low English. MM=medium math-medium English. HL=high math-low English. HH=high math-high English.

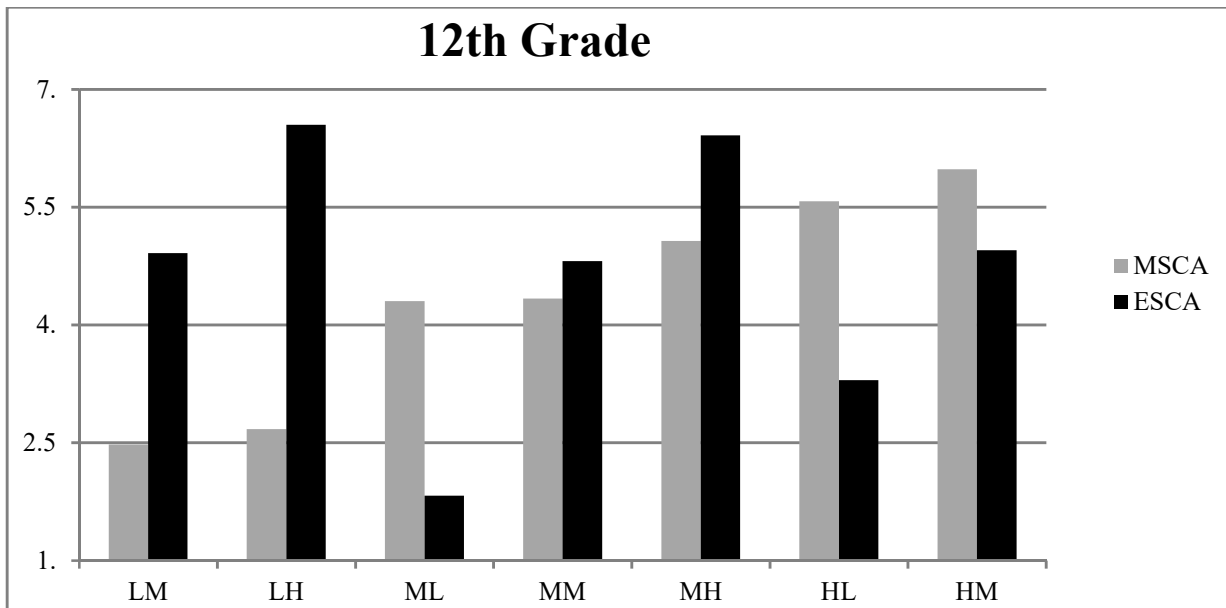


Figure 2.1d. Seven-cluster solution for 12th Grade. MSCA=math self-concept of ability. ESCA= English self-concept of ability. Scores are raw scores of SCA. LM= low math-medium English. LH=low math-high English. ML=medium math-low English. MM=medium math-medium English. MH=medium math-high English. HL=high math-low English. HM=high math-high English.

In the 6th grade, self-concept clusters were labeled as low math-low English (n=136; 18.6%), low math-medium English (n=52; 7.1%), medium math-low English (n=152; 20.8%), medium math-high English (n=175; 23.9%), high math-medium English (n=125; 17.1%), and high math-high English (n=92; 12.6%). In 7th grade, the seven-cluster solution included the clusters low math-high English (n=166; 22.7%) and high math-low English (n=78; 10.7%), although the medium math-high English cluster did not appear. In 10th and 12th grade, the seven-cluster solutions included the largest cluster medium math-medium English (n=151; 20.6% in 10th, n=178; 24.3% in 12th, respectively), although the 12th grade solution did not include the high math-high English cluster. Of all the high math-high English students in 10th grade (n=157), 31.2% fell into the high math-medium English cluster and 31.2% were in the medium math-high English clusters in 12th. Overall, the cluster solutions remained quite stable over time, as most clusters appeared at each wave. However, the mean SCA for both math and English for the same cluster over time generally decreased. For example, whereas the high math-high English cluster in 6th grade had a cluster centroid of 6.39 for math and 6.72 for English, the same cluster in 10th grade had a cluster centroid of 5.95 for math and 6.24 for English (see Table 2.6).

Table 2.6*Contingency Table of Cluster Stability and Movement from 6th to 12th Grade*

12th 6th	LM	LH	ML	MM	MH	HL	HM
LL	20 14.7%	22 16.2%	27 19.9%	37 27.2%	7 5.2%	9 6.6%	14 10.3%
LM	7 13.5%	17 32.7%	2 3.9%	13 25.0%	10 19.2%	1 1.9%	2 3.9%
ML	14 9.2%	23 15.1%	14 9.2%	38 25.0%	19 12.5%	20 13.2%	24 15.8%
MH	14 8.0%	40 22.9%	3 1.7%	42 24.0%	35 20.0%	20 11.4%	21 12.0%
HM	4 3.2%	8 6.4%	0 0.0%	29 23.2%	22 17.6%	26 20.8%	36 28.8%
HH	6 6.5%	6 6.5%	0 0.0%	19 20.7%	39 42.4%	8 8.7%	14 15.2%

Note. Cross tabulation of 6th and 12th grade cluster stability and movement at the person level. LL=low math-low English. LM=low math-medium English. ML=medium math-low English. MM=medium math-medium English. MH=medium math-high English. HM=high math-medium English. HH=high math-high English. First row of each cluster represents the frequency of students who were in each configuration of clusters across 6th and 12th grade. Second row represents the row percentage of students who were in each configuration of 12th grade clusters from the 6th grade cluster.

Cluster Stability and Movement

To investigate cluster stability and movement at the person level we used a contingency table of 6th and 12th grade clusters. The cross-tabulation analysis shows the number and percentage of individuals whose exhibit cluster stability or movement. Overall, 12.5% of students remained stable in clusters. The most stable clusters were those in which students felt highly competent in one domain but not the other (i.e., the medium math-high English and high math-medium English clusters). Approximately 24% of students in these moderately-differentiated clusters remained stable from 6th to 12th grade, whereas 22% showed even further separation between domains by moving to a highly-differentiated cluster (i.e., low math-high

English or high math-low English). Another cluster of interest was the high math-high English cluster in 6th grade, because this cluster did not emerge in 12th grade. Of the 92 students in this cluster, 21% still felt equally capable in both domains but moved to the medium math-medium English cluster, 42% moved to the medium math-high English cluster, and 15% moved to the high math-medium English cluster.

Gender Differences in Cluster Membership

To investigate gender differences in cluster membership we used adjusted standardized residuals (ASR) from cross tabulations at each time point. The results of the chi-squared analyses are presented in Appendix II. Adjusted residuals provide a standardized measure of the strength of the difference in observed and expected values, indicating whether the observed frequency is greater than or less than expected by chance. There were significant gender differences at every wave, generally in line with our hypotheses. In 6th grade, females were overrepresented in the low math-medium English cluster (ASR=2.47, $p<0.05$). In 7th grade, females were overrepresented in the medium math-high English cluster (ASR=2.87, $p<0.01$), whereas males were overrepresented in the high math-low English cluster (ASR=3.68, $p<.001$). In 10th grade, males were overrepresented in the low math-low English cluster (ASR=2.46, $p<.05$), whereas females were overrepresented in the low math-high English cluster (ASR=2.75, $p<.01$). In 12th grade, females were overrepresented in the medium math-high English cluster (ASR=2.17, $p<.05$), whereas males were overrepresented in the high math-low English cluster (ASR=2.49, $p<0.05$).

Associations between Cluster Membership and College Major

Cross tabulation and ASR analyses were conducted to determine if cluster membership was related to the math-intensiveness of chosen college majors. The results of the chi-squared

analyses are available in the supplemental file. The same analysis was then done separately by gender to test whether cluster membership was differentially related to the math-intensiveness of college major for males and females. In 6th grade, students in clusters with low math self-concept were underrepresented in math intensive majors ($ASR=-2.59, p<.01$). Additionally, students in the high math-medium English cluster were overrepresented in math intensive majors ($ASR=4.13, p<.001$), but the students in the high math-high English cluster were neither over-nor underrepresented. This statistically significant finding did not differ by gender. In 7th grade, both the students in the high math-low English cluster ($ASR=2.44, p<.05$) and the high math-medium English cluster ($ASR=3.36, p<.01$) were overrepresented in intensive math majors, but the students in the high math-high English cluster were neither over-nor underrepresented. In the 10th grade, both the students in the low math-medium English ($ASR=-2.08, p<0.05$) and low math-high English clusters ($ASR=-2.32, p<0.05$) were underrepresented in intensive math majors, whereas the high math-low English cluster was overrepresented in intensive math majors ($ASR=4.79, p<.001$). In 12th grade, the same pattern emerged, with the low math-medium English ($ASR=-3.08, p<0.01$) and low math-high English clusters ($ASR=-4.09, p<.001$) were underrepresented in intensive math majors, whereas the high math-low English cluster ($ASR=4.55, p<.001$) and high math-medium English ($ASR=5.35, p<.001$) clusters were overrepresented in intensive math majors. ASR analyses did not reveal any gender differences in representation in math-intensive majors.

One-way ANOVAs were conducted to test whether self-concept of ability clusters differed significantly in the math-intensiveness of college majors. As early as 6th grade, there was already a significant difference between self-concept clusters and the level of math required by college major, $F(5, 716)=4.92, p<.001$. To test the robustness of this result, prior achievement

was controlled for. A one-way ANCOVA revealed that there was a significant difference between cluster membership on college major, controlling for prior math achievement, $F(6,709)=4.90, p<.001$. Next, a two-way ANOVA was run to examine the effect of gender and self-concept cluster membership on level of math required by college major. The overall model was statistically significant, $F(12, 703)=5.02, p<.001$. Both gender and cluster membership were significant ($F=18.67, p<.001$ and $F=3.47, p<.01$, respectively), but the interaction between gender and cluster membership was not significant ($F=.62, p=.69$), implying that the effect of gender on college major was not specific to particular patterns of self-concepts, even though the clusters differed in the ratio of males to females.

The same set of analyses were performed at all subsequent waves, and the results were significant for all tests, with the exception that prior math ability was not a significant predictor in the 12th grade data analyses ($F=3.22, p=.07$). Post hoc analyses using Bonferroni adjusted pairwise comparisons were conducted at every wave to test for mean differences in the math-intensiveness of college majors, controlling for prior achievement. In the 6th grade, none of the three tests (low math-low English vs low math-medium English, medium math-low English vs medium math-high English, and high math-high English vs high math-medium English) were significant. In the 7th grade, although all pairwise tests of equally low math SCA and tests of equally medium math SCA were not significant, the high math-medium English cluster ($M=2.81, SD=1.08$) had a significantly higher mean level of math intensive majors than the high math-high English cluster ($M=2.44, SD=1.03$). In 10th grade, the low math-high English cluster ($M=2.19, SD=0.96$) had a significantly lower mean level of math-intensive college majors than the low math-low English cluster ($M=2.67, SD=1.00$), and the high math-high English cluster ($M=2.66, SD=1.05$) had a significantly lower mean level of math-intensive college majors. than the high

math-low English cluster ($M=3.05$, $SD=0.99$). None of the five tests in 12th grade were significant.

Discussion

The present study drew from expectancy value theory and dimensional comparison theory to examine the development of adolescent math and English self-concepts, their associations with college major, and gender differences. We have added to the literature by including a longitudinal person-centered approach that sheds new light on individual differences in self-concept patterns and how intraindividual hierarchies of self-concepts develop and predict choice of college major.

Variable-Centered Approaches

As predicted, males generally had higher math self-concept than females, and females had higher English self-concept than males. The longitudinal correlations between math and English SCA were particularly noteworthy. In middle school, the two were positively correlated, but by 12th grade they were negatively correlated. Prior research on 15-year old adolescents had found small or near-zero correlations between math and English SCA (Marsh & Hau, 2004). However, our finding may be explained by DCT, which shows that their self-concept of ability in one domain becomes negatively associated with their self-concept in a distal, unrelated domain. DCT further hypothesizes that math and English are the two most distal domains (Marsh, et al., 2015). This developmental pattern suggests that students may perceive themselves as competent in multiple domains early in adolescence, but over time, as hierarchies of SCA develop, they gravitate towards seeing themselves as more of a ‘math’ or ‘verbal’ person. Our regression models supported this finding, showing that over time, the association between English SCA and math intensive college is increasingly negative. This finding may also align

with identity theorists who have proposed the importance of adolescence as a pivotal period for identity achievement, suggesting self-concept clarity is an important part of identity commitment, where the self is clearly defined and internally consistent (Van Dijk, Branje, Keijsers, Hawk, Hale III, & Meeus, W, 2014). It may be that self-concept clarity and consistency occur as one prepares to make important academic choices like college major. The gender patterns of self-concepts would also be consistent with theories on gender intensification (Roberts, Sarigiani, Petersen, & Newman, 1990), where social pressure and norms to think and behave according to sex stereotypes increases in adolescence and the relation between school achievement and a positive self-image should increase among boys and decrease among girls.

Although Nagy et al.'s (2008) analysis using the same dataset failed to show negative cross domain self-concept effects on high school course taking for American students, it is especially interesting that the effect appeared in the present study when investigating its association with math intensive college majors. There could be many reasons for this discrepancy. First, it could be that advanced math and English courses are the typical program for students who have college aspirations, regardless of specific interest or career aspirations (Lauermann et al., 2015). Second, it may be that choice of college major is a more independent choice than high school coursework, and therefore the effect is not fully seen until college. Third, the utility in taking advanced high school courses for college acceptance may be motivating enough to encourage students to take advanced math and English courses, despite a lack of long-term interest in one of them. However, as college major is often the final academic choice that cascades into more narrow career choices, it may be that students opt for a major where they most expect to succeed long term. Although dimensional comparison theory has shown these cross domain self-concepts to negatively predict one another, longitudinally extending its effects

to college major choice is a finding directly related to expectancy-value theory, highlighting the complimentary nature of these two theories.

Person-Centered Cluster Approaches

The cluster analyses revealed a six to seven-cluster solution of various patterns of self-concepts between 6th and 12th grade. Although most patterns of clusters reappeared at each wave, the high math-high English cluster was not evident in 12th grade, with the majority of students previously in that cluster moving either into the high math-medium English or the high English-medium math clusters. This may reflect the need for high achievers to develop a more differentiated academic identity as they move towards college and the need to select majors and future careers. Although individuals with high math achievement may also be competent in the verbal domain, some students may come think of themselves as more of ‘math’ person than a ‘verbal’ person or a 'smart' person. (Marsh & Hau, 2004). DCT theorists suggest this differentiation is a likely consequence of internal comparisons in the ability self-concept formation process (e.g., Marsh & Hau, 2004). However, little scholarship has focused on the exact cues individuals use in making this type of differentiation when their level of objective performance is quite similar. Equally important, scholars have theorized the social and cultural forces that might influence this developmental process. Social contextual characteristics might moderate the rate, direction, and the extent to which differentiated ability self-concepts develop (Markus & Kitayama, 1991). If individuals are forced to specialize in their academic subjects at a younger age, it is possible that the high-high groups will begin the differentiation process at a younger age.

Stereotypical gender differences also emerged in cluster membership. Every gender difference followed the same pattern; females were overrepresented in those clusters with higher

English SCA relative to math, whereas males were overrepresented in those clusters with higher math SCA relative to English. Why does this pattern consistently emerge despite no differences in actual math performance? Perhaps this difference can be explained by varying causal attributions patterns of success, where males and their parents often attribute their success to talent, whereas females and their parents often attribute their success to effort, which over time may lead to gender differences in math self-concept (Räty, Vänskä, Kasanen, & Kärkkäinen, 2002; Sáinz & Eccles, 2012; Wigfield & Eccles, 2002; Yee & Eccles, 1988). Alternatively, it may be that males brag about their math competence more than women, leading to females making upward social comparisons about their ability relative to male classmates (Guimond & Roussel, 2001; Yee & Eccles, 1988). Another possibility is perhaps females work harder than males in their math courses and are thus more likely to attribute their math successes to effort (Yee & Eccles, 1988). We believe these possible explanations need to be replicated with more current data.

Results of the cluster analysis also revealed the predicted associations with college major choice. Students in the high math-medium English cluster in 6th grade were more likely than expected by chance to end up in math intensive majors, but students in the high math-high English cluster were not, despite having similar confidence in their math ability. This interaction did not show up in the variable centered analyses. The same relationship was also found in 7th grade, with the newly emerged high math-low English cluster also more likely than expected by chance to end up in intensive math majors. This pattern suggests that some students are already reaching the point of identifying as a ‘math’ person by the end of elementary school or middle school and committing themselves to pursuing math intensive careers, whereas those who felt competent in both domains were still developing their academic identities. The same pattern is

evident in high school, where clusters high in math and lower in English were overrepresented in math intensive majors, whereas clusters with low math-high English were overrepresented in majors with little to no math. This seems to indicate that by 10th grade, ability belief disparities between domains lead students to identifying with one domain over the other.

Finally, both variable-centered and person-centered results showed that females generally went into less math intensive majors than males, regardless of cluster membership. Beyond considering gender disparities in math SCA, an ipsative approach to intraindividual self-concept hierarchies reveal a more nuanced story of ability self-concepts. However, while the current pattern analysis advances theoretical perspectives on the role of self-concepts in college major choice, what might explain why these self-concept patterns emerge in the first place, such that females end up overrepresented in high English clusters and end up pursuing math intensive majors less than males? One reason may be gender-role stereotyped socialization, where females place higher value than males on the importance of making occupational sacrifices for one's family and on having a job that helps others, whereas males place more value on earning a higher income, seeking out more challenging tasks, and doing work that involves the use of math and computers (Eccles, 2011). Additionally, the role of subjective task values such as interest value, utility value, and attainment value may also explain gender differences in college major selection, as women have reported lower task values in numerous studies (Eccles, 1994; Zarrett, Malanchuk, Davis-Kean, & Eccles, 2006), and EVT research has found that subjective task values are predictive of academic choices (Durik, Vida, & Eccles, 2006; Guo, Parker, Marsh, & Morin, 2015). Another reason may be the perception of math intensive careers such as computer science, engineering, and physics as nerdy, stereotypes that may be incompatible with women's

view of themselves as feminine or may be less acceptable for females than for males (Cheryan, Plaut, Handron, & Hudson, 2013; Margolis & Fisher, 2002).

Limitations and Future Directions

The current study is the first to employ longitudinal cluster analyses of math and English SCA to relate to the choice of college major. The results provide an important contribution to EVT and DCT. However, there are a few limitations that must be considered when interpreting the results. As the study relied on longitudinal correlational data, any causal interpretations are tentative as the relationships between variables are likely bidirectional. Additionally, the sample had limited ethnic or racial diversity, which may limit generalizations to other populations. However, the underlying psychological process of dimensional comparisons in determining self-concept hierarchies does not appear to be unique to a particular racial group. Another possible point of concern is the age of the data. The sixth-grade data were collected in 1984-1985 and the college major data from 1992-1993, and one may question if the findings would replicate today, where there appears to be greater societal emphasis on gender equality in educational attainment. However, recent literature has shown that women, relative to men, are still shunning many math-intensive majors such as physics, computer science, and engineering. Gender stereotypes, lower sense of belonging, and lower self-efficacy amongst women remain prevalent in these fields and may explain these disparities in college major selection (Cheryan, Ziegler, Montoya, & Jiang, 2017). Therefore, although we encourage more longitudinal studies to investigate the development of adolescent ability beliefs and college major choice, we believe that our findings are still relevant.

Overall, these findings have implications for interventions aimed at raising self-concepts, in addition to the theoretical development of SCA. To date, interventions on self-concept have

focused on single domains such as physics (e.g., Häussler & Hoffmann 2002) or math (e.g., O'Mara, Marsh, Craven, & Debus, 2006). If the desire is to increase self-concept in a particular domain, in order to motivate students towards particular careers, then intervention research must realize that the interplay of multiple self-concepts within a person must be considered. Further research should investigate if attempts to increase SCA in one domain leads to a pernicious side effect of decreasing SCA in another domain. This has ethical implications for student autonomy in determining their own educational and career aspirations. Additionally, future research should investigate a larger constellation of self-concepts together, including math, English, and science. Many science majors are math intensive, so understanding how biology, chemistry, and physics self-concepts operate in concert with math SCA would be valuable. As this study was the first to consider a person-centered approach to SCA, replication studies that investigate other populations with different schooling environments would contribute to the robustness of the findings. Additionally, although the current study only focused on math-intensive majors, investigating the choice of college majors requiring strong English language skills would be valuable. For students who see themselves as 'English people, strong verbal skills are relevant to a wide range of majors that may not be as easily classified as high-math fields.

Another important topic for future research would be an investigation into the sources of input for self-concept at different developmental stages. Understanding the unique contributions of parents, teachers, and peers on self-concept at various points in childhood and adolescence may open the door to creating developmentally appropriate interventions. Finally, to better understand gender disparities in the enrollment of math intensive college majors and occupations, cost components from EVT should be studied as possible explanations (Flake, Barron, Hulleman, McCoach, & Welsh, 2015; Gaspard, Häfner, Parrisius, Trautwein, Nagengast,

2017). Women may perceive particular majors and careers as more emotionally costly (e.g., anxiety inducing) or costly in terms of giving up valued alternatives, resulting in lower enrollment and commitment to those fields.

Conclusion

This is one of the first studies focused on the ontogeny of patterns of math and English self-concepts of ability throughout adolescence. The findings stress the importance of the intraindividual hierarchy of self-concepts within a student when attempting to predict and understand academic choices like college major. An ipsative perspective may be key to understanding why a student selects one particular option instead of another.

Although a variable-centered approach provided general insights into the associations of math and English SCA across the sample on the math-relatedness of college majors, means, correlations, and regression coefficients were anchored in the aggregate and therefore could not differentiate group-level from person-level stability or associations (Lamiell, 1981; see Parker, Marsh, Morin, Seaton, & Van Zenden, 2015). Additionally, the predicted interaction did not emerge in variable centered analyses but did emerge in the patterned centered analyses. Thus, these techniques could not properly address the question of the hierarchy of intraindividual self-concepts with respect to stability, change over time, or predicting distal outcomes (Young & Mroczek, 2003). A person-centered approach using cluster analysis was thus an appropriate and sophisticated statistical approach to studying self-concept patterns and their associations with distal outcomes. Further research should consider such statistical methods, including latent class growth analysis (LCGA) and growth mixture modeling (GMM). These person-centered approaches will allow for the emergence of unique subgroups that are meaningful in the study of persons and their individual differences.

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CHAPTER 3

Dimensional Comparisons of Academic Values in High School and College Major Choice

“The reality of choice in human action presents one major opportunity for the study of values. Values are operative when an individual selects one line of thought or action rather than another.” (Kluckhohn, 1951)

As adolescents near high school graduation, the choice of selecting a college major becomes a pivotal life choice. College major selection offers students a rare opportunity to exhibit autonomy in their academic lives, and the major they select will likely influence future career options. From a plethora of choices, how do students decide what major to select? Many theories of motivation posit that values motivate choices and initiate action. For example, Eccles expectancy-value theory posits that, while achievement and ability beliefs play a role in academic choices, the academic task values that students hold for various academic subjects will also influence their choices (Eccles, 1994). Values have also been conceptualized to be hierarchical and integrate into value systems (Rokeach, 1973; Williams, 1979; Locke, 1991; Eccles, 1994), and ultimately there is an “economy of values,” for no student has the resources or time to make all possible choices (Kluckhohn, 1951). Hierarchies of values refer to mental systems in which people rank a value one above the other according to its perceived importance. However, much of the recent literature on values and academic choices has ignored these hierarchies and value systems, focusing only on a single academic value, its relation to achievement, its development, and its association with academic behavior (e.g., Musu-Gillette, Wigfield, Harring, & Eccles, 2015; Simpkins, Davis-Kean, & Eccles, 2006)). Sparse attention has been given to academic value comparisons across domains (e.g., math, English, science),

where value for one subject may positively or negatively influence value for another subject. In this study, we investigate the development of academic values in high school, including how achievement in different domains relate to academic values, how value for one domain relates to value for another domain, and how the collective system of values influences college major choice.

The Nature of Values and Expectancy-Value Theory

Before discussing the relationship between values and behavior, let us define what we mean by values. We begin with the definition of Milton Rokeach (1973), as stated in his seminal work on human values, who defined a value “as an enduring belief that a specific mode of conduct or end-state of existence is personally or socially preferable to an opposite or converse mode of conduct or end-state of existence” (p. 5). He elaborated that these values form a value system that “is an enduring organization of beliefs concerning preferable modes of conduct or end-states of existence along a continuum of relative importance” (p. 5). From this perspective, values are considered antecedents to behavioral choices, and a major goal of values research has been to relate individual differences in value priorities to different behaviors (Schwartz, 2013).

Influenced by the seminal works of Rokeach (1973), the expectancy-value theory (EVT) of achievement performance and choice conceptualized subjective task value as the quality of the task that contributes to the increasing or decreasing probability than an individual will select it (Eccles, 2005). Subjective task value is thus determined by the fit between personal values and characteristics of the task itself (Eccles & Wigfield, 1995). These subjective task qualities include (1) attainment value, or the value an activity has in fulfilling one’s identity or self-image; (2) interest value, which refers to the expected enjoyment in task engagement; (3) utility value, how useful the task is in fulfilling various short and long-term goals; and (4) the personal cost of

engaging in the activity. EVT scholars (Eccles, 2005) were explicit in highlighting how values operate in influencing behavior “as it is the hierarchy of subjective task values that matter, rather than the absolute values attached to the various options under consideration” (p. 107). In the context of deciding one’s college major, academic task values help define which majors are likely to be most interesting, useful, and in line with one’s identity.

Strikingly, despite many theories positing that multiple values compete within a person to influence behavior, most of the modern empirical research on academic values, including Eccles’ and Wigfield’s own specification of the hierarchical nature of activity choice within expectancy-value theory (see Eccles, 2005), has focused on a single academic value that is hypothesized to associate with academic choices, such as course selection or college major (e.g., Musu-Gillette et al., 2015; Simpkins et al., 2006). This incongruence between applied research and theory is problematic. Schwartz (2013) criticized this method of focusing on relations between single values and behavior, claiming that such research leads to a piecemeal accumulation of information about values that is not productive to the development of coherent theories. According to Schwartz, without a broad theory of the relations between values, it is possible that omitted values are just as important to understanding behavior as the single value included. Lastly, single-value approaches neglect the assumption that behavior is not guided by the priority given to a single value, rather through tradeoffs among competing values related to the behavior under consideration. College major selection provides an opportunity to study value conflicts, as students must pick from numerous options and multiple values may influence this choice. It is in the presence of conflict that values are likely to be activated and to be used as guiding principles (Schwartz, 2013). We agree with Schwartz that values may positively or negatively relate to one another. This implies the existence of dynamic relations between values. To date, the empirical

work investigating how subjective academic task values influence one another has been sparse. However, recent developments in self-concept literature provide insights in how to consider the relations between multiple academic domains.

Dimensional Comparisons of Achievement and Self-Concept of Ability

Seminal work on self-concept of ability by Shavelson, Huber, and Stanton (1976) highlighted the evaluative nature of ability beliefs, whereby evaluations of one's ability likely take into account relative standards. Building directly on Shavelson and colleagues work, Marsh (1986) elaborated on how these evaluations operate theoretically and empirically in the internal/external frame of reference model (I/E model), which describes the effects of students' math and verbal achievements on their math and verbal self-concepts of ability. According to the I/E model, math and verbal self-concepts of ability form based on social (external) and dimensional (internal) comparisons. Because of social comparisons, where students compare their achievements with their classmates' achievements, there should be strongly positive effects of students math (verbal) achievement on their math (verbal) self-concept. Because of dimensional comparisons, where students compare their math and verbal achievements with each other, there should be moderately negative effects of students' math (verbal) achievement on their verbal (math) self-concept. Thus, dimensional comparison between math and verbal achievements lead to an increased self-concept in the domain where students show the higher achievement, but to a decreased self-concept in the domain where students show the lower achievement. For example, a student with high math achievement and low English achievement will likely have a much higher math self-concept of ability than a student with high math achievement and even higher English achievement.

To date, more than 100 studies have found support for the assumptions of the I/E model (e.g., Möller, Pohlmann, Köller, & Marsh, 2019, for a meta-analysis). The joint effects of social and dimensional comparisons have been shown in student samples of different ages, gender distribution, and countries. They were shown for different operationalizations of achievement (Möller et al., 2019) and self-concept (Wolff, Helm, Junge, & Möller, 2019; Wolff, Nagy, Helm, & Möller, 2018). In addition, the assumed joint effects of social and dimensional comparisons on students' domain-specific self-concepts have replicated for other methodological approaches, including experimental studies, more introspective studies, and longitudinal studies (e.g., Wolff, Helm, Zimmermann, Nagy, & Möller, 2018).

Whereas the classic I/E model only refers to math and verbal achievements and self-concepts, more recent studies have also tested a generalized I/E model, which includes different combination of school subjects (Möller, Müller-Kalthoff, Helm, Nagy, & Marsh, 2016). The theoretical rationale of this model stems from dimensional comparison theory (DCT; Möller & Marsh, 2013), which has extended the core deliberations of the I/E model concerning dimensional comparisons into a more general comparison theory. DCT assumes that dimensional comparisons take place between different school subjects, whereby the strength and direction of the dimensional comparison effects is assumed to depend on the “similarity” of the subjects compared with each other (see also Marsh et al., 2014). Whereas dimensional comparisons between achievements in two dissimilar subjects, such as one subject of the math/science domain and one subject of the verbal domain, should lead to negative (i.e., contrastive) dimensional comparison effects, these effects might decrease and even turn into positive (i.e., assimilative) dimensional comparison effects if achievements in two similar subjects are compared with each other, like two subjects from the math/science domain or two subjects from the verbal domain.

Previous research has found empirical support for these assumptions (e.g., Arens, Helm, Wolff, & Möller, 2019; Jansen, Schroeders, Lüdtke, & Marsh, 2015; Marsh et al., 2014; Wolff, Helm, & Möller, 2019, Wolff, Nagy, Retelsdorf, Helm, Köller, & Möller, 2018). However, assimilative dimensional comparison effects have been found within the math/science domain rather than in the verbal domain, and especially between math, physics, and chemistry. When biology was considered, dimensional comparison effects within the math/science domain were usually contrastive (e.g., Jansen et al., 2015; Marsh et al., 2015).

Dimensional Comparisons of Academic Task Values

Based on findings from diary studies (Möller & Husemann, 2006) and studies testing the I/E model for different kinds of outcome variables (Möller et al., 2016, for an overview), DCT assumes that dimensional comparisons are not restricted to take place between subject-specific achievements and affect subject-specific self-concepts, but that they do occur between and have effects on several self-related constructs (Möller & Marsh, 2013). Thus, subject-specific academic values should also develop based on dimensional comparisons of achievement and relative value for one domain versus another. Given the applicability of the generalized I/E model to examine dimensional comparisons between a number of different constructs, this framework may help guide our investigation into the development of academic task values and academic choices. The literature on this topic is limited, but the few studies have examined the development of academic emotions and values with consideration to dimensional comparisons. In a study testing the I/E model and academic enjoyment (which is empirically similar to interest), math achievement was associated with lower verbal enjoyment and verbal achievement was associated with lower math enjoyment (Goetz, Frenzel, Hall, & Pekrun, 2008). However, this study did not investigate the effects of enjoyment on future academic choices. In a cross-

cultural study of German and American students (Nagy, Garrett, Trautwein, Cortina, Baumert, & Eccles, 2008), German students' English intrinsic value (i.e., interest value) decreased the likelihood of taking advanced math courses in high school. However, this finding did not replicate on the sample of American students. Nonetheless, the authors suggested that the results indicate that students may engage in intraindividual cross-domain comparisons when making academic choices. Gaspard and colleagues (2018), using a sample of German adolescents in grades five to twelve, compared dimensional comparisons of expectancies (i.e., self-concept of ability) and task-value across five academic domains (German, English, biology, physics, and math) with achievement, finding stronger evidence for dimensional comparisons in self-concept than values. We seek to add to what these studies have found by considering development over time and associations with other academic choices.

Gender Differences in Task Values and College Major Selection

One of the most important aspects of studying values is the association between values and behavior. Central to this literature, especially from an expectancy-value perspective, are the gender differences that have been observed in academic task values and educational choices. Regarding task values in adolescence, females typically report lower task value and enjoyment for math than males (Frenzel, Pekrun, & Goetz, 2007; Simpkins et al., 2006), higher task value for literacy than males (Durik, Vida, & Eccles, 2006; Jacobs, Lanza, Osgood, Eccles, & Wigfield, 2002), and lower task value for science than males (Simpkins et al., 2006). Consequently, as males in adolescence typically report higher task value in math, they select more math intensive majors than females (Musu-Gillette et al., 2015). However, as previously stated, these studies and most others have relied on a single-value approach. They operate under the hypothesis that math intensive college majors are understood by studying math task value.

Although such an approach may be useful for explaining group level mean differences in college major choice, it may not be appropriate for explaining the within-person process of selecting one's college major. At the person level, individuals are selecting from several alternatives. According to Eccles and Wigfield's perspective on EVT, people make such choices by comparing the subjective task values across the relevant options. For example, Eccles (1994, p. 591) argued that "it is assumed that the decision to take advanced math is based primarily on variables related to math. We explicitly reject this assumption, arguing instead that it is essential to understand the psychological meaning of the roads taken, as well as the roads not taken, if we are to understand the dynamics leading to the differences in women's and men's achievement related choices." Thus, in order to better understand college major selection as a central achievement related choice, the inclusion of multiple domains of academic values is necessary for studying both individual and group differences in achievement related choices. In one of the few studies to do so, Chow, Eccles, and Salmela-Aro (2012) used latent profiles to identify that males were more likely than females to be in profiles with high math and science task value, and thus more likely to aspire for physical science and IT-related professions. Another study of Australian youth found that reading achievement had a negative effect on selecting a STEM major, which they explained was mediated by decreased value for math (Guo, Parker, Marsh, & Morin, 2015). They also found gender differences, where males were more likely to select STEM majors.

The Present Study

In the present study, we address some of the gaps in the literature on the development of academic task values and college major choice. Our study considers a more comprehensive model of academic values development and how values specifically relate to the level of math

required by college major. In line with the theoretical assumptions of EVT and DCT, we investigate the extent to which achievement in multiple domains relates to academic task values in these subjects, the ways in which task values develop across the high school years, and ultimately the extent to which hierarchies across multiple values relate to the choice of math intensive college majors. We also consider how gender relates to the development of these task values and educational choices. We focus on the task values for math, English, biology, and chemistry in tenth and twelfth grade, as well as the math intensiveness of chosen college majors. The three broad research questions we seek to answer are the following:

1. To what extent does achievement in each domain relate to subjective task values across these domains?
2. To what extent do task values early in high school (i.e., 10th grade) relate to task values later in high school (i.e., 12th grade)? To what extent are their gender differences in the mean levels of these task values?
3. To what extent does task value in each domain predict the math intensiveness of college major? To what extent does gender moderate the relations between task values and college major choice?

For research question one (RQ1), we hypothesize that achievement in each domain will positively relate to task value in that same domain. Math achievement is hypothesized to negatively relate to English task value and vice versa (Möller & Marsh, 2013). Science achievement (students typically took a general science course in the 9th grade that included aspects of both biology and chemistry) is hypothesized to positively relate to biology and physical science value, but no hypothesis is made regarding the relations between science domains and math and English values (Marsh et al., 2015). Regarding our second research

question (RQ2), we hypothesize that from 10th to 12th grade, math and English task values will negatively relate to one another, math and physical science task value will positively relate to one another, and biology and physical science will positively relate to one another. We do not have specific hypotheses of the relations between each science domain and English. We also hypothesize that males will have higher math and physical science values than females (Chow et al., 2012), and females will have higher English values than males (Archambault et al., 2010). In regard to our third research question (RQ3), we hypothesize that math and physical science values will positively predict math intensive majors, whereas English value will negatively predict math intensive majors. We hypothesize that there will be no relation between biology values and the mathiness of one's college major, as biology is moderately math intensive. We also hypothesize that gender will not moderate the effect of task values on college major based on prior I/E research that did not find gender differences in self-concept of ability relations.

Method

Participants

The data used in this study come from the Michigan Study of Adolescent and Adult Life Transitions (MSALT). MSALT is a longitudinal study that began in 1983, when participants were in the 6th grade and included 2451 students. The data used in the present analysis includes three waves of data, 10th grade (age 16), 12th grade (age 18), and three years after high school graduation (age 21). This study uses a subsample of 1279 students who reported survey data in high school. The subsample participants were predominantly White (91%) and 52% were female. The data used was obtained from student surveys and school records from 12 schools. Students completed surveys in school classrooms in high school and surveys were mailed to the participants homes at age 21. Grades were collected from high school record data.

Measures

Subjective task values (STV). STV was measured for the subjects of math, English, biology, and physical science in both 10th and 12th grade. Three items were used to measure each domain, including one item related to individual interest/intrinsic value, attainment and importance value, and utility value. Each domain included the following items: (1) “How much do you like doing X? (2) For me, being good at is...(3) How useful do you think high school X will be for what you want to do after you graduate and go to work? All items were measured on a Likert scale from 1 (a little/not at all important/not at all useful) to 7 (a lot/very important/very useful). All task value scales had good reliability ($\alpha = .77$ to $.90$).

College major. Students filled in their major in an open-ended item asking, “What is your college major?” College major was coded from 1 to 4 for level of math required based on an adapted version of Goldman and Hewitt’s (1976) scale for coding STEM-related majors. The adapted scale categorizes college majors based on the level of math required from (1) little to no math, (2) some math, (3) moderate math, and (4) intensive math. The level of math required per major was based on the average number of math courses required by each major. The adapted version was utilized and updated by Musu-Gillette et al. (2015). For college majors not existing in the scale, two coders independently categorized majors based on similarities with other majors. The coders initially agreed on 90% of the majors, and any discrepancies were discussed until 100% agreement was reached. 131 students had declared double majors, in which case the major with the highest level of math was considered in the analysis. Categories of college majors by level of math required are shown in Table 3.1.

Table 3.1

College majors classified based on the level of math intensiveness

Little to no math (1)	Some math (2)	Moderate math (3)	Intensive math (4)
Humanities	Psychology	Biology	Math
English/Literature	Sociology	Pharmacy	Engineering
Philosophy	Political Science	Economics	Computer Science
International Studies	Social Work	Science (other)	Chemistry
History	Nursing	Architecture	Physics
Music/Theater/Film	Health	Physiology	Finance
Foreign Languages	Anthropology	Astronomy	Accounting
Art	Counseling	Geology	Electronics

Predictors. Academic achievement was measured using the class grade for each subject at the end of 9th grade as reported by the school district. Grades were scaled from 1 (F) to 16 (A+).

Attrition and Missing Data

The data from MSALT includes a complex pattern of complete and missing data. Of the 1771 participants in 10th grade, only 683 (39%) had completed questionnaires indicating enrollment in college at Wave 7. Females were more likely to have remained in the study by Wave 7 than males. The participants who did not complete Wave 7 questionnaires tended to have lower levels of achievement and task values than those who completed Wave 7 questionnaires. In order to deal with the missing data, full-information maximum likelihood (FIML) was used, as FIML uses all information into account when estimating model parameters. Assuming the data is missing at random, FIML will produce parameter estimates that have optimal large-sample properties of consistency, asymptotic efficiency, and asymptotic normality when sample sizes are large (Allison, 2003). Data are considered missing at random if the pattern of missing data is

captured in other measured variables. As the individuals with missing data varied on a number of measured variables, we feel reassured that our use of FIML is warranted.

Analysis Plan

Structural equation modeling was used to examine the relations between achievement, subjective task values, and college major. All analyses were estimated with structural equation models (SEM) in Mplus v7.4 (Muthén & Muthén, 2015). In preliminary analyses, we followed a multi-step process to develop the measurement model, including testing the factor structure and measurement invariance over time and across gender (see Appendix III for details). After specifying the measurement model, we included the structural components of achievement to test RQ1, cross-lags of values over time to test RQ2, and math intensiveness of college major to test RQ3. Multi group analysis and model constraints were used to test for gender differences. The full longitudinal SEM model included eight latent variables (four at each time point) with three indicators each (see Figure 3.1 for a hypothesized diagram of the SEM model). Science, English, and math grades in 9th grade predicted all four task values in 10th grade. All four task values in 10th grade predicted task values in 12th grade. 12th grade values predicted college major. Residual variances for similar items between math and physical science were correlated, in addition to residual variances for similar items between biology and physical science. The variances were freely estimated for 10th and 12th grade STV.

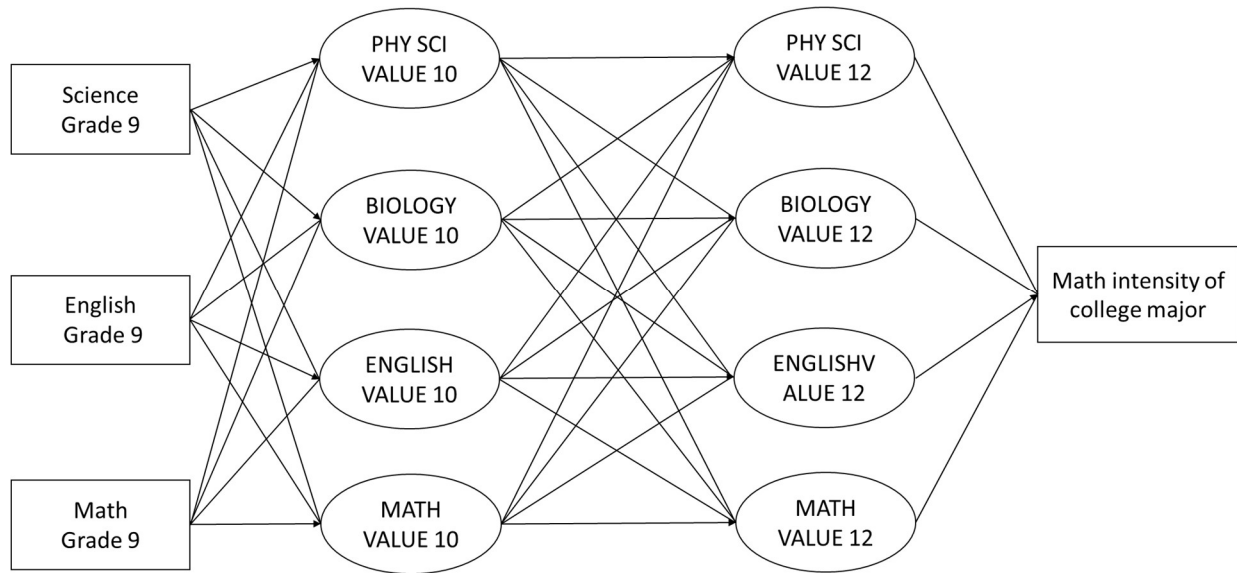


Figure 3.1. Hypothesized SEM of Achievement, Task Values and College Major

Model fit for all models was first assessed using the chi-squared statistic (χ^2), as it is the only inferential statistic in SEM for model fit. However, as χ^2 is sensitive to large sample sizes, we used two alternative fit indices, the root mean error of approximation (RMSEA) and the comparative fit index (CFI). RMSEA values below .08 and CFI values greater than .95 indicated good fit (Acock, 2013; Little, 2013). All nested models were evaluated based on both $\Delta\chi^2 < .05$ or $\Delta CFI < .01$ (Little, 2013).

Results

Preliminary Analyses

Before addressing our specific research questions, there were a few descriptive findings worthy of mention. Descriptive statistics for all study variables can be found in Table 3.2. Task values for all four domains decreased between 10th and 12th grade. Physical science task value was the lowest of all the domains in both Waves, whereas English task value was the highest. Being female was correlated with taking less math intensive majors than men ($r = -.17$). Correlations for all study variables are displayed in Table 3.3.

Table 3.2*Means, standard deviations, and scale alphas of observed variables*

	N	Mean	SD	Min	Max	Scale α
Math STV 10th	1278	4.74	1.47	1	7	0.77
English STV 10th	1274	4.75	1.51	1	7	0.81
Bio STV 10th	1246	4.17	1.65	1	7	0.86
Physical Sci STV 10th	1205	4	1.57	1	7	0.83
Math STV 12th	1231	4.49	1.52	1	7	0.8
English STV 12th	859	4.58	1.59	1	7	0.84
Bio STV 12th	861	3.65	1.78	1	7	0.9
Physical Sci STV 12th	1230	3.76	1.67	1	7	0.85
Math Grade 9th	1623	9.34	3.4	1	16	-
English Grade 9th	1568	10.08	3.34	1	16	-
Science Grade 9th	1471	10.5	3.21	1	16	-
Gender (F)	1771	-	-	-	-	-
Math of Major	673	2.58	1.02	1	4	-

Table 3.3
Correlations of observed and scaled variables

	1	2	3	4	5	6	7	8	9	10	11	12	13
1. MSTV10	1												
2. ESTV10	0.15***	1											
3. BSTV10	0.28***	0.19***	1										
4. PSSTV10	0.34***	0.15***	0.64***	1									
5. MSTV12	0.51***	-0.06	0.12***	0.22***	1								
6. ESTV12	-0.10*	0.52***	0.11**	0.00	-0.10**	1							
7. BSTV12	0.17***	0.01	0.56***	0.42***	0.22***	0.11***	1						
8. PSSTV12	0.24***	0.04	0.42***	0.57***	0.36***	-0.02	0.64***	1					
9. Math 9	0.27***	0.06*	0.09**	0.13***	0.25***	0.03	0.12***	0.13***	1				
10. English 9	0.14***	0.21***	0.15***	0.11***	0.09**	0.20***	0.19***	0.12***	0.55***	1			
11. Science 9	0.19***	0.08**	0.22***	0.23***	0.13***	0.11**	0.23***	0.20***	0.55***	0.67***	1		
12. Female	-0.07**	0.29***	0.03	-0.11***	-0.11***	0.27***	-0.02	-0.15***	0.08***	0.17***	0.07**	1	
13. Major	0.32***	-0.22***	0.10*	0.21***	0.47***	-0.31***	0.11*	0.33***	0.19***	0.07	0.17***	-0.17***	1

Note. Subjective task value (STV) variables are scaled values for each subject. Math 9, Eng 9, and Sci 9 are all end of 2nd semester grades in 9th grade. MSTV = math STV; ESTV = English STV; BSTV= Biology STV; PSSTV= Physical science STV.

* p<0.05, ** p<0.01, *** p<0.001

The structural equation model used to answer our research questions fit the data well ($\chi^2=1371.35(612)$, $p<.001$; RMSEA=.04; CFI=.94). The final model constrained the loadings over time and between genders and constrained the intercepts between genders to achieve strong factorial invariance. See Table 3.4 for detailed results of the nested models. The multigroup analysis yields separate results by gender. Table 3.5 includes standardized SEM coefficients of interest and Figure 3.2 depicts the final SEM with unstandardized coefficients.

Table 3.4
Comparison of nested longitudinal models

Form	$\chi^2(df)$	RMSEA	CFI	$\Delta\chi^2$	df	p-val	ΔCFI
Configural (unconstrained)	1217.8(564)***	0.04	0.95	-	-	-	-
Equal loadings over time	1240.8(580)***	0.041	0.95	23	16	0.113	0.001
Equal loadings over time & gender	1258.9(588)***	0.041	0.949	18.1	24	0.02	0.001
Equal loadings over time & gender & equal intercepts between genders	1371.3(612)***	0.043	0.943	112.4	48	0.00	0.006

*** $p<.001$

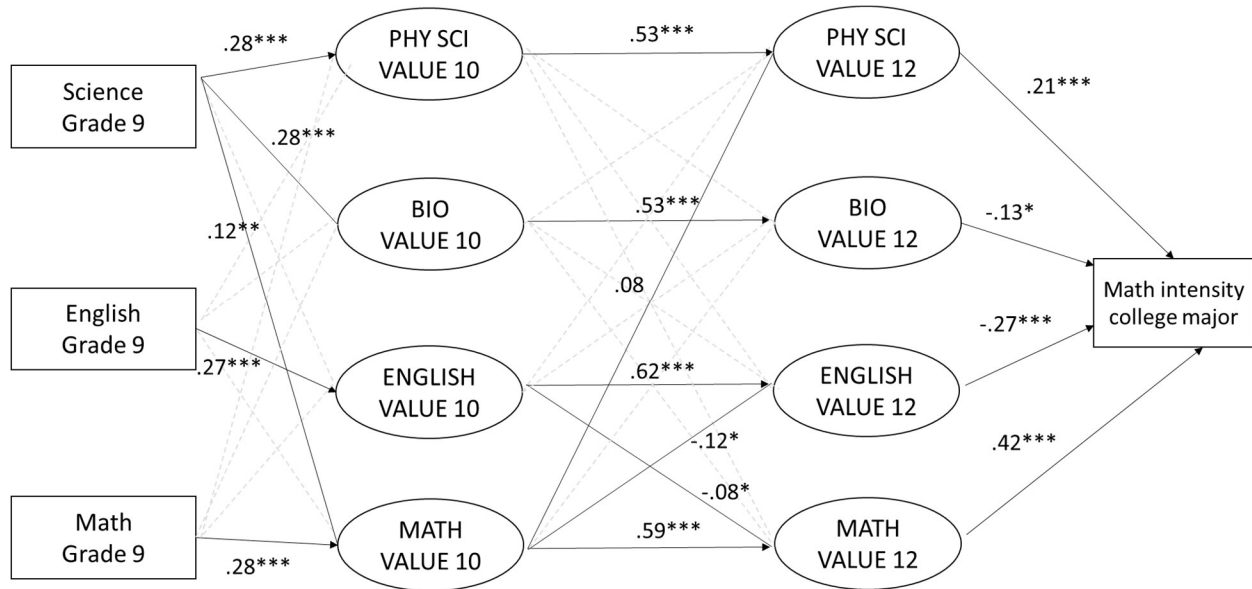


Figure 3.2. Final Structural Equation Model
All coefficients are standardized. Solid lines represent significant paths ($p<.05$). Dashed lines represent path that were not significant ($p>.05$).

Table 3.5*Dimensional comparisons of subjective task values and college major choice*

	<i>B</i>	<i>SE</i>	<i>p</i> -value
<i>Achievement and STV</i>			
Math STV 10			
Math Grade 9	0.276	0.037	0.000
English Grade 9	-0.040	0.043	0.348
Science Grade 9	0.123	0.043	0.004
English STV 10			
Math Grade 9	-0.020	0.037	0.600
English Grade 9	0.274	0.041	0.000
Science Grade 9	-0.025	0.042	0.559
Physical Sci STV 10			
Math Grade 9	0.016	0.037	0.678
English Grade 9	-0.054	0.042	0.202
Science Grade 9	0.282	0.041	0.000
Biology STV 10			
Math Grade 9	-0.042	0.036	0.247
English Grade 9	0.004	0.041	0.925
Science Grade 9	0.281	0.040	0.000
<i>Lagged STV Paths</i>			
Math STV 12			
Math STV 10	0.590	0.038	0.000
English STV 10	-0.085	0.040	0.032
Biology STV 10	-0.001	0.055	0.983
Physical Sci STV10	0.045	0.057	0.435
English STV 12			
Math STV 10	-0.123	0.050	0.013
English STV 10	0.623	0.039	0.000
Biology STV 10	0.072	0.059	0.225
Physical Sci STV10	-0.030	0.063	0.633
Biology STV 12			
Math STV 10	0.050	0.047	0.286
English STV 10	-0.052	0.044	0.237
Biology STV 10	0.532	0.055	0.000
Physical Sci STV10	0.052	0.062	0.402

Physical Sci STV 12			
Math STV 10	0.075	0.041	0.064
English STV 10	-0.052	0.037	0.163
Biology STV 10	0.078	0.052	0.134
Physical Sci STV10	0.534	0.053	0.000
<i>STV 12 & College Major</i>			
Math STV 12	0.415	0.046	0.000
English STV 12	-0.268	0.047	0.000
Biology STV 12	-0.130	0.065	0.047
Physical Sci STV 12	0.208	0.065	0.001

Note. All results are standardized.

Achievement and Task Values

To answer our first research question about the associations between achievement and task values in each domain, we looked at the predictive effects of achievement for math, science, and English at the end of ninth grade on all four task values for math, biology, physical science, and English in grade 10. Math STV in 10th grade was predicted by math achievement at the end of ninth grade ($B=.28, p<.001$). Science achievement also predicted math STV in 10th grade ($B=.12, p=.004$). English achievement did not predict math STV. English STV was only predicted by English achievement ($B=.27, p<.001$). Physical science STV was only predicted by science achievement ($B=.28, p<.001$). Biology STV was only predicted by science achievement ($B=.28, p<.001$).

Relations between Task Values Over Time

To answer our second research question about the associations between task values over time in high school, we looked at the effects of all four task values in 10th grade on all four task values in 12th grade. Math STV in 12th grade was predicted by math STV in 10th grade ($B=.59, p<.001$) and the cross-lag of English STV in 10th grade ($B=-.09, p=.032$). English STV in 12th grade was predicted by English STV in 10th grade ($B=.62, p<.001$) and the cross-lag of math

STV in 10th grade ($B=.12, p=.013$). Physical science STV in 12th grade was predicted by physical science STV in 10th grade ($B=.53, p<.001$) and the cross-lag of math STV was nearly significant at typical alpha levels ($B=.08, p=.064$) Biology STV in 12th grade was only predicted by biology STV in 10th grade ($B=.53, p<.001$).

Task Values and College Major Selection

To answer our third research question about the associations between task values and college major choice, we looked at the effects of all four task values in 12th grade on the math-intensiveness of college major. Math STV in 12th grade was positively associated with math intensive college major ($B=.42, p<.001$). Inversely, English STV in 12th grade was negatively associated with math intensive college major ($B=-.27, p<.001$). Physical science STV was positively associated with math intensive college major ($B=.21, p=.001$). Biology STV was negatively associated with math intensive college major ($B=-.13, p=.047$). In order to test whether gender moderated the associations between task value and college major, test of equal structural paths were imposed on the four STV predictors of college major and evaluated by Wald's test. The difference in coefficients between genders was not significant ($\chi^2=3.77(4), p=.44$).

There were latent mean differences in task values between genders. Females had higher English task value than males in 10th ($d=.94, z=8.65, p<.001$) and 12th grade ($d=.80, z=6.79, p<.001$). Males had higher physical science task value than males in 10th grade ($d=.35, z=4.53, p<.001$) and 12th grade ($d=.51, z=6.75, p<.001$). They had higher math value only in 12th grade ($d=.26, z=3.15, p<.001$). See Appendix IV for information pertaining to latent mean models.

Discussion

The present study, framed by EVT, the I/E model, and DCT, examined the relations between achievement, subjective task-values across four domains, and college major choice. We found that domain-specific achievement in ninth grade predicted subjective task values for those domains in tenth grade, in addition to a few cross-domain dimensional effects. We also found evidence of dimensional comparisons of subjective task values from tenth to twelfth grade. Finally, subjective task values for biology, physical science, math, and English were predictive of the math intensity of selected college majors.

Dimensional Comparisons Between Achievement and Task Values

Pertaining to the relations between achievement and task values, our findings have some similarities and differences from I/E and DCT literature. Overall, our findings provide further evidence that task value in a particular domain is related to achievement in that domain. We also find some evidence that task value in a domain may be related to achievement in a different domain.

Math achievement was positively associated with math task value, and English achievement was positively related to English task value. However, no dimensional comparisons across these two distal domains were observed. Math achievement did not relate to English task value, nor did English achievement relate to math task value. Our findings suggest that the nature of dimensional comparisons between achievement and self-concept may differ from the nature of dimensional comparisons between achievement and task values. This discrepancy may partially be explained by expectancy-value literature that suggests the relations between achievement and task value may be mediated by self-concept of ability (Gaspard et al., 2018, Nagy et al., 2008). Thus, it may be that achievement influences self-concept of ability first, and as students feel a

sense of competence in a domain, they likely attach more value to that domain. Additionally, Wigfield, Eccles, and Moller (under review) found the strength of association from achievement in a domain to a students' valuing of that domain to be much smaller than the association between achievement and self-concept. They suggested that this finding indicates that self-concept is more closely tied to achievement and that students use other sources of information beyond achievement in determining how much they value a task.

Although math and English did not show any dimensional comparisons between achievement and task value, we did find some evidence of dimensional comparisons between science achievement and math task value. Science achievement positively predicted math task value, which is consistent with DCT findings (Marsh et al., 2015). This finding suggests that although the overall relations between achievement and task value are not as strong as typically found between achievement and self-concept, that self-concept may not fully mediate the relationship between achievement and cross domain values. While our findings were generally in line with findings by Gaspard and colleagues (2018), we believe that the differences may partially be explained by how task value was measured. We conceptualized task value as a latent construct comprised on interest value, utility value, and attainment value, whereas Gaspard and colleagues separated each component of value into its own latent construct. Therefore, the strength of associations differed between our studies as our inquiry pertained to the shared variance of the individual properties of task value and its relation to college major. This methodological difference raise an important question about the appropriate method for modeling the latent construct of task value. If the underlying components of task value truly form a common factor, then treating them as part of one latent variable may be more appropriate when

modeling task value as a predictor of academic choice. Future research should investigate this matter further.

Development of Task Values Across Domains

Pertaining to the development of task values over time in high school, we found that task values exhibited a fair amount of stability in high school, as the matching value in 10th grade strongly predicted the same value in 12th grade. A number of cross-domain relations emerged that demonstrate how task values may affect one another over time. Prior math task value was negatively associated with future English task value and prior English task value was negatively associated with future math task value. Prior math value was also positively associated with future physical science task value. Contrary to our hypothesis and DCT findings, task value for each science domain did not relate to each other over time.

These findings are an important extension of dimensional comparison processes. Although dimensional comparisons often consider the relation between achievement and motivation (e.g., self-concept or subjective task value), our findings demonstrate how task values across domains relate to one another over time as a developmental process. A particular subjective task value's developmental process cannot be understood by studying it in isolation, out of its context with other, simultaneously operating subjective task values in the individual.

College Major Selection

We found that multiple values related to the choice of taking a math intensive college major. While math task value most strongly predicted selecting a math intensive major, physical science task value was also a positive predictor. Inversely, English and biology task value were negatively related to selecting a math intensive major. These findings are fundamentally important to theories of motivation. Just as Eccles (1994) rejected the assumption that the

decision to take advanced math courses is based on variables related to math, we find evidence that both far domains such as English and near domains such as physical science may influence math related academic choices. We believe that other task values may reinforce the road one may take, whereby interest, utility, and attainment value for a domain such as physical science may increase the likelihood of taking a math intensive major. Conversely, task value for English may detract someone from a math related major towards a field that allows one to engage in more literacy based activities, as that is what such an individual is interested in, finds useful, and identifies with. Thus, it seems in the presence of a difficult academic choice such as college major, that values are activated and used as guiding principles (Schwartz, 2013).

Finally, we did not find any evidence that gender moderates the relations between task values and major, suggesting that the effect of task value for each domain does not differ between genders. This is consistent with prior research that has found gender differences in educational outcomes to gender differences in motivational beliefs and achievement (Chow et al., 2012; Guo, Parker, Marsh, & Morin, 2015). We similarly found gender differences in the means of math, English, and physical science task value. Moreover, we found a slow decline in values from 10th grade to 12th grade, which is consistent with prior research (Archambault, Eccles, & Vida, 2010; Musu-Gillette et al., 2015).

Practical Implications

In addition to the theoretical implications of our study, our findings have practical implications for research and practice. First, motivational interventions have realized that utility value is a lever that can be pulled to change the value a student associates with a particular domain (for example, see Harackiewicz, Rozek, Hulleman, & Hyde 2012; Hulleman, Godes, Hendricks, & Harackiewicz, 2010). While these interventions have shown some success, our

study highlight that task values do not develop in isolation. Rather, they may be part of a dynamic system of motivational values, where tinkering with task value for one domain may positively or negatively influence task value in another domain. There is some evidence of these unintended side effects, as German students who were given a utility value intervention in math showed declined value for German, even five months after the intervention (Gaspard et al., 2016). Therefore, interventionists need to proceed cautiously when designing interventions to ensure that student autonomy is not short-circuited through manipulation of values, especially if the intervention is given during crucial stages of values and identity development. Additionally, possible side effects may need to be disclosed to parents, teachers, and students. On the flip side, interventions that are ethically designed can also use our findings to consider alternative angles to boost value by using near domains that support the targeted domain. For example, if the intervention is aimed at getting more students to consider math intensive careers such as engineering, interventions may consider targeting a near domain such as physical science.

Conclusion & Limitations

The present study shed light on dimensional comparisons between four academic domains of subjective task value and their role in college major choice. We have made a contribution to the literature on values and motivated academic behavior by considering how internal dimensional comparisons of academic domains relate to the development of subjective academic task values in adolescence and relate to college major choice. Our findings have theoretical and practical implications. Understanding how task values develop and relate to academic choices has been the subject of substantial motivational research. Although most task value research has relied on single-domain analyses, our study demonstrates the utility of

considering the diverse academic domains that students study and value as part of a dynamic motivational system.

The findings shed light on the importance of considering multiple subjective task values on both the development of subsequent task values and on academic choices. However, there are a few limitations that must be considered when interpreting the results. The study relied on correlational data, thus making strong causal claims less tenable. The sample was predominantly White and middle/working class, which may limit generalizability to other populations. The college major data were collected between 1992-1993, and whether or not the findings would replicate today is an empirical question. However, gender differences in college major selection are still evident today, and we do not have any reason to suspect that the underlying mechanisms and psychological processes have changed in the past few decades. Nonetheless, we suggest future studies consider diverse populations and utilize more recent data to test whether the associations have changed in any way.

Future research should also consider directly assessing dimensional comparisons. Within expectancy-value research, self-concept surveys include items about self-concept in a domain relative to other domains. Similarly, subjective task-value surveys should also include items about task value for one domain compared to others. This may help us measure task value more accurately and enhance prediction of motivated behavior. Finally, we believe more person-centered approaches should be utilized to study the cooccurrence of subjective task values, including methods such as cluster analysis and latent profile analysis. These methods may better explain heterogeneity in the profiles of subjective task values and the extent to which these profiles explain academic choices. It is likely that within a motivational system, such as subjective task values, that each operating factor does not function independently of other

factors. The specific role of each operating task value is determined by the role it plays in the task value system. Thus, important individual differences may be discovered in the patterning of task value factors in the motivational system under investigation (Bergman, Magnusson, & El-Khoury, 2003).

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CHAPTER 4

The Motivational System of Subjective Task Values and Anticipated Emotions in the Pursuit of Daily Academic Tasks

Relations between university students' domain specific motivation and their long-term academic choices and behaviors have been extensively studied. However, success in a particular course depends on students completing individual tasks and assignments on a daily and weekly basis, and little is known about how students' study intentions and motivation operate on a micro-level. As Ajzen (1993) pointed out, the principle of aggregation (i.e., the sum of a set of multiple measurements is a more stable and representative estimator than any single measurement) does not explain behavioral variability across situations, nor does it permit prediction of a specific behavior in a given situation. Therefore, relying on macro-models of motivation may not reflect micro-level motivation and behavior. As students approach academic tasks with varying levels of motivation, emotions, and priorities (Eccles et al., 1983; Pekrun, 2006), understanding the interplay of these constructs on a task-specific level is fundamentally important in developing motivational theories of achievement. Furthermore, as technology has created new learning environments, motivational theories need to consider the affordances and challenges of these contexts.

The proliferation of online courses in universities has provided a new context for learning, providing students with extensive control over the time and place that they complete course-related tasks. This new context may be advantageous or problematic for students, depending on their motivation and ability to self-regulate their learning (Kizilcec, Pérez-Sanagustín, & Maldonado, 2017). Prior research shows that expectancies (de Fátima Goulão, 2014; Fryer & Bovee, 2016) and subjective task values (Chiu & Wang, 2008) are significant predictors of students' intentions to persist in e-learning. In this study, we integrate theories of

motivation, emotions, goal-setting, and planned behavior to investigate daily academic intentions in an undergraduate online course and the extent to which motivation at the task level relates to daily task attainment.

When investigating intentions to complete course-related tasks at a daily level, the importance of task hierarchies becomes apparent. With limited time in a day, students may *plan* an activity, but may fail to *complete* it if a confluence of self-regulation, achievement emotions, and task-value leads them to prioritize it lower than other activities. Additionally, students may disengage from a daily academic task for adaptive reasons and reengage with the task at a more appropriate time. Literature on goal intentions (Gollwitzer, 1993), achievement emotions (Pekrun, 2006), the theory of planned behavior (1991), and expectancy-value theory (Eccles et al., 1983) all provide insights into the process of task attainment, and we seek to synthesize these frameworks to better understand student behavior. As multiple theoretical perspectives use different terminology, we consider the terms goals and tasks as fundamentally referring to the same thing.

Synthesizing Theoretical Frameworks

Numerous psychological models seek to explain motivated behavior at the macro or micro-level. The underlying assumption of many of these models is that motivated behavior stems from the formation of an intention to engage in a particular task. These psychological models of motivation have focused on different facets of the motivational system, including the role of expectations of success and subject task values on macro achievement choices and performance (Eccles et al., 1983), the relations between attitudes and intentions on actual behavior at the micro-level (Ajzen, 1991), the role of emotions in achievement contexts (Pekrun, 2006), and the influence of self-regulation on goal pursuit (Gollwitzer, Fujita, & Oettingen,

2004). We seek to synthesize the focal constructs in each theory in order to better explain daily behavior in an achievement context at the person-level. We proceed to explain each theory of motivated behavior and the utility of weaving the focal constructs into an organized model to study daily academic behavior.

Expectancy-value Theory

According to expectancy-value theory (EVT), achievement-related behaviors are directly influenced psychologically by relative expectations of succeeding in a task and the subjective task value associated with the task compared to other tasks. Subjective task value refers to the subjective aspects of a task that contribute to the increasing or decreasing probability that an individual will select and accomplish it (Eccles, 2005). Subjective task value is an emergent property of the task and determined by the perceived fit between the characteristics of the task itself and the actor (Eccles & Wigfield, 1995). Highlighting expectancy and subjective task value as task specific is important, as different academic tasks, such as homework assignments and quizzes, within a course may have differing expectancies of success and value. Subjective aspects of a task emerge from (1) attainment value, or the value an activity has in fulfilling one's identity or self-image; (2) interest value, which refers to the expected enjoyment in task engagement; (3) utility value, how useful the task is in fulfilling various short and long-term goals; and (4) the cost of engaging in the activity, which can be psychological, financial, or time and energy related. Interest has been conceptualized as both an emotion (Pekrun, 2006; Silvia, 2008) and as part of task value in expectancy-value research.

Most prior EVT literature has measured expectancies and subjective task values at the general domain level as predictors of future academic intentions and aspirations, college major selection (Umarji, McPartlan, & Eccles, 2018), college major persistence (Andersen & Ward,

2014), and achievement (Wigfield & Eccles, 2000). For example, typical survey items will ask students how good they think they are at math and how interested they are in the subject.

However, on both a micro- and macro-level, intentions, persistence, and achievement are distinct outcomes that are likely manifested through separate processes with unique predictors, although expectancies and subjective task values likely share variance with each of these outcomes.

Furthermore, intentions do not always translate into behavior. Within expectancy-value theory, the relative expectancies and subjective task values across available tasks is considered critical in linking intentions and behaviors, as intended tasks may be coopted by more valued tasks (Eccles & Wigfield, 2019). This intention-to-behavior-gap has received significant attention (Sheeran, 2002), and the theory of planned behavior (Ajzen, 2005) has addressed some of the mechanisms relating intentions to behavior.

Theory of Planned Behavior & Goals

When investigating motivation for daily academic tasks, motivational beliefs should be measured at the level of the specific tasks under consideration. Thus, when a specific behavior is to be predicted, such as task completion, the compatibility principle should be relied upon. The principle states that attitudes will better predict behavior if the specificity of a measured attitude matches the specificity of the behavior under consideration (Ajzen, 1988; Ajzen & Fishbein, 2005). Lack of utilizing this principle may be considered a limitation of some expectancy-value research that has measured attitudes at a general domain level to predict specific behaviors like enrolling in a math course or persisting in a major. Furthermore, intentions and actualization of the intention must be disentangled in conceptualizing how motivation relates to daily academic tasks.

Task-related intentions are considered fundamental antecedents of task attainment. The formation of an intention is seen as being dependent on both the person's attitude toward the behavior and the experienced normative pressures to execute it (Fishbein & Ajzen, 1975). When behavioral attitudes are positive and subjective norms favor the execution of a critical behavior, chances are high that the respective behavioral intention is formed. Students have many different desires and needs of what academic and non-academic behaviors to engage in daily, and some of these desires and needs may be in conflict with each other due to time constraints or the energy and effort required to realize them (Eccles, 2005). For example, on a particular day, a student may plan to go work, go to the gym, attend multiple class, and complete a number of required and optional school assignments. However, after attending multiple classes and going to work, the student may not have the energy or time to go to the gym or complete their assignments. Goal (e.g., task) intentions may help organize what people plan to achieve. Additionally, daily tasks vary in priority and understanding the hierarchy of goal intentions is important in the study of goal attainment (Cropanzano, James, & Citera, 1993; Eccles, 2005). Goal hierarchies refer to a mental system in which a person ranks a goal one above the other according to its perceived importance. Goal attainment has been found to be more likely to occur when based on personal value rather than controlled motives (Koestner, Otis, Powers, Pelletier, & Gagnon (2008). However, in an academic course, assignments are typically not negotiable and must be completed by a certain time and in a certain manner. Thus, goal setting in an academic contexts may operate differently than setting personal goals such as weight loss. Another important distinction in the study of goals can be made between goal intentions and goal expectations (Warshaw & Davis, 1985). Intentions refer to what a person intends to do, whereas expectations refer to how likely a person expects to do something. Expectations are theorized to

capture unobserved factors that may cause a person to be unsuccessful in fulfilling their intention (Sheppard, Hartwick, & Warshaw, 1998).

Emotions & Goal-directed Behavior

In addition to considering task expectancies and subjective values in the study of academic goal intentions and attainment, emotions are also a key component of motivated behavior (Baumeister, Vohs, DeWall, & Zhang, 2007; Pekrun, 2006). Emotions consist of psychological subsystems that may be affective, cognitive, and motivational (Damasio, 2004), and they are the ways in which someone experiences value judgments of objects, events, and situations. Situations that include negative appraisals and threaten one's values may give rise to negative emotions, whereas situations with positive appraisals and that align with one's values may produce positive emotions (Locke, 1996). In goal-setting contexts, the immediate value standard is the level of performance desired, whereby goal achievement leads to satisfaction and goal failure to regret (Locke, 1996).

The effect of emotions on performance likely depends on the mechanisms facilitated by the emotion and their interactions with task demands. Positive emotions may focus attention, foster interest, and promote self-regulation of a task (Pekrun & Stephens, 2009). Achievement emotions have been conceptualized as either pertaining to the academic activity in the moment or the outcome that one anticipates (Pekrun, 2006). The combination of previous emotional outcomes and current affect contribute to the formation of anticipating emotional outcomes and engaging in subsequent behavior according to these expected emotions (Baumeister, Vohs, DeWall, & Zhang, 2007). Anticipated emotions are expectations of how the individual will feel once the gains or losses associated with that decision are experienced (Loewenstein & Lerner, 2003). Anticipated emotions include satisfaction (positive) and regret (negative), and these

emotions relate to expectancies and values (Ketonen et al., 2018). For example, anticipated feelings of satisfaction for completing a task or regret for failing to complete a task are likely more intense when that goal has high task value. Similarly, anticipated regret may also be considered a psychological cost that relates to the perceived value of the task. The functioning of anticipated emotions is considered key to the emotional goal system. In an achievement context, a student may identify and evaluate the consequences if he or she were to achieve their goal or not. The student may then generate alternative consequences to imagined goal success and goal failure, which then serve as input for appraisals and the generation of anticipated emotional responses. For anticipated emotions, focus is on a single goal, and the emotions reflect both how positively one would feel if the goal were achieved and how negatively one would feel if it were not (Bagozzi & Pieters, 1998).

Goals serve as the reference standard for feelings of satisfaction versus dissatisfaction (Mento, Locke, & Klein, 1992). People who anticipate experiencing discontent or regret when they fall short of their goals will likely intensify goal pursuit (Gollwitzer, 1993). Regret is intrinsically aversive, and individuals are motivated to avoid it (Zeelenberg, Beattie, Van der Pligt, & De Vries, 1996). Anticipated regret refers to the extent of regret, tension, or distress a person would feel if they did not perform a particular behavior. Anticipated regret has strong associations with intentions to perform behaviors after other predictors have been controlled (Richard, van der Pligt, & de Vries, 1995). Anticipating regret about failing to perform a behavior might bind people to their intentions, such that participants who both intend to perform a behavior and anticipate considerable regret if they do not perform it, should exhibit greater intention behavior consistency than participants with equivalent intentions who do not anticipate regret (Sheeran & Orbell, 1999b).

Self-Regulation

Goal intentions, expectations, values, and anticipated emotions do not automatically lead to goal attainment. The actions required to accomplish one's goal must ensue after the intention has been made. The ability to self-regulate behavior in the face of challenges and distractors thus functions as an important determinant of successful goal attainment (Gollwitzer, 1993; Oettingen, Hönig, & Gollwitzer, 2000). Self-regulation is especially salient in the context of online courses where students have significantly more autonomy of when to engage with course content and have to manage their time, study environment, and help seeking behaviors (Lynch & Dembo, 2004). Self-regulation also relates to anticipated emotions, as the act of imagining positive or negative emotional outcomes may initiate self-regulated behavior.

Person-centered Research on Motivated Behavior

Based upon the prior discussed theories and constructs related to motivated behavior, situational heterogeneity of motivation is likely present both within and across students. For example, anticipated emotions, interest, and opportunity cost may differ for numerous reasons depending on the type of activity (e.g., reading or completing a homework assignment), the valued alternatives available to an individual that day or moment (e.g., opportunities to hang out with friends or the need to study for another exam), or a host of other situation or person specific reasons. Person-centered approaches that investigate such heterogeneity within or between people and moments have gained popularity due to considerations of increased ecological validity by not assuming ergodicity in psychological processes and due to the finer-grained details that they allow (Howard & Hoffman, 2017). The assumption of ergodicity assumes that the structures of interindividual and intraindividual variation are asymptotically equivalent, and violations of this principle may lead to incorrect inferences, including the ecological fallacy. The

ecological fallacy occurs when statistical inferences from groups are inappropriately generalized to individuals (Fisher, Medaglia, & Jeronimus, 2018). To avoid these concerns, recent research in the field of educational psychology has utilized person-centered approaches to understand heterogeneity in undergraduate science courses and students patterns of engagement across contexts (Robinson et al., 2017), situational fluctuations in expectancies and values (Dietrich, Moeller, Guo, Viljaranta, & Kracke, 2019; Dietrich, Viljaranta, Moeller, & Kracke, 2017;), and academic emotions in adolescence (Ganotice, Datu, & King, 2016; Moeller, Ivcevic, Brackett, & White, 2018). These studies consistently identified unique profiles with respect to key motivational constructs. In a study focusing on profiles of expectancies, values, and costs in an undergraduate science course, the authors found four profiles that included low motivation situations, highly motivating situations, low cost motivation settings, and motivating but costly situations (Dietrich et al., 2019). Although the authors investigated associations between global motivational dispositions, they did not investigate how these profiles associated with subsequent behavior on a task. Another study by Robinson and colleagues (2017) found four affective profiles of situations in a college anatomy course (positive activated, positive deactivated, negative activated, and negative deactivated) and found that behavioral and cognitive engagement in these situations mediated the effects of the profiles on a course exam. These studies provide support for investigating the heterogeneity in experiences depending on the situation or task, yet it is important to note that each of these studies considered profiles within a set of constructs from a single theory (e.g., expectancy-value and control-value) only.

Current Study

In the present study, we build upon the task motivation literature by integrating expectancy-value, control-value, goal setting, and the theory of planned behavior perspectives.

Our study contributes to the literature in a number of ways. First, we study task motivation in the novel context of an asynchronous online course, which allows students the autonomy to plan and engage with the course material on their own time. This allows us to investigate “motivation in the wild”. Second, we investigate the cooccurrence of subjective task values (interest and opportunity cost) and anticipated emotions intraindividually and across multiple tasks to understand heterogeneity in these motivational profiles. Third, we investigate the associations between motivational profiles and both task intentions and task attainment. See Figure 4.1 for a conceptual model of the hypothesized relations between constructs. We seek to answer the following research questions:

1. What motivational profiles of subjective task values (e.g., interest and cost) and anticipated emotions (e.g., satisfaction and regret) cooccur within students across tasks?
2. To what extent do these motivational profiles relate to expected and actual task completion?
3. To what extent do these motivational profiles, effort regulation and task hierarchy relate to expected and actual task completion?

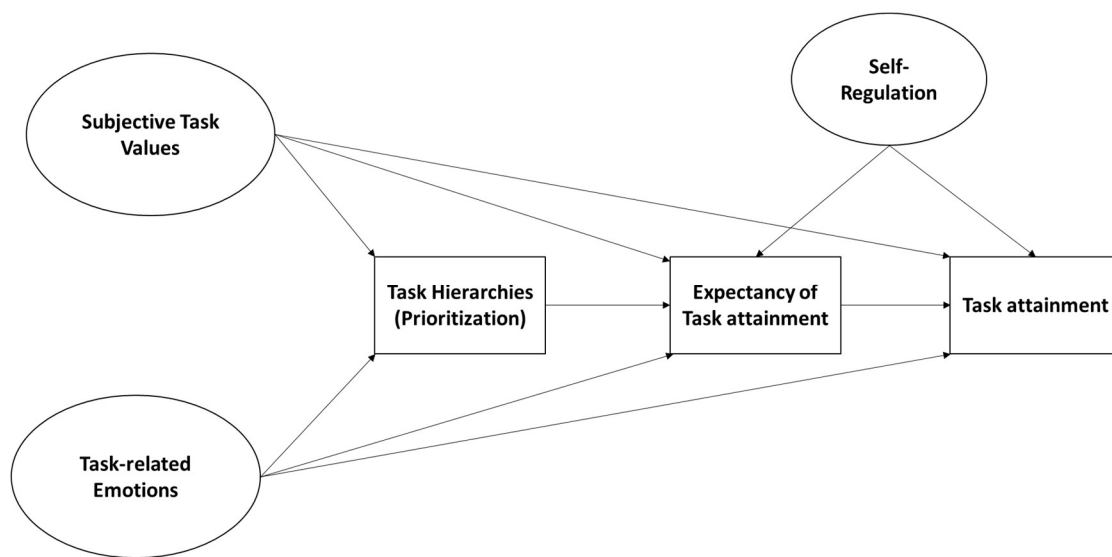


Figure 4.1. Conceptual Model of Daily Task Motivation

Method

Participants

The participants in this study were recruited from an undergraduate summer online class at a large public university in Southern California. The class was an elective course on the biology and chemistry of cooking for non-biology majors. The data in this study were collected over five weeks in the summer of 2018, and include intensive survey data, clickstream data (i.e., user-logs of all student behavior within the learning management system), and institutional data on the students demographics. The total sample included 147 students and included a complex survey design intended to understand stability and change over days, weeks, and from the start to end of the course. Students completed surveys related to course motivation before and after the course (pre and post), at the start of every week (weeks one to four), and for seven continuous days during the third week of the course. Students were sent text messages with links to personalized online surveys for the daily and weekly surveys. This study utilizes a subsample of students ($n=101$) who completed the daily diary surveys during the third week of the course.

Measures

Daily activity. Students were asked to enter up to five course-related activities and five non-course-related activities that they planned to do that day. Responses were open-ended and coded for type of activity (e.g., reading, watching videos, take a quiz) and specificity of activity (low, medium, or high). Two research assistants independently coded each activity.

Task importance rank. Students were asked to rank order all their planned daily activities from the most important to least important, with one being the most important activity of the day.

Interest. Interest for each daily course activity was assessed with the single item “how interesting is this course-related activity” on a Likert scale from 1 = not at all interesting to 7 = very interesting.

Opportunity Cost. One item was used to assess opportunity cost for each daily course activity (item, “how much will you have to give up to complete this activity?” on a Likert scale from 1 = nothing to 7 = a lot).

Anticipated regret. One item was used to assess anticipated regret for each daily course activity (item, “How much regret will you feel if you do not complete this activity?” on Likert scale from 1 = none at all to 7 = extreme).

Anticipated satisfaction. One item was used to assess anticipated satisfaction for each daily course activity (item, “How much satisfaction will you feel if you complete this activity?” on Likert scale from 1 = none at all to 7 = extreme).

Expectation of activity completion. One item was used to assess expectancy of activity completion (item, “to what extent do you expect to complete this activity?” on a Likert scale from 1 = not at all to 7 = completely). Due to the skewed distribution of the response, where the majority of activities were rated a 7, the item was recoded into a dichotomous variable of whether or not the student absolutely expected to complete the activity or not. Absolute expected complete was coded as 1 if the response was 7. Otherwise, it was coded as 0.

Actual activity completion. One item was used to assess actual activity completion on the following day (item, “to what extent did you complete this activity?” on a Likert scale from 1 = not at all to 7 = completely). Due to the skewed distribution of the response, where the majority of activities were rated a 7, the item was recoded into a dichotomous variable of

whether or not the student absolutely completed the activity or not. Absolute completion was coded as 1 if the response was 7. Otherwise, it was coded as 0.

Effort regulation. Effort regulation (ER) was measured prior to the start of the course in the pre-survey. Six items were used to assess students' self-reported ability to regulate their effort (Cronbach's $\alpha = .79$) related to academics (sample item, "Even when course materials are dull and uninteresting, I manage to keep working until I finish", measured on a Likert scale from 1= strongly disagree to 5 = strongly agree). See Appendix V for a complete list of survey items.

Attrition and Missing Data

The data in this study include a complex pattern of complete and missing data. Students were able to complete up to five course-related and five non-course related activities daily. If students did not respond to the daily survey, then the data were treated as missing. However, if the student put in at least one activity, the data was considered complete. Students who participated in the daily surveys had higher final course grades than those who did not participate in the daily surveys. However, t-tests showed that there were no significant differences between daily survey participants and non-participants in any other key motivational constructs, including course importance, course interest, effort regulation, and self-efficacy. Of the 101 students who participated in the daily surveys, 26 were dropped from our analysis sample due to missing data at the person level, as hierarchical linear modeling will not allow missing values at level two (Raudenbush & Bryk, 2002). The final analysis sample included 75 students with valid daily survey data (i.e., they responded to at least one daily survey) and baseline data on effort regulation, yielding 561 total daily tasks reported.

Analysis Plan for Research Questions 1 & 2

Cluster analysis was used to investigate patterns of task values (e.g., interest and cost) and anticipated emotions (satisfaction and regret). Cluster analysis allows for classifying each task into homogeneous subgroups with respect to the patterns of task values and emotions reported by the student by maximizing within-cluster homogeneity and between-cluster heterogeneity (Magnusson & Törestad, 1993; Wormington, Corpus, & Anderson, 2012). Raw scores for interest, cost, regret, and satisfaction were used for each task, as standardizing introduces numerous problems with interpreting the data for longitudinal studies, especially in profile analyses, as the z-score represent rank in relation other students, not the extent to which an item was endorsed by a student (Moeller, 2015). A multi-step analysis was carried out using ROPSTAT (Vargha, Torma, & Berman, 2015), a statistical package for person-centered analyses. The following steps were performed:

4. Preparatory steps of removing outliers;
5. Hierarchical cluster analysis followed by K-means relocation clustering.
6. Random sample validation procedure to confirm cluster stability and reliability.

Multivariate outliers were identified using the RESIDAN method (Bergman, 1988b), which identifies outliers prior to clustering. Hierarchical clustering methods are sensitive to outliers that may bias the hierarchical structure at any level of merging, and the cutoff point was a squared Euclidean distance greater than 0.7 (Berman et al., 2003). Three outliers were removed from the analysis sample.

After the preparatory steps were completed, cluster analysis was performed using Ward's method, a hierarchical agglomerative method that initially assigns each case to its own cluster and step-by-step the most similar clusters are joined together, eventually resulting in one cluster

with all cases (Clatworthy, Buick, Hankins, Weinman, & Horne, 2005). Ward's method is based on squared Euclidian distances to create a similarity/dissimilarity matrix, aiming to minimize the within-cluster sum of squares (Wormington et al., 2012). Additionally, it makes no assumptions about the distribution of the data being used. In order to determine the most suitable cluster solution, both a priori theorizing of clusters and statistical considerations based on the percent of variance explained were considered. The error sum of squares (ESS), a measure of cluster heterogeneity, and the explained error sum of squares (EESS) were calculated for all possible cluster solutions.

$$EEES=100*((TotalESS-ESSofthegivencustersolution)/TotalESS)$$

An EEES value of 100 implies perfect cluster homogeneity, whereas 0 implies the complete absence of cluster homogeneity (Bergman et al., 2003). ESS values were plotted against EEES values to display an array of possible cluster solutions based on how much additional error was included by reducing a cluster from the previous solution. This analysis was carried out at every wave independently, as it is possible that a different number of clusters would emerge at different developmental stages.

K-means clustering was performed to fine-tune cluster homogeneity by reassigning cases to the optimal cluster. In K-means clustering, the number of clusters is chosen before relocation using the initial hierarchical method. Centroids (i.e., profiles of means for the variables in the clusters) from the Ward's analysis were used as starting points, and all cases within a certain distance of the centroid became assigned to that cluster until all cases were assigned (Wormington et al., 2012). The K-means analysis reduced the homogeneity coefficient of the clusters at each wave, confirming that case relocation was appropriate. Cluster stability and reliability was tested by drawing a random split of the sample and confirming that similar

clusters appeared. After all cluster solutions were completed, cross-tabulations with adjusted standardized residuals were used to test for differences in cluster membership and expected and actual task completion.

Analysis Plan for Research Question 3

Hierarchical logistic regression was used to predict the likelihood of expected and actual task completion based on cluster membership, effort-regulation, and task importance rank. Two models were estimated, one for expected task completion and one for actual task completion. Repeated measures of cluster membership and goal hierarchy (level-1) were nested within students (level-2). Effort regulation (level-2) was grand-mean centered, allowing us to analyze inter-individual differences (Enders & Tofighi, 2007).

To address missing data issues, restricted maximum likelihood (REML) was used for estimation of variance and covariance components. REML estimates of variance components account for the uncertainty of the fixed effects. Full maximum likelihood estimates were computed as a robustness check, and the results were very similar. All analyses were estimated using HLM 7 software (Raudenbush, Bryk, Cheong, Congdon, & Du Toit, 2011) using robust standard errors.

The final model for each outcome was:

Level-1 Model

$$\begin{aligned} \text{Prob}(\text{Task Completion}_{i}=1|\pi_i) &= \phi_i \\ \log[\phi_i/(1 - \phi_i)] &= \eta_i \\ \eta_i &= \pi_{0i} + \pi_{1i}*(C1_C_{ii}) + \pi_{2i}*(C3_C_{ii}) + \pi_{3i}*(C4_C_{ii}) + \pi_{4i}*(C5_C_{ii}) + \pi_{5i}*(C6_C_{ii}) + \\ &\pi_{6i}*(\text{taskimportancerank}_{ii}) \end{aligned}$$

Level-2 Model

$$\begin{aligned}\pi_{0i} &= \beta_{00} + \beta_{01}*(ER_i) + r_{0i} \\ \pi_{1i} &= \beta_{10} \\ \pi_{2i} &= \beta_{20} \\ \pi_{3i} &= \beta_{30} \\ \pi_{4i} &= \beta_{40} \\ \pi_{5i} &= \beta_{50} \\ \pi_{6i} &= \beta_{60}\end{aligned}$$

where η_{it} represents the outcome (expected/actual task completion) of the i th student on the t th task measured and e_{it} represents the level-1 residual. The parameters, β_{10} to β_{50} , represent the estimates of the likelihood of expected and actual completion by each cluster, relative to the average cluster, C2. The parameter, β_{60} , represents the association between task importance rank and the likelihood of expected/actual task completion. β_{01} represents the effect of effort regulation on expected/actual task completion. Heterogeneity in the intercept is captured by the random effects, r_{0i} .

Results

Preliminary Findings

Before presenting our findings on the patterns of task values and anticipated emotions and their association with task attainment, we provide a summary of the descriptive findings as a necessary backdrop to the forthcoming analyses. Means and standard deviations are provided in Table 4.1. Students expected to complete 55% of all their daily tasks but reported completing approximately 43% of them. Of all the task-related motivational constructs, anticipated emotions of regret and satisfaction were the highest on average, whereas opportunity cost had the lowest mean but the largest standard deviation. Correlations for all study variables are found in Table 4.2. Task values and anticipated emotions were associated with expectations and actual task completion, with the exception that interest value was not associated with actual task attainment.

Table 4.1*Means, standard deviations, and ranges for all study variables*

	<i>Mean</i>	<i>SD</i>	<i>Min</i>	<i>Max</i>
Expected completion (dichotomized)	0.55	0.50	0	1
Expected completion	6.20	1.21	1	7
Actual completion (dichotomized)	0.43	0.50	0	1
Actual completion	5.16	2.27	1	7
Interest	4.90	1.38	1	7
Cost	3.76	1.70	1	7
Anticipated regret	5.66	1.49	1	7
Anticipated satisfaction	5.78	1.50	1	7
Effort Regulation	3.48	0.64	2.43	5
N_{tasks}	561			

Table 4.2*Correlations of all study variables*

	Expected	Actual	Interest	Cost	Regret	Satisfaction	Task rank	ER
Expected	-							
Actual	0.44***	-						
Interest	0.09*	0.03	-					
Cost	-0.14***	-0.15***	0.11**	-				
Regret	0.29***	0.23***	0.25***	0.09*	-			
Satisfaction	0.14***	0.13**	0.47***	0.14***	0.36***	-		
Task rank	0.22***	0.21***	0.08	-0.07	0.18***	0.10*	-	
ER	0.20***	0.14***	0.06	0.12***	0.11**	0.19***	-0.12**	-

Note. All variables are repeated measures except for ER = Effort Regulation.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Clusters of task values and anticipated emotions

The initial results from Ward's hierarchical method revealed that a cluster solution between six and nine clusters could be considered by analyzing the ESS and EESS plots. After investigating the specific patterns in each cluster solution, we determined that a six-cluster solution best fit and explained the data parsimoniously. Every cluster solution beyond the six-cluster solution began to break one distinct cluster into subgroups that were not theoretically meaningful. Larger solutions also did not explain substantially more variance. Additionally, K-means clustering was used to relocate cases, correcting preliminary classification and increasing cluster homogeneity. The final six-cluster solution accounted for 67.6% of the variance, above prior used thresholds of 50% or 67% (Hayenga & Corpus, 2010; Wormington et al., 2012).

We describe the clusters in terms of the extent to which interest (as an emotion & aspect of task value), opportunity cost, anticipated regret, and anticipated satisfaction were high, medium, or low relative to other clusters. Cluster means and homogeneity coefficients are displayed in Table 4.3 and Figure 4.2 illustrates clusters visually. Motivational clusters were labeled as Cluster 1: High emotions/high cost ($n = 171$; 30%), Cluster 2: medium emotions/medium cost ($n = 87$; 15%), Cluster 3: low cost/high satisfaction ($n = 83$; 15%), Cluster 4: high emotions/low cost ($n = 124$; 22%), Cluster 5: high regret ($n = 47$; 8%), and Cluster 6: low emotions/low cost ($n = 54$; 10%). The high emotions/ high cost cluster (1) and the low emotions and low cost cluster (6) refer to daily tasks that were considered high or low in all four constructs of interest, cost, anticipated regret, and anticipated satisfaction. The low cost/high satisfaction cluster (3) referred to daily tasks where opportunity cost was considered very low, interest was medium, anticipated regret was somewhat low, but anticipated satisfaction was very high. The high emotions/low cost cluster (4) referred to daily tasks that were quite high on the

three emotions of interest, anticipated regret, and satisfaction, but were low on opportunity cost.

The high regret cluster (5) was low on interest, cost, and anticipated satisfaction, but high on regret only.

Table 4.3
Cluster Centroids, Size, and Homogeneity Coefficients

Name	Interest	Cost	Regret	Satisfaction	Cluster Size	HC
1. High emotions/high cost	5.49	5.30	6.64	6.73	171	1.22
2. Medium emotions/medium cost	4.84	5.11	4.78	5.24	87	1.86
3. Low cost/high satisfaction	5.08	2.56	4.25	6.62	83	1.88
4. High emotions/low cost	5.66	2.10	6.61	6.47	124	1.26
5. High Regret	3.38	2.91	6.51	4.02	47	2.08
6. Low emotions/low cost	3.24	3.21	3.19	3.23	54	2.52

Note. HC = Homogeneity coefficient.

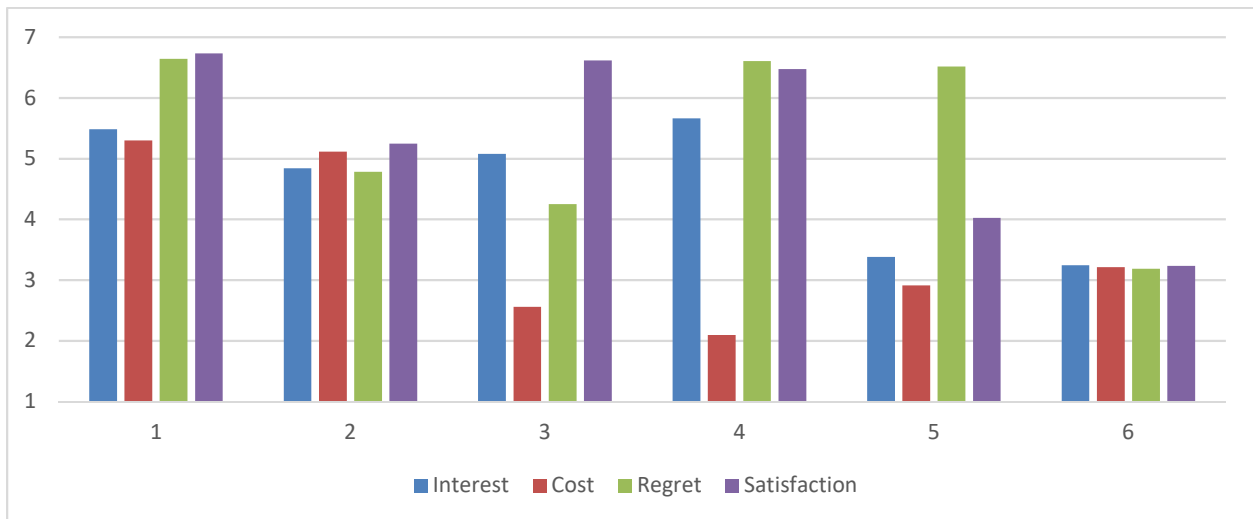


Figure 4.2. Six-cluster solution for task values and emotions profiles.

Cluster membership and task completion

Cross tabulation and adjusted standardized residual analyses (*ASR*) were conducted to determine if cluster membership alone was related to expected and actual task completion.

Separate analyses were done for expected task completion and actual task completion reported the following day. The results of the chi-squared analyses are available in Table 4.4. Tasks in the high emotions/high cost cluster (1) were expected to be completed significantly more than

expected by chance ($ASR=3.38, p < .001$), as were tasks in the cluster of high emotions/low cost ($ASR=5.00, p < .001$), whereas tasks that were low emotions/low cost (cluster 2; $ASR = -2.96, p < .001$) and medium emotions/medium cost (cluster 2; $ASR = -.6.33, p < .001$) were significantly less likely to be completed than expected by chance (e.g., these clusters were underrepresented in expected task completion). Regarding actual task completion, the medium emotions/medium cost tasks (cluster 2; $ASR = -.3.35, p < .001$) and the low emotions/low cost tasks (cluster 6; $ASR = -4.12, p < .001$) were completed significantly less than expected by chance, whereas the high emotions/low costs tasks (cluster 4; $ASR = -.5.24, p < .001$) were more likely to report completing a task than expected by chance. Low cost/high satisfaction (cluster 3) and high regret (cluster 5) completed tasks as often expected by chance ($p > .05$).

Table 4.4*Chi-squared test for Cluster Membership and Task Completion*

Cluster		Expected	
		0	1
High emotions/high cost	Observed	70	135
	ASR	-3.381	3.381
Medium emotions/medium cost	Observed	85	36
	ASR	6.331	-6.331
Low cost/high satisfaction	Observed	48	45
	ASR	1.558	-1.558
High emotions/low cost	Observed	47	124
	ASR	-4.995	4.995
High regret	Observed	36	48
	ASR	-0.246	0.246
Low emotions/low cost	Observed	40	25
		2.963	-2.963

Note. Overall $\chi^2 = 71.14$, $df = 5$, $p=0.000$

ASR - Adjusted standardized residuals

Cluster		Actual	
		0	1
High emotions/high cost	Observed	84	74
	ASR	-0.317	0.317
Medium emotions/medium costs	Observed	75	35
	ASR	3.247	-3.247
Low cost/high satisfaction	Observed	45	30
	ASR	1.07	-1.07
High emotions/low cost	Observed	47	89
	ASR	-5.238	5.238
High regret	Observed	34	38
	ASR	-1.275	1.275
Low emotions/low cost	Observed	41	9
	ASR	4.115	-4.115

Note. Overall $\chi^2 = 47.87$, $df = 5$, $p=0.000$

ASR - Adjusted standardized residuals

Hierarchical Logistic Regression

To better understand differences in task completion based on task-specific motivational clusters, in addition to task importance rank (e.g., relative hierarchy of task importance) and effort regulation, we conducted a hierarchical logistic regression for expected and actual task completion. The results are available in Table 4.5. Each cluster was dummy coded, with the reference group for the analysis being the medium emotions/medium cost tasks (cluster 2). This cluster was chosen as the reference group as it was considered the most average of all the clusters with respect to the four variables. We begin by explaining the results for expected task completion. At the task-level, task importance rank was positively associated with expected task completion ($OR=1.37, p < .001$), meaning that the higher a task was ranked within the hierarchy of all daily tasks for a student, the more likely a student expected to complete that task. Relative to the reference cluster (medium emotions/medium cost), a task in Cluster 1 (high emotions/high cost) or Cluster 4 (high emotions/low cost) was significantly more likely to be rated by a student as a task that they expected to fully complete (Cluster 1: $OR = 3.97, p < .001$; Cluster 4: $OR = 5.52, p < .001$). Cluster 3 (low cost/high satisfaction), Cluster 5 (high regret), and Cluster 6 (low emotions/low cost) did not significantly differ from the reference cluster (medium emotions/medium cost) in the likelihood of expected task completion ($p > .05$). At the person level, self-reported effort regulation was positively associated with expecting to complete a task ($OR = 1.37, p < .05$).

For actual task completion, task importance rank was also positively associated with actual task completion ($OR = 1.40, p < .001$). Relative to the reference cluster, a task in the high emotion/high cost cluster was not more likely to be completed ($p > .05$), after controlling for effort regulation and task importance rank. However, a task in the high emotions/low cost cluster was more likely to be completed than a task in the medium cluster ($OR = 2.57, p < .05$), after

controlling for effort and task importance rank. All other clusters did not significantly differ from the medium cluster. Self-reported effort regulation was positively associated with actually completing a task ($OR = 1.66, p < .05$).

Table 4.5

Hierarchical Logistic Regression Models of Expected and Actual Task Completion

Fixed Effect	Expected Task Completion		Actual Task Completion	
	Odds Ratio	SE	Odds Ratio	SE
Intercept	1.20	(0.34)	1.25	(0.40)
Effort Regulation	1.68*	(0.21)	1.66*	(0.23)
Cluster 1:High emotions/high cost	3.97***	(0.40)	1.71	(0.35)
Cluster 3:Low cost/high satisfaction	1.99	(0.44)	1.40	(0.39)
Cluster 4:High emotions/low cost	5.52***	(0.39)	2.57*	(0.38)
Cluster 5:High regret	1.79	(0.43)	1.56	(0.45)
Cluster 6:Low emotions/low cost	0.97	(0.54)	0.54	(0.39)
Task rank	1.37***	(0.10)	1.40***	(0.11)
	<i>Variance</i>	χ^2 <i>df</i> = 68	<i>Variance</i>	χ^2 <i>df</i> = 68
Random Intercept	1.00***	151.83	1.00***	151.84

Note. Results are presented as odds ratios. SE=Standard error, which are based on the log odds. * $p < .05$. ** $p < .01$. *** $p < .001$.

Post-hoc analysis

The high emotions/high cost cluster (1) and high emotions/low cost cluster (4) were both overrepresented in expectations of task completion. However, only tasks in the high emotions/low cost cluster (4) were completed more often than expected. As a robustness check, we performed a test of proportions to confirm whether the difference between the two clusters was statistically significant. There was no difference in the proportion of expected task completion ($z = -1.19, p = .23$) between the two clusters, but there was a significant difference in the proportion of actual task completion ($z = -2.55, p = .01$).

Discussion

The current study integrated aspects of expectancy-value theory, control-value theory, the theory of planned behavior, and goal setting theories in order to better understand daily task motivation and task achievement for students in an undergraduate online course. We have made a contribution to the literature by synthesizing psychological theories of behavior using a person-centered approach that sheds light on intraindividual and interindividual differences in motivation and its relationship with task attainment on a daily level. Significant heterogeneity in cluster membership was observed, suggesting that the motivational system of values and emotions substantially varies between tasks within and between students. Clusters were predictive of both expected task completion and actual task completion, suggesting that the motivational system of task values and emotions relates to daily academic task behavior.

The cluster analysis at the task level suggested that a six-cluster solution of profiles for task interest, cost, anticipated regret, and anticipated satisfaction fit the data best. The largest cluster (30% of all tasks) was high emotion/high cost (Cluster 1), which included tasks that were perceived as very interesting, requiring students to give up a lot in order to complete, and elicited dual anticipated feelings of satisfaction if completed and regret if not completely. The second-largest cluster (4) included tasks perceived as very interesting, not requiring students to give up a lot, and high in anticipated emotions (22% of tasks). These two clusters, which comprise over 50% of reported tasks, were both expected to be completed, but the high emotion/high cost cluster was not actually completed as often as the high emotions/low cost cluster. This is an interesting finding that is in line with expectancy-value theory. If the only difference between two tasks is that one has significantly higher opportunity cost than the other, then this may subtract from the overall value of the task, as students have to give up investing time in other

valued tasks and this decreases the likelihood of achieving it. However, it is odd that despite the high cost of the task, students still expected to complete it as frequently as they expected to complete the task with lower cost. Why did students miscalibrate their expectations of task completion despite reporting the task as costly? One possibility is that although they were aware of the high opportunity cost, they were overly optimistic about finding the time to do it. In other words, they underestimated the actual cost of a perceived costly task. Alternatively, perhaps students disproportionately weighed their high level of interest and anticipated emotions toward these tasks above their considerations of the time investment required. This dilemma may relate to motivation regulation and metamotivational control, which refers to the process by which a student attempts to maintain the level and type of motivation required to optimally pursue a goal (Miele & Scholer, 2018).

Another interesting finding pertains to the relation between anticipated regret and task behavior. For tasks in the high regret cluster, students neither expected to complete those tasks, nor actually completed them more than expected by chance. This finding differs from previous variable-centered and interindividual approaches that find that anticipated regret is associated with stronger intentions and behavior (Gollwitzer, 1993; Richard, van der Pligt, & de Vries, 1995; Sheeran & Orbell, 1999b). Considering anticipated regret as a part of a complex motivational system that includes other anticipated emotions and values may provide a more holistic lens into how anticipated regret relates to intentions and actual behavior. In the high regret cluster, the task was not interesting, and quite low in opportunity cost and anticipated satisfaction. However, in the two other clusters with high regret (clusters 1 and 4), the tasks were also interesting and anticipated satisfaction was high, and both had stronger expectations of being completed than the high regret cluster. This finding suggests that high regret alone does

not lead to task completion unless accompanied by other motivational forces. We believe that the divergent findings on the relationship between anticipated regret and task behavior between prior variable-centered methods and our person-centered methods highlight the limitations of variable-centered approaches that attempt to isolate the unique effect of one component of a dynamic motivational system that fundamentally cannot be teased apart from other components. Such approaches lead to misunderstandings between the practical and theoretical significance of the relations between these constructs, because the relationship between them may very well be non-linear in their impact in the real world (Hunter and Schmidt, 1990).

The low cost/high satisfaction cluster (3) represented tasks that were considered not to be overly time-consuming nor very interesting but completing them was anticipated to be quite satisfying. Students did not expect to complete and did not complete them more or less than expected by chance. This suggests that these tasks may have been tasks that were not due immediately and thus were not inducing feelings of anticipated regret. Therefore, if a student completed such a task then they would feel satisfied, but if they did not complete the task that they wouldn't care all that much. This highlights that not completing a particular task or goal should not be always be construed as negative. There are sensible reasons that a student may not complete a task that they hoped to accomplish but did not put a lot of importance in. Task reengagement can occur in numerous ways and may relate to goal hierarchies (Ntoumanis & Sedikides, 2018), where a task that is rated low in priority today because it is not due may rise in priority as the deadline approaches. Being ambitious in setting numerous tasks to complete but failing to complete all of them is not necessarily worse than setting fewer tasks and accomplishing them.

Limitations and Future Directions

The present study is one of the first to employ an intensive longitudinal analysis of daily task values and emotions and their relations to daily academic task attainment. The results provide an important contribution to the educational psychology literature. However, there are a few limitations that must be considered when interpreting the results. As the study relied on longitudinal correlational data, no claims can be made about the causal relationships between variables. Additionally, the sample was restricted to undergraduates in an elective online course, which may limit generalizations to other age groups and achievement contexts. Although we conceptualized task values and emotions as task specific and thus subject to change depending on the nature of the task, we operationalized effort regulation in the presurvey as a stable trait in our study. However, effort regulation may also be conceptualized as task-specific, as it is possible that effort regulation varies in a state-like manner depending on the subjective task value of the task itself. We believe future studies should investigate effort regulation at the task level to investigate heterogeneity in regulating effort depending on the value of the task. Finally, we recommend that future research on task behavior measures the specific behavior under study and whether task disengagement may be adaptive at times. It may be that ambitious students intend to do assignments and schoolwork ahead of time and strategic disengagement from a task with low cost and value may be adaptive and beneficial to other more tasks that are time sensitive and important. In our current analysis, we did not identify if certain motivational profiles were related to particular types of tasks (e.g., homework, quizzes, video watching, etc.) nor related to task deadlines, although this is intended in future analyses.

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CHAPTER 5

Final Reflections and Future Directions

The scientific study of motivation is of utmost interest, utility, and importance to society. Understanding what motivates people to learn is fundamentally important to a literate society. The study of motivation is useful both descriptively and prescriptively. Descriptively, it provides explanations for why students engage or disengage in academic tasks, such as whether to complete a homework assignment or persist in a challenging college major. Prescriptively, it can be used to initiate and sustain academic behavior. In this dissertation, I examined motivation from a motivational systems perspective, shedding light on the multifaceted nature of motivation that includes hierarchies and dynamic relationships amongst complex components of the motivational system. In the following chapter, I reviewed some of the major findings and discuss their implications. I then proceeded to share some reflections on my evolution in thinking about motivational processes and future directions of research.

Summary of the Findings

The central finding of the first two studies was the importance of considering student motivation towards multiple academic domains when studying the development of motivation towards any one particular domain. In Chapter 2, I investigated the development of math and English self-concept between sixth grade and twelfth grade and the role of both self-concepts on college major choice. The major finding was the emergence of hierarchies of math and English self-concept of ability that develop in adolescence and their predictive relation to college major at various developmental timepoints in elementary, middle school, and high school. Students in profiles with higher math self-concept relative to English self-concept selected more math intense majors than profiles where self-concept was high in both domains, highlighting the

importance of the relative position of self-concept within a motivational system. The person-centered analyses also explained that gender differences in math-intensive college major selection could be explained by the greater distribution of women in profiles where English self-concept was higher than math self-concept and the greater distribution of men in profiles where math self-concept was higher than English self-concept. However, within a profile, no gender differences were observed. Multiple regression was unable to capture this nuance, as it could only explain the effect of one variable while holding all other variables in the model constant (i.e., at the mean level), which may not accurately reflect the distribution of variables within the students in the sample.

Chapter 3 was a study investigating the existence of dimensional comparisons between academic achievement, subjective task values, and college major choice. The results of the longitudinal structural equation model showed evidence of some dimensional effects from achievement and subjective task value in one domain to subjective task value in another domain. Although some gender differences emerged in mean levels of subjective task values, gender did not moderate the relation between subjective task values and college major choice. Subjective task value across the four domains each predicted the mathiness of a one's college major.

Chapter 4 investigated daily task motivation in an undergraduate online course. The main finding was the existence of six task profiles of subjective task values and anticipated emotions that were associated with both expectations of task completion and actual task completion. The hierarchy of an academic task within all the tasks intended for the day was predictive of both the likelihood of expecting to complete and actually completing the task. This study synthesized theories of motivated before to explain task motivation at the daily level.

Implications of the Findings

The findings within the chapters of this dissertation have implications for motivation theory and practice. Regarding theory, the most substantial implication is the necessity of considering motivation as dynamic and hierarchical. Although these ideas have been theoretically proposed for decades, empirical work on academic motivation, especially subjective task values, had largely ignored the theoretical frameworks that insisted on considering them. The findings in this dissertation echo the thoughts of Schwartz (2013) and Eccles (1994) who argued that such research leads to a piecemeal accumulation of information that is not productive to the development of coherent theories and that the omitted values (or self-concepts) are just as important to understanding behavior as the single value included. Eccles specifically argued that a single variable approach would fail to explain gender differences, and the findings in Chapter 2 indeed reflect that considering English self-concept when studying decisions related to math helped explain why women selected less math-intensive majors than men.

Another theoretical contribution of the dissertation was the synthesis of motivational theories. Theories of self-concept, including the internal/external frame of reference model and dimensional comparison theory are intrinsically related to the core construct of expectations of success from expectancy-value theory, and utilizing such theories furthered our understanding of the development of self-concepts of ability and their relation to academic choice. Similarly, in Chapter 3, dimensional comparison theory was utilized to explain the second core construct of subjective task values in expectancy-value theory. Finally, in Chapter 4, I incorporated the theory of planned behavior, control-value theory, and theories of goal setting into an expectancy-value framework to understand task specific motivation. While expectancy-value theory had been initially developed to explain task engagement at a larger level, such as career choice, college

major, and course selection, other theories of motivation focused more on task engagement at the micro-level. Synthesizing these theories was informative in understanding student behavior at a daily level. Additionally, such an effort leads to unifying theories of motivation and demonstrating the conceptual shared variance between constructs developed from different frameworks. For example, interest value is a considered a subjective task value, whereas literature on emotions posits interest is an emotion. Rather than see these theories in conflict, interest is likely both an emotion and a component of task-value. Similarly, anticipated emotions, such as anticipated regret and satisfaction, may also be considered a part of task-value, as tasks that are high in anticipated satisfaction may be highly valued. The findings in this dissertation may help us avoid jangle fallacy that similar constructs are different because they are labeled differently. The findings may also aid in conceptualizing what gives a task value, as a host of emotions, whether they be anticipatory or anticipated, may influence the subjective value of a particular task.

There were also methodological implications within the findings of this dissertation. As I demonstrated in Chapter 2, using variable-centered and person-centered approaches in tandem may help avoid confounding interindividual and intraindividual findings. As the results demonstrated areas of convergence and divergence, assuming ergodicity can be problematic if not explicitly tested. Cluster analysis demonstrated the ability to uncover complex interactions that were not hypothesized or not captured in variable-centered methods. The use of cluster analysis in Chapter 4 was another case of finding differences between regression analysis and person-centered analyses. The relation between anticipated regret and task behavior differed from prior literature. Previous variable-centered and interindividual approaches found that anticipated regret is associated with stronger intentions and behavior. However, cluster analysis

modeled anticipated regret as part of a complex motivational system that included other anticipated emotions and task values and did not find regret alone to predict behavior. This person-centered method may provide a more ecologically valid approach to studying how components in a complex motivational system cooccur, and that behavior depend on the specific patterns of cooccurrence. We believe that the divergent findings between prior variable-centered methods and our person-centered methods highlight the limitations of variable-centered approaches that attempt to isolate the unique effect of one component of a dynamic motivational system that fundamentally cannot be teased apart from other components. Such approaches lead to misunderstandings between the practical and theoretical significance of the relations between these constructs, because the relationship between them may very well be non-linear in their impact in the real world.

In addition to the theoretical and methodological implications of this dissertation, the findings have practical implications for intervention work. Interventionists have realized that certain motivational constructs are levers that can be pulled to change the beliefs and behaviors of students within a particular domain. For example, both self-concept and subjective task value have been operationalized in intervention work with adolescents. While these interventions have shown some success, the studies in this dissertation and other empirical work highlight that motivational components, such as subjective task values, do not develop in isolation. Rather, they are part of a dynamic system of motivational values, where tinkering with subjective task value for one domain may positively or negatively influence task value in another domain. Similarly, increasing self-concept in one domain will likely influence self-concept in another domain. These unintended side effects require substantial reflection. Interventionists need to proceed cautiously when designing interventions to ensure that student autonomy is not short-

circuited through manipulation of motivational constructs such as subject task values. This is especially concerning if the intervention is given during crucial stages of identity development. Additionally, just as side effects of drugs are disclosed to patients in medicine, possible side effects of motivational interventions may need to be disclosed to parents, teachers, and students. These findings do not suggest that interventions need to be halted immediately. In fact, the findings provide some evidence that if motivational interventions are ethically designed that they can consider alternative entry points into the motivational system to boost subjective task value or self-concept by using near domains that support the targeted domain. For example, if the intervention is aimed at getting more students to consider math intensive careers such as engineering, interventions may consider targeting a near domain such as physical science.

Final Reflections and Future Directions

The scientific study of human motivation has been an incredibly rewarding and challenging endeavor. Coming from an electrical engineering background, heterogeneity of effects, individual differences, and ergodicity were not issues of concern when dealing with electricity, microelectromechanical resonators, or semiconductor physics. However, dynamic systems, theorems from physics, and signal-to-noise ratios were central to my training and engineering career. I now believe there are many parallels to these two seemingly different worlds of the physical sciences and social sciences, and that the study of human behavior may benefit from principles and theories from the physical sciences.

The Measurement of Latent Constructs

Measuring latent constructs is at the core of psychological research. Constructs such as interest, self-concept of ability, and self-regulation are all latent, in that we cannot directly measure them, and the underlying goal of measurement models is to minimize the

amount of error in our model. Therefore, utilizing compositive scores has been criticized for ignoring the error inherent in measurement, and confirmatory factor analysis (as utilized in Chapter 3) is often considered best practice in psychological research (Borsboom, 2008), which attempts to utilize the shared variance between a number of items (i.e., indicators) that are conceptualized to be caused by the latent variable. All the information that is unique to each item is considered unique, unexplained variance that we call measurement error and ignore. However, recent research has shown this may be problematic and introduce substantial bias unless the set of items truly conform to a common factor model (Rhemtulla, van Bork, & Borsboom, 2018).

Another concern arises in utilizing confirmatory factor models if we assume non-ergodicity as the norm in the relation between a latent variable (as a predictor) and an outcome variable. If subjective task value is comprised of items representing interest value, attainment value, utility value, and cost, it is possible that although their shared variance may accurately convey a common factor in the population, and that the unique variance of each indicator differentially relates to motivated behavior. For example, in addition to the influence of the shared variance of the latent construct, a subpopulation of students may be additionally motivated to pursue a task because of the unique (error) variance of interest, whereas another subpopulation may be motivated to pursue a task because of the unique (error) variance of cost? Thus, if we treat the unique variance of an item as error in the population when in reality it is part of the true score for a subpopulation of students, then we have attenuated our signal and introduced bias.

Nonlinear Modeling

Another perspective on measurement error can be drawn from an engineering analogy. We can consider the true score and the measurement error in a latent construct akin to the signal-to-noise ratio (SNR) in signals processing in engineering. The SNR provides a measure of the signal power relative to the noise present. SNR takes into account numerous noise sources, from systematic noise due to the nature of measurement and random noise caused by random thermal motions. However, if we assume that there is only one type of noise in our latent construct, then we miss out on other potential disturbances that may threaten construct validity. In engineering applications, frequency response is also considered important in the quality of a signal. Frequency response refers to how a device responds to a response across a range of frequencies (e.g., an audio speaker). In other words, it gives a range of how well the device operates from the lowest to highest tones. If the volume is amplified too much, the device is unable to adequately represent that sound. Similarly, in latent variable modeling, consideration needs to be given to the range of responses we are trying to capture and model. Does a survey instrument accurately capture the construct of interest at low and high levels? This question is rarely asked as linearity is often assumed. However, there are many situations where a nonlinear model is substantially better. Take the case of a typical motivation survey given to students in undergraduate biology courses for students majoring in biology. As these instruments were typically “validated” using a different sample of non-biology majors, these surveys typically do not discriminate between highly motivated students who exhibit ceiling effects (often the majority of incoming biology majors), but the survey discriminates well for those with low motivation. This possibly implies the existence of a nonlinear relationship between the motivational scores and actual motivation

(Yalcin & Amemiya, 2001). Nonlinear factor models should thus be considered when appropriate in order to draw valid inferences.

Dynamic Systems of Motivation

Ultimately, we must consider why our psychological models, including those of motivation, typically explain a small fraction of the variance in an outcome. Surely, explaining 10-15% of the variance cannot be considered as satisfactory in explaining human behavior. One reason for the low variance explained may be that the relations between variables in our models are non-linear in their impact in the real world and modeling them as linear neither increases explanatory power nor does it benefit theory. Thus, I would like to reiterate the idea of dynamic systems in motivation. There are numerous principles and theories within dynamic systems that may be applicable to the non-linear relationships that likely exist amongst these psychological variables. Nonlinear differential equations, oscillation, and damping may all have analogs in motivated behavior.

Let us consider the motivational construct of interest, an important aspect of subjective task value, as operating within a person as a dynamic system. Interest has been found to relate to attention, goals, and learning (Hidi & Renninger, 2006). Theories of interest differentiate between phases of situational interest (in the moment) and personal interest (sustained over time), arguing that interest is a psychological state when situational and a trait-like predisposition in later phases of development. In the case of a student who had their interest piqued in chemistry due an element of a lesson, such as seeing chemicals mixed in a flask react into a fantastical display of smoke, we would label that student as situationally interested in chemistry. This would be considered a temporary psychological state. From a dynamic systems perspective, we may use the terms equilibrium and momentum to explain the processes (e.g.,

phases) that the interest system undergoes. Equilibrium describes the state when the net force on interest is zero. Momentum, in Newtonian mechanics, is a vector quantity with a magnitude and direction, and is the product of mass times velocity. The psychological analog of momentum has been theorized in psychological momentum theory (PMT; Deemer, Derosa, Duhon, & Dotterer, 2019), which postulates that the change in response rate (in behavior) is directly related to the magnitude of the stimulus (the exciting lesson in our example). Thus, equilibrium was the initial state of the student before the lesson began, implying the lack the interest in chemistry. However, upon observing the exciting lesson, the interest system becomes displaced from equilibrium and motivational momentum has developed in the student. The dynamic motion a mechanical spring may illustrate how the interest system subsequently operates. If a spring gains momentum by attaching a weight to it or pulling it (i.e., a stimulus), it begins to oscillate as the kinetic energy is converted into potential energy at the extreme points of contraction and then the potential energy is converted back to kinetic energy as the spring expands again. This process continues until the dissipative forces, such as friction, convert energy into heat and bring the spring back into equilibrium. The effect of slowing down this dynamic system is called damping, and the oscillation decays over time unless there is a positive source of energy added to the system. Therefore, in the case our situationally motivated student, we can now ask how long the state of situational interest will last? What are the forces that dampen the oscillating momentum of interest? What positive forces are required to keep the oscillation from decaying back to equilibrium? As we have now modeled interest as a dynamic system of motivation, we can use differential equations to answer the questions posed. The damping ratio, a measure describing how the oscillation decays, could be identified that would indicate how the oscillation of interest decays, which would provide a theoretical explanation of why students lose situational interest

after possessing it momentarily. We could also identify how situational environment influences (e.g., teacher practices and peer attitudes) and trait-like influences (e.g., IQ) may moderate the damping ratio. Such models would permit experimenting with situational factors that could keep the interest system oscillating and developing the momentary, triggered situational interest into emerging and sustained personal interest. In addition to enhancements in theoretically modeling the motivational system, I believe this perspective would also permit different measures of motivation, as both the brain and heart undergo oscillations that may capture interest more accurately than self-reports.

Cognitive neuroscience has begun linking of neural oscillations found in electroencephalogram (EEG) tests to learning processes such as working memory and attention (Ward, 2003). As the technology has improved and become more accessible to use in educational settings, the opportunities to measure aspects of motivation and learning from brain activity has become an exciting and potentially fruitful avenue of research. As wearable EEGs are already being utilized in classrooms and educational experiments, they could be used to measure interest from the dynamic systems perspective just explained. The raw EEG measures could be utilized as measures of subcomponents of motivation and dynamically modeled. Physiological biomarkers may also be utilized to capture aspects of interest. Heart rate variability measures are easily accessible using wearable monitors and could be used to capture the oscillatory behavior of the heart. Using EEG and HRV measures may allow us to understand the neural and physiological correlates of situational interest (and possibly components of executive function), including the conditions under which motivational dampening is observed in the brain and the heart.

In conclusion, this dissertation was focused on the multifaceted nature of academic motivation. The theoretical frameworks and research methods employed revealed hierarchical and dynamic motivational processes by utilizing both variable-centered and person-centered approaches. I believe future motivational research needs to consider nonlinear dynamic systems modeling, rely less on self-report data, and focus on explaining behavior at the person level. Additionally, theoretical and methodological approaches need to be synchronized, ensuring that scholars utilize the appropriate tools to answer their questions. Ultimately, the scientific study of motivation is one that has the potential to explain human behavior and help the educational stakeholders that aim to optimize learning and goal-directed behavior for all students.

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Appendix I

Self-Concept of Ability Measures for Math and English

Math self-concept of ability

1. How good at math are you? (1 = not at all good; 7 = very good)
2. If you were to rank all the students in your math class from the worst to the best in math, where would you put yourself? (1 = the worst; 7 = the best)
3. Compared to most of your other school subjects, how good are you at math? (1 = much worse; 7 = much better)

English self-concept of ability

1. How good at English are you? (1 = not at all good; 7 = very good)
2. If you were to rank all the students in your English class from the worst to the best in English, where would you put yourself? (1 = the worst; 7 = the best)
3. Compared to most of your other school subjects, how good are you at English? (1 = much worse; 7 = much better)

Appendix II

Chi-squared test for Gender Differences by Cluster

6th Grade Cluster		Males	Females
Low math-low English	Observed	62	74
	ASR	0.595	-0.595
Low math-medium English	Observed	14	38
	ASR	-2.474	2.474
Medium math-low English	Observed	70	82
	ASR	0.768	-0.768
Medium math-high English	Observed	76	99
	ASR	0.038	-0.038
High math-medium English	Observed	60	65
	ASR	1.163	-1.163
High math-high English	Observed	35	57
	ASR	-1.089	1.089

Note. Overall $\chi^2 = 8.6$, $df = 5$, $p=0.13$.

ASR stands for Adjusted standardized residuals.

7th Grade Cluster		Males	Females
Low math-low English	Observed	30	32
	ASR	0.844	-0.844
Low math-medium English	Observed	24	42
	ASR	-1.193	1.193
Medium math-low English	Observed	44	65
	ASR	-0.671	0.671
Medium math-high English	Observed	42	89
	ASR	-2.867	2.867
High math-low English	Observed	49	29
	ASR	3.68	-3.68
High math-medium English	Observed	82	84
	ASR	1.801	-1.801
High math-high English	Observed	46	74
	ASR	-1.202	1.202

Note. Overall $\chi^2 = 24.89$, $df = 6$, $p<.001$ ***.

10th Grade Cluster		Males	Females
Low math-low English	Observed	58	49
	ASR	2.462	-2.462
Low math-medium English	Observed	31	60
	ASR	-1.901	1.901
Low math-high English	Observed	25	60
	ASR	-2.75	2.75
Medium math-low English	Observed	15	15
	ASR	0.756	-0.756
Medium math-medium English	Observed	61	90
	ASR	-0.81	0.81
High math-low English	Observed	57	54
	ASR	1.857	-1.857
High math-high English	Observed	70	87
	ASR	0.365	-0.365

Note. Overall $\chi^2 = 19.13$, $df = 6$, $p = .004^{**}$.

12th Grade Cluster		Males	Females
Low math-medium English	Observed	24	41
	ASR	-1.088	1.088
Low math-high English	Observed	46	70
	ASR	-0.865	0.865
Medium math-low English	Observed	25	21
	ASR	1.561	-1.561
Medium math-medium English	Observed	81	97
	ASR	0.681	-0.681
Medium math-high English	Observed	46	86
	ASR	-2.166	2.166
High math-low English	Observed	47	37
	ASR	2.486	-2.486
High math-medium English	Observed	48	63
	ASR	-0.014	0.014

Note. Overall $\chi^2 = 13.66$, $df = 6$, $p = .03^*$.

Appendix III

Measurement Model

Model fit indicators for 1- and 4-latent variable models

Model	(df) χ^2	RMSEA	CFI	$\Delta\chi^2$	Δ CFI
Subjective Task Values					
1-latent model	(54)3399.6***	0.22	0.539		
4-latent model	(48)641.26***	0.10	0.918	2758.39	0.379

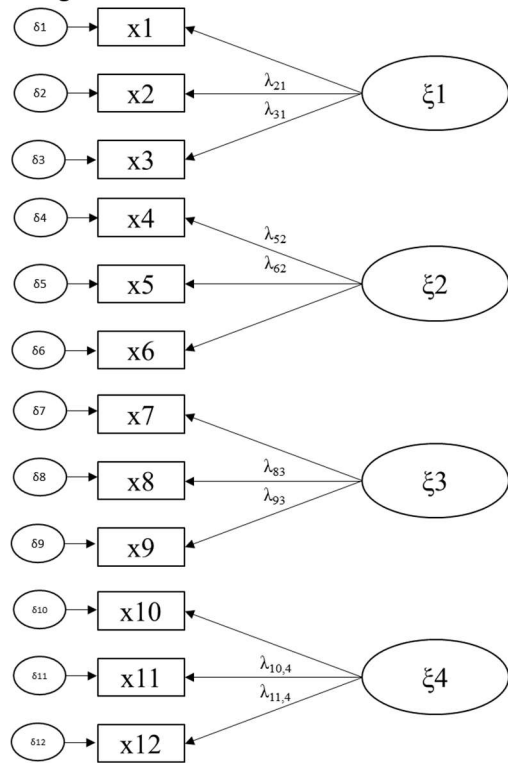
*** $p < .001$

Final factor model

Four-factor model of subjective task values

	B (unstandardized)	β (standardized)	r-squared
Math STV			
Math Interest	1.00	0.64	0.41
Math Importance	1.19	0.90	0.81
Math Utility	0.95	0.66	0.44
English STV			
English Interest	1.00	0.64	0.41
English Importance	1.33	0.93	0.86
English Utility	1.07	0.75	0.56
Biology STV			
Biology Interest	1.00	0.77	0.59
Biology Importance	1.21	0.95	0.90
Biology Utility	1.02	0.77	0.59
Physical Science STV			
Physical Sci Interest	1.00	0.75	0.56
Physical Sci Importance	1.22	0.93	0.86
Physical Sci Utility	1.04	0.70	0.49

Diagram for 4-factor measurement model



Indicator Matrix (Λ_x)

	Math STV	Eng STV	Bio STV	Phy Sci STV
	ξ_1	ξ_2	ξ_3	ξ_4
x1	1	0	0	0
x2	λ_{21}	0	0	0
x3	λ_{31}	0	0	0
x4	0	1	0	0
x5	0	λ_{52}	0	0
x6	0	λ_{62}	0	0
x7	0	0	1	0
x8	0	0	λ_{83}	0
x9	0	0	λ_{93}	0
x10	0	0	0	1
x11	0	0	0	$\lambda_{10,4}$
x12	0	0	0	$\lambda_{11,4}$

Measurement model matrix

$$\begin{bmatrix} x1 \\ x2 \\ x3 \\ x4 \\ x5 \\ x6 \\ x7 \\ x8 \\ x9 \\ x10 \\ x11 \\ x12 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ \lambda_{21} & 0 & 0 & 0 \\ \lambda_{31} & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & \lambda_{52} & 0 & 0 \\ 0 & \lambda_{62} & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & \lambda_{83} & 0 \\ 0 & 0 & \lambda_{93} & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & \lambda_{10,4} \\ 0 & 0 & 0 & \lambda_{11,4} \end{bmatrix} \begin{bmatrix} \xi_1 \\ \xi_2 \\ \xi_3 \\ \xi_4 \end{bmatrix} + \begin{bmatrix} \delta_1 \\ \delta_2 \\ \delta_3 \\ \delta_4 \\ \delta_5 \\ \delta_6 \\ \delta_7 \\ \delta_8 \\ \delta_9 \\ \delta_{10} \\ \delta_{11} \\ \delta_{12} \end{bmatrix}$$

Appendix IV

Multi-group analyses were used to generate latent means for all subjective task values in 10th grade and 12th grades for males and females. The means for all latent variables for males were fixed at zero, and the corresponding females means were interpreted as differences in means. Corresponding p-values were used to determine whether mean differences were significant or not.

The model fit was acceptable for the two models for grades 10 and 12 ($\chi^2=397.153/358.404$, $p<.001$, RMSEA=.069/.065, CFI=.959/.961). Females had significant ($p<.001$) latent mean differences in English and physical science STV compared to males in 10th grade. For English, females had a mean English STV that was .94 greater than that of males. Conversely, females had a mean physical science STV that was .35 less than that of males. In 12th grade females had a latent math STV mean that was .35 less than males ($p=.001$), English STV mean was .92 greater than males ($p<.001$), and physical science STV that was .72 less than males ($p<.001$). There were no significant differences in biology STV at either grade ($p=.823/.145$).

Appendix V

Survey Items for Effort Regulation (1=strongly disagree to 5 = strongly agree)

1. I often feel so lazy or bored when I study for this class that I quit before I finish what I planned to do.
2. When coursework is difficult, I give up or only study the easy parts.
3. Even when course materials are dull and uninteresting, I manage to keep working until I finish.
4. I work hard even if I do not like what I am doing.
5. I continue working even if there are better things to do.
6. I keep on working until I finish what I am supposed to do.