The Role of Instructional Relevance and Teacher Competence Support in Student Motivation and Achievement in High School Math Classrooms

DISSERTATION

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Yujin Chang

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The Ohio State University

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Dissertation Committee:

Eric M. Anderman, Advisor
Lynley H. Anderman
Ann A. O’Connell
Abstract

In this dissertation, I explored high school students’ math class motivation profiles, how these profiles are predicted by students’ perceptions of their teachers’ instructional practices (i.e., instructional relevance and teacher competence support), and how students’ math class motivation profiles relate to their achievement, enrollment intentions, and effort regulation. Survey data were collected in the fall semester of the 2013-2014 academic year from 355 ninth- and tenth-graders in three high schools in a Midwestern city in the United States. Students’ achievement and demographic information were gleaned from school records. A person-centered approach was used to identify subgroups of students based on six indicators of math class motivation, including efficacy beliefs, attainment value, intrinsic value, endogenous instrumentality, cost, and math anxiety. Using Latent Profile Analysis, a four-profile model of high motivation, moderate motivation with high efficacy, moderate motivation with high cost and anxiety, and low motivation was chosen as a final model. Students’ perceptions of cost and anxiety were important indicators that differentiate the groups when students exhibit moderate levels of math class motivation. Multinomial logistic regressions were used in order to examine whether students’ perceptions of teacher practice (i.e., instructional relevance and teacher competence support) predict latent profile membership. Both students’ perceptions of instructional relevance and teacher competence support were
significantly associated with students’ math class motivation profile membership, even after controlling for their prior math achievement and other demographic characteristics. When students had teachers whom they perceived as trying to make math content more relevant and supporting students’ competence, there was a higher probability that the students belonged to the more adaptive motivation profiles. When students had teachers who used instructional relevance strategies, but whom they did not perceive as adequately supporting their competence, they were more likely to belong to the less-desirable motivation profile, which is associated with high cost and anxiety. Students’ math class motivation profiles also significantly predicted their achievement, future enrollment intentions, and effort regulation. Using a person-centered approach, this study contributes to the current literature on motivation, by providing a unique perspective on group differences in math class motivation and showing how these differences can be predicted with different types of instructional practices.
To my beloved parents,

Seokjoo Chang and Hyunsook Jung.
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Vita

2004. B.A. English Language Education, Seoul National University


March 2006 to February 2008. High School English Teacher, Somyong Girls’ High School, Bucheon, South Korea

March 2008 to February 2009. Researcher, Korean Institute for Research in the Behavioral Sciences (KIRBS), Seoul, South Korea

September 2009 to August 2010. Graduate Fellow, Graduate School, The Ohio State University

September 2010 to June 2011. Graduate Research Associate, School of Educational Policy and Leadership, The Ohio State University

September 2011 to December 2012. Graduate Teaching Associate, School of Educational Policy and Leadership, The Ohio State University

June 2012 to May 2013. Graduate Teaching Fellow, Department of Educational Studies, The Ohio State University

January 2013 to December 2013. Graduate Fellow, Graduate School, The Ohio State University

October 2013 to May 2014. Graduate Learning Specialist, Walter E. Dennis Learning Center, The Ohio State University
January 2016 to May 2016. Graduate Teaching Associate, Walter E. Dennis Learning Center, The Ohio State University

Publications


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Chapter 1: Introduction

Statement of the Problem

The Science, Technology, Engineering, and Mathematics (STEM) workforce is critical to innovation and competitiveness in industries around the world. As the National Science Board report states, nearly 20% of all U.S. jobs require significant STEM knowledge and skills (National Science Board, 2014). There has been an ongoing debate over whether the U.S. has a shortage in the STEM workforce. Whereas some researchers and policy makers claim that there is in fact a surplus of STEM professionals in the U.S., numerous reports and studies highlight concerns regarding a shortage of STEM graduates and employees (Atkinson, 2013; Atkinson, Hugo, Lundgren, Shapiro, & Thomas, 2007; National Science Board, 2014; President’s Council of Advisors on Science and Technology, 2012).

Despite the need for graduates and employees in the United States to have better technical skills and knowledge, there are not enough college and high school graduates who are equipped with adequate technical skills and knowledge. According to the President’s Council of Advisors on Science and Technology (2012), U.S. schools need to produce one million more STEM professionals than those who will graduate from a STEM-related field over the next decade. Therefore, there has been growing emphasis on STEM education in the United States for the past several decades (Atkinson et al., 2007).
In addition, there is a strong consensus that we need a more diverse workforce that includes underrepresented populations, such as females, minorities, and individuals from lower socioeconomic backgrounds, as well as individuals with disabilities in the STEM field (Summers & Hrabowski, 2006; Villarejo, Barlow, Kogan, Veazey, & Sweeney, 2008). In order to ensure U.S. preeminence in science and technology, education must play an important role in fostering a strong and more diverse STEM-skilled workforce.

When students choose a STEM degree, their math skills play a crucial role in their success. Despite the importance of math skills, not many high school students see math as relevant or important. Research shows that as students progress through secondary school, the extent to which they value learning math decreases (Gottfried, Marcoulides, Gottfried, Oliver, & Guerin, 2007; Jacobs, Lanza, Osgood, Eccles, & Wigfield, 2002; Watt, 2004). Since motivation significantly influences students’ achievement, effort, and course enrollment decisions (see Eccles, 2005 and Wigfield & Cambria, 2010, for reviews), it is crucial to understand what motivates students to learn math.

The results of numerous studies that have examined what factors predict students’ math motivation indicate that both individual and contextual factors influence motivation in math (e.g., Cleary & Chen, 2009; Eccles et al., 1983; Gunderson, Ramirez, Levine, & Beilock, 2012; Levpuscek & Zupancic, 2009; Simpkins, Davis-Kean, & Eccles, 2006). In this study, I focus on high school math classes, exploring ways to motivate students so they can excel in math, put more effort toward their math learning, and choose to enroll in more advanced math courses. Hopefully in the long term, this motivation for math at the high school level will equip students with the necessary
technical skills required to work in the STEM field, and additionally result in more students choosing a STEM career path.

**Student Motivation and Instructional Practices in Math Classrooms**

Among various individual and contextual factors that have been found to influence student motivation in the previous literature, teachers’ instructional practice as a contextual factor is one of the significant predictors of student motivation in a math class. In this study, I will examine how different instructional practices predict students’ motivation profiles in math classrooms and how these profiles are related to their achievement, enrollment intentions in future math courses, and effort regulation.

One type of instructional practice that can help students find a value in learning math is instructional relevance. Relevance has been examined in several different disciplines (e.g., educational psychology, instructional technology, instructional communication, etc.). Previous research on relevance suggests that it is important for students to perceive what they learn as relevant to their needs, interests, and goals, in terms of their motivation as well as their learning outcomes (e.g., Frymier & Shulman, 1995; Hulleman, Godes, Hendricks, & Harackiewicz, 2010; Keller, 1987). However, it is relatively unclear which specific instructional relevance strategies relate to students’ perceptions of course motivation and achievement, and under what conditions those instructional strategies are more or less effective.

Results of previous studies also suggest that relevance strategies alone may not be enough to ensure student motivation, and these strategies may need to be combined with other appropriate instructional practices (Behrens, 1999; Chang, Levitt, Kovach, & Anderman, 2012; Frymier & Houser, 1998). One such instructional practice is teacher
support of students’ academic competence. Research indicates that students’ perceived competence increases when their teachers provide encouraging feedback and instrumental help (McRae, 2012; Wentzel, 2009). On the other hand, when teachers do not provide adequate support when needed or when they respond negatively to students’ requests, this lack of support can lead to maladaptive motivational and learning outcomes, such as avoidance of help-seeking and lower achievement (Ryan, Gheen, & Midgley, 1998).

Therefore, if emphasis on instructional relevance is not combined with a sufficient amount of support of students’ academic competence, students may incur high anxiety or cost associated with learning math. For example, if a student does not feel competent in math and is told by his or her teacher that learning math is an important and useful skill, but the teacher does not provide adequate support for the student’s competence, the student may feel discouraged or develop a fear of failure in math. In the present study, therefore, I will examine the relations of students’ perceptions of instructional relevance and teacher competence support to students’ motivation and achievement in high school math classrooms. I propose that students should be ideally motivated in math classes when their teachers both emphasize instructional relevance and provide competence support.

**Objectives and Research Questions**

In this study, my primary aim is to understand how different types of instructional practices predict student motivation and achievement in high school math classrooms. Three research questions have been developed for this purpose:

1) What are the emerging profiles of high school students’ math class motivation?
2) Are high school students’ math class motivation profiles significantly predicted by their perceptions of teacher practices (i.e., instructional relevance & teacher competence support), and how?

3) Do high school students’ math class motivation profiles significantly predict their math achievement, enrollment intentions in future math courses, and effort regulation, and how?

In order to answer these questions, quantitative data are analyzed using a person-centered analysis. Data were obtained from school records and a survey of students’ perceptions.

**Significance of the Study**

The findings of this study will contribute to expanding the existing literature on relevance by identifying effective instructional strategies that are associated with students’ perceptions of course relevance as well as other important indicators of student motivation in math class. By employing a person-centered approach using multiple indicators of student motivation, results of this study will also add to the literature on motivation by providing a more comprehensive understanding of math class motivation profiles of high school students and of the predictive relationships between students’ motivation profiles and their achievement, enrollment intentions in future math courses, and effort regulation.

The results of this study are also expected to provide practical implications for math classroom teachers. The findings will provide math teachers with information about different patterns of students’ math class motivation based on multiple motivational indicators, both positive and negative. The findings will also provide useful information
about how teachers can help their students develop more adaptive motivation profiles. Specifically, the findings will suggest some instructional strategies math teachers can use to help their students value learning math, while helping them decrease math anxiety and the perceived cost of learning math. By highlighting the important role of teacher competence support, the current study will provide practical implications regarding how teachers can help students develop competence in math. By employing a person-centered approach, the findings of the current study will also provide insights into how to plan and implement effective interventions for students with different motivational profiles in their math classes.

The Every Student Succeeds Act (ESSA, 2015), the most recent revision of the Elementary and Secondary Education Act (ESEA, 1965), places emphasis on the need to broaden school accountability systems that were heavily based on students’ standardized test scores. Given that the ESSA requires states to use at least one non-cognitive indicator of a school’s success, the findings of the current study can contribute to the successful implementation of the ESSA.

**Organization of the Dissertation**

This dissertation consists of five chapters. Chapter Two presents a review of empirical research on major variables used in the study. Based on the theoretical framework provided by the literature review, research questions and hypotheses for the present study are presented at the end of the chapter. Chapter Three presents the method used to answer the research questions. Specifically, participants, data collection procedures, measures, and data analysis are described. Chapter Four presents the results
of the data analysis, which answers each research question. Finally, Chapter Five includes a summary of the research findings, implications of the results for both research and practice, and suggested directions for future research.
Chapter 2: Literature Review

The current study examines the roles of instructional relevance and teacher competence support in students’ motivation and achievement in high school math classrooms. This chapter begins with a review of Expectancy-Value theory, within which the present study is framed. The roles of students’ expectancies, subjective task values, and perceived cost in their motivation and achievement are discussed. A review of the literature on perceived instrumentality is followed as a significant indicator of student motivation that is closely related to perceptions of relevance. Next, as characteristics of teachers’ instruction that can significantly affect student motivation in math classrooms, instructional relevance and teacher competence support are reviewed. There is also a brief review of the literature on other related variables such as math anxiety and gender. Then, I provide a section defining a person-centered approach and discussing why the current study employed the approach. Based on the literature review, the research questions and hypotheses of the present study are presented at the end of this chapter.

Expectancy-Value Theory and Student Motivation

Expectancy-Value Theory: Expectancies, Task Value, and Cost

In the contemporary model of expectancy-value theory (Eccles et al., 1983; Wigfield & Eccles, 1992; 2000), students’ expectancies for success and perceived task values are two important predictors of students’ achievement-related choices and
performance. Expectations for success refer to individuals’ beliefs about how well they will perform on a task. According to the theory, these expectancies are determined by individuals’ concepts of their abilities and their perceptions of task difficulty. Ability beliefs and expectations for success are theoretically different; ability beliefs are focused on individuals’ beliefs about their current perceived ability, whereas expectations are individuals’ beliefs about performance on future tasks. These two constructs are, however, closely related to each other in empirical studies (Eccles, Wigfield, Harold, & Blumenfeld, 1993; Wigfield & Eccles, 2000).

There are four different components of task values in the model: (a) attainment value, (b) intrinsic value, (c) utility value, and (d) cost. Attainment value refers to the perceived importance of doing well on a certain task. This component of value involves identity issues; when doing well on a certain task is consistent with individuals' identities or central to their own sense of themselves, they perceive the task as important. Intrinsic value, or interest, is defined as perceived enjoyment one can gain through doing a task. Utility value refers to perceived usefulness of a task in terms of helping one reach one’s future goals. Whereas these three value components are about positive aspects of engaging in a task, the final component, cost, is more about negative aspects of engaging in a task. By definition, cost refers to what one needs to sacrifice in order to engage in a task, or the negative aspects of engaging in a task including emotional cost and effort for a task (Eccles et al., 1983; Wigfield & Eccles, 1992; 2000).
The Roles of Expectancies and Task Values in Student Motivation

Previous studies using expectancy-value models have examined how individuals’ expectations for success and task values are associated with their achievement behaviors including persistence, choice, and performance (e.g., Bong, 2001; Durik, Vida, & Eccles, 2006; Eccles et al., 1983; Simpkins et al., 2006; see Eccles, 2005 and Wigfield & Cambria, 2010, for reviews). The results of these studies suggest that individuals who report higher expectations for success and greater perceived values (i.e., when they believe that they can do well on a task and that the task is useful, important, and interesting) are more likely to choose to engage in the task, persist longer in the face of difficulty, show deeper levels of engagement, and perform better on the task.

When researchers examined the effects of expectancies and task values separately, they found that individuals’ expectancies are more strongly related to their achievement outcomes, whereas task values are stronger predictors of individuals’ choice of engagement (Eccles, 2005; Eccles et al., 1983; Eccles & Wigfield, 1995). Previous studies also indicate that task values have long-term effects on students’ achievement-related behaviors (Durik et al., 2006; Simpkins et al., 2006). For example, Durik and colleagues (2006) reported that fourth graders’ perceptions of attainment value in reading were significantly associated with the number of English classes the students took in high school.

Cost and Student Motivation

Cost has been given less attention in many empirical studies than the other three value components, despite its importance in individuals’ decision-making (Anderson, 2000; Flake, Barron, Hulleman, McCoach, & Welsh, 2015; Wigfield & Cambria, 2010).
Many of the previous studies that examined task value did not include perceived cost and only focused on the other three task values (cf., Battle & Wigfield, 2003; Conley, 2011; Gaspard et al., 2015).

When Eccles and her colleagues developed the expectancy-value model, the effect of perceived cost on task value was conceptualized in relation to a “cost/benefit ratio” (Eccles et al., 1983, p. 93). In a decision-making situation, individuals consciously or unconsciously consider cost/benefit ratios (i.e., how much they will benefit from engaging in a task based on what they have to sacrifice). When the cost/benefit ratio increases, individuals become less likely to engage in the task.

Several factors have been discussed as important influences on perceptions of cost including perceived effort, loss of valued alternatives, and psychological cost of failure, which reflect different aspects of cost (Eccles et al., 1983). When individuals perceive that the estimated amount of effort they need to put forth to succeed in a task is greater than what they believe is worthwhile, or when they think they have to give up many other valued activities to engage in a certain task, their perceptions of cost increase. Also, if individuals believe they might not be able to succeed despite all of their efforts, this fear of failure can increase perceived cost, and the individuals may be less likely to engage in the task.

A small number of empirical studies that examined the role of perceived cost indicate that cost is empirically distinct from other types of value and competence beliefs, and that students are less likely to engage in a task when the perceived cost is too high (Anderson, 2000; Battle & Wigfield, 2003; Chiang, Byrd, & Molin, 2011; Conley, 2011;
Perez, Cromley, & Kaplan, 2014; Watkinson, Dwyer, & Nielson, 2005). For example, in Battle and Wigfield’s (2003) study, students reported that they were less likely to enter graduate school when they believed pursuing graduate school involved high perceived cost.

**The unique role of cost perceptions.** Some of the recent studies that examined the role of perceived cost suggest that cost may play a unique role and it may need to be separately examined from the other value components. In a qualitative study by Watkinson and colleagues (2005), children were interviewed about reasons for participating in or avoiding various recess activities. Children’s reasons reflect some types of costs including physical cost (e.g., fatigue when engaging in an activity) and social or psychological cost (e.g., facing teasing), as well as the other components of values. Interestingly, the results of the study suggest that utility value and perceived cost could be high motivators even when children’s expectancy beliefs, intrinsic value, and attainment value for the activity are low. For example, if the perceived cost of not engaging in a task (e.g., being left out when not participating) is very high, students might be more likely to persist in activity engagement to avoid the possible negative consequences, even though they had poor physical ability.

Conley (2011) found a unique contribution of cost in differentiating students’ motivational patterns. Using a person-centered approach integrating achievement goal and expectancy-value perspectives, Conley identified seven different motivational patterns in math among seventh grade students. Notably, perceived opportunity cost plays a significant role in differentiating more- and less- adaptive patterns of motivation. The
seven groups separated into two groups based on perceived cost that led to different achievement and affective outcomes. Specifically, among those with high interest and high mastery level goals, the low-cost group reported lower negative affect and achieved higher than did the high-cost groups (i.e. students who perceive they have to give up a lot to do well in math). The study highlights the importance of cost in discriminating students’ different patterns of motivation.

Although relatively few studies examined the role of psychological cost separately from the other aspects of cost (physical cost, opportunity cost, etc.), the possible relationship could be inferred from several studies on “fear of failure” or “achievement anxiety” (e.g., Elliot & Sheldon, 1997; Sagar, Lavallee, & Spray, 2007; Smith, Smoll, Cumming, & Grossbard, 2006). Research indicates that fear of failure serves as a barrier that prevents students from participating in achievement activities. Perceived negative consequences of failure can include shame in self and no sense of achievement, and if individuals perceive the outcomes of failure as aversive, that becomes the basis for fear of failure. When students perceive high cost of failure and still have to participate in an activity, they might be more likely to use maladaptive strategies such as self-handicapping strategies and academic cheating (e.g., Martin & Marsh, 2003; Monte & Fish, 1989).

In addition to opportunity cost and the psychological cost of failure, some researchers have investigated the unique role of other aspects of cost, such as social cost. For example, using national survey data, Kirkpatrick, Chang, Lee, Tas, and Anderman (2013) explored the role of perceived social cost of time and effort devoted to math and
science in high school students’ educational attainment expectations and Advanced Placement (AP) course enrollment intentions. They defined social cost as the potential loss of social status among peers and the potential loss of opportunities for socially enjoyable activities that are associated with time and effort invested in academic learning. The results indicated that higher perception of social cost was significantly related to lower expectations for future academic attainment. More interestingly, the results of multilevel logistic regression analyses suggest that perceived social cost plays a role for students who make an early declaration of no plan for AP enrollment: students who did not intend to take either math or science AP courses were more likely to report high levels of social cost.

The results of the previous studies indicate a unique role of perceived cost in student motivation; therefore, in the current study, it is reasonable to include students’ perceived cost as a separate indicator of their motivation in their math classrooms.

Utility Value and Relevance

Whereas all four of the task values discussed above can possibly influence students’ perceptions of the relevance of a certain task, utility value seems to be the one which is most closely related to the concept of relevance. There can be two different types of utility value one might perceive. For example, a student might believe taking a math class would be useful because it would fulfill his science degree requirement. In this case, the nature of the task does not have to be related to the student’s personal goals because taking the course would be just a means to an end. The motivation seems to be extrinsic in this situation (Eccles, 1995; Ryan & Deci, 2000). On the other hand, a student
might believe taking a math class would be useful because she or he would like to become a mathematician. Unlike the previous case, the nature of the task in this case is related to the individual’s important personal goals.

Whereas a broader definition of relevance includes perceptions that a task satisfies one’s needs, interests, and goals, utility value captures how the task satisfies one’s personal goals, whether present or future goals. A more specific aspect of relevance which implies future time orientations might be better captured in a definition of perceived instrumentality, which is discussed in the following section.

**Perceived Instrumentality**

**Exogenous instrumentality vs. endogenous instrumentality.** Based on the relationship between the nature of a task and individuals’ future goals, two different types of perceived instrumentality have been discussed in the literature (Husman, Derryberry, Crowson, & Lomax, 2004; Husman & Lens, 1999). *Exogenous instrumentality* is perceived when the nature of a task is not related to an individual’s future goal but the task “is useful for jumping hurdles” (Husman et al., 2004, p. 66). For example, in a statistics course, a graduate student who believes she will not need to use statistics in her future might perceive that taking the course and getting a good grade is still useful only because it would fulfill the requirement for her masters’ degree.

On the other hand, *endogenous instrumentality* (or *intrinsic instrumentality*) is perceived when the nature of a task is related to one’s future goals. For example, in the same statistics course, other graduate students majoring in educational psychology might perceive high utility value of taking the statistics course because they believe they need to
apply what they learn from the course in the future. In this case, the task (i.e., learning
statistics) itself is perceived to be useful for realizing a future goal (e.g., becoming an
educational psychologist) and can be expected to support one’s intrinsic motivation.
Husman and Lens (1999) argue that when individuals perceive endogenous
instrumentality and understand that developing competence in a task is beneficial for
realizing their future goals, these perceptions support their enjoyment and intrinsic
motivation.

Research investigating the associations among instrumentality, task value, and
intrinsic motivation suggests that future-oriented endogenous instrumentality is
empirically distinguished from task value and intrinsic motivation. In addition,
endogenous instrumentality also contributes to differentiating study behavior levels
(Husman et al., 2004). Endogenous instrumentality also seems to be related to adopting
mastery goals. Greene, Miller, Crowson, Duke, and Akey (2004) examined both the
effects of classroom structure on student motivation including perceived instrumentality
and the effects of the motivation on students’ cognitive engagement and achievement.
Results indicate that when students perceive classroom tasks as relevant, interesting, and
meaningful, these perceptions also increase students’ perceived instrumentality. Greene
et al. (2004) also argue that when individuals perceive instrumentality because the nature
of the task is relevant, they are more likely to adopt mastery goals.

In summary, when students perceive endogenous instrumentality in the
classroom, they understand clear connections between the skills or knowledge learned in
class and their future goals. Therefore, they might be more likely to perceive that what
they learn in class is relevant to their personal goals, and these perceptions seem to be
related to several adaptive motivation and learning behaviors, including increased intrinsic motivation, self-regulation, and cognitive strategy use, and adoption of mastery goals.

Research on perceived instrumentality emphasizes the importance of having future goals that individuals value and having proximal subgoals. It is notable, however, that Miller and Brickman (2004) argue that even when students hold clear future goals and subgoals, they can still fail to perceive instrumentality if (a) they have insufficient knowledge about connections between the school tasks and their goals, and if (b) they have low self-efficacy for completion of the tasks. These two possible cases seem to highlight the significant role of instruction.

In the current study, endogenous instrumentality is used as one of the motivational indicators in math classrooms as it is closely related to students’ perceptions of relevance. Since there is much overlap between perceived instrumentality and utility value, utility value is not examined in the current study.

**Teacher Effects on Expectancies, Task Values, and Cost**

Eccles and her colleagues (1983) incorporated a broad range of social and cultural factors as well as individual psychological factors into their expectancy-value model. According to the model, different types of teacher behaviors and expectations can in turn significantly influence students’ expectations and task values.

In terms of improving students’ expectancies and task values, and decreasing their perceived cost, two characteristics of teachers’ instructional practice are examined in the current study: instructional relevance and teacher competence support. In the following
section, I first review the research on instructional relevance, which refers to teachers’ instructional behaviors intended to make the content relevant to students’ interests, needs, and goals, and discuss its limitations and implications for the current study.

**Teachers’ Instructional Practices and Student Motivation**

**Instructional Relevance**

**Relevance as an instructional design.** Relevance has been examined as an important component of instructional design that enhances student motivation and learning in the field of instructional technology. Most studies in instructional design that address the importance of relevance in the classroom are based on Keller’s (1983, 1987) work. Keller developed the Attention, Relevance, Confidence, and Satisfaction (ARCS) model of instructional design by expanding his original model that consists of four categories (i.e., interest, relevance, expectancy, and outcomes), which was grounded in the expectancy-value theory of Tolman (1932) and Lewin (1938). The ARCS model defines four major conditions that influence students’ motivation to learn. Among the four conditions, in the present study I am primarily concerned with "relevance" because it can be enhanced by instructional strategies and it can have a significant impact on student motivation as evidenced by the literature (Hulleman et al., 2010; Hulleman & Harackiewicz, 2009; Shechter, Durik, Miyamoto, & Harackiewicz, 2011).

Relevance is closely related to the question “Why do I need to learn this?” According to Keller (1987), relevance can be perceived when a course of instruction provides opportunities for individuals to satisfy their personal desires, needs, and goals. The model proposes that relevance does not necessarily come from the content itself, but
rather, that the way the content is taught can also produce it. The model also proposes some specific instructional strategies can be used to increase students’ perceived relevance, such as linking content to students’ familiar experiences, stating the present intrinsic value of learning the content, asking students to relate the instruction to their own future goals, and providing choices for organizing their work (Keller, 1987).

**Relevance as a teacher communication behavior.** Based on Keller’s (1987) definition of relevance, research in instructional communication focuses on examining relevance as an effective teacher communication behavior that impacts student motivation. Communicating relevance is separate from teacher immediacy. Whereas teacher immediacy refers to physical and/or psychological closeness between a teacher and a student, teachers’ relevance is not relationship-oriented between students and the teacher; rather, it focuses on the association between what students learn and their interests and goals (Richmond, Gorham, & McCroskey, 1987).

Research indicates that when teachers communicate the relevance of the content, students’ motivation to learn increases. For example, Frymier and Shulman (1995) developed a 12-item content relevance scale to assess students’ reports of their teachers’ use of relevance strategies and examined the relation between students’ perceptions of relevance and their "state motivation". They operationally defined "state motivation" as students’ feelings toward studying for the class they took immediately before the students participated in the survey. Frymier and Shulman distinguished this state motivation from trait motivation, and they defined the latter as being more enduring toward learning in general. The results suggest that relevance was associated with state motivation, but not with trait motivation, which supported Frymier and Shulman's initial hypothesis.
Furthermore, relevance explained a significant proportion of unique variance in state motivation when controlling for teacher immediacy. Whereas the scale used by Frymier and Shulman (1995) is labeled “content relevance,” in the present study I use the term “instructional relevance” to refer to teachers’ instructional behaviors intended to make the content relevant to the students’ needs, interests, and goals.

On the other hand, in subsequent studies that examined the effects of relevance manipulation on student motivation, relevance was not a significant predictor of student motivation (e.g., Behrens, 1999; Frymier & Houser, 1998). For example, Frymier and Houser (1998) extended Frymier and Shulman’s (1995) research by examining the interactional effects of immediacy and relevance on student motivation and learning by using a 2 (high and low immediacy) X 2 (high and low relevance) experimental design. In each condition, college students attended a 15-minute lecture by a guest lecturer in their public speaking classes. In high relevance conditions, the lecture included examples that were intended to be familiar to students. The authors hypothesized that relevance alone would not be effective if students did not pay attention and immediacy would allow relevance to have an effect by arousing students’ attention. The results, however, indicated that only immediacy had a significant effect on students’ motivation and learning, whereas relevance did not. The authors attributed these inconsistent results to the unsuccessful manipulation of relevance, admitting that the high and low relevance conditions might have been too similar. The study, however, did not explain how the students perceived relevance differently in each condition, because the manipulation check (i.e., whether there were significant differences between the high and low
relevance conditions) was only done by the coders, and the students were not asked whether they perceived each lecture as being relevant or not.

Although students’ reports on their instructors’ use of relevance strategies were associated with students’ motivation, which was consistent with what the ARCS model claims, when researchers attempted relevance manipulation using the same relevance strategies, they did not work. Questioning whether there is something missing from the existing conceptualization of relevance based on these inconsistent results, Muddiman and Frymier (2009) examined relevance strategies from the students’ perspective in order to understand the relevance construct more completely.

Muddiman and Frymier (2009) asked college students to list the behaviors of their previous instructors that made the course content relevant to them. After a qualitative analysis, students’ responses about relevance behaviors produced five separate categories. The first category was “Outside Course Relevance,” which connects what is learned in the classroom and the student’s interests and needs outside of the course (e.g., future lives and careers). The second category was “Teaching Style Relevance,” which is related to instructors’ teaching styles or character that contributed to students’ perceptions of relevance (e.g., enthusiasm and knowledge). The third category was “Methods and Activities Relevance,” which involves course activities and instructional methods that lead to students’ perceptions of course relevance (e.g., applications or group activities). The fourth category was “Inside Course Relevance,” which relates to students’ interests and goals within a single course (e.g., note-taking or assignments). The final category was “No Relevance,” which means students did not believe their instructors tried to make the course content relevant to them.
Whereas other categories seemed to support the existing conceptualization of relevance, the authors noted that some of the categories such as “teaching style” and “inside course” seemed to reflect other instructional constructs than relevance. The teacher behaviors in these categories (e.g., enthusiasm and knowledge in the category of "teaching style," note-taking in the category of "inside course") seemed to be more strongly related to immediacy, humor, and clarity, rather than relevance (i.e., creating connections between the content and the students). Regarding these unexpected results, Muddiman and Frymier (2009) speculated that perceived relevance might not be a component, but an outcome, of effective teaching. That is, a variety of effective teaching strategies could result in an increase in perceived relevance as an outcome. The authors also suggested that the previously identified relevance strategies need to be redefined as teaching strategies, and relevance could be better measured as a perception rather than as a teaching strategy.

Limitations of Previous Research on Instructional Relevance

There are some limitations of previous research on relevance in the field of instructional communication that led to the research questions of the current proposed study. First, in the previous studies, the researchers did not examine specific aspects of motivation such as competence and task values in relation to instructional relevance. Most studies that examined the relation between relevance and motivation used a single indicator of motivation (e.g., state motivation) without examining other variables that are extensively studied in educational psychology. In a math classroom, for example, there are various indicators of students’ motivation in math, including perceived course value
and cost (Eccles et al., 1983; Wigfield & Eccles, 1992; 2000), math anxiety (Meece, Wigfield, & Eccles, 1990; Wigfield & Meece, 1988), self-regulated learning (Pintrich & De Groot, 1990; Wolters, 1999; Wolters & Benzon, 2013), and enrollment intentions (Bong, 2001; Meece et al., 1990). Therefore, it is meaningful to examine how perceived instructional relevance relates to these various aspects of student motivation.

Second, the previous studies that focused on instructional relevance did not closely look at the relations of different types of instructional relevance to other outcomes. For example, the relevance scale developed by Frymier and Shulman (1995) contains 12 items asking students to report on the frequency of their instructors’ behaviors that are specifically related to increasing content relevance. Whereas some items are about teacher’s use of examples and emphasis on the importance of the content (i.e., using teacher-generated relevance), other items reflect what a teacher asks students to do in terms of making the content relevant (i.e., “asks me to apply content to my own interests”), which can be considered student-generated relevance. For example, in an algebra class, if a teacher gives her students a real-life example about buying food at a grocery store, the teacher uses an instructional relevance strategy using teacher-generated relevance. If the same teacher asks her students to come up with a situation where they can use an algebraic equation, this time the teacher uses an instructional relevance strategies using student-generated relevance.

It might be that these different types of instructional relevance strategies are more or less strongly associated with different aspects of student motivation. Some of the
recent studies that examined the effect of value-interventions seem to support this speculation, which is discussed in the following section.

**Value-Intervention Studies and their Implications for Research on Instructional Relevance**

Some educational psychologists have attempted value interventions by manipulating relevance using experimental designs (e.g., Hulleman et al., 2010; Hulleman & Harackiewicz, 2009; Shechter et al., 2011). For example, Hulleman and his colleagues (2010) conducted two experimental studies, where they manipulated relevance through a writing task. Students who were assigned to the relevance condition were asked to write about the relevance of the material they were learning to their lives. Both in a laboratory setting and an actual college classroom, the students in the relevance condition exhibited higher academic interest after the intervention. They also performed better than the students in the control group after the intervention in the laboratory setting and in the final course grade in the college classroom. Similarly, Hulleman and Harackiewicz (2009) found this values intervention to positively influence high school students’ interest and course grades in science classes. The results of these studies suggest that classroom activities encouraging students to connect what they learn in the course to their lives can increase student motivation and learning. Hulleman et al. (2010) also proposed that simply informing students about the relevance of the material might not be effective for students who do not do well in math or who have low initial interest in math. The authors argue that encouraging students to discover the relevance of the course material for themselves would be a more effective approach.
In terms of the two different types of instructional relevance strategies (i.e., using teacher-generated relevance vs. using student-generated relevance), these value-intervention studies are more closely related to the ones using student-generated relevance because students were asked to think about the relevance of the subject matter for themselves. Considering the inconsistent results of the effectiveness of instructional relevance in the aforementioned studies, it could be helpful to examine whether these two types of instructional relevance are empirically distinguished from one another and how they relate to students’ motivation and learning differently.

**Instructional Relevance Combined with Other Characteristics of Teachers’ Instructional Practice**

The results about the effect of instructional relevance from previous studies were mixed as discussed above (e.g., Behrens, 1999; Frymier & Houser, 1998) and there was a significant gap between instructional relevance strategies and relevance from students’ perspectives as found in Muddiman and Frymier’s (2009) work. These findings suggest that instructional relevance strategies alone might not be enough to motivate students, unless they are combined with other effective teacher practices. Therefore, it is necessary to explore other characteristics of teacher instruction that can be combined with instructional relevance to more effectively motivate students in their math classrooms.

For example, even though a teacher emphasizes the importance and usefulness of the material, if the teacher does not provide adequate competence support, students with low perceived competence might perceive a higher cost of learning the materials (e.g., students may not believe it's worth their time and effort to learn the materials) and might
be more likely to become disengaged. Therefore, in the following section, I review the literature on teachers’ support of the students’ competence in terms of how it can affect student motivation and learning.

**Teacher Competence Support**

Teacher support behaviors encompass various aspects of the ways teachers help students to learn. Different types of teacher support behaviors have been studied extensively in previous studies (e.g., Skinner & Belmont, 1993; Weinstein, Marshall, Sharp, & Botkin, 1987; Wentzel, 2009). Previous studies of teacher support have identified several different types of teacher support including emotional support, instructional feedback, teacher expectations, academic competence support, social competence support, and provision of resources (Malecki & Demaray, 2003; Wentzel, 2009).

Among these different types of teacher support, emotional support is one of the most extensively studied aspects of teacher support. Emotional support has often been measured with students’ perceptions of teacher caring (Wentzel, 1997). The results of the research on teacher caring indicate that students’ perceptions of teacher caring are positively associated with students’ motivation and achievement for K-12 students (Murdock & Miller, 2003; Wentzel, 1997). For example, when teachers are perceived as caring by their students, students are more likely to adopt goals that are valued by the teacher, such as achieving academically (Wentzel, 1999). In Roeser, Midgley, and Urdan’s (1996) study, students’ perceptions of teacher support (in the forms of respect,
trust, and caring) were positively associated with students’ sense of school belonging, which also positively related to students’ self-efficacy.

**Teacher support for students’ academic competence.** Whereas teachers’ emotional support has been extensively studied in the literature, teacher behaviors that are associated with students’ academic competence as a distinct dimension of teacher support have not been given much attention in previous studies, although there is often overlap between competence support and emotional support (McRae, 2012). McRae (2012) examined the unique role of academic competence support by teachers. She developed a teacher competence support scale by adapting previous teacher support items including three different dimensions: encouraging feedback, teacher expectations for students’ academic performance, and instrumental help. The results of the factor analyses indicated that the dimension "expectations" belongs to a different factor than the other two dimensions. In addition, the items measuring expectations were not reliable as shown in their reliability measures; therefore, the author removed the “expectations” dimension and only included encouraging feedback and instrumental help in the final scale.

**Components of teacher competence support.** Following McRae’s operationalization, in the current study I assume that teacher competence support is composed of two different types of teacher behavior: giving encouraging feedback and providing instrumental help. Encouraging feedback is a type of teacher feedback, which refers to teachers’ positive verbal statements in response to students in the classroom. These verbal statements can include information about academic tasks, appraisals of students’ ability, or observations about student behavior. The teacher feedback can significantly influence how students perceive themselves as well as their competence
beliefs in an academic task (Skinner & Belmont, 1993; Wentzel, 1997). Instrumental help, which refers to the provision of teachers’ advice, information, and modeled behavior, has been shown to relate to students’ self-efficacy and autonomy in the previous studies (Wentzel, 2009).

**Teacher competence support and student outcomes.** McRae (2012) examined the relations of African-American and European-American students’ perceptions of teacher competence support to 1) students’ reading self-efficacy and 2) their reading achievement. The results of the study show that students’ perceptions of teacher competence support significantly relate to their self-efficacy in reading regardless of students’ ethnic groups. These researchers also reported that perceived teacher competence support was related positively to students’ reading achievement, but only for African-American students, not for European-American students.

Based on these findings, I hypothesize that when a teacher provides adequate competence support by giving encouraging feedback and instrumental help to students, students will exhibit positive motivation with increased competence and decreased cost and anxiety toward their math course. Especially in math classrooms, if a student does not feel competent or perceives low self-efficacy in math, the teacher’s competence support will be particularly critical in terms of determining students’ motivation to learn in the class. Therefore, it is necessary to examine the role of teacher competence support combined with instructional relevance in students’ math class motivation.
Related Variables

Math Anxiety

Math anxiety can be defined in many different ways. In general, it refers to negative feelings that students may harbor toward math and their worries about performing well when they carry out tasks requiring math (Ashcraft, 2002; Richardson & Suinn, 1972).

Previous research found several outcomes associated with math anxiety. Higher levels of math anxiety are significantly associated with lower achievement in math, fewer math courses a student takes, and lower intention to enroll in a math course, all of which can influence a student’s career decisions. High levels of math anxiety may impede math performance regardless of a student’s ability (Ashcraft, 2002; Ashcraft & Moore, 2009; Suinn & Edwards, 1982). Studies that examine associations between math anxiety and other math attitude variables suggest that math anxiety correlates negatively with positive indicators of math motivation, such as self-confidence in math, enjoyment of math, or perceived usefulness of math. Research also indicates that students’ interpretations of their achievement outcome influence their math anxiety more strongly than their actual outcomes (Hackett, 1985; Meece et al., 1990).

Previous research on math anxiety suggests two major types of math anxiety: affective and cognitive (Choi & Clark, 2006; Wigfield & Meece, 1988). Whereas affective anxiety encompasses negative emotional reactions to math, such as fear and nervousness, cognitive anxiety includes worries and negative expectancy of doing well in math.
Research in math education suggests teachers’ beliefs or instructional strategies can influence students’ math anxiety (Gunderson et al., 2012; Im, 2012). For example, Shen (2009) conducted an intervention study to examine the effects of interventions for decreasing students’ math anxiety. The results showed that students’ math anxiety was alleviated when they received emotional support from their teachers focusing on coping strategies, which had the positive effect of increasing the students’ math learning.

Based on the importance of math anxiety established in prior literature, the present study used math anxiety as one of the math class motivation indicators along with other efficacy- and value beliefs and cost.

**Gender**

Expectancy-value theory (Eccles et al., 1983) is generally used to explain gender differences related to motivation in math education. According to this theory, the norms and expectations emphasized by social values placed on gender can influence students’ identity formation, which in turn influences the expectancy and value beliefs in the math education context (Eccles, 2009; Watt & Eccles, 2006). Consequently, male students tend to view math more positively and to have higher competence beliefs for math than female students do (Eccles et al., 1989, Wigfield et al., 1991; 1997). This gender difference can possibly influence students’ math performance and their choices in carrying out math activities (Wigfield & Eccles, 2002).

Previous studies using a longitudinal design (Jacobs et al., 2002; Wigfield et al., 1997) showed this difference is more salient in students’ earlier ages. In a longitudinal study, Jacobs and colleagues (2002) examined children in primary and secondary grades,
1st- through 12th grade, to investigate how their competence beliefs and task values changed over time in each domain. Overall, students’ math competence beliefs decreased over time for both genders. Despite starting school with higher competence beliefs, male students’ beliefs in their math ability decreased more rapidly than did those of female students, so the gender gap in math competence beliefs was significantly reduced by the end of high school.

However, the results of research on gender differences are somewhat inconsistent across studies (Spinath, Eckert & Steinmayr, 2014), and there is evidence that many other factors play a part in this process. A recent study conducted by Gaspard and colleagues (2015) investigated more detailed aspects of the four value components, and determined whether gender differences were related to those aspects. Their results suggest that gender differences may relate to variations in personal value beliefs and emphasis on a particular facet of the value components related to math. Whereas the value beliefs structure was similar among the students, the females perceived a higher emotional cost, and put less intrinsic value on math, which could appear to be less useful and less important for their long-term goals. As stated in the literature, female students tend to believe math is academically important, but not personally relevant (Gaspard et al., 2015; Steinmayr & Spinath, 2008).

**A Person-Centered Approach to Motivation Research**

**Person-Centered Approach vs. Variable-Centered Approach**

Previous studies on the link between math motivation and learning outcomes have tended to use variable-centered analyses, which describe associations between variables.
For example, much of the research on students’ math motivation has focused on how different motivational constructs are related to specific outcomes. This variable-centered approach supports the importance of each variable in predicting outcomes for the entire population, not focusing on how multiple variables work together within an individual. In the variable-centered approach, relations among variables are usually assumed to be the same for the entire population or most individuals.

In the present study I used a person-centered approach rather than a variable-centered approach in order to understand different patterns of high school students’ math class motivation. The person-centered approach, which focuses on individuals instead of variables, identifies homogenous groups of students who share similar patterns based on multiple observed variables. For example, in this approach, students' motivation profiles can be identified based on multiple motivational indicators such as math competence, anxiety, cost, values, etc. This approach allows researchers to examine relations among multiple variables in one measurement model (Laursen & Hoff, 2006; Masyn, 2013). Compared to variable-centered approaches that focus on single dimensions, the person-centered approach focuses on individuals. Unlike the variable-centered approach, the person-centered approach assumes that populations are heterogeneous (Bergman & El-Khoury, 2003; Laursen & Hoff, 2006; Masyn, 2013) and that relationships among variables can be different for different groups of individuals. This person-centered approach will allow researchers and practitioners to gain insights into how to plan and implement effective interventions for groups who have different profiles.
Latent Class Analysis vs. Cluster Analysis

Two different types of person-centered approaches are commonly used to identify subgroups of students: Latent Class Analysis and Cluster Analysis. These two analyses share the same purpose, but some important differences exist between them. Latent Class Analysis is similar to cluster analysis in that both use observed indicators to identify groups of individuals. Like Latent Class Analysis, cluster analysis is a person-centered approach in which individuals are clustered into homogeneous groups based on the patterns of their responses on multiple indicators.

However, Latent Class Analysis has advantages over cluster analysis in several ways (Macyn, 2013). Unlike cluster analysis, which shares the same assumptions as regression analysis, Latent Class Analysis does not have to meet the assumption of data normality. That is, individuals’ scores on the observed variables do not need to be normally distributed. Instead, it assumes that there can be several different distributions in one dataset. Individuals with similar response patterns on a series of observed variables are classified into the same latent class. In addition, whereas cluster analysis only can use continuous predictors, Latent Class Analysis uses wider array of predictor variables including categorical predictors. For these reasons, I use Latent Class Analysis in this study.

Current Study

Based on the literature review, in the current study I examine the relations among students’ perceptions of their teacher’s instructional practices, math class motivation, and
achievement and motivational outcomes in high school math classrooms. The theoretical model for the current study is presented in Figure 2.1.

For students’ math class motivation indicators, I focus on math class efficacy beliefs, attainment value, intrinsic value, endogenous instrumentality, cost, and math anxiety. For perceived teacher practices in math class, perceived instructional relevance and teacher competence support will be examined. For achievement and motivational outcomes, I focus on students’ choices, persistence, and achievement. Students’ course enrollment intentions (Bong, 2001; Meece et al., 1990) will be used as an indicator of student’s future choices, and their effort regulation behaviors (Pintrich et al., 1991) will be used as an indicator of their persistence in their math class. Students’ semester grades in their math course will be used as an indicator of their achievement.

In order to understand how to motivate high school students to learn about math, and what instructional environments are more or less effective in terms of promoting student motivation and achievement in math classrooms, I employ a person-centered approach. The research questions and the hypotheses of the current study are as follows.

**Research Question 1. What are the emerging profiles of high school students’ math class motivation?**

In order to understand what motivates high school students in math class, it is crucial to examine different patterns of motivational beliefs and attitudes that high school students have toward their math class; thus, as the first step, students' math class motivation profiles will be explored. For Research Question 1, Latent Profile Analysis (LPA) will be conducted in order to identify subgroups of students based on their math class motivation profiles. Since this is an exploratory approach, it is difficult to predict
how many profiles will emerge and how each profile will look. Based on the review of
the literature on math motivation in high school students, however, it is expected that
there will be at least one high motivation group where students show high efficacy,
attainment value, intrinsic value, endogenous instrumentality, and low cost and anxiety,
and at least one low motivation group where students show low efficacy, attainment
value, intrinsic value, endogenous instrumentality, and high cost and anxiety. It is
difficult to predict how many additional groups may emerge, but there might be a mixed
motivation group where students show both positive and negative motivation in their
math class.

**Research Question 2. Are high school students’ math class motivation profiles
significantly predicted by their perceptions of teacher practices (i.e., instructional
relevance & teacher competence support) while controlling for their demographic
characteristics and prior math achievement, and how?**

After exploring students’ math class motivation profiles, in order to understand
how to promote more positive motivational beliefs in math class, I will examine how
different teacher practices are associated with different motivation profiles. In terms of
Research Question 2, I will examine whether students’ perceptions of teacher practice
(i.e., instructional relevance and teacher competence support) predict latent class
membership after controlling for students’ prior achievement and other demographic
variables (e.g., gender, grade level, free/reduced-priced lunch status, and whether a
student was taking an honors class).

I hypothesize that high motivation profiles are more positively associated with
high instructional relevance and high teacher competence support. Based on the findings
of previous studies, it is also hypothesized that students are more likely to belong to more adaptive motivation profile groups when they perceive that their math teacher's instruction is relevant, and when they perceive that the teacher supports the students' competence by providing encouraging feedback and instrumental help.

**Research Question 3. Do high school students’ math class motivation profiles significantly predict their achievement and motivational outcomes including math course grades, math course enrollment intentions, and effort regulation, and how?**

In terms of Research Question 3, I will examine whether students’ math class profiles significantly predict their achievement and motivational outcomes after controlling for students’ prior math achievement and other demographic variables. Whereas it is difficult to predict what motivation profiles will emerge from Research Question 1, I hypothesize that being in a high motivation group will be a significant predictor of positive outcomes such as high math course grades, high enrollment intentions, and high effort regulation whereas being in a low motivation group will be a significant predictor of negative outcomes such as low math course grades, low enrollment intentions, and low effort regulation.

The findings of this study will contribute to expanding the existing literature on relevance by identifying effective instructional strategies that are associated with students’ perceptions of course relevance as well as other important indicators of student motivation in math class. The results of this study are also expected to provide practical implications for math classroom teachers about how teachers can help students develop competence in math as well as value learning math, while also helping them decrease math anxiety and perceived cost of learning math.
Figure 2.1. A theoretical model of the role of instructional relevance and teacher competence support in students’ math class motivation.
Chapter 3: Methods

Subject of Study

The sample for this study consists of 355 ninth and tenth graders taught by 31 different teachers in high school math classrooms. The participants were from three high schools in one large mid-western state.

At the conclusion of data collection and reduction of the sample to include only complete responses, a total of 355 responses were used for the final analyses. Among the participants, 56.1% were female, and 55.5% were ninth graders. Students ranged in age from 13 years to 17 years. In terms of ethnicity, 70.4% were Caucasian, 10.7% were African-American, 6.5% were Hispanic/Latino, 6.2% were Asian, and 6.2% were others. Among the participants, 14.4% received a free or reduced-priced lunch. In terms of a math course that the participants were taking, 34.4% were taking CCSS Math 1, 31.0% taking CCSS Math 2, 13.8% taking FST (Functions, Statistics, and Trigonometry), 12.7% taking Algebra, 5.4% taking Geometry, 2.7% taking other courses. Among the participants, 34.1% were taking an honors course.
Procedures

The present study was conducted with the approval of the Institutional Review Board (IRB) of the Ohio State University. The IRB approval letter is attached as Appendix A.

Data were collected in the fall and spring semester of the 2013-2014 academic year from three high schools. Whereas the participants from all three schools responded to the same survey instrument, the recruitment and survey administration procedures were slightly different for each school as described below.

Recruitment

I visited each school to recruit survey participants approximately 8-10 weeks after the fall semester of the 2013-2014 academic year started. For each school, the same recruitment packet was distributed to the ninth and the tenth grade students. Each recruitment packet included a letter of research request to the parents, a parental permission form, an assent form, and extra copies of both forms for students to keep. The methods of recruiting participants (e.g., when/where the recruitment took place, who read the verbal script regarding what the study is about and how to participate in the study) were slightly different for each school depending on each school’s availability and convenience.

For school A, the recruitment was conducted during the students’ math classes. I went to every math classroom that had ninth or tenth graders. I delivered the recruitment packets and a recruitment verbal script to each math teacher, and the math teachers read
the verbal script and distributed the recruitment packets to their ninth and tenth grade students. The verbal script can be found in Appendix B. I stopped by each classroom to answer any questions the students had.

For school B, the recruitment took place during ninth and tenth grade students’ home room period. A two-minute-long recruitment video that I had recorded was shown in each home room class and the recruitment packets were handed out to the students by each home room teacher. I entered each homeroom to answer any questions students had.

For school C, the recruitment happened during a study hall period. I entered each study hall classroom, read the verbal script, and handed out the recruitment packets.

For all three schools, if students were willing to participate, they were asked to return the permission slip with their parents’ signature to me when I came back to each classroom, or submit the signed slip through a locked drop box located in an office. Students were informed that their participation would be totally voluntary and their survey responses would be kept completely confidential. Students were also informed that they would have an opportunity to enter a drawing to win one of the 20 (for school B and C) or 30 (for school A which is much larger than the other two schools) $20 restaurant gift cards if they return the permission slip and participated in the survey.

**Survey Administration**

After recruiting study participants, a survey was administered to students approximately 12-14 weeks after the start of the fall semester of the 2013-2014 academic year. Only students who received parental consent for their participation in the study were allowed to sign the assent form and take the surveys. For Schools A and C, the
surveys were administered during the students’ study hall periods. For School B, the survey was administered during an extended homeroom period. The survey participants were asked to come to a large space such as a library or a cafeteria to take the survey. Students who did not participate in the survey were asked to work on their own during the class period (either home room or study hall) in their classroom. After the surveys were distributed, students were asked to think about the math class they were currently taking during the semester when they responded to each item. Students’ perceptions of teacher practices (i.e., instructional relevance, teacher competence support, and teacher credibility), motivational beliefs (i.e., efficacy, attainment value, intrinsic value, cost, endogenous instrumentality, and math anxiety), math course enrollment intentions, and effort regulation were measured.

In order to match individual students’ survey responses with their demographic and achievement information from school records, each student was assigned a unique six-digit identification number. These numbers were not related to any of the students’ information and were randomly distributed to protect their privacy. The identification number was printed on the bottom of the first two and the last pages of the survey. Students were asked to write their first and last name on the detachable first page of the survey. They were asked to separate this front page (with their names) from the rest of the survey. After completing the rest of the survey, students were asked to submit the first page of their survey in one box and the rest of the survey in another. These separate boxes were located at the front of the classroom.
Data from School Records

After the winter break, students’ math course information and some demographic information (gender, ethnicity, grade, age, free/reduced school meal status) were collected from school records. After the end of the year, students’ math course grades for semester 1 and 2 were collected from school records.

Measures

With the exceptions of students’ achievement outcome (i.e., course grades), math course information, and demographic information (i.e., gender, ethnicity, grade, age, free/reduced school meal status, etc.), which were collected from school records, all the other measures used in this study were self-reported. All the survey items referred to students’ current math class. All of the variables were measured by using established scales with minor adaptations as discussed in detail as follows; the one exception is the perceived instructional relevance scale, which required additional modifications. (A complete list of all survey items is attached as Appendix C.)

Measures of Perceived Teacher Practice

Measures of students’ perceived teacher practice in their math class included instructional relevance, teacher competence support, and teacher credibility.

Instructional relevance. Instructional relevance was measured by adapting items from Frymier and Shulman’s (1995) Relevance Scale. This scale contains 12 items that ask students to report on the frequency of their instructors’ behaviors that are specifically related to increasing content relevance (alpha = .88). Frymier and Shulman intended to develop items that reflect instructors’ explicit teaching behavior so that students can be
less affected by their subjective feelings. Whereas half of the items are about teachers’ use of examples to make the content relevant (e.g., “[My instructor in this course] uses examples to make the content relevant to me.”), some items are about what a teacher asks students to do to makes the content relevant (e.g., “[My instructor in this course] asks me to apply content to my own interests”). Based on the hypothesis of this study that different types of instructional relevance will be associated in different ways with student motivation, the scale has been adapted for this study so that it has two separate subscales: instructional relevance using teacher-generated relevance and instructional relevance using student-generated relevance.

Instructional relevance using teacher-generated relevance was measured using eight items from the original scale with minor adaptations. In order to make the scale format more consistent with other scales in the survey, instead of asking students to report on the frequency of their teachers’ behavior described in each item, they were asked to rate how much they agree or disagree with the statement about their teacher’s behaviors that are specifically related to increasing content relevance. Some item examples are: “[My math teacher] clearly states how the material relates to my career goals or to my life in general,” and “[My math teacher] uses explanations that demonstrate the importance of the content.” Responses were made on a five-point scale ranging from 1=strongly disagree to 5=strongly agree. The alpha reliability of the eight items in the current sample was .87.

Instructional relevance using student-generated relevance was measured using seven items adapted from the original scale. In the original scale, only three items
assessed whether teachers ask students to generate their own relevant examples (i.e., using student-generated relevance). So the other four items have been adapted from the items about using teacher-generated relevance. For example, an original item “[My instructor in this course] links content to other areas of content” has been adapted to “[My math teacher] asks me to relate what I’m learning in this math class to what I am learning in other classes.” Responses were made on a five-point scale ranging from 1=never to 5=very often. The alpha for the seven items in the current sample was .84.

Because the original relevance scale was developed using college students as research subjects, a cognitive interview was conducted in order to identify and correct any incongruities with these two subscales of instructional relevance (i.e., instructional relevance using teacher-generated relevance and instructional relevance using student-generated relevance). The purpose of the cognitive interview was to check whether each item statement transfers over to high school students (i.e., whether the instructors' behaviors stated in the original items can be applied to high school math teachers' instructional behaviors, and whether there were any vocabulary issues that might hinder students' understanding). Five high school students were asked to take the draft survey including the two subscales and to give verbal feedback about each scale. The students were asked questions such as “Are the questions easy to understand?” and “Does the scale capture math teacher’s behavior to make content relevant well?” Feedback on the scales was also collected from three high school math teachers. Further adjustment of the scale was made as a consequence of cognitive interviewing.

Since the factor analysis did not support that these two subscales are two different factors, (See the results of the factor analysis in Chapter Four for details), instructional
relevance was used as a single scale including 15 items. The alpha reliability of the 15 items in the current sample was .92.

**Teacher competence support.** In order to measure students’ perceptions of teacher competence support, items from Teacher Competence Support Questionnaire (McRae, 2012) were adapted. This questionnaire is a student self-report of perceptions of teacher behaviors that support competence in reading. The scale combined items adapted from Skinner and Belmont (1993) and Weinstein and colleagues (1982). A total of nine items of this scale reflect teachers’ supportive behaviors including encouraging feedback and instrumental help. The alpha from McRae’s (2012) study was .83. In this study, the items were adapted to measure students’ perceptions of their math teachers’ support behavior. For example, an original item “In the last four weeks in Reading/Language Arts class my teacher helped me meet challenges in reading” was adapted, which resulted in “(In my math class, my math teacher) helps me overcome challenges in math.” One item which is specifically about reading (“My teacher said I did well when I read aloud”) was removed and two more items from Skinner & Belmont (1993)’s Help/Support scale were added (“[My math teacher] shows me how to solve problems for myself,” and “[My math teacher] shows me different ways to try to, if I can’t, solve a problem.”) because these items seem to capture math teachers’ support behavior well. Therefore, a total of 10 items were used to measure students’ perceived teacher competence support. The responses to the items were made on a 5-point scale ranging from 1=strongly disagree to 5=strongly agree. The alpha reliability of the 10 teacher competence support items in the current sample was .88.
Measures of Math Class Motivation.

Measures of students’ math class motivation included competence, attainment value, intrinsic value, cost, and endogenous instrumentality.

Efficacy Beliefs. Students’ efficacy beliefs in their math course were measured by adapting five items of Academic Efficacy scale from PALS (Midgley et al., 2000). These items assess the degree to which students feel that they are competent to do their class work. The alpha from the previous study was .78. In order to make the items refer to students’ current math class, a phrase “in this math class” was added to each item. A sample item is “In this math class, even if the work is hard, I can learn it.” Responses to the items were made on a 5-point scale ranging from 1=strongly disagree to 5=strongly agree with high scores indicating greater perceived efficacy. The alpha reliability of the five efficacy beliefs items in the current sample was .92.

Attainment value. In order to measure students’ perceived attainment value in their math course, four items from Eccles and Wigfield (1995)’s and Conley (2011)’s subjective task value scale were used with minor adaptations. Conley adapted items from the work of Eccles, Wigfield, and their colleagues (Eccles & Wigfield, 1995; Eccles et al., 1993; Wigfield et al., 1997) by combining the existing items with new items in order to make them explicitly measure each of the four task value components (i.e., intrinsic value, utility value, attainment value, and cost value), which was supported by confirmatory factor analysis. Since the items measure attainment value about math in general, only items that can be adapted to reflect students’ math course attainment value were selected. Items were adapted so that they refer to students’ perceived importance
about what they learn in their current math class. For example, an original item “Being good at math is an important part of who I am,” was adapted, which resulted in “Being good in this math class is an important part of who I am.” Responses to the items were made on a 5-point scale ranging from “1=strongly disagree” to “5=strongly agree” for three items while using different anchors for one item (“1=not at all important/ 5=very important”). The alpha reliability of the four attainment value items in the current sample was .88.

**Intrinsic value.** In order to measure students’ perceived interest in their math course, four items from Eccles and Wigfield (1995)’s and Conley (2011)’s subjective task value scale were adapted. Since the original items measure perceived interest about math in general, only items that can be adapted to reflect math class intrinsic value were selected. Item were adapted so they refer to students’ perceived interest about what they learn in their current math class. For example, an original item “Math is exciting to me,” was adapted, which resulted in “What I learn in this math class is exciting.” Responses to the items were made on a 5-point scale ranging from “1=strongly disagree” to “5=strongly agree” for three items while using different anchors for one item (“1=very boring/ 5=very interesting”). The alpha reliability of the four intrinsic value items in the current sample was .92.

**Cost.** In order to measure students’ perceptions of cost in their math class, Battle and Wigfield’s (2003) cost items from The Valuing of Education Scale (VOE) were adapted. After a series of factor analyses, Battle and Wigfield finally selected 11 items for their perceived cost scale, which measured the anticipated costs associated with the pursuit of graduate school (alpha = .85). The items reflected estimated effort, loss of time
for other goals, and psychological cost of failure. Among the 11 cost items, six items were selected to be adapted for this study. The purpose of the adaptation was to make the items measure students’ perceived cost of studying math in their current math class. For example, an original item “I worry that spending all the time in graduate school will take time away from other activities I want to pursue while I’m still young” (*loss of time for valued alternatives*) was adapted, resulting in “I worry that spending all the time for this math class will take time away from other activities I enjoy.” Other sample items are “When I think about all the work required to do well in this math class, I’m not sure it is going to be worthwhile in the end,” (*perceived effort*) and “My self-esteem would suffer if I tried hard in this math class, and was unsuccessful at it.” (*psychological cost of failure*). Responses to the items were made on a 5-point scale ranging from “strongly disagree” to “strongly agree” with high scores indicating greater perceived cost. The alpha reliability of the six cost items in the current sample was .80.

**Endogenous instrumentality.** In order to measure students’ perceived endogenous instrumentality in their math class, four items of endogenous instrumentality from the Perceptions of Instrumentality Scale (Husman et al., 2004) were used (alpha = .73). The four items measure students’ perceived utility of learning the course content for future goals. An item example is “What I learn in the course selected above was important for my future occupational success.” Responses to the items were made on a 5-point scale ranging from “strongly disagree” to “strongly agree” with high scores indicating greater perceived instrumentality. The alpha reliability of the four endogenous instrumentality items in the current sample was .84.
Math anxiety. In order to measure students’ math anxiety, five items of Negative Affective Reactions scale from The Math Anxiety Questionnaire (Wigfield & Meece, 1988) were used (alpha = .77). The five items represent strong negative affective reactions to math, which can be considered a form of debilitating math anxiety (Meece et al., 1990). Sample items are “When I am in math, I usually feel (not at all at ease and relaxed, very much at ease and relaxed)” and “Taking math tests scares me (I never feel this way, I very often feel this way)”. The alpha reliability of the five math anxiety items in the current sample was .83.

Measures of Achievement and Motivational Outcomes

Measures of students' learning and motivational outcomes included math course grade, course enrollment intentions, and effort regulation. These three measures were used as proxies for students' course achievement, choices, and persistence in their math class, respectively.

Course grade. Students' end of semester math course grades for semester 1 and semester 2 were collected from their school records. Each letter grade was converted to a numeric equivalent using a point scale ranging from 0 = F to 4.3 = A+.

Course enrollment intentions. Two items were used to measure students’ intentions to take additional math classes. One item is adapted from a course enrollment intentions item used in Meece and colleagues’ (1990) work. The item asks students’ intentions to take more math classes in the future when they do not have to. Another item has been added which asks students how much they would like to take more math classes
next year. The two items are: “Even if I no longer had to, I would take more math classes in the future,” and “How much would you like to take more math classes next year?” Responses were made on a 5-point scale ranging from 1=strongly disagree to 5=strongly agree, and from 1=not at all to 5=very much, respectively. The correlation between the two enrollment intention items in the current sample was .63.

Effort regulation. As a proxy for students’ effort or persistence in their math class, students’ perceived effort regulation was measured. Students’ regulation of their own effort in their current math class was measured using four items from the Motivated Strategies for Learning Questionnaire (Pintrich et al., 1991). The items ask students whether they persist when faced with boring or difficult tasks in their math class. Students were asked to rate each statement based on their behavior in their current math class. An example item is “When course work is difficult, I give up or only study the easy parts” (Reversed). Responses were made on a 5-point scale ranging from 1=not at all true of me to 5=very true of me. The alpha reliability of the four effort regulation items in the current sample was .74.

Prior math achievement. As a measure of students' prior achievement in math, statewide standardized eighth grade math assessment scores were collected from their school records. This assessment is administered every spring to all eighth graders in public schools in the state. The test results show whether students learned the level of mathematics expected at the end of eighth grade. Students' scaled scores that were converted from their raw scores were used for analysis.
Demographic Variables

Gender. Students' gender information was collected from their school records. Gender was coded as 1 = male, 0 = female.

Grade. Students' grade information was collected from their school records. Since only ninth and tenth graders participated in the study, grade was coded as 1 = ninth grade, 0 = tenth grade.

Honors class status. Information about whether students' math course was an honors class or not was collected from their school records. Honors class status was coded as 1 = honors class, 0 = non-honors class.

Math course. Students’ math course enrollment information was collected from their school records. In order to more closely examine students’ math course enrollment distribution by their grade level, a cross-tabulation was conducted on “math course” and “grade level” for each school. As shown in Table 3.1, 3.2, and 3.3, each school had its own math curriculum offering slightly different math courses.

After examining each school’s math curriculum, I concluded that, in School A, if a ninth grader was taking Algebra 1 or a tenth grader was taking Algebra 1 or 2, the student was taking a math course below her or his grade level. In schools B and C, if a tenth grader was taking CCSS Math 1, the student was taking a course below his or her grade level. Considering that whether or not students were taking a math course below their grade level could affect their math class motivation, I checked how many survey
participants were taking a math course below their grade level using the cross tabulations.

Only 35 out of 355 students (9.86%) were taking below-grade-level math courses.

Table 3.1
**Grade Level * Math Course Cross Tabulation for School A (n = 66)**

<table>
<thead>
<tr>
<th>Course Name</th>
<th>Algebra1</th>
<th>Algebra 2</th>
<th>Geometry</th>
<th>Algebra 3 &amp; Trigonometry</th>
<th>Honors Algebra 2</th>
<th>Honors Geometry</th>
<th>Honors Precalculus</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Grade Level 9</td>
<td>9</td>
<td>4</td>
<td>20</td>
<td>0</td>
<td>0</td>
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<td>5</td>
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<tr>
<td>Grade Level 10</td>
<td>10</td>
<td>1</td>
<td>2</td>
<td>9</td>
<td>3</td>
<td>0</td>
<td>5</td>
<td>27</td>
</tr>
<tr>
<td>Total</td>
<td>5</td>
<td>22</td>
<td>9</td>
<td>3</td>
<td>3</td>
<td>10</td>
<td>7</td>
<td>66</td>
</tr>
</tbody>
</table>

Table 3.2
**Grade Level * Math Course Cross Tabulation for School B (n = 211)**

<table>
<thead>
<tr>
<th>Course Name</th>
<th>CCSS Math 1</th>
<th>CCSS Math 2</th>
<th>FST</th>
<th>Algebra3</th>
<th>Honors CCSS Math 2</th>
<th>Honors FST</th>
<th>Honors Precalculus &amp; Discrete Math</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Grade Level 9</td>
<td>9</td>
<td>70</td>
<td>4</td>
<td>0</td>
<td>0</td>
<td>41</td>
<td>4</td>
<td>119</td>
</tr>
<tr>
<td>Grade Level 10</td>
<td>10</td>
<td>19</td>
<td>42</td>
<td>10</td>
<td>2</td>
<td>16</td>
<td>2</td>
<td>92</td>
</tr>
<tr>
<td>Total</td>
<td>89</td>
<td>45</td>
<td>10</td>
<td>1</td>
<td>43</td>
<td>20</td>
<td>2</td>
<td>211</td>
</tr>
</tbody>
</table>

Table 3.3
**Grade Level * Math Course Cross Tabulation for School C (n = 78)**

<table>
<thead>
<tr>
<th>Course Name</th>
<th>CCSS Math 1</th>
<th>CCSS Math 2</th>
<th>FST</th>
<th>Block Algebra2</th>
<th>Honors CCSS Math 2</th>
<th>Honors FST</th>
<th>Physical Science &amp; CCSS Math 1</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Grade Level 9</td>
<td>9</td>
<td>23</td>
<td>1</td>
<td>0</td>
<td>12</td>
<td>2</td>
<td>1</td>
<td>39</td>
</tr>
<tr>
<td>Grade Level 10</td>
<td>10</td>
<td>9</td>
<td>9</td>
<td>2</td>
<td>4</td>
<td>0</td>
<td>15</td>
<td>39</td>
</tr>
<tr>
<td>Total</td>
<td>32</td>
<td>10</td>
<td>2</td>
<td>4</td>
<td>12</td>
<td>17</td>
<td>1</td>
<td>78</td>
</tr>
</tbody>
</table>

**Free/reduced-priced lunch status.** As an indicator of socioeconomic status, students' free or reduced-priced lunch status was collected from their school records.
Free/reduced-priced lunch status was coded as 1 = free/reduced-priced lunch, 0 = full-priced lunch.

**Data Analysis**

As a preliminary analysis, an exploratory factor analysis was conducted to uncover the underlying structure of students’ responses to the instructional relevance items. Principal Axis Factoring was used and the number of factors was determined based on eigenvalues and a scree plot. Following the factor analysis, descriptive statistics and bivariate correlations among the variables were computed. Missing data were treated using the EM algorithm.

**Research Question 1. What are the emerging profiles of high school students’ math class motivation?**

In order to identify subgroups of students based on their math class motivation profiles, Latent Class Analysis (LCA) was conducted using Mplus 7.2. LCA allows researchers to identify unobservable subgroups within a population, as well as to understand both antecedents and consequences of latent class membership (Lanza, Bray, & Collins, 2013). More specifically, this study used Latent Profile Analysis (LPA), a type of LCA where indicator variables are continuous variables and not binary variables.

In this study, students’ motivation profiles were identified based on six indicators: 1) efficacy, 2) attainment value, 3) intrinsic value, 4) endogenous instrumentality, 5) cost, and 6) math anxiety. As an exploratory approach, I ran several models with different numbers of profiles (i.e., 2 profiles, 3 profiles, 4 profiles, 5 profiles, and 6 profiles).
Both absolute fit and relative fit indices were compared to decide which model had the best fit. More specifically, Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), sample-size adjusted BIC, Entropy, and Lo-Mendell-Rubin adjusted likelihood ratio test (LMR) were compared in order to assess model fit. For AIC, BIC, and adjusted BIC, smaller values indicate a better model. Entropy gives information about the separation of profiles, and values greater than .80 indicate a good separation (Celeux & Soromenho, 1996). Lo-Mendell-Rubin adjusted likelihood ratio test (LMR) provided information about which model contained the ideal number of profiles (Nylund, Asparouhov, & Muthen, 2007). Based on these multiple indicators of model fit and model diagnostics and on theoretical evidence and interpretability, a final measurement model was selected.

**Research Question 2. Are high school students’ math class motivation profiles significantly predicted by their perceptions of teacher practices (i.e., instructional relevance & teacher competence support) while controlling for their demographic characteristics and prior math achievement, and how?**

After I chose the final measurement model of LPA, multinomial logistic regression was used to examine whether students’ perceptions of teacher practice (i.e., instructional relevance and teacher competence support) predict latent class membership after controlling for students’ prior achievement and other demographic variables (e.g., gender, ethnicity, grade level, free/reduced-priced lunch status, whether a student was taking an honors class). A three-step approach suggested by Asparouhov and Muthén (2014) was used in order to avoid potential disadvantages of a one-step approach. In one-
step approaches where the latent profiles and the latent profile regression models are estimated simultaneously, the covariates (i.e., predictors) can influence the process of forming latent profiles so results can be biased. Accordingly, students’ latent profiles were estimated first, and the predictors were then introduced in the three-step approach in order to avoid obtaining mis-specifications in the latent profile model and biased predictions of latent profiles.

**Research Question 3. Do high school students’ math class motivation profiles significantly predict their achievement and motivational outcomes including math course grades, math course enrollment intentions, and effort regulation, and how?**

I conducted hierarchical linear regression analyses to examine how students’ math class motivation profile membership predicts their achievement and motivational outcomes. Students’ most likely profile membership was saved as a single variable from the Latent Profile Analysis. Using dummy variables, students’ math class motivation profile membership variables were created. For each dependent variable (i.e., Semester 1 math course grade, Semester 2 math course grade, math course enrollment intentions, and effort regulation), identical analyses were run. At the first step of the model, students’ gender, grade, SES, honors class status, and prior math achievement were entered; at Step 2, the dummy variables indicating students’ motivation profile membership were entered.
Chapter 4: Results

Missing Data Treatment

The survey data and the school record data included some missing cases on certain variables. Missing data were treated using the EM algorithm, which utilizes maximum likelihood estimates in parametric models for incomplete data (Dempster, Laird, & Rubin, 1977; Little & Rubin, 2002).

Fewer than 2% of the cases have missing values in each variable, except for prior achievement (i.e., eighth grade standardized math test score), which had about 8% (n=30) missing cases. In order to check whether these missing cases affect any of the research questions, the following steps were taken. First, bivariate correlations were computed using the smaller dataset (not including the 30 cases that have missing values for prior achievement). Second, the same bivariate correlations were computed for the larger dataset, using the EM method to replace the missing values. The descriptive statistics and the two correlation tables were compared. Both means and standard deviations for all the variables in the two datasets were very similar. In terms of bivariate correlations, the directions of the correlations were all the same and the size and the significance level were very close for most of the correlation terms. As shown in Table 4.1 and Table 4.2, among the 136 cells of each table, only 7 cells (5.14%) were slightly different in terms of their significance levels and the size of the correlations. In addition, there was no
difference in terms of how students’ prior math achievement correlates with the other variables; Therefore, I concluded that the missing cases of prior math achievement would not have any significant impact on the subsequent analyses and decided to use the dataset with the bigger sample (i.e., the complete dataset after the EM method has been applied).

**Preliminary Analyses**

**Factor Analysis**

In order to uncover the underlying dimensions of students’ responses to the 15 instructional relevance items, an exploratory factor analysis was used. The sampling adequacy measure (KMO = .92) and Bartlett’s test of sphericity ($\chi^2_{(100)} = 2510.46$, $p < .001$) indicated that the data were appropriate for a factor analysis. Principal Axis Factoring was used and the number of factors was determined based on eigenvalues and a scree plot. Figure 4.1 is a scree plot displaying the eigenvalues on the y-axis and the number of factors on the x-axis. It shows which factors explain most of the variability in the data. In general, the factors above the point where the curve starts to level off are retained. Figure 4.1 suggests that instructional relevance consists of one factor (eigenvalue for the first factor = 6.91, eigenvalue for the second factor = 1.19). Since the two different types of instructional relevance strategies (using teacher-generated relevance vs. student-generated relevance) were not empirically distinguished, I used instructional relevance as a single variable in the subsequent analyses.
Figure 4.1. Scree plot of the eigenvalues from the factor analysis of instructional relevance

**Descriptive Statistics and Bivariate Correlations**

Table 4.1 contains means, standard deviations, and bivariate correlations for all the observed variables used in the analysis. As expected, students’ perceptions of instructional relevance and teacher competence support were correlated positively with their math motivation indicators such as efficacy, attainment value, intrinsic value, and endogenous instrumentality, and were correlated negatively with perceived cost and math anxiety.
Table 4.1
Descriptive Statistics and Correlation Coefficients for Observed Variables (N=355)

<table>
<thead>
<tr>
<th>Variable</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
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<th>10</th>
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<th>12</th>
<th>13</th>
<th>14</th>
<th>15</th>
<th>16</th>
<th>17</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Gender</td>
<td>-</td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>2. Grade</td>
<td>- .05</td>
<td>-</td>
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<tr>
<td>3. SES (free/reduced lunch status)</td>
<td>- .04</td>
<td>.03</td>
<td></td>
<td></td>
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<tr>
<td>4. Honor Class Status</td>
<td>- .03</td>
<td>.08</td>
<td>-.26***</td>
<td></td>
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<tr>
<td>5. Prior Math Achievement</td>
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<td>.06</td>
<td>-.38***</td>
<td>.61***</td>
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<tr>
<td>6. Instructional Relevance</td>
<td>.20***</td>
<td>.20***</td>
<td>.08</td>
<td>-.02</td>
<td>-.07</td>
<td></td>
<td></td>
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<td>7. Competence Support</td>
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<td>.03</td>
<td>.02</td>
<td>.03</td>
<td>.59***</td>
<td></td>
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<td>8. Efficacy</td>
<td>.16***</td>
<td>.11***</td>
<td>-.07</td>
<td>.09</td>
<td>.21***</td>
<td>.53***</td>
<td>.54***</td>
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<td></td>
</tr>
<tr>
<td>9. Attainment Value</td>
<td>.11***</td>
<td>.18***</td>
<td>-.01</td>
<td>.11***</td>
<td>.09</td>
<td>.41***</td>
<td>.33***</td>
<td>.43***</td>
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<tr>
<td>10. Intrinsic Value</td>
<td>.13***</td>
<td>.09</td>
<td>.06</td>
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*M = 440.14  3.04  3.80  4.01  4.72  2.73  3.68  2.74  2.74  3.01  2.94  3.26  3.78
SD = 30.28  .86  .80  .95  .99  1.15  .98  .93  1.03  1.04  1.13  1.26  .85

Note. Gender was coded as 1 = male, 0 = female; 0 = other; Grade Level was coded as 1 = 9th grade, 0 = 10th grade; SES was coded as 1 = free/reduced-priced lunch, 0 = full-priced lunch; *p < .05; **p < .01; ***p < .001
Table 4.2
Descriptive Statistics and Correlation Coefficients for Observed Variables (N=325, Prior Achievement Missing Cases Deleted)

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Note. Gender was coded as 1 = male, 0 = female; Grade Level was coded as 1 = 9th grade, 0 = 10th grade; SES was coded as 1 = free/reduced-priced lunch, 0 = full-priced lunch; *p < .05; **p < .01; ***p < .001; The correlation coefficients in the boxed cells were slightly different from those in the bigger sample (N=355) in terms of the significance level or the size of correlations.
Research Question 1. What are the emerging profiles of high school students’ math class motivation?

In order to identify subgroups of students based on their math class motivation profiles, Latent Profile Analysis (LPA) was conducted using Mplus 7.2. Students’ motivation profiles were identified based on six indicators including efficacy, attainment value, intrinsic value, endogenous instrumentality, cost, and math anxiety.

Latent Class Analysis generally assumes that observed variables (i.e., indicators) are independent of each other within latent class. This local independence assumption is often untrue, and in fact some indicators can be related or dependent within latent class (i.e., conditional dependence) (Uebersax, 2000). In this study, I allowed two pairs of variables, “efficacy and anxiety” and “endogenous instrumentality and cost,” to covary within each class. Based on prior research, it is generally assumed that students’ efficacy beliefs are associated negatively with their math anxiety. Also, students’ endogenous instrumentality is generally expected to relate negatively to their perceived cost. However, the directions and the size of these associations can be different depending on students’ math class motivation profiles. As discussed in Chapter Two, some students may still have high perceptions of cost related to math learning even though they believe math is useful. In order to see how these two pairs of math motivation indicators are correlated differently in each profile, the two correlation terms
(i.e., “efficacy with math anxiety” and “endogenous instrumentality with cost”) were added to each class as well as to the overall model.

First, I ran five models with different numbers of profiles (i.e., 2 profiles, 3 profiles, 4 profiles, 5 profiles, and 6 profiles). In order to determine which number of profiles is the most appropriate for the data, multiple indices including both absolute and relative fit indices were utilized. More specifically, Log Likelihood values, entropy (Ramaswamy, DeSarbo, Reibstein, & Robinson, 1993), Akaike Information Criterion (AIC, Kaplan, 2000), Bayesian Information Criterion (BIC, Kaplan, 2000), sample-size adjusted BIC, and Lo-Mendell-Rubin adjusted likelihood ratio test (LMR) were compared. For AIC, BIC, and adjusted BIC, smaller values indicate a better model. Entropy gives information about the separation of profiles, and values greater than .80 indicate a good separation (Celeux & Soromenho, 1996). Lo-Mendell-Rubin likelihood ratio test (LMR) is a measure of a relative fit where a significant p value implies that a model with k + 1 profiles is better than a model with k profiles (Lo et al., 2001). The final model was determined based on these indices as well as on theoretical background and interpretability of each profile membership (Jung & Wickrama, 2008). Table 4.3 shows these multiple indicator values of each model. Even though LMR results suggest a five-profile model is significantly better than the four-profile model, the four-profile model was chosen as a final model based on theoretical background and interpretability. The entropy of this model was .84 indicating that approximately 84% of the students were correctly classified using this model.
Table 4.3  
Results of the Latent Class Enumeration and Measures of Absolute and Relative Fit of Latent Profiles

<table>
<thead>
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<th>Profiles</th>
<th>LL*</th>
<th>Entropy</th>
<th>AICb</th>
<th>BIC1c</th>
<th>BIC2d</th>
<th>LMR-LRT* (p value)</th>
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</thead>
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<td>5,466.19</td>
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<td>5482.28</td>
<td>428.27 (p &lt; .01)</td>
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<td>3 Profiles</td>
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<td>.83</td>
<td>5,326.60</td>
<td>5450.51</td>
<td>5348.99</td>
<td>154.66 (p &lt; .01)</td>
</tr>
<tr>
<td>4 Profiles</td>
<td>-2,600.52</td>
<td>.84</td>
<td>5,283.05</td>
<td>5,441.81</td>
<td>5,311.74</td>
<td>60.41 (p = .17)</td>
</tr>
<tr>
<td>5 Profiles</td>
<td>-2,565.19</td>
<td>.80</td>
<td>5,230.37</td>
<td>5,423.98</td>
<td>5,265.36</td>
<td>69.36 (p &lt; .05)</td>
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<tr>
<td>6 Profiles</td>
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<td>5,194.69</td>
<td>5,423.15</td>
<td>5,235.97</td>
<td>52.68 (p = .37)</td>
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</tbody>
</table>

Note. N=355, *Log Likelihood; bAkaike’s Information Criteria (AIC); cBayesian Information Criteria (BIC), dSample-size adjusted BIC; eLo-Mendell-Rubin likelihood ratio test (LMR-LRT)

Figure 4.2 shows the final four math class motivation profiles based on the six indicators; and Table 4.4 shows the estimates of the means and correlations for each profile. The largest profile (47.9%) represents the High Motivation group comprised of students with high efficacy, high values, and low cost toward their math class, and with low math anxiety. On the other hand, the smallest profile (9.3%) represents the Low Motivation group comprised of students who reported low efficacy, low values, and high cost toward their math class, and had high math anxiety. The other two profiles were between these high and low motivation groups in terms of their math class motivation levels. One of these profiles was labeled as the Moderate Motivation with High Efficacy profile. Students who belonged to this
profile (30.14%) exhibited neither high nor low motivation toward their math course, but they reported relatively higher efficacy than those with the other moderate motivation profile. The other profile was labeled as the Moderate Motivation with High Cost and Anxiety profile. Whereas students who belonged to this profile (12.68%) also reported moderate levels of overall motivation, this group was distinguished from the Moderate Motivation with High Efficacy profile group, in that they reported high levels of cost and anxiety.

Notably, students with this profile reported significantly higher attainment value and slightly higher endogenous instrumentality than those in the other profile group. In other words, these students think learning math is important and useful, but still perceive high level of cost and anxiety.

In terms of the correlation between efficacy and anxiety, whereas students’ perceptions of efficacy and anxiety were associated negatively for those who displayed the High Motivation \((r = -.12, p < .001)\) and the Moderate Motivation with High Efficacy profiles \((r = -.16, p < .01)\), the association between efficacy and anxiety was positive for students who displayed the Moderate Motivation with High Cost and Anxiety profile \((r = .17, p < .01)\). The correlation between endogenous instrumentality and cost was significant only for students who belonged to the High Motivation profile group \((r = -.10, p < .05)\).
Figure 4.2. Math Class Motivation Profiles among High School Students: Final Four-Profile Model (N=355)
### Table 4.4
**Model Results: Four Math class Motivation Profiles**

<table>
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<tr>
<th>Motivation PROFILE</th>
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<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Efficacy</td>
<td>Attainment</td>
<td>Intrinsic</td>
<td>Value</td>
<td>Endogenous</td>
<td>Instrumentality</td>
<td>Cost</td>
<td>Anxiety</td>
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<td>-.10*</td>
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<td>Moderate Motivation w. High Efficacy</td>
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<td>2.65</td>
<td>2.83</td>
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<td>.03</td>
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<td>Moderate Motivation w. High Cost &amp; Anxiety</td>
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<td>3.47</td>
<td>3.46</td>
<td>3.79</td>
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<td>-.05</td>
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<td>Low Motivation</td>
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<td>2.35</td>
<td>3.74</td>
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</table>

*Note. *p < .05. **p < .01. ***p < .001*
Research Question 2. Are high school students’ math class motivation profiles significantly predicted by their perceptions of teacher practices (i.e., instructional relevance & teacher competence support) while controlling for their demographic characteristics and prior math achievement, and how?

I used multinomial logistic regressions in order to examine whether students’ perceptions of teacher practice (i.e., instructional relevance and teacher competence support) predict latent class membership after controlling for students’ prior math achievement and other demographic variables (e.g., gender, grade level, free/reduced-priced lunch status, and whether a student was taking an honors class). The Moderate Motivation with High Efficacy profile was used as a reference group.

Table 4.5 presents the results from the multinomial logistic regression models. Instructional Relevance and Teacher Competence Support were added to the model as covariates along with other demographic variables for statistical control.

Both perceived Instructional Relevance and Teacher Competence Support were significantly associated with students’ math class motivation profile membership. Overall, as hypothesized, High Motivation profiles were more positively associated with high instructional relevance and high teacher competence support. Controlling for the demographic variables, students who reported higher Instructional Relevance were more likely to be in the High Motivation profile group ($p < .001$), and less likely to be in the Low Motivation...
profile groups \((p < .05)\), than to be in the *Moderate Motivation with High Efficacy* group. In terms of perceived Teacher Competence Support, students who reported high competence support were more likely to be in the *High Motivation* profile group \((p < .01)\), and less likely to be in the *Moderate Motivation with High Cost and Anxiety* group \((p < .05)\), than to be in the *Moderate Motivation with High Efficacy* group.

Among the demographic variables, students’ honors class status and prior math achievement were significantly associated with their profile membership. Relative to the *Moderate Motivation with High Efficacy* group, students in honors class were more likely to be in the *Moderate Motivation with High Cost and Anxiety* profile group \((p < .05)\) and in the *Low Motivation* profile group \((p < .01)\) than students in non-honors classes. This unexpected result could be due to the small sample size of this study. A majority \((n = 71, 58.68\%)\) of the students who were enrolled in honors courses \((n = 121)\) was in the *high motivation* profile.

In terms of students’ prior math achievement, higher prior math achievement increased the odds of membership in the *High Motivation* profile \((p < .05)\) and decreased the odds of membership in the *Moderate Motivation with High Cost and Anxiety* profile \((p < .05)\) and in the *Low Motivation* profile \((p < .01)\), compared to the *Moderate Motivation with High Efficacy* profile.
Table 4.5
Multinomial Logistic Regression Predicting Latent Profile Membership

<table>
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<tr>
<th></th>
<th>High Motivation</th>
<th>Moderate Motivation with High Cost and Anxiety</th>
<th>Low Motivation</th>
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</thead>
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<tr>
<td></td>
<td>b</td>
<td>SE</td>
<td>Odds ratio</td>
</tr>
<tr>
<td>aGender</td>
<td>.21</td>
<td>.36</td>
<td>1.24</td>
</tr>
<tr>
<td>bGrade</td>
<td>-.25</td>
<td>.38</td>
<td>.78</td>
</tr>
<tr>
<td>cSES</td>
<td>.34</td>
<td>.54</td>
<td>1.40</td>
</tr>
<tr>
<td>Honors Class</td>
<td>.80</td>
<td>.46</td>
<td>2.23</td>
</tr>
<tr>
<td>dPrior Math Achievement (z score)</td>
<td>.49*</td>
<td>.24</td>
<td>1.63</td>
</tr>
<tr>
<td>Instructional Relevance</td>
<td>1.20***</td>
<td>.28</td>
<td>3.31</td>
</tr>
<tr>
<td>Teacher Competence Support</td>
<td>.90**</td>
<td>.31</td>
<td>2.45</td>
</tr>
</tbody>
</table>

Note. The reference group is the Moderate Motivation with High Efficacy profile.

a Gender (1 = male, 0 = female).
b Grade (1 = 9th grade 0= 10th grade).
c SES (1=free/reduced-priced lunch, 0=full-priced lunch).
dStandardized z scores were used for Prior Math Achievement.

*p < .05. ** p < .01. *** p < .001.
Research Question 3. Do high school students’ math class motivation profiles significantly predict their achievement and motivational outcomes including math course grades, math course enrollment intentions, and effort regulation, and how?

In order to examine how students’ math class motivation profile membership predicts their achievement and motivational outcomes, hierarchical linear regression analyses were conducted using SPSS 21. To create students’ motivation profile membership variable, each student’s most likely profile membership was saved as a single variable from the Latent Profile Analysis. Students’ assignment into profiles was based on the highest probability of being in a given profile. Three dummy-coded variables were created to indicate whether a student belonged to each profile: High motivation (1) vs. other (0), Moderate motivation with high cost and anxiety (1) vs. other (0), and Low motivation (1) vs. other (0). The Moderate Motivation with High Efficacy profile was used as a reference group.

Identical analyses were run for each dependent variable (i.e., Semester 1 math course grade, Semester 2 math course grade, math course enrollment intentions, and effort regulation). At the first step of the model, students’ prior math achievement and demographic variables including gender, grade (ninth grade vs. other), SES (free/reduced-priced lunch vs. full-priced lunch), honors class status, were entered; at Step 2, the three dummy variables indicating students’ motivation
profile membership status (i.e., high motivation, moderate motivation with high cost & anxiety, and low motivation) were entered.

**Math Class Motivation Profiles Predicting Math Course Grades**

Table 4.6 shows the results of the regression analyses. In terms of predicting students’ Semester 1 math course grades, demographic variables that were significant predictors included gender (Step 2 $b = -.47$, $p < .001$) and prior math achievement (Step 2 $b = .56$, $p < .001$). Male students and those with higher prior math achievement received significantly higher grades in their math course.

Students’ math class motivation profile membership significantly predicted their Semester 1 math course grade. Whereas being in the *High Motivation* profile group was associated with higher math course grade at Semester 1 ($b = .23$, $p < .05$), being in the *Low Motivation* profile group was associated with lower math course grade ($b = -.54$, $p < .001$), compared to being in the *Moderate Motivation with High Efficacy* profile group. Similar to being in the *Low Motivation* profile membership, being in the *Moderate Motivation with High Cost and Anxiety* profile group was also associated negatively with students’ Semester 1 math course grades. Students’ motivation profile membership variables in Step 2 explained an additional 6.0 % of the total variance in Semester 1 grade ($\Delta R^2 = .06$, $p < .001$).

In terms of predicting students’ Semester 2 math course grades, the results showed similar patterns as displayed in Table 4.6. This indicates that students’ math class motivation profile membership in the fall semester is still significantly predictive of their course grades in the following semester.
Table 4.6
Hierarchical Regressions Predicting Students' Math Course Grades

<table>
<thead>
<tr>
<th></th>
<th>DV: Semester 1 Math Course Grade</th>
<th>DV: Semester 2 Math Course Grade</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Step 1 $b$</td>
<td>$sr$</td>
</tr>
<tr>
<td>(Constant)</td>
<td>3.24***</td>
<td></td>
</tr>
<tr>
<td>$^a$Gender</td>
<td>-.39***</td>
<td>-.19</td>
</tr>
<tr>
<td>$^b$Grade</td>
<td>-.01</td>
<td>-.01</td>
</tr>
<tr>
<td>$^c$SES</td>
<td>-.19</td>
<td>-.06</td>
</tr>
<tr>
<td>Honors Class</td>
<td>-.07</td>
<td>-.02</td>
</tr>
<tr>
<td>$^d$Prior Math Achievement (z score)</td>
<td>.62***</td>
<td>.46</td>
</tr>
<tr>
<td>Step 2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>High Motivation</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Moderate w. High Cost &amp; Anxiety</td>
<td>-.37**</td>
<td>-.10</td>
</tr>
<tr>
<td>Low Motivation</td>
<td>-.54***</td>
<td>-.14</td>
</tr>
<tr>
<td>$R^2$</td>
<td>.40</td>
<td>.46</td>
</tr>
<tr>
<td>Change in $R^2$</td>
<td>.40***</td>
<td>.06***</td>
</tr>
</tbody>
</table>

*Note. The reference group is the Moderate Motivation with High Efficacy profile.

$^a$ Gender (1 = male, 0 = female); $^b$ Grade (1 = 9th grade, 0 = 10th grade); $^c$ SES (1 = free/reduced-priced lunch, 0 = full-priced lunch).

$^d$ Standardized z scores were used for Prior Math Achievement; $sr$: semi partial correlation.

* $p < .05$. ** $p < .01$. *** $p < .001$. 
Math Class Motivation Profiles Predicting Motivational Outcomes

For students’ motivational outcomes, their math course enrollment intentions and perceived effort regulation were used. Table 4.7 shows the results of the regression analyses predicting these two outcome variables. Among the demographic variables, only students’ honors class status was significantly predictive of their enrollment intentions ($b = .43, p < .05$). Students who were taking an honors class reported significantly higher intentions to enroll in future math courses than those who were taking a non-honors class. Although gender and prior math achievement were significant predictors of students’ enrollment intentions in the first model, they were no longer significant predictors when students’ motivation profile membership variables were included in the model.

Students’ math class motivation profile membership significantly predicted their intentions to enroll in future math courses. Whereas being in the High Motivation profile group was associated with higher enrollment intentions ($b = 1.19, p < .001$), being in the Low Motivation profile group was associated with lower enrollment intentions ($b = -1.00, p < .001$), compared to being in the Moderate Motivation with High Cost and Anxiety profile group. On the other hand, being in the Moderate Motivation with High Efficacy profile group was not a significant predictor of students’ enrollment intentions when the Moderate Motivation with High Efficacy group was used as a comparison group. Students’
motivation profile membership variables in Step 2 explained an additional 31% of
the total variance in enrollment intentions ($\Delta R^2 = .31, p < .001$).

In terms of predicting students’ perceived effort regulation, gender was the
only significant predictor among the demographic variables (Step 2 $b = -.31,
p < .001$). Male students reported significantly lower perceptions of effort
regulation than did female students.

Students’ math class motivation profile membership also significantly
predicted their perceived effort regulation. Whereas being in the High Motivation
profile group was associated with higher perceptions of effort regulation ($b = .55,
p < .001$), being in the Low Motivation profile group was associated with lower
perceptions of effort regulation ($b = -.43, p < .01$), compared to being in the
Moderate Motivation with High Efficacy profile group. Being in the Moderate
Motivation with High Cost and Anxiety profile group was not a significant
predictor of students’ perceived effort regulation when the Moderate Motivation
with High Efficacy group was used as a reference group. Students’ motivation
profile membership variables in Step 2 explained an additional 16% of the total
variance in effort regulation ($\Delta R^2 = .16, p < .001$).
Table 4.7
Hierarchical Regressions Predicting Students' Enrollment Intentions and Effort Regulation

<table>
<thead>
<tr>
<th>Step 1</th>
<th>DV: Enrollment Intentions</th>
<th>DV: Effort Regulation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Step 1</td>
<td>sr</td>
</tr>
<tr>
<td>(Constant)</td>
<td>2.86***</td>
<td>2.55***</td>
</tr>
<tr>
<td>a Gender</td>
<td>.38**</td>
<td>.15</td>
</tr>
<tr>
<td>b Grade</td>
<td>.13</td>
<td>.05</td>
</tr>
<tr>
<td>c SES</td>
<td>.05</td>
<td>.01</td>
</tr>
<tr>
<td>Honors Class</td>
<td>.45</td>
<td>.14</td>
</tr>
<tr>
<td>d Prior Math Achievement (z score)</td>
<td>.20*</td>
<td>.12</td>
</tr>
</tbody>
</table>

Step 2

<table>
<thead>
<tr>
<th></th>
<th>DV: Enrollment Intentions</th>
<th>DV: Effort Regulation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Step 1</td>
<td>sr</td>
</tr>
<tr>
<td>High Motivation</td>
<td>1.19***</td>
<td>.40</td>
</tr>
<tr>
<td>Moderate w. High Cost &amp; Anxiety</td>
<td>.14</td>
<td>.03</td>
</tr>
<tr>
<td>Low Motivation</td>
<td>-1.00***</td>
<td>-.21</td>
</tr>
</tbody>
</table>

Change in $R^2$

<table>
<thead>
<tr>
<th></th>
<th>DV: Enrollment Intentions</th>
<th>DV: Effort Regulation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>.11***</td>
<td>.31***</td>
</tr>
</tbody>
</table>

Note. The reference group is the Moderate Motivation with High Efficacy profile.

a Gender (1 = male, 0 = female); b Grade (1 = 9th grade 0= 10th grade); c SES (1=free/reduced-priced lunch, 0=full-priced lunch).

d Standardized z scores were used for Prior Math Achievement; sr: semi partial correlation.

* $p < .05$. ** $p < .01$. *** $p < .001$. 75
In sum, the results of the hierarchical regression analyses showed that students’ math class motivation profiles were significant predictors of all four dependent variables (i.e., Semester 1 grades, Semester 2 grades, enrollment intentions, and effort regulation). When the *Moderate Motivation with High Efficacy* profile was used as a reference group, being in the *High Motivation* profile was a significant predictor of positive outcomes such as higher course grades, higher enrollment intentions, and higher perceived effort regulation. On the contrary, being in the *Low Motivation* profile was a significant predictor of negative outcomes such as lower course grades, lower enrollment intentions, and lower perceived effort regulation.

Even though being in the *Moderate Motivation with High Cost and Anxiety* group was not significantly predictive of students’ enrollment intentions and effort regulation, it was a significant predictor of students’ math course grades both at Semester 1 and Semester 2. Compared to being in the *Moderate Motivation with High Efficacy* profile, being in the *Moderate Motivation with High Cost and Anxiety* profile was associated with lower course grades at both Semester 1 and Semester 2.
Chapter 5: Discussion

The following discussion is organized around the three research questions that guided this study:

1. What are the emerging profiles of high school students’ math class motivation?

2. Are high school students’ math class motivation profiles significantly predicted by their perceptions of teacher practices (i.e., instructional relevance & teacher competence support) while controlling for their demographic characteristics and prior math achievement, and how?

3. Do high school students’ math class motivation profiles significantly predict their math achievement, enrollment intentions in future math courses, and effort regulation, and how?

First, I will discuss the patterns of high school students’ math class motivation identified in the study (Research Question 1). Next, I will discuss how teachers’ instructional practices predict students’ motivation profiles (Research Question 2). Then, I will discuss how students’ math class motivation profiles predict their achievement and motivational outcomes (Research Question 3). Finally, some limitations of the study will be discussed and future research directions will be suggested, followed by a conclusion.
High School Students’ Math Class Motivation Profiles

With respect to Research Question 1, four profiles of math class motivation were identified as described in Chapter Four: high motivation, moderate motivation with high efficacy, moderate motivation with high cost and anxiety, and low motivation. Each of the four profiles was characterized by a unique combination of six indicators of math class motivation (i.e., efficacy, attainment value, intrinsic value, endogenous instrumentality, cost, and anxiety).

Overall, the profiles that I identified are fairly consistent with what other researchers have found using person-centered analyses. Other researchers who examined motivation profiles using similar variables (e.g., competence, values, etc.) have also identified groups of high, moderate, and low motivation, even though there are some variations in terms of how indicators are clustered in each profile (e.g., Conley, 2011; Maita-Keppeler, Chavez, & Henderlong, 2016; Rosenzweig & Wigfield, 2016; Usher, Danner, & Tonks, 2016). For example, Rosenzweig and Wigfield (2016) identified four clusters of seventh-grade students’ motivation for reading, using cluster analysis. They used students’ reading self-efficacy, value, devalue, and perceptions of difficulty as indicators of reading motivation, and identified high efficacy-high value, high efficacy-high devalue, moderate difficulty-moderate value, and high difficulty-high devalue groups. Whereas the high efficacy-high value group displayed a more adaptive motivational profile, the high difficulty-high devalue group displayed a less adaptive motivational profile.
The profiles that emerged from the data are also consistent with the established theoretical framework. The general ways in which the motivation indicators (i.e., efficacy, attainment value, intrinsic value, endogenous instrumentality, cost, & anxiety) were clustered in each profile are consistent with the findings of prior literature (Eccles, 2005; Wigfield & Eccles, 2000). For example, I did not find any profiles where students exhibited very high attainment value, but very low endogenous instrumentality. Even though the patterns that emerged were relatively consistent with other studies, there were some new combinations, particularly among the two moderate motivation groups.

Students with a moderate motivation profile with high efficacy were characterized by moderate perceptions of attainment value, endogenous instrumentality, cost and anxiety, somewhat low perceptions of intrinsic value, and relatively higher perceptions of efficacy than those with a moderate motivation profile with high cost and anxiety. Those with a moderate motivation profile with high cost and anxiety were characterized by moderate perceptions of efficacy, somewhat high perceptions of attainment value and endogenous instrumentality, somewhat low perceptions of intrinsic value, and high cost and anxiety.

In the present study, students’ perceptions of cost and anxiety were important indicators that differentiated the groups when the students exhibited moderate levels of math class motivation. This finding is consistent with what Conley (2011) found. As discussed in Chapter Two, cost was found to make a unique contribution in differentiating students’ motivational profiles in her study, and more specifically,
students’ perceptions of opportunity cost played a significant role in differentiating more- and less-adaptive patterns of motivation.

On the other hand, in Conley’s study, utility value was less helpful in differentiating students’ motivation profiles. In the present study, I used students’ perceptions of endogenous instrumentality instead of utility value because endogenous instrumentality seems to better capture students’ perceptions of relevance. Similar to Conley’s findings, in the present study, endogenous instrumentality was relatively less helpful in differentiating the two moderate motivation profiles, compared to cost and anxiety.

Still, students’ perceptions of endogenous instrumentality were significantly different across their math class motivation profiles (i.e., the high motivation profile with “high” endogenous instrumentality, the moderate motivation profiles with “moderate” endogenous instrumentality, and the low motivation profiles with “low” endogenous instrumentality), and the results of bivariate correlation analysis indicated that students’ perceptions of endogenous instrumentality were most strongly associated with their perceptions of instructional relevance ($r = .51$), among all the predictors.

It is notable that students with a moderate motivation with high cost and anxiety profile exhibited significantly higher perceptions of attainment value and slightly higher endogenous instrumentality than did those with a moderate motivation with high efficacy profile. That is, they appeared to believe that learning math is important and useful for their future. However, despite the desirability of these beliefs, their higher perceptions of cost and anxiety indicated less adaptive motivation than the perceptions of those with
moderate motivation with high efficacy. The importance of differentiating these two moderate motivation profiles will be further highlighted in the following sections, when discussing how these profiles are predicted by students’ perceptions of instructional practice and how the profiles differ in terms of students’ achievement and motivational outcomes.

In sum, the motivation profiles identified in the present study using the person-centered analysis provide a more thorough understanding of patterns of high school students’ motivation in math classes, contributing to the current literature on math motivation. The person-centered approach helps us understand how various motivational indicators operate as a whole within an individual, complementing what has been found in previous studies using a variable-centered approach.

Math Class Motivation Profiles

Predicted by Instructional Relevance and Teacher Competence Support

The second research question of this study focused on examining how high school students’ math class motivation profiles are predicted by their perceptions of instructional relevance and teacher competence support. Students’ demographic information and their prior math achievement were also included in the model as covariates. Given the established validity of the four profiles identified in the study, it is important to examine how these profiles differ in terms of students’ perceptions of instructional relevance and teacher competence support.

I hypothesized that high motivation profiles would be more positively associated with high perceptions of instructional relevance and teacher competence support. I also
hypothesized that students would be more likely to belong to more adaptive motivation profile groups if they perceived that their math teacher's instruction is relevant, and at the same time, perceived that their teacher supports their competence by providing encouraging feedback and instrumental help. The findings confirmed these hypotheses. Both students’ perceptions of instructional relevance and teacher competence support were significantly associated with students’ math class motivation profile membership, even after controlling for their prior math achievement and other demographic characteristics.

As shown in the findings, when students had teachers whom they perceived as trying to make math content more relevant and supporting their competence, there was a higher probability that the students belonged to the more adaptive motivation profiles. When students had teachers who used instructional relevance strategies but were not perceived as adequately supporting their students’ competence, those students were more likely to belong to the motivation profile associated with high anxiety and cost, which is less desirable. In this situation, even though the students still believed math was important and relevant, their anxiety and cost perceptions became important considerations. As expected, when students had teachers who were perceived as not trying to make math relevant to their students and not supporting their students’ competence either, they had the least adaptive motivation profiles.

In the present study, “instructional relevance” refers to teachers’ instructional behaviors intended to make the content relevant to students’ interests, needs, and goals. The significant association between students’ perceptions of instructional relevance and
their membership in an adaptive math class motivation profile is consistent with the findings of previous studies that have established positive effects of relevance on student motivation (Frymier & Shulman, 1995; Hulleman et al., 2010; Keller, 1987). As discussed in Chapter Two, some previous studies also showed mixed results of the effect of instructional relevance (e.g., Behrens, 1999; Frymier & Houser, 1998) and indicate a significant gap between instructional relevance strategies and relevance from students’ perspectives (Muddiman & Frymier, 2009). These findings suggest that instructional relevance strategies alone may not be enough to motivate students, unless they are combined with other effective teacher practices; results of the present study, which examined the role of teacher competence support when it was combined with instructional relevance, suggest that other variables (e.g., perceived competence support) also are related to effects of instructional relevance.

On the other hand, the results of the preliminary factor analysis indicated that instructional relevance strategies using teacher-generated relevance and instructional relevance strategies using student-generated relevance were not empirically distinguished. Therefore, the present study used instructional relevance as a single variable. It might be that teachers who were perceived by students as using instructional relevance strategies tended to use both teacher-generated and student-generated examples. Also, teachers who were perceived as not using instructional relevance strategies might not have used any relevant examples. In order to see different effects of these two types of instructional relevance strategies, a study using an experimental design should be conducted.
Teacher competence support refers to teachers’ instructional behaviors intended to support students’ academic competence. More specifically, in the present study I assume that teacher competence support is composed of two different types of teacher behavior: giving encouraging feedback and providing instrumental help. Results of previous studies show that when teachers provide competence support by making positive verbal statements in response to students in the classroom and providing advice, information, and modeled behavior, students’ competence-related beliefs are positively influenced (McRae, 2012; Skinner & Belmont, 1993; Wentzel, 1997, 2009). The findings of the present study support the prior literature demonstrating significant associations between students’ high perceptions of teacher competence support and their membership in an adaptive math class motivation profile. Furthermore, the findings contribute to research on teacher support by showing that teacher competence support is related to students’ perceptions of lower cost and anxiety.

It is notable that students’ perceptions of instructional relevance and teacher competence support were significant predictors of their math class motivation profile membership even after their prior math achievement was controlled. Research on students’ motivation profiles using a person-centered approach is growing, but not many studies have examined the role of different types of instructional practices such as instructional relevance and teacher competence support in predicting students’ motivation profiles. The findings of the present study add to the current knowledge of patterns of high school students’ math class motivation by demonstrating significant roles of instructional relevance and teacher competence support.
Relation of Math Class Motivation Profiles to Achievement and Motivational Outcomes

The third research question of this study focused on whether and how students’ math class motivation profiles predict their achievement, math course enrollment intentions, and effort regulation. Specifically, students’ Semester 1 math course grades, Semester 2 math course grades, future math course enrollment intentions, and perceived effort regulation were used as outcome variables in the regression analyses.

I hypothesized that being in a high motivation group would be a significant predictor of positive outcomes such as high math course grades, high enrollment intentions, and high effort regulation, whereas being in a low motivation group would be a significant predictor of negative outcomes, such as low math course grades, low enrollment intentions, and low effort regulation. Overall, the results confirmed these hypotheses and the findings of prior literature.

For all four outcome variables (i.e., Semester 1 grades, Semester 2 grades, enrollment intentions, and effort regulation), students’ math class motivation profiles were significant predictors. Overall, students who displayed the high motivation profile exhibited the most adaptive outcomes. In contrast, students who displayed the low motivation profile exhibited the least adaptive outcomes. These findings were all expected from prior literature. For example, I did not find a pattern of students with a high motivation profile exhibiting low intention to enroll in future math classes, nor a pattern of students with a low motivation profile exhibiting high achievement. These findings
validated my model, indicating that the student profiles identified in this study likely represent real students.

When the moderate motivation with high efficacy profile was used as a comparison group, being in the moderate motivation with high cost and anxiety profile group was significantly associated with lower math course grades both in Semester 1 and Semester 2, even after controlling for their prior math achievement and other demographic characteristics. Even though these two groups seem to be somewhat similar in terms of their motivational beliefs, the higher perceptions of cost and anxiety for one group and the higher efficacy beliefs for the other group may lead to a significant difference in their achievement levels.

On the other hand, this difference was not found in these two groups’ immediate motivational outcomes. Both students who displayed the moderate motivation with high efficacy profile and those who displayed the moderate motivation with high cost and anxiety profile reported similar levels of future math course enrollment intentions and effort regulation.

Research has shown that students’ perceptions of cost and anxiety are associated with some maladaptive motivational outcomes such as disengagement, fear of failure, and use of maladaptive strategies (Battle & Wigfield, 2003; Elliot & Sheldon, 1997; Meece et al., 1990; Wigfield & Meece, 1988). Even though I did not find a significant difference in the immediate motivational outcomes between the two moderate motivation profiles, considering the prior literature on cost and math anxiety, students with these two profiles might exhibit different motivational and learning outcomes in the long term. That
is, students’ high perceptions of cost and anxiety may possibly lead to negative effects on their long-term motivation and achievement.

Implications for Practice

The findings of the current study have some implications for practice in both teacher preparation programs and in the math classroom.

Implications for Teacher Preparation Programs

With regard to teacher preparation, it is important to train preservice teachers in developing an appreciation for the importance of motivating students with regard to math. Preservice teachers need to be trained in developing instructional strategies to motivate their students. For example, results of this study suggest that preservice math teachers should be taught to make the material they teach relevant and to help their students find relevance in what they are learning. In addition, results of this study also suggest that preservice teachers should be trained in providing encouraging feedback and instrumental help in order to support student competence.

Another implication for teacher preparation is that preservice teachers should understand different math class motivation profiles that students present. In turn, they need to learn how to develop different intervention strategies for different motivation profiles. For example, one math class motivation profile identified in the current study was moderate motivation with high cost and anxiety. One implication of identifying this profile would be to provide training to preservice teachers in how to help students who display this profile reduce their feelings of perceived cost and anxiety.
Implications for the Math Classroom

The current study also has implications for the math classroom. One implication is that teachers should take into consideration the many aspects of student motivation, rather than focusing on a single aspect. For example, if teachers only emphasize relevance or utility value, they may overlook other important aspects of student motivation, such as students’ competence. In that case, some students can believe, “This [math] problem is really useful and important, and I need to learn how to solve it, but I can’t.” That situation may cause the student to develop a fear of failure, leading to high anxiety and cost, which can be detrimental to the student’s motivation and learning in the long term.

I also found in my study that students have different math class motivation profiles. This finding has an important implication for math classroom teachers: they need to understand the different math class motivation profiles their students display and to realize how these profiles affect their learning. However, classroom teachers need to guard against labeling their students based on the profiles students present because profiles are not stable traits, but can change over time. As implied in my study, students’ motivation profiles – i.e., less or more adaptive – can be shaped by teachers’ instructional practices and other factors. Therefore, math classroom teachers need to understand how their instructional strategies are associated with different math class motivation profiles and adjust them accordingly.
Limitations and Future Research Directions

Some limitations should be taken into consideration when interpreting the results of this study. These limitations can provide useful directions for future research.

First, except for students’ achievement information (i.e., prior math achievement, Semester 1 math course grade, Semester 2 math course grade), the data were collected through a one-time survey. Even though the model of the current study is firmly grounded in theory, the findings from this design can point only to associations, though not causal, among the variables in the present study.

In future studies, researchers can use experimental designs to examine causal links between instructional practices and student motivation, and also utilize longitudinal designs to examine any long-term effects of instructional relevance and teacher competence support on student motivation and learning.

Second, a relatively small ($N=355$), and homogeneous sample puts restrictions on the generalizability of the results of the present study. All participants were from suburban schools, and were mostly White, upper-middle class students. Therefore, it may not be possible to replicate the findings of the present study with a more ethnically diverse group, with a sample including a significant proportion of low SES students, or with students from urban schools.

Also, since survey participation was completely voluntary, the sample might be biased. The motivation profile displayed by the largest number of students in this study was the one with high motivation, and the profile displayed by the smallest number of students was the one with low motivation. It might be that students who enjoyed math
were more likely to choose to participate in the study than those who did not enjoy math; therefore, the proportion of each profile could grow or shrink in another sample. Nevertheless, the profiles that emerged in the data were highly consistent with previous research, which supports the validity of the profiles identified in the present study. Since the data do not include a large number of students per classroom, they cannot account for possible classroom effects using a multilevel analysis. In future studies, it would be helpful to use a large sample with a sufficient number of students in each classroom, which would make it possible to examine classroom and school effects by considering a nested structure.

Third, I used students’ self-reported data, with the exception of demographic and achievement data collected from school records. Students’ perceptions of teacher practices were used as predictor variables of their motivation profiles. Since the data only tell us about students’ perceptions, it is difficult to know what teachers are actually doing in the classroom that leads students having high or low perceptions of instructional relevance and competence support, and what instructional practice is associated with students’ perceptions of cost and anxiety. The present study could have benefited from using other data sources, including classroom observations and interviews in addition to the self-reported data. Still, it is notable that research consistently indicates students’ perceptions of teachers are more influential on their motivation and learning than teachers’ perceptions of their own practice. Some previous studies in fact suggest that students’ reports of teacher characteristics are highly consistent with classroom observations of

In this study, I focused on the role of teachers in students’ math class motivation. Research indicates that student motivation is influenced by multiple contextual factors, including parents and peers in addition to teachers (e.g., Gunderson et al., 2012; Levpuscek & Zupancic, 2009; Murdock & Miller, 2003). Therefore, it would be helpful for future studies to also include parent and peer variables in order to gain a more thorough understanding of how these contextual factors impact students’ motivation in their math classes.

Endogenous Instrumentality was used as one of the six indicators of students’ math class motivation profiles; by definition, it is perceived when the nature of a task is related to one’s future goals. However, some high school students may not have formed their future goals yet, and it might have been somewhat difficult for them to respond to the survey items measuring this construct. In previous studies, the endogenous instrumentality scale (Husman et al., 2004) was validated with college students, so I conducted cognitive interviews with five high school students and three high school math teachers to ensure that the items are clear and easy enough for ninth and tenth graders to understand. Only one of the four items addresses students’ future goals (e.g., “What I learn in this math class will be important for my future occupational success”), whereas the other three items address whether students believe they will use what they learn in their math class in other classes or in the future, in general. Even though none of the cognitive interviewees addressed any concern about using these items, it may still be a
good direction for future research to develop a more valid and reliable scale that measures high school students’ perceptions of endogenous instrumentality.

I did not test whether there are any interaction effects between students’ math motivation profiles and other predictor variables related to students’ achievement, enrollment intentions, and effort regulation. In future studies, researchers may wish to explore possible interactions by adding interaction terms between the profiles and other predictors to the regression models.

**Conclusion**

In summary, this study provided evidence of how students’ perceptions of their teachers’ *instructional relevance* and *competence support* predict their math class motivation profiles, and how these motivation profiles predict students’ achievement, future math course enrollment intentions, and effort regulation. Both instructional relevance and teacher competence support significantly predicted students’ math class motivation, with higher perceptions being associated with more adaptive motivation profiles. Students’ perceptions of cost and math anxiety played an important role in differentiating the profiles when students exhibited moderate levels of motivation. When students perceive that their teachers use instructional relevance strategies but do not support their academic competence, the findings of the study suggest these perceptions are associated with high cost and anxiety. As expected, students’ math class profiles also significantly predicted their achievement, future enrollment intentions, and effort regulation. Using a person-centered approach, this study contributes to the current literature on motivation by providing a unique perspective on group differences in math
class motivation and how these group differences can be predicted with different types of instructional practices.
References


Appendix A: IRB Approval

August 6, 2015

Protocol Number: 2013B0294
Protocol Title: THE ROLE OF PERCEIVED INSTRUCTIONAL RELEVANCE AND TEACHER COMPETENCE SUPPORT IN STUDENT MOTIVATION AND LEARNING IN HIGH SCHOOL MATH CLASSROOMS. Eric Anderman, Yuqin Chang, Educational Policy & Leadership
Type of Review: Initial Review— Expedited
IRB Staff Contact: Jacob R. Stoddard
Phone: 614-292-0526
Email: stoddard.13@osu.edu

Dear Dr. Anderman,

The Behavioral and Social Sciences IRB APPROVED BY EXPEDITED REVIEW the above referenced research. The Board was able to provide expedited approval under 45 CFR. 46.110(b)(1) because the research meets the applicability criteria and one or more categories of research eligible for expedited review, as indicated below:

Date of IRB Approval: August 6, 2015
Date of IRB Approval Expiration: August 6, 2014
Expedited Review Category: 7

In addition, the protocol has been approved for the inclusion of children (permission of one parent).

If applicable, informed consent (and HIPAA research authorization) must be obtained from subjects or their legally authorized representatives and documented prior to research involvement. The IRB-approved consent form and process must be used. Changes in the research (e.g., recruitment procedures, advertisements, enrollment numbers, etc.) or informed consent process must be approved by the IRB before they are implemented (except where necessary to eliminate apparent immediate hazards to subjects).

This approval is valid for one year from the date of IRB review when approval is granted or modifications are required. The approval will no longer be in effect on the date listed above as the IRB expiration date. A Continuing Review application must be approved within this interval to avoid expiration of IRB approval and cessation of all research activities. A final report must be provided to the IRB and all records relating to the research (including signed consent forms) must be retained and available for audit at least 3 years after the research has ended.

It is the responsibility of all investigators and research staff to promptly report to the IRB any serious, unexpected and related adverse events and potential unanticipated problems involving risks to subjects or others.

This approval is issued under The Ohio State University’s OHRP Federalwide Assurance #00006378.

All forms and procedures can be found on the OHRP website – www.osu.edu. Please feel free to contact the IRB staff contact listed above with any questions or concerns.

Michael Edwards, PhD, Chair
Behavioral and Social Sciences Institutional Review Board
Appendix B: Recruitment Verbal Script

(The script was read by math teachers for recruitment purposes.)

OSU researchers are conducting a study to examine what motivates high school students to succeed in math. They would like you to participate in a survey, which will take approximately 20-30 minutes to complete.

I’m going to hand out these recruitment packets.

In each envelop, there are a letter from the OSU researchers, a parental permission form and an assent form.

If you bring back the permission slip and participate in the survey, you will be entered into a drawing for a $20 restaurant gift card.

The survey will be given either during an extended homeroom period or a study hall period in November.

There will be no additional time commitment outside of school. Participation in this study is totally voluntary, and all your responses will be confidential and will not be shared with your teachers, parents, or any other person.

If you are interested in participating, please bring your parent’s signed permission form and submit it to the OSU researcher when she comes in or submit the signed slip through a lock drop box located in the XXX office.

Your participation will help researchers and teachers identify effective instructional strategies that can be used to improve math instruction.

Thank you for your attention.
Appendix C: Survey Items

(Instructional Relevance)
Regarding your current math teacher, how much do you agree or disagree with each of the following statements?
(strongly disagree … strongly agree)

1. Uses examples to make the content relevant to me.
2. Provides explanations that make the content relevant to me.
3. Uses explanations that demonstrate the importance of the content.
4. Clearly states how the material relates to my career goals or to my life in general.
5. Uses his or her own experiences to introduce or demonstrate a concept.
6. Uses student experiences to demonstrate or introduce a concept.
7. Uses current events when teaching a topic.
8. Uses examples to make the content interesting to me.
9. Asks me to apply content to my own interests.
10. Gives assignments that involve the application of the content to my personal interests.
11. Asks me to apply mathematical concepts to real-life examples.
12. Asks me to think about how mathematics relates to my future career goals.
13. Asks me to relate what I’m learning in this math class to what I am learning in other classes.
14. Asks me to come up with situations where I need to use what I know about mathematics.
15. Asks me to think about why learning mathematical concepts is important to my life.

(Teacher Competence Support)
Regarding your current math teacher, how much do you agree or disagree with each of the following statements?
(strongly disagree … strongly agree)

1. shows me how to solve problems for myself.
2. shows me different way to try to, if I can’t solve a problem.
3. goes out of his or her way to help me as often as possible.
4. usually gives me a hint or clue when I do not know the answer.
5. helps me overcome challenges in math.
6. gives me enough time to finish my work well.
7. lets me know when I do something right in class.
8. gives me encouraging feedback on assignments, quizzes, or tests.
9. shows me how to improve in math.
10. usually knows when I need help.

(Efficacy Beliefs)
To what extent, do you agree or disagree with the following statements?
    (strongly disagree … strongly agree)

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

(Attainment Value)
To what extent, do you agree or disagree with the following statements?
    (strongly disagree … strongly agree)

6. For me, being good in this math class is very important.
7. Compared to other activities, it is very important for me to be good in this math class.
8. Being good in this math class is an important part of who I am.
9. It is important for me to be someone who is good at solving problems in this class.

(Intrinsic Value)
To what extent, do you agree or disagree with the following statements?
    (strongly disagree … strongly agree)

1. What I learn in this math class is exciting to me.
2. I am fascinated by what I learn in this math class.
3. I enjoy doing math in this class.
4. I find working on math assignments in this class: (very boring…very interesting)

(Endogenous Instrumentality)
To what extent, do you agree or disagree with the following statements?
    (strongly disagree … strongly agree)

1. I will use the information I learn in this math class in other classes I will take in the future.
2. I will not use what I learn in this math class. (REVERSED)
3. What I learn in this math class will be important for my future occupational success.
4. I will use the information I learn in this math class in the future.

(Cost)
To what extent, do you agree or disagree with the following statements?
(strongly disagree … strongly agree)

1. I worry that spending all my time studying for this math class will take time away from other activities I enjoy.
2. Success in this math class requires that I give up many other activities I enjoy.
3. It frightens me that the work required to do well in this math class will be more difficult than the work in my other classes.
4. My opinion of myself would suffer if I tried hard in this math class, and was unsuccessful at it.
5. Success in this math class really requires more effort than I am willing to make.
6. When I think about all the work required to do well in this math class, I'm not sure that the work is going to be worth it in the end.

(Math Anxiety)
1. When I am in math class, I usually feel : (REVERSED)
   (not at all at ease and relaxed … very much at ease and relaxed)
2. When I am taking tests, I usually feel:
   (not at all nervous and uneasy …very nervous and uneasy)
3. Taking math tests scares me.
   (never feel this way …very often feel this way)
4. I dread having to do math.
   (never feel this way …very often feel this way)
5. It scares me to think that I will be taking advanced high school math.
   (not at all …very much)

(Enrollment Intentions)
1. How much would you like to take more math classes next year?
   (not at all…very much)

How much do you agree or disagree with the following statement?
2. Even if I no longer had to, I would take more math classes in the future.
   (strongly disagree … strongly agree)
(Effort Regulation)
Based on your behavior in your current math class, please rate the following statements.
(not at all true of me...very true of me)

1. I work hard to do well in this class even if I don’t like what we are doing.
2. Even when the course materials are dull and uninteresting, I manage to keep working until I finish.
3. When course work is difficult, I give up or only study the easy parts.
   (REVERSED)
4. I often feel so lazy or bored when I study for this class that I quit before I finish what I planned to do. (REVERSED)