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Expectancy-Value Classes as Predictors of Science, Technology, Engineering, and Mathematics (STEM) Occupational Choice: Differences Related to Ability, Gender, Race/Ethnicity, and Socioeconomic Status

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Expectancy-Value Classes as Predictors of Science, Technology, Engineering, and Mathematics (STEM) Occupational Choice: Differences Related to Ability, Gender, Race/Ethnicity, and Socioeconomic Status

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Chapter One

Introduction

An adolescent's choice to pursue a career is a complex decision in which expectancies and values play integral roles. When children highly value mathematics or science and expect to be successful in those domains, they are likely to be motivated to continue taking courses and to choose science, technology, engineering, and mathematics (STEM) careers. High school students who have high ability or demonstrate superior performance in mathematics and science form a talent pool from which the future scientists, mathematicians, and engineers of our nation should come. Of the large number of individuals who qualify to join th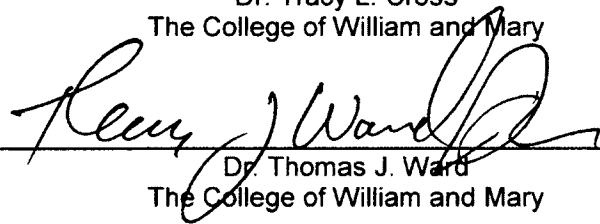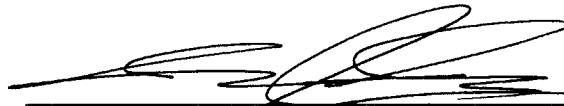is pool of talent, relatively few choose STEM occupations (National Science Board, 2010). What distinguishes those who choose STEM occupations from those who do not? Motivation theorists posit that individuals choose occupations based on psychological, sociocultural, and environmental factors (Eccles et al., 1983; Lent, Brown, & Hackett, 1994). In this study, the relationships of profiles of domain-specific expectancies and subjective task values to ninth-grade students' occupational decisions will be investigated. Increasing knowledge of these motivation variables is important to national efforts to increase the number of students who earn college degrees in STEM disciplines. This knowledge could lead to the development of educational interventions that develop the expectancies and values that will have the greatest effect on student decisions to pursue careers in STEM.

Purpose

The purpose of this study was to investigate expectancy-value motivational profiles of ninth grade students and the relationships of those profiles with occupational

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choice, ability, achievement, and demographic variables. The Expectancy Value Model of Achievement-Related Choices (Eccles et al., 1983) was the primary theoretical framework used to examine motivation. The Eccles et al. (1983) framework explains expectancies and values as dependent on cultural role expectations and differences in the way individuals interpret their experiences. Other theory-based mechanisms that were used to explain variations in expectancy value constructs included stereotype threat (Steele, 1997) and stigma theory (Coleman & Cross, 2005). Members of different race, gender, and socioeconomic groups have differential exposure to stereotypes and degrees of stigmatization that are associated with their general cognitive abilities, domain-specific abilities, and race-gender identities. Individuals live in multiple, different cultural contexts, each with its own norms and role expectations. Thus, theories such as stereotype threat and stigma theory predict and explain differences in expectancies and values between gender, race/ethnicity, and socioeconomic groups. A holistic-interactionist approach was taken, under which the unit of analysis is the individual (Bergman, Magnusson, & El-Khouri, 2003). Expectancy-value constructs are viewed as operating together within individuals to collectively result in choice, persistence, and performance. Multiple, unique configurations of these constructs were identified that were predictive of occupational choice. This study investigated the following research questions:

1. What distinct profiles emerge from measures of mathematics self-efficacy and mathematics task values (interest-enjoyment value, utility value, and attainment value)?

2. What distinct profiles emerge from measures of science self-efficacy and science task values (interest-enjoyment value, utility value, and attainment value)?

3. How is cost related to math and science profile memberships?

4. How does the membership of the mathematics expectancy-value subgroups compare to the science expectancy-value subgroups?

5. How do these profiles relate to mathematics ability?

6. Which set of profiles (mathematics or science) explains more of the variance in STEM occupational choice?

7. How do these profiles relate to giftedness?

8. How does membership in these latent classes differ by (a) race-gender group and (b) socioeconomic status?

Rationale

The journey toward STEM occupational expertise is a transformational process that begins as young children develop interest and demonstrate potential in the domains of mathematics and science, and progresses as decisions are made to engage in activities that allow abilities to develop (Bloom, 1985). One critical decision in this transformation is the occupational choice, which represents an adolescent's intention to pursue a specific course of talent development. What motivates individuals to make these choices? One longstanding motivation theory is expectancy-value theory, which explains choice, task commitment, and performance as a result of the beliefs that individuals have about how well they will perform and how much the task is valued (Wigfield & Eccles, 2000). Expectancy-value theory is a social-cognitive approach that frames expectancies and values as products of the interactions between an individual and the environment

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(Murdock, 2009). In social-cognitive approaches, sociocultural norms, as well as prevailing stereotypes of individuals, abilities, and domains are said to influence how individuals construct expectancies and values. Characteristics of individuals such as gender, race, ethnicity, and socioeconomic status are each associated with their own cultural norms and stereotypes, thus differences in expectancies and values are expected between and within groups. Although students with high ability are likely to have high expectancies for success, these students may not value the domain or may possess inaccurate self-perceptions of their own abilities. Therefore, students with high ability in mathematics or science may choose to not pursue STEM careers for a variety of reasons.

Young high-ability students are often labeled gifted based on their cognitive abilities or achievements and these labels may be retained indefinitely, regardless of the behavior that individual exhibits. This practice is representative of a traditional, entity view of giftedness in which giftedness is thought of an as an inherited, stable trait. A contrasting view is of giftedness as a developmental phenomenon, meaning that as students' grow older the retention of the gifted label requires performance (Cross, 2009; Subotnik, Olszewksi-Kubilius, & Worrell, 2011). In other words, creative-productive output is required to be a gifted adult. When the child is young, aptitude is enough to qualify the gifted label. As a child grows older, the retention of the gifted label is performance dependent (Cross & Coleman, 2005). In this study, the second view was adopted, namely that giftedness is not about being, it is about doing.

To get from being to doing requires motivation; gifted individuals are often described as more motivated than those who are not gifted (Tannenbaum, 1983). From an expectancy-value perspective, gifted individuals are more likely to have greater

expectations of their own performance, which should increase motivation. However, some research has identified groups of students who have been identified as gifted but are not motivated, as *gifted underachievers* (e. g. Reis & McCoach, 2000). Expectancy-value theory explains this underachievement as a lack of motivation due to low task value for particular activities. Thus, the presence of high self-efficacy alone is insufficient for gifted behavior to emerge and task value must also be present to motivate performance. Similarly, Renzulli (1978) defined giftedness as an interaction between above-average ability, task commitment, and creativity in his Three Ring Conception of Giftedness (TRCG). In other words, gifted behavior is dependent on a commitment to perform tasks needed to master the domain and produce knowledge. This task commitment, or motivation, is the key concept within expectancy-value theory because expectancies and values are thought to cause, or motivate, academic choices (Wigfield & Eccles, 2000).

The rationale for studying the expectancy-values of students in the context of STEM occupational choice arises from the combined application of E-V theory and the TRCG. First, the TRCG model implies that it is possible to establish giftedness by building motivation if an individual has above-average ability and creativity. Second, expectancy-value theory provides a model for motivation, which can be strengthened by increasing expectancies for success and values of activities. Therefore, better understandings of individuals' expectancies and values could help direct interventions designed to increase motivation and also increase the number of students who exhibit gifted behaviors in STEM.

Previous studies have examined the factors related to the choice of a STEM career using an expectancy-value framework (e .g. Eccles, 1985; Simpkins & Davis-Kean,

2005; Watt, Eccles, & Durik, 2006). This is the first study that uses a nationally representative sample to identify domain-specific, expectancy-value profiles and relate these profiles to STEM occupational choice. Previous studies have used methods such as logistic regression, path analysis, structural equation modeling, or multiple regression to find relationships between mean values for groups. This study took a holistic-interactionist, or person-centered approach, in which the individual was the unit of analysis and variables operated in concert to produce motivation. The bulk of previous studies have taken a variable-centered approach that isolated relationships between mean values of variables for groups on the outcome of interest. Furthermore, these variable-centered approaches were limited by the assumptions of the general linear model and the relationships between the variables of interest. The examination of multiple domain-specific components of task-value in a single model has been hampered by the multicollinearity of task-values (e. g. Li & Adamson, 1995; Simpkins & Davis-Kean, 2005). The use of profiles removed this constraint and enabled multiple task-values to be included. The use of profile analysis also meant that the assumption of linear relationships between variables no longer applied. The profiles found in this study describe how groups of expectancies and values work together in individuals to motivate these individuals to choose STEM careers. Findings from this study could lead to the development of educational interventions that aim to develop the expectancies and values that are conducive to STEM-career interest in students.

Definitions of Terms

1. *Above-average ability*: Individuals who scored at least one standard deviation above the mean within their race/ethnicity group on the mathematics achievement test

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administered as part of the base-year HSLS: 2009. The mathematics achievement test

is a measure of general ability (Renzulli, 2005), which is a reasonable proxy of

potential in the STEM domains in the absence of other information such as teacher

observations (J. Renzulli, personal communication, November 12, 2012). This

definition is based on Renzulli's (1978) TRCG.

2. *Giftedness*: Creatively productive behavior that arises due to an interaction among

   three factors: above-average ability, task-commitment or motivation, and creativity.

   This definition is based on Renzulli's (1978) TRCG.

3. *STEM occupation*: Occupations that involve science, technology, engineering, or

   mathematics. Health sciences careers are included in this categorization.

4. *Expectancies*: How well a student thinks he or she will do on future tasks.

5. *Self-efficacy:* The confidence a student has that he or she can successfully perform a

   future task, in this case to successfully complete future mathematics or science

   courses (Bandura, 1986).

6. *Subjective task values*: How much value an individual assigns to a task. Task value

   has four components: interest-enjoyment value, attainment value, utility value, and

   cost (Eccles et al., 1983).

7. *Interest-enjoyment value*: A component of task value; how much the task is liked or

   enjoyed (Eccles et al., 1983).

8. *Attainment value*: A component of task value that describes the instrumentality or

   importance of the task. A measure of how well the task aligns with the individual's

   identity (Eccles et al., 1983).

9. *Utility Value*: A component of task value that describes how well the task aligns with the individual's future goals (college or career; Eccles et al., 1983).

10. *Cost*: A component of task value that describes the perception of how much engagement in this task will preclude other activities, require excessive effort, or affect relationships with peers (Eccles et al., 1983).

Organization of the Study

In Chapter 1, the introduction, statement of the problem, research questions, significance of the study, definitions of terms, limitations, and delimitations were presented. Chapter 2 contains the review of related literature and research related to the problem investigated in this study. First, an overview of the expectancy value model of achievement related choices is provided. Second, the constructs of expectancy and value are described. Findings of research concerning relative values of these constructs and the relationships to mathematics and science course taking plans or STEM occupational choices are discussed. Third, expectancy value concerns related to gender, race/ethnicity, and socioeconomic status are discussed. Fourth, the relationship of motivation to the theories and models associated with giftedness are described and relevant research findings are reviewed. Fifth, the differences between a variable-centered and a person-centered approach are discussed; the choice of a person-centered approach is justified. Lastly, examples of person-centered expectancy value research are reviewed. Findings from critical analyses of these studies are used to design of this study. In Chapter 3, the methodology and data-collection procedures for this study are presented. The results of analyses and findings that emerge from the study are contained in Chapter 4. Chapter 5

contains a summary of the study and findings, conclusions that follow from the findings, discussion of the implications of these findings, and recommendations for further studies.

Chapter 2

Literature Review

This chapter provides an extensive review of the literature related to mathematics and science course-taking decisions and STEM occupational choice. It will be divided into sections that include: (1) expectancy value theory, (2) motivation and giftedness, (3) special populations, and (4) person-centered approaches. This chapter begins with a brief description of the expectancy-value model of achievement-related choices, followed by an examination of each of the key constructs in the model that includes the research findings that inform this study. The importance of motivation to giftedness is discussed. Issues particular to females, high-ability students, underrepresented minority students and students from low socioeconomic status are discussed, with an emphasis on potential expectancy-value influences on STEM-related outcomes. Person-centered approaches are described including the advantages of these approaches and why this approach is appropriate for this study. A rationale for the current study is presented.

The expectancy-value model of achievement-related choices has been used extensively in education research. Before reviewing the literature concerning the constructs contained in the model, an overview of the expectancy-value model will be provided. Discussion of the expectancy-value constructs will be focused on applications to career choice and course taking in the STEM domains.

Expectancy-Value (EV)

The EV model is a social-cognitive theory of motivation that was first formalized by Atkinson (1957) and later refined by Eccles et al. (1983). In the model, the immediate predictors of academic performance and choice are expectancies and values (Figure 1).

When making choices, individuals choose among the options that are perceived to be available, and the perception of availability is affected by cultural stereotypes and parental, familial, or peer influences. These choices are generally not made in isolation; multiple options are compared relative to each other. The considerations that drive decisions include: (1) the expectations for success if the choice is selected; (2) how well the choice aligns with short- and long-term goals, with one's identity and basic psychological needs; (3) the individual's role schema based on gender, race or ethnicity; and (4) the potential cost of devoting time to this activity over another activity (Wigfield & Eccles, 2000). The first of these considerations is called *expectancy* and the remaining three collectively comprise *subjective task value.*

This model explains choice, persistence, and performance based on an individual's expectation of success and the subjective task value held of the activity. In the model, expectation of success and subjective task values directly influence task choice and performance. However, these predictors are influenced by self-beliefs, future goals, and identities. Beliefs, goals, and identities have been affected by previous experiences, beliefs and behaviors of key socializers, social role systems, cultural stereotypes, ethnicity, gender, aptitudes, and demographics. In other words, the sociocultural contexts in which children live shape their beliefs about their abilities, personal goals, and identities, which directly affect their expectancies and values, which in turn affect the choices they make, how much effort they will exert, and how well they will perform. Decades of research have shown that expectancies and values are good predictors of future course taking and career choice (Eccles, 1985; Eccles, Adler, &

Meece, 1984; Simpkins & Davis-Kean, 2005; Simpkins, Davis-Kean, & Eccles, 2006; Watt et al., 2006). In the next section the construct of expectancy will be described.

Expectancy

Expectancy describes the confidence an individual has in his or her ability to successfully perform a task (Wigfield & Eccles, 2000). This construct is distinguished from other beliefs about ability, such as self-concept, by its reference to the future performance of a task instead of current, comparative levels of performance (Wigfield, Tonks, & Klauda, 2009). In this way, expectancy is very similar to the *self-efficacy* construct as defined by Bandura (1997). Much like self-efficacy theory (Bandura, 1986), EV theory predicts that individuals who have higher expectancies for success in mathematics or science will be more likely to continue to take such courses and choose careers in STEM fields. What determines expectancy? Prior achievement is a predictor of expectancy, but expectancy is also influenced by sociocultural factors such as the stereotypes people hold for activities and of the abilities of members of certain groups, as well as individual differences in affective reactions to previous experiences. In other words, self-efficacy is positively related to ability, but students who internalize stereotypes about their ability to perform or who adopt familial or cultural views about which kinds of people can be successful at certain activities are likely to have reduced self-efficacies in the STEM domains. These lower expectancies reduce the likelihood of choosing a STEM occupation. However, in general, most EV research has found that expectancy effects on choice are mediated by task value (e. g. Andersen & Ward, in press; Watt et al., 2006) while expectancy affects performance directly.

Figure 1

Eccles et al. (1983) Expectancy-Value Model

Distal Cultural Milieu e.g. 1. Gender and other social role systems 2. Stereotypes of activities and the nature of abilities		Emerging Self Knowledge and Future Goals e.g. 1. Self-concept of one's abilities 2. Self-schemata	Expectation of Success	

Individual's Perceptions and Interpetation of All of Column 1 Characteristics and Experiences

Beliefs and Behaviors of Key Socializers

Task, Activities, and Behavioral Choices

Person and Proximal Family Characteristics
e.g.
1. Aptitudes
2. Sex
3. Ethnic group
4. Family demographics

Individual's Affective Reactions and Memories of All Previous Experiences

Emerging Personal and Collective Identities

Subjective Task Value

1. Interest-enjoyment value
2. Attainment value
3. Utility value
4. Relative cost

Previous Personal Experiences

Across Time

Source: Eccles (2009). Reprinted with permission.

A large body of research has explored various types of self-efficacy and their precursors (for a review of this literature see Usher & Pajares, 2008). However, the present review is confined to findings regarding self-efficacy in the STEM domains and its relation to course taking and career choice. In general, domain-specific self-efficacy and interest in the domain have a reciprocal relationship (Lent et al., 2001; Lent, Lopez, & Bieschke, 1991; Navarro, Flores, & Worthington, 2007; Rottinghaus, Larson, & Borgen, 2003). In other words, students who had higher self-efficacy in a particular domain had more interest in that domain. Furthermore, the effect of self-efficacy on choice was indirect and mediated by interest (Navarro et al., 2007); this mirrors the aforementioned observation that the effect of expectancy on choice was mediated by task value.

Expectancy measurement issues. Researchers who use expectancy-value frameworks conceptualize expectancy differently than those who use other theoretical frameworks, such as social cognitive career theory. This difference means that findings from such studies have limited external validity. For example, outcome expectancy has been operationalized as the gain the individual expects as an outcome of the activity, such as financial reward or intrinsic enjoyment (Lent et al., 2003). Other studies have conflated self-efficacy and self-concept by using items such as "How good are you at science?" to measure self-efficacy or expectancy (Mau, 2003; Miller, Lietz, & Kotte, 2002; Riegle-Crumb, Moore, & Ramos-Wada, 2011; Simpkins & Davis-Kean, 2005). An appropriate question to measure science self-efficacy would be "How confident are you that you can earn a B or better in your science class next year?" (Bandura, 2006). The conflation of constructs invalidates many comparisons between studies. In defense of this

practice, Wigfield and Eccles (2000) stated that within domains, self-concepts and self-efficacy loaded on the same factor and were not "empirically distinguishable" (p. 74). Wigfield, Tonks, and Klauda (2009) further suggest that ability and expectancy "comprise a single concept for children age 6-18" (p. 60). Although self-efficacy and self-concepts have loaded onto the same factor in some previous studies, substituting self-concept for self-efficacy may not be good practice.

Combining self-concept and self-efficacy may not be valid for high school students, some high-ability students, or students who are culturally different. When students enrolled in courses which were more challenging or ability-grouped, such as high-school mathematics and science courses, self-concept tended to decrease, because it was based on comparisons of the self with a referent group that was of higher mean ability, while self-efficacy is unaffected by such comparisons (Bandura, 1993; Marsh, 1986; Plucker & Stocking, 2001; Rinn, Plucker, & Stocking, 2010). This is called the Big Fish Little Pond Effect. Further evidence of the volatility of self-concept comes from Denissen, Zarrett, and Eccles (2007) who found a sharp decline in the coupling between academic achievement and academic self-concept after tenth grade. In other words, as students got older, the same increase in achievement resulted in a smaller increase in self-concept. However, Denissen et al. (2007) did not examine domain specific self-concepts. On the other hand, task-specific self-efficacies increase with age (Wigfield, Eccles, Schiefele, Roeser, & Davis-Kean, 2006; Wigfield & Wagner, 2005). Comparisons of self-efficacy findings between studies are further complicated by the task-level nature of self-efficacy measures. For example, a student's confidence in his or her ability to be able to solve an Algebra problem will increase with age and mathematics experiences, but the

confidence in her or his ability to earn a B in a math course may decline with age as course content becomes more challenging (e. g. calculus is more challenging than geometry). The comparative nature and relative volatility of self-concept mean that it is not an equivalent of self-efficacy. According to Wigfield et al. (2009),

> Too often researchers state that they are measuring a certain construct but use a measure that perhaps does not capture the construct in the way it is defined theoretically. This can lead to conceptual confusion and conflicting results, and thus impede the advancement of the field (p. 59).

Conceptual confusion is an apt description of how the field has dealt with the measure of expectancy. Self-efficacy measures will be used to represent expectancy in this study because self-efficacy best represents the construct of expectancy as defined by Wigfield and Eccles (2000).

Mathematics and science self-efficacy. Bandura (2006) emphasized the importance of the domain-specificity of self-efficacy. However, most studies of choice have neglected science self-efficacy and used mathematics self-efficacy as a proxy for STEM self-efficacy (e.g. Mau, 2003; Moakler, 2011; Zarrett & Malanchuk, 2005). A few studies have used latent variables of self-efficacy that combined mathematics and science self-efficacy items (e. g. Navarro et al., 2007). The predictive validity of mathematics self-efficacy for STEM occupation choice was put into question by the findings of Andersen and Ward (in press) that science self-efficacy was a significant predictor of the course taking and career plans of ninth-grade students while mathematics self-efficacy was not a significant predictor. Further research is needed into the importance of science

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self-efficacy to such choices and to compare the relative predictive power of mathematics self-efficacy and science self-efficacy.

Self-efficacy theory. Observed differences in self-efficacy can be explained by Bandura's (1986) social cognitive theory, which attributes changes in self-efficacy to four mechanisms: mastery experiences, social persuasion, vicarious experiences, and physiological arousal. When an individual completes an activity competently, this is a mastery experience. Vicarious experiences occur when the individual learns about a peer who has had a mastery experience. Feedback from significant others in an individual's life provide social persuasion. Mastery experiences, vicarious experiences, and social persuasion positively affect self-efficacy. On the other hand, negative physiological arousal related to attempts to perform a task, or anxiety, will negatively affect self-efficacy. In the context of EV theory, self-efficacy is positively related to choice, persistence, and performance. Bandura's (1986) self-efficacy theory will be used in conjunction with the EV model to explain observed differences.

Subjective Task Value

According to expectancy value theory (Eccles et al., 1983), volitional decisions are based on comparisons of the value of mathematics and science to the individual and the perceived personal cost of learning mathematics and science. This comparison allows children to answer the question "Do I want to do this?". *Subjective task value* (STV) describes the net value ascribed to a task by an individual and this value is influenced by some of the same mechanisms that influence expectancies (Wigfield et al., 2009). Past experiences that influence value include: how interesting an activity was, how much it was liked, and the nature of the feedback provided by parents or teachers as to the

importance or usefulness of a task. This feedback can come from a variety of sources. In this way, cultural expectations and peer expectations influence the values children place on activities. Cultural norms or stereotypes and the level of internalization of these by the individual affect the personal cost of choosing to do an activity. In general, studies have found that STV is a better predictor of choice than ability or expectancy. To understand how these sociocultural factors influence STV requires further examination of this concept. Eccles et al. (1983) defined STV as comprised of four constructs: interest-enjoyment value, attainment value, utility value, and relative cost. In the next section, each of the four constructs will be described.

Interest-enjoyment value. Interest-enjoyment value describes how much the individual is interested in the activity; this is also known as intrinsic value. This construct has been operationalized as how much the task is liked or enjoyed (Wigfield & Eccles, 2000). Individuals who like or enjoy mathematics or science are more motivated to take courses and pursue STEM careers. Many studies of STEM-related career choice have found that interest is strongly correlated to career choice (Jacobs, Finken, Griffin, & Wright, 1998; Lent, Lopez, Lopez, & Sheu, 2008; Lent, Paixão, Silva, & Leitão, 2010; Miller et al., 2002) and future course taking (Eccles et al., 1984; Watt et al., 2006).

Measurement of interest. Although interest has been found to be an important predictor of choice, it has been operationalized in many different ways. Many studies have used *science attitudes* as a predictor of choice (e. g. Maple & Stage, 1991; Mau, 2003; Miller et al., 2002; Tai, Liu, Maltese, & Fan, 2006). In general, science attitudes have been found to be predictive of choice and some measures of science attitudes have included the interest/enjoyment value of science. In a review of 66 science attitude

instruments, Blalock et al. (2008) found less than one-third of these were measures of interest-enjoyment and that most of the instruments were developed without adequate attention to treatment of missing data, validity, and reliability. Some studies do not describe the science attitude measures that were used, making it difficult to determine what constructs were actually measured and to interpret findings appropriately (e. g. Maple & Stage, 1991). Some career choice researchers have operationalized interest as interest in a STEM career (Maltese & Tai, 2011; Sadler, Sonnert, Hazari, & Tai, 2012; Tai et al., 2006), while others measured interest in STEM subjects, such as mathematics or science (Chow & Salmela-Aro, 2011; Eccles et al., 1984; Farenga & Joyce, 1998; Jacobs et al., 1998; Jones, Taylor, & Forrester, 2011; Lent et al., 2001, 2008; Maltese & Tai, 2010; Navarro et al., 2007; Pearson & Miller, 2012; Quimby, Wolfson, & Seyala, 2007; Simpkins & Davis-Kean, 2005; Watt et al., 2006). In the EV framework, interest is conceptualized as the intrinsic value of these activities; therefore the latter conceptualization of interest is a better fit to the EV model. In general, interest in the mathematics and science domains was a strong predictor of choice and a moderator of the relationship between self-efficacy and choice.

Attainment value. Attainment value describes how important the activity is to the individual. This value is an assessment of how much the performance of the task confirms salient aspects of one's identity (Wigfield et al., 2009). For example, when a child considers him or herself to be a "science person", taking a chemistry class holds a greater value than taking a history class. Thus, STEM course taking and career choices will be influenced by how much the person identifies with mathematics or science, the greater the identification, the more likely those option will be selected. Factors that affect

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attainment value include: individual perceptions of the domains of mathematics and science and internalization of gender, racial, or ethnic role stereotypes. In other words, attainment value is closely related to identity and how well a science or mathematics identity aligns with other components of the individual's identity such as ethnicity, gender, or culture. In the vast majority of EV research, attainment value has been operationalized as importance and combined with interest and utility value into one variable (Wigfield & Eccles, 2000; Wigfield et al., 2009). Thus, the relative importance of attainment value as compared to the other STV variables is unknown. However, recent research on the relationships between the identities and career choices of minority students and women supports the importance of attainment value as a predictor of choice, persistence, and performance (e. g. Oyserman & Destin, 2010).

Identity incongruence. When the student's perception of a mathematics or science identity conflicts with what the student believes is appropriate for his or her gender, race, or ethnicity, STEM-related choices will be seen as identity-incongruent and will have lower attainment value (Eccles, 2009). Low attainment value reduces the likelihood of the choice to pursue that activity. For example, a female student may perceive taking a science class to be identity-incongruent because science is a male-dominated field and she has internalized that stereotype. Therefore, she would have a lower attainment value for science, or a science career, and be less likely to choose those options.

Identity congruence may also be an issue for African American and Hispanic males because science has been dominated by White males and has its own culture that was built on European male culture. Many aspects of this culture do not align well with

the norms of African American and Hispanic culture (Brickhouse, 1994). Research on students' perceptions of scientists over the past 50 years, across gender and culture, has revealed persistent and pervasive stereotypes of scientists that include descriptors such as: exceedingly clever, amoral, insensitive, obsessive, unemotional, unsocial, unkempt, and uncaring (Barba, 1998; Finson, 2002; Seymour & Hewitt, 1997). These stereotypes are very similar to negative stereotypes of giftedness (Subotnik, Olszewksi-Kubilius, et al., 2011). Related to the issue of identity, "scientist" may be viewed as a stigmatized identity because scientists are often stereotyped as geniuses, which is also a stigmatized identity in an anti-intellectual culture such as the U. S. (Coleman & Cross, 1988; Hofstadter, 1963; Howley, Howley, & Pendarvis, 1995). Recent qualitative research using the framework of identity-based motivation supports the positive relationship of attainment value to STEM-related choices and the importance of the compatibility of science identities to individual identities for persistence in STEM (Carlone & Johnson, 2007; Kao, 2000; Oyserman & Destin, 2010). However, little quantitative research has been done in this area.

Measurement of attainment value. Few studies have used attainment value as a predictor of occupational choice. Some EV studies have included importance as part of the STV measure and have generally found that STV is a good predictor of choice (Chow & Salmela-Aro, 2011; Conley, 2012; Eccles et al., 1984; Simpkins & Davis-Kean, 2005; Watt et al., 2006). In one of the few studies that used identity as a separate variable, identity was found to partially mediate the relationship between self-efficacy and commitment to a science career for science graduate students (Chemers, Zurbriggen, Syed, Goza, & Bearman, 2011). However, this study was conducted with graduate

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students, not high school students. National longitudinal studies prior to the High School Longitudinal Study of 2009 have not included measures of identity or attainment value, which has limited previous large-scale studies of this aspect of STV (e. g. Maltese & Tai, 2011; Mau, 2003; Tai et al., 2006). Further studies of the effect of identity on choice are needed.

Utility Value. Utility value describes the degree of alignment with a student's future goals, such as college or career. For example, a chemistry class may have utility value because it is required to become a physician. Students who have short- or long-term goals that are related to mathematics or science will place higher utility value on mathematics or science courses. Utility value has been found to be a significant predictor of STEM career choice (Andersen & Ward, in press; Maltese & Tai, 2011), although it remains to be determined if the utility value of mathematics and the utility value of science are equally important to STEM career choices. In large-scale studies, Andersen and Ward (in press) found that a STEM utility value factor comprised of math and science utility was predictive of ninth-grade students' plans to persist in STEM, while Maltese and Tai (2011) found that science utility value predicted who would earn a STEM major in college. In a study of supports and barriers to continuation in science and mathematics in a sample of minority middle school students, the relevance of utility value was supported by the internal or individual supports that students reported, such as identification with a career goal and the ability to see how mathematics and science applies in careers (Fouad et al., 2010). In general, utility value is predictive of course taking and career choices but it is unknown if math and science utility value are equally influential.

Relative Cost. Relative cost is the individual's assessment of how much engagement in this activity will preclude other activities, require excessive effort, or will affect relationships with peers. In other words, relative cost refers to what has to be given up to complete an activity. When a student chooses to devote time to mathematics and science, he or she may be ridiculed by peers or have less time for hanging out with friends. Individuals decide if the anticipated cost is tolerable. Only two empirical EV studies that included the cost construct were identified (Battle & Wigfield, 2003; Conley, 2012). In the first study, cost was found to negatively predict women's intentions to attend graduate school (Battle & Wigfield, 2003). However, cost was conceptualized differently in that study; 6 of the 11 items that were used to measure cost had poor content validity because the items were actually measures of the students' competency beliefs. Second, in a cluster analysis of EV profiles, Conley (2012) found that relative cost was an important discriminator between more or less adaptive patterns of motivation and a good predictor of student affect. Nonetheless, relative cost is the least studied of measures of subjective task value (Wigfield et al., 2009). Therefore, future research should examine the effect of cost.

In the social cognitive career theory (SCCT) literature, the constructs of social supports and barriers overlap the EV construct of cost. A taxonomy of supports and barriers for continuing in mathematics and science was developed through interviews and focus groups with culturally diverse middle and high school students; many of the social barrier items are similar to EV constructs (Fouad et al., 2010). For example, social barriers that were identified included "perception of peer rejection" and "little to no social integration" (Fouad et al., 2010, p. 365). Thus, the importance of cost to choice is

supported by other theories of occupational choice, such as SCCT. On the other hand, in a study of 600 Portuguese high school students, social supports and barriers were found to have non-significant associations with occupational choice and moderate associations with self-efficacy (Lent et al., 2010). However, that study did not examine STEM occupations specifically, and cultural differences between that sample and U.S. students minimize the generalizability of that finding to US students. Thus, although relative cost is thought to be important to choice (Wigfield & Eccles, 2000), only limited empirical evidence has been found to support this claim. More research is needed that investigates the influence of cost on students' choices.

Research on components of STV. Subjective task value has been shown to predict choice after controlling for prior achievement (Eccles et al., 1984; Simpkins & Davis-Kean, 2005; Watt et al., 2006), but these studies have operationalized STV as a single score that represented interest-enjoyment, attainment, and utility values. Few studies have examined the effects of individual components of STV or how these components may work in combination to motivate performance. One study was located that examined all four components of mathematics STV (Conley, 2012), reminding researchers of the importance of the cost aspect. Most of the studies that have shown relationships between STV and choice have focused on the subjective task value of mathematics and how it predicted mathematics course taking or career choice. Few studies have examined the STV of science. In one such study, Simpkins and Davis-Keen (2005) found that science expectancy (operationalized as self-concept) was a better predictor of health and science career choice than the value of science. In other words, most previous studies of STV have not examined the relative importance of the four

constructs and have neglected science. Furthermore, the findings of Simpkins and Davis-Keen (2005) show that science STV may have less predictive power than science expectancy and that science self-efficacy may be more important than math self-efficacy in the prediction of career choices.

Summary. In the literature, the EV model has been successfully used to explain STEM occupational choice in populations that were largely White and middle class. The EV model has explained choices through individuals' expectancies for success and subjective task values. Although EV theory posits that expectancies and values are individually constructed and are influenced by many factors that are experiential and/or sociocultural, this has been explored extensively with regard to gender differences but not nearly as much for race, ethnicity, or SES differences. The Eccles et al. (1983) construct of expectancy is very similar to self-efficacy because it represents the beliefs that students have about their abilities to succeed in future activities. Nonetheless, expectancy has been measured as self-concept in most studies. Both ability and achievement predict expectancy, but expectancy is also influenced by sociocultural factors as explained by Bandura's (1997) self-efficacy theory. Expectancies should be domain-specific, but prior research has emphasized math self-efficacy while science self-efficacy has been relatively neglected. Furthermore, the construct confusion among self-efficacy and self-concept has hampered the development of the field of achievement motivation. Another barrier to this development is that other theoretical frameworks that have been used to investigate choice have operationalized constructs very differently than EV research. This difference makes generalizations of findings across frameworks difficult.

Subjective task value is comprised of four factors – interest-enjoyment value, attainment value, utility value, and relative cost – but only one study was found that included all four factors. Interest and utility value were explored more frequently than attainment value and relative cost. In studies that have included more than one of these factors, the individual scores were typically combined into an STV composite that was found to predict choice. Each of the STV factors is individually constructed and influenced by many of the same factors that influence expectancy. Sociocultural concepts that explain these influences include stereotype threat and stigma theory. Members of different race, gender, and socioeconomic groups have differential exposure to stereotypes and degrees of stigmatization that are associated with their general cognitive abilities, domain-specific abilities, and race-gender identities. These individuals live in multiple, different cultural contexts, each with its own norms and role expectations. Thus, differences in STV factors are expected between gender, race/ethnicity, and socioeconomic groups.

In most EV research, the first three STV factors (interest, attainment, and utility) have been investigated as a domain-specific, single score representing a global STV construct and some research has incorporated one or two of the value constructs. No research has compared the relative influence of the various components of STV on occupational choice. Overall, STV has been found to be a stronger predictor of choice than self-efficacy while self-efficacy has been a better predictor of future levels of performance. However, differences between the influence of mathematics values and science values on STEM choices remain to be explored. Some evidence of the superior predictive ability of science values over math values has been noted for science-related

choices, but more research is needed that uses the self-efficacies and values of both domains to compare the relative predictive effects.

Of the extant mathematics and science course taking and career choice literature, some common problems exist. In the most of the EV-based studies, external validity is limited by the use of convenience samples or samples that lack adequate representation of racial or ethnic diversity. Thus, little is known about how EV theory functions to predict choices for underrepresented minority students. The social science literature is fraught with convenience sample studies that have limited generalizability, particularly to racial and ethnically diverse populations. In response to this concern, several occupational choice studies have been conducted using national datasets (e. g. Maltese & Tai, 2011; Mau, 2003; Riegle-Crumb et al., 2011). However, problems exist with these secondary data analyses, such as: (1) studies that are not grounded in strong theoretical frameworks (e. g. Maltese & Tai, 2011; Maple & Stage, 1991; Miller et al., 2002); (2) constructs that are only weakly supported by individual survey items (e. g. Maltese & Tai, 2011; Riegle-Crumb et al., 2011; Shaw & Barbuti, 2010); (3) overcapitalization on chance through the testing of many variables and retaining only significant predictors in models (e. g. Maltese & Tai, 2011); (4) conflation of constructs, particularly self-efficacy and self-concept (e.g Mau, 2003; Riegle-Crumb et al., 2011); and (5) the use of poorly defined constructs, such as science attitude (Blalock et al., 2008). Each of these concerns will be directly addressed in this study.

In the next section, a summary of the findings on gender differences will be presented.

Gender and EV

The Eccles et al. (1984) model was created to explain gender differences in choices, particularly in mathematics course taking and careers. Children begin to develop gender-specific identities that lead to gender-specific behaviors, attitudes and interests between 3 to 8 years of age. From age 9 to 13, occupational interests begin to develop based on social group affiliations and ability self-concepts. Vocational interests narrow as options that do not fit with self-concept or identity are eliminated (Wigfield, Eccles, Roeser, & Schiefele, 2006). A large body of research has investigated gender differences using EV theory. The findings of these studies will be briefly summarized in order to discuss how these findings might be different for underrepresented minority girls and economically disadvantaged girls in the next section.

Gender differences in expectancy. Gender differences in expectancy beliefs often favor males in gender-role stereotyped domains, such as science (Simpkins & Davis-Kean, 2005). Early research indicated that mathematics stereotyped gender differences begin in early in elementary school and grow larger during later adolescence (Eccles et al., 1984), but more recent research suggests that these self-concept differences grow smaller over time and that by twelfth grade the difference is negligible (Jacobs, Lanza, Osgood, Eccles, & Wigfield, 2002). A large-scale study using eighth grade 2003 TIMSS data found that White females and Black females have lower self-concepts in the domains of mathematics and science than White males and Black males who had similar self-concepts (Riegle-Crumb et al., 2011). Furthermore, these researchers found that within race groups, gender patterns of self-concept mirror the patterns of mathematics and science ability scores. Thus, current research confirms the continued existence of

gender-stereotypical patterns of self-concept and achievement in mathematics and science but indicates that race/ethnicity differences may be decreasing.

The amount of distortion of self-beliefs in the stereotyped direction depends on how much the individual endorses the stereotype. Girls are susceptible to stereotype threat, a condition in which heightened anxiety occurs because she is afraid of confirming a stereotype with her performance and this results in reduced performance. Greater anxiety levels lead to lower self-efficacy and lower expectancy. Stereotype threat has been experimentally tested and results have generally confirmed theoretical predictions regarding effects on achievement, however, the cognitive mechanism involved in this process is not yet fully understood (Good, Aronson, & Inzlicht, 2003). Many studies have found that girls generally have lower expectancies in domains that are stereotypically male such as mathematics and science, although these differences seem to be decreasing in mathematics.

Gender differences in values. Research over the past two decades has shown that the gap between boys' and girls' valuing of math has disappeared, however, girls remain less interested in the physical sciences (Wigfield, Eccles, Schiefele, et al., 2006). Females may disidentify with subject areas in which females are stereotyped as less competent than men and attach a lower value to these areas to maintain self-esteem (Spencer, Steele, & Quinn, 1999). This theory of disidentification for science is supported by research findings that females had lower STV for science than males but equal STV for mathematics (Simpkins & Davis-Kean, 2005).

Race/ethnicity and EV

The extant literature provides substantial evidence of differential functioning of EV constructs among students from different race groups (Graham, 1994; Graham & Taylor, 2002). However, little research has examined the EV model in minority populations. The potential interactions between race/ethnicity, expectancies and values can be predicted through Bandura's (1997) self-efficacy theory. This widely accepted theory explains how students develop their expectancy beliefs. In the next section, these predictions will be examined in detail.

Expectancies and values are each influenced by the specific experiences of racial and ethnic minority students that may include stereotyping and institutionalized racism. Standardized achievement measures have consistently measured a sizeable gap between White and non-White students favoring White students. Nonetheless, previous research has found that African American students often rate their self-concepts higher compared to White students of equivalent achievement (Graham, 1994; Winston, Eccles, Senior, & Vida, 1997). This means that Black children's ratings of their abilities are less strongly correlated to their performance than European American children's ratings. This has been cited as evidence of Black students' disassociation of self-esteem from achievement (Winston et al., 1997). However, there have been few studies of the math and science self-efficacies of minority students. The available evidence supports that Black students are likely to have equivalent self-concepts to White students, thus it seems that any differences in expectancy for these students may stem from differences in self-efficacy.

Self-efficacy and race/ethnicity. In general, minority students tend to be more optimistic about their abilities even when achievement is low (Graham, 1994; Schunk &

Pajares, 2002). On the other hand, in one study Black high school students were found to have lower mathematics self-efficacy than White students (Pajares & Kranzler, 1995). Potential differences in self-efficacy for racial or ethnic minority students can be examined through self-efficacy theory. Self-efficacy theory identifies four ways to affect self-efficacy: mastery experiences, vicarious experiences, social persuasion, and physiological states (Bandura, 1997). Mastery experiences are previous successes, and higher ability students are likely to have had a greater number of such experiences. An important element of vicarious experience is that the person who has the experience must be someone who the student identifies with as similar to him or herself. For African American or Hispanic students who are often racial or ethnic minorities in an advanced mathematics or science class, finding appropriate role models may be challenging. Thus, vicarious experiences may occur less frequently for minority students, contributing to lower self-efficacy. The interpretation of feedback received via social persuasion may be affected by the racial identity or race centrality orientation of the individual receiving the input (Rodgers, 2008). If the person has a strong racial identity and race centrality, opinions of same-race teachers and peers would hold more value than the opinions of others. This difference in value could lessen the effect of social persuasion if there are insufficient numbers of same-race persons in that educational context. Experiences of negative stereotypes and racism can elevate levels of anxiety for minority students and decrease self-efficacy (Steele, 1997). Thus Bandura's self-efficacy theory provides a rationale for differences that may exist between and within race/ethnicity groups. Furthermore, the conflation of self-efficacy and self-concept in EV studies, combined

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with the differential functioning of achievement and self-concept makes it difficult to generalize the findings of EV research to this study.

Subjective task value and race/ethnicity. Most of the popular theories about potential differences between the STVs of minority students and White students come from deficit perspectives and have little empirical support. Rodgers (2008) suggests that motivational patterns are likely to be different for African American students compared to White students, in that the profiles "favor group or social acceptance over academic achievement" (p. 118). In the EV framework, this may indicate greater concern for the potential effect of spending time doing mathematics and science on peer relationships than White students would have. In other words, African American students may have stronger perceptions of the potential cost of studying mathematics and science than White students. Mathematics and science task values have been studied even less for Hispanic students than for African American students. In one study of the science attitudes of Hispanic middle school students, after an intervention that significantly improved attitudes about science there was no significant change in the percentages of students who thought they might consider a science career (Sorge, Newsom, & Hagerty, 2000). This result was explained by the student's lack of science identity due to a shortage of same-race role models. No studies have examined the perceived cost of mathematics and science across race or ethnicity groups.

Recent evidence supports more similarity than difference between Black males and White males valuing of science. In a study of 2003 TIMSS data, the same percentages of Black male and White male eighth-grade students (26%) reported that they wanted a job in science. In an EV framework, this implies that Black male and

White male students had very similar STVs for science. The rates of wanting a science job for Black females, White females, and Hispanic students of both genders were significantly lower, indicating lower science STVs for these groups of children. Furthermore, the same percentage of Black and White males (40%) reported that they strongly enjoyed science. Black, Hispanic, and White females all reported significantly lower science enjoyment (Riegle-Crumb et al., 2011). Thus, minority adolescent boys had similar interest-enjoyment values of science as compared to White boys, despite a substantial achievement gap between the groups. However, all female students had lower interest-enjoyment values of science than the Black males and White males. These findings imply that males valuing of science may be similar across race groups and that the largest differences will be seen between genders.

Race-gender interactions. The findings of Riegle-Crumb et al. (2011) and Graham and Taylor (2002) show that race-gender interactions are likely to occur in expectancies and values. In a series of studies by Graham and her colleagues, Black boys and Hispanic boys displayed very different patterns of the valuing of academics as compared to Black girls and Hispanic girls (Graham & Taylor, 2002). In particular, a large shift in the boys' ideas of which students were most admired occurred between fourth and seventh grade. Before seventh grade, boys and girls both valued high achievement but in seventh grade boys' values of achievement were dramatically lower while girls' continued to value achievement. These studies provide support for comparing race-gender groups instead of grouping by either variable alone. Notably, the stereotypes that the children held for race-gender achievement behaviors were remarkably similar across all groups. White girls were stereotyped as working hard and doing well in school,

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while Latino boys were stereotyped as not caring and doing poorly. Therefore, Graham and Taylor (2002) concluded, "there are complex ethnicity by gender by age interactions" (p. 140).

Summary. Smaller correlations between expectancy and achievement have been noted for minority students compared to White students. Winston et al. (1997) noted that the linkage between achievement and self-concept is weaker for African American students, thus there may be differences in how well the expectancy value model works in different populations. This relationship has not been studied for Hispanic students. The effects of this weaker linkage may be protective, in that these students are less daunted by negative feedback on their performance, but may also be harmful in that these students get less of an increase in self-efficacy from a given increase in achievement. The effect of this difference on these student's choices is not known. The differences between gender groups seem to be larger than the differences between race groups for science expectancies and values. Large race-gender interactions have been found in examinations of students' expectancies and values that have important implications for the design of this study. These design implications are addressed in Chapter 3.

Socioeconomic status and EV

Very little is known about the effects of socioeconomic status on expectancies and values. Collecting SES data is problematic and researchers have operationalized this construct in a variety of ways. Most of the SES measures were derived from various combinations of parent education, parent occupation, family income, or number of books or computers in the home. However, the validity and reliabilities of these measures are unknown. Students who are economically disadvantaged may not have access to high

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quality mathematics and science instruction, which may hamper their development of self-efficacy in those domains. Poor students are subject to many negative stereotypes, thus they are susceptible to stereotype threat. Few studies have disaggregated race and SES effects, thus the overrepresentation of Black and Hispanic students in low socioeconomic status groups has resulted in some previous research findings being attributed to race/ethnicity when they may have been more correctly attributable to SES (Graham, 1994). This study disentangled the effects of race/ethnicity and SES.

An important aspect of this study is the examination of the relationship between domain-specific abilities and motivations. In the next section, the relationship between ability and motivation will be discussed. As previously mentioned, giftedness will be operationalized via Renzulli's (1978) Three Ring Conception of Giftedness (TRCG) that defines giftedness as creative productive behavior arising from the interaction between above average ability, task commitment, and creativity. This study examined task commitment using the lens of EV theory. In the next section, issues of giftedness that are important to the EV model are discussed.

Giftedness

This study frames the occupational decision as a decision within a talent development trajectory. The Mega Model of Talent Development (Subotnik, Olszewksi-Kubilius, et al., 2011) describes a three-stage process, in which the career decision represents a preparation to enter the second stage of development, or the transition from competence to expertise. High school students are preparing to enter this stage as they choose careers and develop occupational identities. Subotnik et al. (2011) emphasized the importance of motivation to the talent development process. "[G]eneral ability is

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necessary but not sufficient to explain optimal performance or creative productivity. It remains a component of talent development along with domain specific abilities, psychosocial skills, motivation, and opportunity" (p. 14). Thus to successfully navigate the talent development process requires a nominal level of ability, but also requires motivation. Motivation is an important characteristic of giftedness and a requisite trait for talent development. Furthermore, it has been suggested that motivation should be part of the process of identifying giftedness in adolescence (Coleman & Cross, 2005), which provides support to the importance of the examination of expectancies and values as a possible means of identifying potentially gifted students.

In the Three Ring Conception of Giftedness, Renzulli (1978) describes creative-productive giftedness as a behavior arising from the interaction among three constructs: above-average ability, task commitment, and creativity. Above-average ability was used in the TRCG model rather than the more typical 95th percentile designation because research has shown that for IQ scores above 120, other variables become more important to creative production. In other words, creative productivity is not predicted by intelligence for individuals who are at least one standard deviation above the mean in intelligence (Renzulli, 2005). However, this notion of a threshold value above which ability is no longer correlated to creative production is not universally accepted. Recent studies have found significant differences in the STEM creative productivity of doctoral degree holders who were in the top quartile of the top one percent compared to those who were in the bottom quartile of students who took the SAT mathematics test at age 13 (Park, Lubinski, & Benbow, 2008; Robertson, Smeets, Lubinski, & Benbow, 2010). However, it may be that those individuals who were more productive were also had

higher subjective task value and were more motivated; motivation variables were not measured in these studies. Furthermore, the top one percent represents a very elite group and these findings may not generalize to all potentially gifted students. Above-average ability designates a group that is vastly larger than the top one percent group. Therefore, more research is needed regarding the relative effects of ability and motivation on achievement or creative-productive giftedness, especially an examination of students who are more typical of the gifted population.

Although the TRCG advocates a more liberal ability criteria of "above-average", in practice, gifted program identification criteria are generally much more stringent. The strict adherence to a threshold global percentile rank as identification criteria has resulted in the underrepresentation of minority students in U.S. gifted program (Ford, 2010). A persistent achievement gap exists between the achievement test scores of White and minority (Black and Hispanic) students. The gap between the achievement tests scores of these two groups has been consistently 0.75 standard deviations or larger in favor of White students. This omnipresent gap, along with the common practice of using standardized test scores to identify giftedness, has resulted in the underrepresentation of Black and Hispanic students in gifted programs. There is no evidence to support the attribution of intelligence differences to race (Nisbett et al., 2012). Thus, students of all races and ethnicities should be proportionally represented in the gifted population. A solution to this underrepresentation problem is to use different cutoff scores on tests for various groups such that equal proportions of each group are identified (Coleman & Cross, 2005; Lohman, 2005, 2006). This approach will be taken in this study.

Task commitment

The task commitment component of the TRCG model (Renzulli, 1978) incorporated motivation into the concept of giftedness. Renzulli defined task commitment as "a refined or focused form of motivation" (Renzulli, 2005, p. 263) that is described by terms such as perseverance and endurance and enhanced by "the synergistic effects of extrinsic motivators on intrinsic motivation" (p. 263). Gifted individuals are intensely interested in, or passionate about their talent areas and willing to spend large amounts of time engaged in talent development activities, Bloom (1985) explained this as due to their identification with the talent domain. In STV terminology, task commitment is represented by a combination of high interest-enjoyment value and high attainment value. Such individuals believe that the value of the activity outweighs the potential cost of the activity. The development of talent requires the individual to engage in *deliberate practice,* a term that describes those activities specifically designed to improve skills (Ericsson et al., 1993). Unlike play, which has an intrinsic reward, and work, which has extrinsic rewards, deliberate practice has no reward other than skill development. Deliberate practice is undertaken, despite its high cost, because it holds utility value for the individual who wants to develop expertise. Individuals who are gifted in mathematics and science would be expected to have higher STV (interest-enjoyment, attainment, and utility value) than students who are not gifted in these domains. On the other hand, school subjects may not be as valued as much as more authentic learning contexts, such as scientific investigations or self-directed learning activities. For example, a recent study of academically gifted and artistically talented students showed that none of the academically talented students were passionate about school work in academic subjects

(Fredricks, Alfeld, & Eccles, 2010). More research needs to be done regarding task commitment and the self-regulatory mechanisms that sustain engagement such as the relative influences of interest-enjoyment, attainment, and utility values.

The findings of Fredericks, Alfeld, and Eccles (2010) raise the question as to why none of the academically talented students were passionate about academics. This may indicate some level of intentional disidentification with academics by these students. Why would students disidentify? The Information Management Model (Coleman & Cross, 1988) provides an explanation for why gifted students may disidentify with academics. Gifted students encounter mixed messages in different contexts and often must decide between achievement and social acceptance. In the typical American high school, passion about academics is viewed as socially unacceptable or stigmatizing. High-ability students desire popularity and social acceptance just as other children do. However, most gifted children feel different from their nongifted peers, and some of those who feel different engage in social-coping strategies to manage their identities at school and feel less different. Some of the most common strategies are to hide their abilities or to disidentify. In terms of the EV model, such students are likely to report a higher cost of studying mathematics and science and lower levels of attainment value. No research has been done on gifted students' disidentification with the STEM domains specifically.

Gifted students and STEM occupational choice

One of the dilemmas of STEM talent development is that substantial numbers of students who have high levels of performance in science and mathematics in high school do not pursue careers in science (Subotnik, Edmiston, & Rayhack, 2007). Paralleling the

substantially lower rates of female and minority participation in STEM careers that have

been noted for decades in the general education literature, lower rates of creative

productivity have been observed for gifted women as compared to their male peers (Dai,

2002). These gender differences have been attributed to gender differences in interest. In

studies of highly gifted students, educational-occupational interests had incremental

predictive value above measures of ability for occupational choice (Achter, Lubinski,

Benbow, & Eftekhari-Sanjani, 1999; Robertson et al., 2010; Webb, Lubinski, & Benbow,

2002). Although the studies within the gifted education literature have been conducted

with very high-ability students, the predictive power of interest-enjoyment value above

ability or expectancy is supported by research with other populations. In general,

students' interest in science follows gender-stereotyped patterns and interest takes

precedence over ability in occupational choice.

Another explanation for lower participation rates in STEM for females is

differences in cultural gender role expectations. Females have traditionally been the

primary caregivers in families and tend to value family over career interests. Females are

more affected than males by internal conflicts concerning spending time in support of

family concerns versus career advancement. Furthermore, females seem to be more

concerned with conformity to gender-role expectations and science identities are

perceived to be at odds with feminine roles. This identity-incongruence is a barrier to

girls' decisions to persist in STEM. A study of gifted elementary school students showed

that science attitudes including enjoyment of science, science leisure activities, and

perceptions of the normality of scientists were predictive of the science course selections

for girls but not for boys (Farenga & Joyce, 1998). On the other hand, some evidence

supports that gender differences in male-stereotyped domains are less in the gifted population. Alfeld-Liro and Eccles (1997) found that patterns of AP science course taking were related to ability and not gender, thus it may be that for gifted students the effects of gender on choice are significantly smaller than for other students. Therefore, it seems that gender differences exist in the reasons why boys and girls choose to pursue mathematics and science activities, but gifted girls take as many mathematics and science courses as gifted boys in high school.

Gifted Students and Mathematics and Science Expectancy

It is important to note that an adolescent's self-perception of his or her competence may not align well with objective measures of ability. For example, a high-ability student may not view mathematics as an area of strength, even when achievement measures are above the 90th percentile because his or her achievement in another domain, such as English, is at the 98th percentile. Low self-assessments of ability in math and science reduce the likelihood of decisions to study those domains. In high school, math and science self-concept tend to decrease (Jacobs et al., 2002). Mathematics content increases in difficulty, and grouping within tracked math and science classes yields comparison groups that have higher mean levels of ability. Children receive more evaluative feedback about their school performance while improvements in students' cognitive processing and understanding lead to more realistic self-assessments. Student's self-concepts within a domain are based on two types of comparisons: (1) comparisons of the self to others in the domain, and (2) comparisons of one's abilities in one domain to another domain (Plucker & Stocking, 2001). Thus, changes in academic grouping can cause a lower self-concept and a subsequent decrease in academic motivation (Wigfield

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& Wagner, 2005). For high-ability students, self-concept will come from comparisons of the self with the most salient social comparison group. When this comparison group consists of other gifted students, self-concept is usually reduced. As these students enroll in advanced classes during high school, they are likely to encounter such comparison groups and experience declines in self-concept in the domain for which that comparison group is relevant. Furthermore, Rinn, McQueen, Clark, and Rumsey (2008) found that self-concepts in the verbal domains were negatively correlated with self-concepts in mathematics. Therefore, high-ability students' math and science self-concepts are likely to be lower in high school and this contributes to lower likelihood of continuing studies of science and mathematics.

Gifted girls tend to have lower mathematics and science self-concepts than gifted boys. This difference may be attributable to girls' tendencies to have higher self-concept in language arts that create internal comparisons of relative ability which, favor language arts over science.

The self-efficacy research has identified gender differences in the gifted population, particularly in male-stereotyped domains such as mathematics and science (Dai, 2002). Gifted boys tend to have higher expectancy beliefs for STEM-related activities than gifted girls despite lower achievement in high school coursework. Overall, gifted students have been found to have more accurate self-efficacy assessments than non-gifted students and to have the tendency to underestimate their chance of solving a particular mathematics problem. Gifted girls underestimated their abilities more than gifted boys. The evidence implies that gifted girls are affected by cultural gender stereotypes. Much research has been done on gender differences and STEM-related

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outcomes. In general, gifted girls seem to have many of the same issues non-gifted girls. As a group, girls appear to be susceptible to the pervasive gender stereotyping that exists within US culture. Therefore, gifted girls are likely to have higher self-efficacies in STEM domains than non-gifted girls and that are lower than the self-efficacies of gifted boys. Evidence also supports that gifted girls are more responsive to social-evaluative feedback and stereotype threat than gifted boys (Dai, 2002). In the EV framework, this may be interpreted as a higher cost for mathematics and science activities for gifted girls than for gifted boys.

Gifted students and STV

A key element of subjective task value is interest and enjoyment of the domains of mathematics and science. *Academic intrinsic motivation* is demonstrated by enjoyment of learning, curiosity, persistence, and the ability to learn challenging or difficult tasks (Gottfried, Marcoulides, Gottfried, & Oliver, 2009). This concept is similar to the STV construct of interest-enjoyment value. It seems natural that students who have high ability would also be intrinsically motivated, however, this is not always true. Students with high achievement in math or science are more likely to have high interest in those domains (Denissen, Zarrett, & Eccles, 2007). On the other hand, Gottfried, Cook, Gottfried, and Morris (2005) compared academic ability and intrinsic motivation and found that when students were grouped by high academic ability and by high academic intrinsic motivation, a minority of students were members of both groups. Furthermore, Gottfried et al. (2005) found that the high intrinsic motivation group had higher levels of achievement than the high-ability group. However, the sample for this study was a small (N = 111), non-diverse, convenience sample, which limits the generalizability of this

finding. High achievement may or may not be coincident with high intrinsic motivation, however studies that include diverse populations or that focus on domain-specific intrinsic motivation have not yet been conducted.

Summary

Adolescents' decisions to study mathematics and science or pursue STEM occupations depend on determinations of domain-specific value, cost, self-efficacy, self-concept, interest, and intrinsic motivation (Eccles, 2011; Maltese, 2008; Zarrett & Malanchuk, 2005). The students with the highest abilities or prior performance within the domains of mathematics and science are thought to be the best candidates for talent development in that domain. However, other variables may be more important than ability to the development of talent. For example, many external factors can affect students' levels of interest in science and mathematics (and subsequent cost-value assessments of activities in STEM) such as parent encouragement, peer influences, sociocultural influences, and stereotypes. Students who are motivated to pursue STEM talent development believe that they *can* do it, and that they *want* to do it. They must value the domain and determine that the cost of the task is tolerable. Insufficient numbers of our nation's high-ability students are choosing STEM careers. President Obama has established a goal of recruiting more students to study mathematics and science in college (The White House, 2010). To accomplish this goal, a better understanding of mathematics and science motivation in needed, and the literature base across the disciplines of psychology, counseling, science education, and gifted education support the idea that this understanding needs to be differentiated between race and gender groups. In the next section, each of the race-gender groups will be examined separately to

highlight the differences that are thought to exist between these groups and how these differences may affect STEM occupational choice. As students may be members of more than one of these special groups, multiple effects that are attributable to specific characteristics may have opposing predictions for differences in expectancies and values.

Gifted White Males

The comparison of the gifted subpopulations begins with White males because this group has the fewest barriers to science talent development. Coleman and Cross (2005) labeled White middle-class children as the *modal gifted* children, who were more easily identified and most likely to receive gifted education services. In this study, this concept is extended to the domain of science and narrowed to exclude females because females are underrepresented in STEM occupations. In the domain of science, White, middle-class males are the modal gifted and they experience the fewest barriers to talent development. Science culture is closely associated with White male culture, thus White males are likely to have the highest attainment value for science relative to other groups. Generally, White males are positively stereotyped to have greater abilities in mathematics and science relative to the other groups in the study (White females, Black males, Black females, Hispanic females, Hispanic males). This stereotype supports the high self-efficacy of this group. An achieving White male who is gifted in mathematics or science is expected to have high self-efficacy and high-value in the corresponding talent domain. Nonetheless, all White males who have above average ability in these domains may not have high subjective task values. Influences from adolescent peer culture may create a high perception of cost that lowers STV. In particular, for underachieving White males, increased cost may create overall lower STV. However, underachievers have been found

to have high self-efficacy despite lower achievement. Nonetheless, White males are represented in the STEM professions in proportion to their representation in the general population (NSF, 2012) and this is evidence of their modal status.

Gifted White Females

Previous research supports that there are significant differences between gifted White females and their male counterparts. Gifted White females have additional barriers to identification with STEM occupations. First, these occupations are stereotypically male and girls may view these careers as identity-incongruent. From an EV standpoint, these girls would have lower interest and attainment value for STEM. Second, cultural gender role expectations may influence girls to value home and family over career. This expectation would be reflected in a lower utility value for STEM. Third, girls are stereotyped as having lower abilities in mathematics and science and higher abilities in language arts. According to Marsh's (1986) I/E model, girls' self-concept beliefs in mathematics and science will be reduced when these girls believe their relative strengths are in the verbal domain even if performance in the mathematics and science domains is high. The prevalence of negative stereotypes concerning girls in mathematics and science subjects girls to stereotype threat. A variety of responses can result from this stereotype threat including reduced self-efficacy caused by an anxiety response, or disidentification with the domain to protect self-esteem. For equivalent levels of performance, gifted White girls have been observed to have lower mathematics and science self-efficacies than gifted White boys. Thus, a typical gifted White girl is expected to have a lower self-efficacy, lower attainment value, lower utility value, lower interest-enjoyment value, and higher perception of cost than a gifted White boy.

Gifted Black Students

In general, Black students have distinct cultural characteristics and values that affect expectancies and values. Black students tend to be more socially oriented and demonstrate strong needs for social acceptance, belonging, and affiliation (Ford, 2011). From an EV standpoint, this difference may create a higher perception of cost for Black students. However, gender differences between gifted Black boys and gifted Black girls may be larger than the race differences between Black and White gifted children.

Gifted Black Boys

Previous research has found that for equivalent levels of achievement, Black students generally rate their self-concepts higher than White students. Riegle-Crumb et al. (2011) found that Black males and White males had equivalent science and math self-concepts despite a substantial achievement gap between the groups that favored Whites. However, self-efficacy theory predicts effects for Black students resulting from social-cognitive influences. For example, Black males are often negatively stereotyped with regard to academics, including mathematics and science. As previously stated, responses to a stereotype threat may include reductions in self-efficacy and STV. However, there have been few studies of Black boys mathematics and science self-efficacy to support or refute the predictions of self-efficacy theory. An additional barrier to the persistence of Black males in STEM is caused by differences in Black cultural norms and the norms of science culture (Brickhouse, 1994). This identity dissonance is likely to reduce the attainment value these students have for STEM. On the other hand, in the study conducted by Riegle-Crumb et al. (2011) using middle school TIMSS data, Black boys and White boys demonstrated the same levels of interest in science occupations, which

were significantly higher than those of all girl groups and Hispanic boys. Thus, some evidence suggests there are more similarities than differences between these two groups. More research is needed with gifted Black boys.

Gifted Black Girls

Little research has been done with this subpopulation of gifted students. Previous research supports that gifted Black girls may have higher self-concepts than White girls of equivalent ability (Graham, 1994). However, gifted Black girls encounter additional barriers to STEM persistence as compared to White girls. Riegle-Crumb et al. (2011) found that Black girls self-concepts in science were lower than those of all White students and those of Black boys. Negative stereotypes exist for Black students' abilities both overall and in STEM domains as well as for girls' abilities in mathematics and science. Thus, Black girls must overcome barriers associated with race and gender stereotypes to persist in STEM. However, Black girls do not experience the same degree of stigmatization of their race-gender identities as Black boys.

Hispanic Gifted Students

Scant research exists on this subpopulation of gifted students. Many Hispanic students also are English Language Learners, which is a barrier to identification of giftedness and access to gifted education services (Gándara, 2005). High-achieving Hispanic students are five times as likely to have parents who are not high school graduates and half as likely to have parents who have completed college. These students are disproportionately affected by poverty (Gándara, 2005). For example, attending a local public school had a larger negative effect on achievement for Latinos than Whites because Whites typically attended schools with more resources. The typical Hispanic

student has a mother with significantly less education that the typical White student and this was negatively associated with high-ability students progress in school, and resulted in the loss of early high-ability status for most of these students. Gándara (2005) created profiles of typical high-ability Hispanic students and described how language barriers, undocumented immigrant status, and poverty affected students academically. For Hispanic students, duty to family is often placed ahead of personal accomplishment. Thus, high-achieving Hispanic students often do not fulfill their academic potential. Furthermore, high-ability Hispanic students also experience stigmatization of giftedness and use coping strategies such as hiding their talents to avoid social consequences (Castellano, 2011).

Gifted Hispanic Boys

Riegle-Crumb et al. (2011) found that Hispanic boys had lower science self-concepts than Black boys and White boys. Hispanic boys encounter similar negative stereotypes about their academic abilities as Black boys. At the same time, Hispanic boys enjoyment of science was equal to that of Black boys and White boys and their enjoyment of math was greater than that of White boys but less than that of Black boys. The grade eight TIMSS data indicated that all three groups of boys desired science careers at rates that were between 20 and 26%, with the lowest rate for Hispanic boys, the highest rate for White boys, and Black boys with a rate in the middle of the two. However, these data were for a mixed ability sample. This limited evidence suggests that Hispanic boys interest-enjoyment value of science and math is likely to be as high as for White boys.

Gifted Hispanic Girls

The achievement gap between Hispanic boys and girls has been sustained while the gaps between White boys and girls have narrowed (Gándara, 2005). Riegle-Crumb et al. (2011) found that Hispanic girls were significantly less likely to report wanting a science job and had lower science self-concepts than White males. Castellano (2011) explains that high-ability Hispanic students utilize social coping strategies such as hiding their talents because being smart may not be socially acceptable. The limited available research suggests that Hispanic girls will have lower expectancies and values for math and science than White boys and girls.

Summary

Each of the gifted subpopulations described above encounters varying degrees of dissonance between cultural norms and the norms of science culture, conflict between gender-role expectations and STEM career expectations, negative racial/ethnic stereotypes, and negative gender stereotypes. All gifted students feel stigmatized to some degree due to their differentness from other students. STEM identities are also stigmatizing due to the negative stereotypes associated with these occupations that directly oppose the characteristics and traits that adolescents desire and thus threaten their potential for popularity and peer acceptance. These sociocultural phenomena may affect gifted students' decisions to pursue STEM occupations if these students use coping mechanisms such as disidentification. However, recent research has shown that some students respond with increased persistence and determination to prove the stereotype to be incorrect and placing a higher value on achievement. Furthermore, research also supports gender differences in ability and failure attributions that may influence females

to disidentify with STEM domains. More empirical research is needed to study the actual expectancy value patterns of above average ability students to assess the actual state of affairs. Some theories regarding how individuals will respond to stigma, stereotypes, and prejudice have not been widely supported. A large-scale study of students' expectancies and value will provide some baseline data to guide further research into why some students persist and others disidentify.

Table 1

Potential Barriers to STEM Talent Development Across Gender-Race Groups

Barrier	Gender-Race Groups					
	White males	White females	Black males	Black females	Hispanic males	Hispanic females
Stigma of giftedness increases perception of cost of devoting time to academic/STEM activities	Y	Y	Y	Y	Y	Y
Lack of connection between STEM school subjects, personal context, and potential career reduces utility value	Y	Y	Y	Y	Y	Y
Stigma of scientist stereotypical identity lowers attainment value and increases perception of cost of STEM activities	Y	Y	Y	Y	Y	Y
Personal culture norms are a poor match for science culture norms resulting in lower attainment value		Y	Y	Y	Y	Y
Negative stereotype about personal race and intellectual ability influence self-beliefs about ability and lowers value of STEM			Y	Y	Y	Y
Negative stereotype about personal gender and STEM abilities influences self-beliefs about ability and lowers value of STEM		Y		Y		Y
Cultural gender role expectations are a mismatch for a science career role expectations		Y		Y		Y
Greater sensitivity to social persuasion increases perception of cost of devoting time to academic/STEM activities		Y	Y	Y	Y	Y
Tendency to attribute failure/difficulty to ability interferes with progression in STEM courses reduces self-beliefs about ability		Y		Y		Y

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Which patterns of expectancy and value are predictive of STEM occupational choices? This question remains to be answered empirically and needs to be answered to solve national problems of underrepresentation in STEM occupations. A relatively small number of students who have high ability in STEM have chosen STEM occupations (Atkinson & Mayo, 2011; Lowell, Salzman, & Henderson, 2009; National Science Board, 2010). Therefore, a large number of students who have high ability in STEM, particularly culturally diverse students, have not chosen STEM occupations. This implies that high expectations of success are insufficient to motivate these choices. Students who have chosen a particular occupation have higher STV in that domain. Do all students who have higher STV have high ability in STEM? If not, what patterns of expectancy and value are associated with student interests in STEM occupations? This study will look for answers to these questions.

Person-Centered Approaches

Rationale for approach

The vast majority of quantitative studies have been variable-centered approaches. In a variable-centered study, the level of a variable for one person is compared to other people in the sample, while in a person-centered approach the level of a variable for that person is compared to the levels of the other variables for that person. In this study, a person-oriented approach will be used to find classes, or profiles, of variable configurations present in individuals, instead of using group-level mean values of variables to make inferences about individuals. Variable-centered approaches include ANOVA, multiple regression, and structural equation modeling while examples of

person-centered approaches include cluster analysis, latent class analysis, and latent profile analysis. These processes will be discussed in more detail in Chapter 3.

Person-centered approaches represent a holistic-interactionist perspective to model building that considers the person and his or her context as a system and the unit of study (Bergman, Magnusson, & El-Khouri, 2003). Individuals are considered to be active agents who take intentional actions as they interact with the environment in a dynamic, complex, and adaptive process. Such an approach should be adopted only when this perspective is a good match for the process under study (Bergman et al., 2003). In this study, a person-centered approach is proposed for several reasons including: (1) EV variables function in constellations instead of singly, (2) relationships between variables within the EV model are different for each individual, and (3) the need for the removal of methodological constraints of the general linear model. These reasons will be explained in the next section.

Focus on constellations of variables. Individuals make choices based on combinations of expectancies and values. Thus considerations of single variables in isolation, examined out of context from other relevant variables that are operating simultaneously, are not psychologically significant. The assumption that relative position in the distribution of a variable has equivalent meaning for each individual does not hold in the EV model. Previous research has shown that some groups tend to over- or underestimate in their self-perceptions of ability and that these expectancies have different relationships with choice, persistence, and performance. Thus, it is expected that the EV model will have differential functioning across and within gender, ethnic, and socioeconomic groups. The use of a person-centered approach recognizes the person as

an organized whole, instead of a linear combination of variables. Classes of people will be identified by the patterns of variables that exist within the population.

Differential functioning of variables. A variable-centered analysis, such as a regression or a structural equation model, assumes that the variables within the model operate identically for all individuals in the group. In such analyses, relationships between group means on the independent variables are used to make inferences about individuals. In such an approach, an observed statistical relationship may appear to be small because it only applies to a small group or class of individuals within the sample. This is a concern for STEM motivation research because of the relatively small percentages of students who chose STEM careers. Thus, the relationships that have been found between particular variables and persistence may be underestimated because the effects only occurred in a small portion of the sample. Furthermore, differences in how individual variables function within and between groups means that previous models may have not detected effects that were important for subgroups of individuals within the sample. The use of a person-centered approach permits the identification of such classes within the larger sample and the sizes of the effects for these classes to be compared.

Constraints of the general linear model. Collinearity is a concern when building models using regression or structural equation modeling. In general, collinearity reduces the amount of explained variance that is attributed to individual variables within a set of independent variables. In EV research, the collinearity of the STV constructs has already been noted. Most previous EV research has handled this concern by using a composite variable that represented the three STV constructs of interest-enjoyment value, utility value, and attainment value. However, this combination of constructs masked any

differences in their relative contributions to outcomes or how the STV constructs may have worked together in those models. In a person-centered approach, patterns of expectancies and values will be examined to identify classes within the population. Thus, the function of each of the STV constructs within the EV profile of classes of individuals can be examined. The use of a person-centered approach permits the use of collinear variables and facilitates study of the contributions of the components of STV. In the next section, the few previous person-centered studies of STV will be reviewed.

Previous person-centered research

Only one study was found that studied all four STV constructs using a person-centered approach. Conley (2012) used cluster analysis to study patterns of achievement goal and expectancy-value for mathematics in a large sample (N = 1,870) of primarily Latino (69%) and Vietnamese (17%) seventh-grade students. The seven-cluster solution indicated complex motivational processes as each cluster was characterized by a unique pattern of the four STV components. Utility value was almost uniformly high, but cost was an important discriminator between clusters. The classes reported either high or low cost levels with no groups reporting average levels of cost. Cost was an important predictor of math achievement and affective outcomes. Overall, STV measures were good predictors of achievement, but not affect. However, the generalizability of this study is limited by the nature of the sample. Furthermore, this study did not examine race-gender groups; race and gender were examined separately, ignoring the potential for interactions that has been demonstrated by previous research (Graham & Taylor, 2002; Riegle-Crumb et al., 2011). Analyses showed that combination of the four STV variables reduced distinct patterns to an identical overall score that was a good predictor of math

achievement but not of affect. The only domain included in this study was mathematics and an expectancy measure was not included in the analysis.

Chow and Salmela-Aro (2011) used latent profile analysis to examine patterns of task-values across four school subject domains for a sample of Finnish ninth-grade students (N = 638). The relationships between class membership and decisions to further their education at the completion of compulsory education were investigated. Four distinct task-value groups were identified, including a high-math-and-science group (20.2%) and a low-math-and-science group (19.1%). The membership of these groups followed gender-stereotypical patterns. Boys were overrepresented in the high group (98% compared to 2%) while girls were overrepresented in the low group (82% compared to 18%). The high group members were more likely to decide to continue their educations. The researchers operationalized subjective task value as a scale score based on a composite of importance, usefulness, and interest. A logistic regression was used to assess how well group membership predicted educational choice and researchers found that class membership was a significant predictor of choice that remained significant after controlling for achievement. In particular, the high math group was significantly more likely to further their educations than the low group after controlling for ninth-grade GPA (OR = 4.11, p < .05). However, this study did not provide sufficient information or analyses to validate the four-group solution and the contributions of the individual components of STV were not examined.

Another Finnish study used similar task value profiles (across five school subjects) to predict educational expectations and occupational aspirations. Viljaranta, Nurmi, Aunola, and Salmela-Aro (2009) used cluster analysis with a group of 614

students who were at the end of comprehensive school. A six-cluster solution was identified, including a *math and science motivated* group (14.5%) in which boys were overrepresented. A significant task-value group x gender interaction was found. For girls, task-value grouping had a significant effect on educational expectations, but this effect was not seen for boys. After controlling for SES and GPA, task-value was not a significant predictor of whether students would follow an academic or vocational track (Viljaranta, Nurmi, Aunola, & Salmela-Aro, 2009). The generalizability of this study to a U.S. population is unknown. Race/ethnicity data were not provided for this sample.

Roeser and Peck (2003) and Roeser, Eccles, and Samaroff (2000) used cluster analysis to investigate patterns of competence beliefs, values, and mental health for a sample of 1,500 seventh-grade students in Maryland, of which 60% were African American. In the six-cluster solution, half of the clusters were classified as "problematic" due to scores that indicated negative mental health or perceived academic value. White females were equally represented among all clusters, but Black females were overrepresented in the poor mental health group (Roeser, Eccles, & Sameroff, 2000; Roeser & Peck, 2003). Black males were overrepresented in all three problematic groups while White males were overrepresented in the low valuing of school group. Students in the problematic groups were less likely to attend college. Motivational factors differentiated outcomes for students of equivalent abilities. However, this study used a single score for the value of academics, thus it was not domain-specific and the individual components of STV were not examined. The findings of these studies further emphasize the importance of race-gender groups due to likely interactions. This study

used general academic values and competence beliefs, thus its usefulness for predicting outcomes of this study is limited.

Summary. Person-centered approaches are much less widely used than variable-centered approaches. However, the nature of the EV model is a good fit for the holistic-interactionist perspective taken by a person-centered approach. Students make choices based on their own unique set of expectancies and values that work together to support choice, persistence and performance. The features of person-centered approaches provide new techniques that will reduce the number of compromises that must be made to analyze EV data. Pattern-based analyses nullify concerns about collinearity and will enable analyses of all four STV constructs simultaneously. The ability to identify classes of individuals within the sample who exhibit similar patterns based on EV constructs and to measure effects for those group means that research is no longer confined to examining effects based on gender, ethnicity, or socioeconomic status. The characteristics shared by these classes and the representations of demographic groups within those classes provide a means to examine similarities and differences between and among members of such groups. Person-centered methods do not assume that models function identically for all members of the sample as variable-centered modeling methods do. Little extant research has examined expectancy value profiles. However, the alignment between the perspectives of the person-centered, analytic approach and the social-cognitive EV model means that this approach is more likely to yield useful information.

The match between the theory and the method of this study is important. Variable-centered and person-centered approaches can be complementary and both types of studies contribute valuable knowledge to advance the field of achievement motivation.

In this study the goal is to identify naturally occurring EV profiles and examine these profiles with regard to their alignment with STEM occupational choice. A person-centered approach will describe the different ways that students are motivated. Then a variable-centered approach will be used to identify differences in occupational choice and course taking plans that are associated with the different expectancy value patterns.

Statement of the Problem

The domestic need for STEM innovators and experts is both critical and nationally recognized (National Science Board, 2010). The proportion of U.S. students who majored in the sciences or engineering is much lower than in other countries, and 35% of the PhDs in the domestic science and engineering workforce are foreign-born (Atkinson & Mayo, 2011). Meanwhile, a large amount of domestic STEM potential remains undeveloped, as evidenced by the acute underrepresentation of minorities in these disciplines. In 2008, Blacks and Hispanics comprised 31.8% of the 18 to 24-year-old U.S. population, while they represented only 15.1% of students enrolled in undergraduate engineering programs. Meanwhile, the corresponding figures for White students were 61.3% of the population and 68.1% of engineering enrollment (NSF, 2012). Demographic trends in the U.S. indicate that population diversity is rapidly increasing. Therefore, it is important to understand the variables that facilitate STEM persistence for talented Black and Hispanic students, not only to provide equitable outcomes for these students compared to the outcomes attained by their White and Asian peers, but also to ensure the viability of the STEM workforce. Of course, these outcomes will only be attained after students take appropriate science and mathematics coursework in high school, ensuring their readiness to enter the postsecondary STEM pipeline.

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Therefore, achieving a greater understanding of adolescents' decisions to embark on a trajectory of STEM talent development through appropriate high school course-taking is important to increasing the numbers of students who opt to do so.

Increasing understanding of the motivational mechanism behind mathematics and science is a problem of international concern. What affects students' occupational choices? The extant literature suggests that occupational choice is a result of interactions between internal, psychological factors and external, sociocultural factors. Each of these influences may encourage or discourage STEM persistence. Sociocultural norms within the school context may stigmatize students who have ability and interest in these domains. Racial, ethnic, and gender stereotypes may influence self-beliefs or the value of the STEM domains. The expectancy-value theory of motivation frames choice as a result of social cognitive formation of expectancies and values. When students choose a science or mathematics occupation, or trajectory of talent development, they have responded affirmatively to two questions: "Can I do this?" and "Do I want to do this?". When students have expectations of success and value the activity they are more likely to choose to engage in that activity. Thus, to increase the numbers of students who choose STEM occupations, particularly those who are women or underrepresented minorities, a better understanding of what motivates students to make these choices is needed. No research has examined expectancy-value profiles and the relationship of these profiles to STEM occupational choice. Although a great deal is known about the effects of individual expectancy value variables on choice, persistence, and performance, little is known about how the variables function together within individuals. More research is

needed with diverse samples to examine the validity of the expectancy value model with different race/ethnicity groups.

If expectancy-value theory is shown to be robust, programs of STEM talent development may need to reconsider the foci of their programs to include activities that foster the growth of self-efficacy and increase the value students have for STEM. The goals of STEM education should include the identification and nurturance of potential. Models of talent development support the importance of motivation at every stage of the process. Particularly for students who come from economically disadvantaged environments, or whose families lack the cultural capital to provide their children with the experiences necessary to develop potential, it is critical that public schools actively participate in the process of talent development. Thus, educators must understand what motivates students in order to redesign instruction and school environments to build subjective task value and expectancies while reducing the perception of cost.

Teachers are in prime positions to help students develop self-efficacy in STEM subjects and increase the value of these subjects. Using the lens of expectancy-value, methods to adapt instruction can be created. If the teacher is to accomplish this; he or she needs to have the necessary awareness, knowledge, and skills to address individual student's needs. First, teachers need to understand how students make academic choices. An understanding of this process will enable teachers to design lessons that increase engagement and promote the value of STEM. Second, the teacher needs to be aware of the unique social-emotional needs of gifted students and how some ways that students may cope with giftedness affect their expectancies and values. Third, differences arising from cultural background and SES must be understood and how these differences may

affect expectations and values. Fourth, teachers must be able to identify and develop STEM talent. Taken together, these can be conceptualized as the core of best practices in the development of STEM talent.

It is necessary to determine whether or not expectancy-value is a good model for the basis of occupational choices, to justify recommendations for changes in practice that will improve the school's capacity to identify, nurture, and develop STEM talent. Previous research has correlated self-efficacy expectations and task-values to career choices, however no studies have been conducted on large-scale, diverse populations. This study will identify expectancy value profiles that are supportive of students' STEM-related choices. The extant literature supports the hypothesis that there exist multiple profiles that promote such choices and other profiles that do not promote those choices. Profile analysis has the potential to reveal how expectancy-value constructs function together.

Chapter 3

Method

In this chapter the method that was employed is described. First, the subjects and sample selection are described. Second, the instruments that were used and the corresponding reliability and validity information are provided. Third, the statistical analyses that were conducted are explained.

Purpose

The purpose of this study is to investigate expectancy-value motivational profiles of ninth grade students and the relationships of those profiles with occupational choice, ability, achievement, and demographic variables. The Expectancy Value Model of Achievement-Related Choices (Eccles et al., 1983) was the primary theoretical framework used to examine motivation. Secondary data analysis of the High School Longitudinal Study of 2009 (HSLS: 2009) was conducted. This study investigated the following research questions:

Research Questions

1. What distinct profiles emerge from measures of mathematics self-efficacy, and mathematics task values (interest-enjoyment value, utility value, and attainment value)? Based on previous cluster-analytic research using subjective task values (Conley, 2012), it was hypothesized that subgroups comprised of high expectancy-value and low expectancy-value will emerge. It was also hypothesized that a number of subgroups with mixed levels of expectancy-value will emerge.

2. What distinct profiles emerge from measures of science self-efficacy, and science task values (interest-enjoyment value, utility value, and attainment value)? Based on previous cluster-analytic research using subjective task values (Conley, 2012), it was hypothesized that subgroups comprised of high expectancy-value and low expectancy-value will emerge. It was also hypothesized that a number of subgroups with mixed levels of expectancy-value will emerge.

3. How is cost related to mathematics and science profile membership? Based on expectancy-value theory, it is expected that cost will be positively related to profile membership. Students in both high mathematics and science motivation profiles are expected to have more positive perceptions of cost.

4. How do the memberships of the mathematics and science profiles compare? It is expected that students who in the high mathematics motivation profiles will be more likely to be in the high science motivation profiles; there will be some correspondence between the mathematics and science profiles.

5. How do these profiles relate to mathematics ability? Based on previous research on the relationship of ability and intrinsic motivation (Gottfried & Gottfried, 2004), it was hypothesized that high expectancy-value profiles will be positively, but not strongly related to mathematics ability. This relationship is expected to be weaker between science expectancy-value and mathematics ability than between mathematics expectancy-value and mathematics ability because students with higher mathematics ability should have higher mathematics self-efficacy, but this is not as good a predictor of science self-

efficacy. Self-efficacy is domain specific and only mathematics ability was measured in this study.

6. How do these profiles relate to STEM occupational choice? It is hypothesized that high expectancy-value profiles will have a stronger relationship to STEM occupation choices. Students who place a high value on mathematics and science should be more motivated to pursue careers in these domains.

7. How do these profiles relate to giftedness? It is hypothesized that expectancy value profiles will not be strongly related to giftedness. This prediction is based on the work of Gottfried and Gottfried (2004) who found that only a small percentage of students were in both the high-ability and high-motivation groups.

8. How does membership in these profiles differ by (a) race-gender group and (b) socioeconomic status? It is hypothesized that males (Black and White) will be overrepresented in high expectancy value profiles. This prediction is based on the previous work of Riegle-Crumb et al. (2011) which showed that Black boys and White boys had similar opinions of mathematics and science careers. It was hypothesized that low-SES students will be overrepresented in low expectancy value profiles. This prediction is based on the extant underrepresentation of low-SES students in gifted programs and STEM occupations.

Subjects and Sample Selection

The High School Longitudinal Study of 2009 (Ingels et al., 2011) is the fifth in a series of secondary longitudinal studies from the National Center for Education Statistics

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(NCES) that track nationally representative samples of secondary students from high school through their postsecondary years. The data used in this study come from the base year of HSLS: 2009. The sample design is a stratified, two stage random sample design with primary sampling units defined as schools selected at the first stage and students randomly selected from schools at the second stage. The sample is designed to be representative of ninth grade students in public and private schools in the U.S. in 2009.

School selection was stratified by school type (public or private), region (Northeast, Midwest, South, and West) and locale (city, suburban, town, rural). A study identified 1,889 schools as eligible for the study and schools in ten states were selected. The number of schools that participated was 944. Within each school, a stratified random sample of students was selected based on race/ethnicity (White, Black, Hispanic, Asian, Native Hawaiian/Other Pacific Islander, and American Indian/Alaskan Native); Asians were oversampled to increase the power of the study. An average of 27 students per school were selected and the total number of students who participated in the study was 21,444. The response rate was 86%; non-response bias analyses were conducted to determine if unit non-response increased bias. Analytic weights were used with software in statistical analyses to adjust for non-response bias and produce estimates of the target population (Ingels et al., 2011).

Instrumentation

The design of HSLS: 2009 differs from previous NCES longitudinal studies in ways that were important to its use in this study. The HSLS: 2009 is designed to examine "the paths into and out of science, technology, engineering, and mathematics; and the educational and social experiences that affect these shifts" (Ingels et al, 2011, p. iii). The

questionnaire items support the important constructs of EV theory, and this study, very well. Thus, the researcher chose to use the first wave of HSLS: 2009 data instead of selecting a dataset with more available waves of data. A copy of the student questionnaire is available at http://nces.ed.gov/surveys/hsls09/pdf/2012_student.pdf.

Procedures for Data Collection

Students were surveyed in 90-minute in-school sessions where they were given a 35-minute questionnaire and a 40-minute adaptive algebraic reasoning assessment. Although some questions were identical to questions used in previous NCES studies, many new questions were created to support the unique goals of HSLS: 2009. Questions were field-tested and revised one year before the data collection began. After data collection, item non-response analyses were conducted and the general rate of non-response was found to be low. A total of 18 variables were imputed by NCES to produce a complete set (Ingels et al., 2011).

Variables

A list of the variables used in this study is provided in Appendix A.

Background characteristics.

Race/ethnicity. Student race or ethnicity groups were obtained from the NCES composite variable X1RACE. Existing categories - Black/African-American non-Hispanic (10.34%), Hispanic, no race specified (0.95%), Hispanic, race specified (15.44%), and White non-Hispanic (55.28%) - were collapsed into four categories in a variable called RACE. This variable has values corresponding to the race categories of Asian, Black, Hispanic, and White.

Gender. Data was obtained from the student questionnaire, parent questionnaire, and/or school-provided sampling roster by NCES in the dichotomous variable X1SEX.

Gender-race groups. The race/ethnicity and gender variables were used to assign cases to a eight new dummy variables, called WM, WF, BM, BF, HM, HF, AM, and AF.

Socioeconomic status. A continuous, composite variable (X1SES) created by NCES that uses parent/guardian education (X1PAR1EDU and X1PAR2EDU), occupation (X1PAR1OCC2 and X1PAR2OCC2), and family income (X1FAMINCOME). Data for non-responding parent/guardians was imputed by NCES. The values of the standardized variable X1SES range from -1.93 to 2.88, with an approximate mean of zero and approximate standard deviation of one.

Expectancies. Expectancies were operationalized as self-efficacies, or the confidence that the student has in their ability to be successful at specific mathematics or science tasks. Self-efficacy scales for science and math were included in HSLS: 2009. Self-efficacy item responses used a four-point Likert-type scale.

Science self-efficacy (SSE). A continuous, composite variable was created by NCES derived from factor analysis of four items, S1STESTS, S1STEXTBOOK, S1SSKILLS, and S1SASSEXCL. Cronbach's Alpha for this scale is 0.88.

Math self-efficacy (MSE). A continuous, composite variable was created by NCES derived from factor analysis of four items, S1MTESTS, S1MTEXTBOOK, S1SMKILLS, and S1SASSEXCL. Cronbach's Alpha for this scale is 0.90.

Subjective Task Values. Subjective task values represent the degree that the student valued mathematics or science. Separate scales for three of the STV constructs, for each of the two domains, were included in HSLS: 2009.

Math attainment value (MAV). Math attainment value describes how well the domain of mathematics fits with the student's identity. A continuous, composite variable was created by NCES derived from factor analysis of two items, S1MPERSON1 and S1MPERSON2. The responses for each item used a four-point Likert-type scale. Cronbach's Alpha for this scale is 0.84.

Math utility value (MUV). Math utility value describes how much the student thinks mathematics will be useful in life, for college, or for a future career. A continuous, composite variable was created by NCES derived from factor analysis of three items, S1MUSELIFE, S1MUSECLG, and S1MUSEJOB. The responses for each item used a four-point Likert-type scale. Cronbach's Alpha for this scale is 0.78.

Math interest-enjoyment value (MIV). Interest-enjoyment value describes how much the student is interested in or enjoys the subject. A continuous, composite variable was created by NCES derived from factor analysis of six items, S1FAVSUB, S1LEASTSUBJ, S1MENJOYING, S1MENJOYS, S1MWASTE, and S1MBORING. The responses for the first two items are dichotomous and the last four used a four-point Likert-type scale. Cronbach's Alpha for this scale is 0.75.

Science attainment value (SAV). Science attainment value describes how well the domain of science fits with the student's identity. A continuous, composite variable was created by NCES derived from factor analysis of two items, S1SPERSON1 and S1SPERSON2. The responses for each item used a four-point Likert-type scale. Cronbach's Alpha for this scale is 0.83.

Science utility value (SUV). Science utility value describes how much the student thinks science will be useful in life, for college, or for a future career. A continuous,

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composite variable was created by NCES derived from factor analysis of three items, S1SUSELIFE, S1SUSECLG, and S1SUSEJOB. The responses for each item used a four-point Likert-type scale. Cronbach's Alpha for this scale is 0.75.

Science interest-enjoyment value (SIV). Interest-enjoyment value describes how much the student is interested in or enjoys the subject. A continuous, composite variable was created by NCES derived from factor analysis of six items, S1FAVSUB, S1LEASTSUBJ, S1SENJOYING, S1SENJOYS, S1SWASTE, and S1SBORING. The responses for the first two items are dichotomous and the last four used a four-point Likert-type scale. Cronbach's Alpha for this scale is 0.73.

Cost. Four questions asked students about the impact of spending a lot of time and effort in math and science classes on the amount of time available to spend with friends, time to spend on other activities, popularity, and being made fun of. The response choices for this set of questions used a four-point Likert-type scale. To create a score for COST, an exploratory factor analysis was conducted using SPSS for a scale consisting of the items S1TEFRNDS, S1TEACTIV, S1TEPOPULAR, and S1TEMAKEFUN. Principal component analysis with Varimax rotation was used to create factor scores for the cost scale. Cronbach's Alpha for this scale was determined; the acceptability threshold value was .65. An acceptable factor solution should explain 70% or more of the variance in the original variables. The scores were stored in two variables called COST-Time and COST-Popular.

Above-average ability. In alignment with procedural recommendations for the identification of underrepresented groups (eg. Lohman, 2005) students in each racial group were selected using within-group scores. Students who scored at least one standard

deviation above the mean within their racial group (Asian, Black, Hispanic, or White) on the mathematics IRT-estimated number right score, X1TXMSCR, were identified as having above-average ability in STEM. This criterion was chosen based on the Three Ring Conception of Giftedness definition (Renzulli, 1978). The mathematics achievement test score is an acceptable proxy for above-average ability in STEM (J. Renzulli, personal communication, November 2, 2012). Using SPSS, the data file will be split by race, and descriptive statistics were run to determine the 84th percentile score for each group. Syntax was used to assign each case meeting this criteria a value of "1" in a dummy variable called HABILITY while all other cases will be assigned the value "0".

Dependent Variable. The dependent variable of this study will be a categorical variable with two levels that indicates the student's decision in grade 9 to pursue a STEM-related occupation that requires a bachelor's degree or higher. The HSLS: 2009 variable X1STUOCC6 identifies the occupation expected at age 30. Students were asked to write in the name of the occupation. The written names were coded by NCES into six digit O*NET codes. The written occupation titles were checked against the codes to ensure accuracy. *The Occupational Outlook Handbook* distributed by the U.S. Department of Labor's Bureau of Labor Statistics was used to classify these jobs as STEM or not. Jobs that require education in the STEM disciplines above the high school level were coded as STEM. Variable transformation was used to assign the value of "1" to a dummy variable called STEMOCC. Educational level was determined by the value of the variable X1STUEDEXPCT. Variable transformation were used to assign the value of "1" to a dummy variable. Students who expected to be in STEM occupations and who expected to earn a bachelor's or higher were coded as "1" in a variable called STEM.

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Analysis

Data Cleaning

Data were examined for missing values and accuracy. Data cleaning was done in SPSS and the remaining analyses were done using Mplus. In each analysis, the complexity of the sample was taken into account and standard errors were adjusted for the clustering of students within schools. A table of descriptive statistics was generated that includes the means, standard deviations, and zero order correlations for each of the nine indicators: mathematics self-efficacy, science self-efficacy, mathematics attainment value, science attainment value, mathematics utility value, science utility value, mathematics interest-enjoyment value, science interest-enjoyment value, and cost. The coefficient alphas for each scale were calculated. Descriptive statistics for the correlates (race-gender and SES) as well as the dependent variable, occupational choice, were determined.

Question 1

The first research question asked if distinct student profiles emerged from four expectancy value measures (latent class indicators): mathematics self-efficacy (MSE), mathematics attainment value (MAV), mathematics utility value (MUV), and mathematics interest-enjoyment value (MIV). Latent profile analysis (LPA) was used to find a parsimonious set of patterns that accounted for variability in mathematics expectancy and values. The number of latent classes was unknown and could not be directly estimated from a single model. To identify the best model, various models with different numbers of classes were estimated and compared. Models with 2 through 7 latent classes, using five different parameterizations (A, B, C, D, and E) were tested;

these structures are described in Table X. As the models progressed from parameterization A to E constraints were released and variances or covariances were allowed to vary within and between classes. The simplest covariance structure was tested first and gradually constraints were released to test more complex models.

Table 2

Description of Model Parameterizations

Parameterization	Variance Structure	Covariance Structure
A	Variances differ across clusters but not within clusters.	Covariances are zero.
B	Variances are equal across clusters but vary within clusters.	Covariances differ within clusters but are equal across clusters.
C	Variances differ across clusters and within clusters.	Covariances are zero.
D	Variances vary within clusters and across clusters.	Covariances vary within clusters but are equal across clusters.
E	Variances vary within and across clusters.	Covariances vary within and across clusters.

In LPA, the latent variable is a categorical variable that describes class membership. The individual's value on this variable is assumed to be the cause of his or her levels on the observed dependent variables or latent class indicators. In this study, a vector of four indicator variables described each case. The data were thought of as samples from a population that consists of a mixture of distributions, one for each class. Each class had its own unique combination of levels of the observed variables, weights for each class were determined and these weights sum to one (Pastor, Barron, Miller, & Davis, 2007).

Following recommended practices of LPA researchers (Chen, 2012; Pastor et al., 2007), the final model was decided by using several indicators of model fit. First, the log-likelihood (LL) is a measure of model fit; values closer to zero indicate better fit. Second, for models with the same number of classes that are nested, the chi-square difference test was used to test for significant improvements to model fit. Third, the Lo-Mendell-Rubin (LMR) tests the null hypothesis that the K class and the K-1 class models are equivalent. If the LMR was not significant the K class model was not a significant improvement in fit over the K-1 class model. A small p-value indicated the more complex solution should be retained. Fourth, the Bayesian Information Criterion (BIC) was used to compare models with different number of clusters and/or specifying different parameterization. Lower values of the BIC indicated better model fit. However, BIC does not provide a significance test to compare models. Thus, the chi-square difference test and the LMR were also employed. A table of that lists the number of groups, parameterization, log-likelihood, number of free parameters. BIC, LMR p value, entropy, and smallest class frequency was created.

To determine the optimal number of latent classes within a particular parameterization, a plot of BIC versus the number of classes was created. This plot was used similarly to the scree plots in Exploratory Factor Analysis. The point in the graph where the slope decreases notably, or the "elbow", was used to judge the number of classes for which additional classes do not significantly reduce the BIC. The cluster profiles were examined and theory, sample size, and uniqueness of the profiles were used to evaluate the model. For a model to be accepted, the identified classes must have had reasonable size compared to the whole sample; classes that were very small were not

used. The profiles were distinguishable by the uniqueness of the constellations of indicator values and the utility of these constellations for explaining variations in the outcomes of interest and differences between characteristics of subgroups in the population.

Once the final model decision has been made sample statistics for each cluster were computed. Item profile plots were created and the resulting clusters were labeled and described qualitatively according to the characteristics of the profile. The profiles were examined for reliability. The classification table was examined to ensure that the probability of correct class membership was acceptable (0.70 or greater; Wang & Wang, 2012). The value of the entropy indicates good classification and should be at least 0.60 (Clark, 2010). The estimated parameters of the model were checked to ensure that the values conformed to the population parameters estimated by the model. The sample covariances and correlations were checked to ensure that they fit with the parameterization of the model.

Question 2

The second research question asked if distinct student profiles emerged from four expectancy value measures: science self-efficacy (SSE), science attainment value (SAV), science utility value (SUV), and science interest-enjoyment value (SIV). The same procedure that was used to answer Question 1 was employed to answer Question 2.

Question 3

Question 3 asked about the relationship of cost to profile membership. The relation between each cluster membership and cost was examined using the Mplus 7 function, AUXILIARY (e), that tests for equality of means of variables that were not

used in forming the latent classes. The Wald chi-square test statistic will be used to determine if there is a statistically significant difference in mean cost across classes.

Question 4

Question 4 asked how the membership of the math classes compared to the science classes. To answer this question, each case was assigned to the most probable class and a crosstabulation was performed. To test for a relationship between science and math latent class assignment, a chi-square analysis was conducted.

Question 5

Question 5 asked about the relationship between cluster membership and mathematics ability. The relation between each cluster membership and ability was examined using the Mplus 7 function, AUXILIARY (e). The Wald chi-square test statistic was used to determine if there was a statistically significant difference in mean mathematics ability across classes.

Question 6

Question 6 asks about whether there is a relationship between cluster membership and STEM occupational choice, a distal outcome. Occupational choice is a categorical, dependent variable with two possible values. The relation between each cluster membership and occupational choice was examined using the Mplus 7 function, AUXILIARY (e). The Wald chi-square test statistic will be used to determine if there was a statistically significant difference in mean STEM occupational choice across classes.

Question 7

Question 7 asked about the representation of high-ability students in the classes. For this study, the high-ability qualification was defined according to the Three Ring Conception of Giftedness (J. Renzulli, personal communication, November 2, 2012). Students who had a score on the mathematics achievement measure that was at least one standard deviation above the mean were identified as having high ability. A dummy variable called HABILITY was created that has a value of "1" or "0". The AUXILIARY (e) function will be used to answer this question in a fashion similar to question 2. The mean value of HABILITY for each class represents the percentage of the members of that class who have mathematics achievement test scores that meet the criterion described above. If there is a significant difference on this variable favoring a class, that class has a greater representation of high-ability students.

Question 8a

Question 8 asked about the relationship of membership in the latent classes to race-gender group. The AUXILIARY (e) function in Mplus was used to answer this question. For race-gender, a case may belong to one of eight categories (White-male, White-female, Black-male, Black-female, Hispanic-male, Hispanic-female, Asian-male, Asian-female). A set of eight dummy variables was created to represent the race-gender categories (WM, WF, BM, BF, HM, HF, AM, AF). The decision to use these race-gender categorizations was based on previous research that showed large interactions between gender and race on expectancy-value constructs, particularly for underrepresented minority students (Graham & Taylor, 2002; Taylor & Graham, 2007). The presence of similar interactions would be seen in under- or overrepresentation of race-gender groups

in latent classes. The mean value of the race-gender variable represents the percentage of that latent class were occupied by members of that race-gender group. The mean values of the race-gender variable were visually inspected to compare the representation of that group in the class to the level in the overall sample.

Question 8b

Question 8b asked about the relationship of SES to class membership. The AUXILIARY (e) function was used to test for equality of means on the variable SES. Socioeconomic status is a continuous variable that is scaled as a z-score. Significant differences between classes on the SES variable indicate differential representation of cases within the classes. If it is found that a particular class has a significantly lower mean SES, this means that lower SES students were classified into the class at higher frequencies.

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Limitations and Delimitations

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For any study, there are factors that affect validity, and these factors are grouped into two categories: limitations and delimitations (Locke, Spirduso, & Silverman, 2007). Limitations are threats to internal validity, or factors that impact the researcher's ability to establish a direct relationship between the independent and dependent variables (Gall, Gall, & Borg, 2007). Delimitations are factors within the researcher's control that affect external validity, or the generalizability of the study results to a larger population.

Limitations

This study had some limitations. First, a limitation of this study was the lack of a standardized measure of science achievement. In HSLS: 2009 a mathematics IRT achievement test was administered, however, a science achievement test was not given.

The mathematics achievement test score was used as a proxy for high-ability in science. Second, although 21,444 ninth grade students participated in the HSLS: 2009 study, a significant percentage of these students were not enrolled in a mathematics (9.85%) or science (16.83%) course when the survey was given. This led to a large number of legitimate skips on items that pertained to the students' Fall 2009 mathematics or science courses. The distribution of these non-enrollments across race and SES would have caused bias in the data if these cases were deleted. To reduce the amount of bias, the missing data estimation capabilities of Mplus 7 were utilized; however, this caused the entropy of the latent class models to be reduced. Third, this cohort of ninth-graders occupied a specific moment in history and had a unique set of experiences that make history a limitation of this study (Gall et al., 2007). Fourth, the *cost* scale did not have as high of reliability as the NCES-created scales and was highly skewed and kurtotic. Cost was originally planned to be a latent class indicator, however, when cost was included as an indicator the latent class models would not converge. Therefore, the decision was made to use cost as a correlate instead of an indicator.

The nature of the expectancy-value questionnaire items was a limitation. The questions were asked specifically about the Fall 2009 mathematics and sciences courses that the students were enrolled in. Students' expectancies and values about a specific mathematics or science course may be different than their expectancies and values about the domains of mathematics and science in general. Furthermore, expectancies and values for technology and engineering were not addressed in the HSLS: 2009 questionnaire. It may be that students valuing of technology and engineering could affect their motivation to pursue a STEM occupation.

Delimitations

The operationalization of giftedness in this study was a delimitation. Using the TRCG (Renzulli, 1978) high-ability was defined as a score greater than or equal to +1Z within a race group on the mathematics achievement test. Students who scored at least +1Z within their own race group were identified as high-ability students. This definition may differ from other definitions because it used within group norms instead of global norms. The bulk of studies on gifted students have used identification standards that are more stringent that this standard.

The operationalization of STEM occupation is also delimitation. No standard definition of STEM occupation could be found; therefore, the researcher identified occupations that required STEM knowledge beyond high school content, according to the O*NET database, as STEM occupations. This included the health sciences and the social sciences. The method used to identify the education level of that occupation is a delimitation. Inconsistencies in the education requirements for occupations that were listed in the O*NET database and difficulties in coding the occupations that students wrote in as their answers to the survey led to the decision to use the student response to the educational expectations question as the education level. Many students answered "don't know" to the educational expectations question and these cases were not included in the STEM plus bachelor's or higher code. Furthermore, students may not have accurate knowledge of the educational requirements for the occupation that they wrote in as their expected occupation at age 30.

A methodological limitation is that the latent profile indicators were scale scores and the use of scale scores instead of the actual items assumes that the factor structure for

the scales is invariant across groups. This assumption was used by NCES for the extant scales in HSLS: 2009 and was applied to the researcher-created scale for cost. More accurate models may be possible if the actual items are used instead of scale scores. However, the trade-off is the tremendous amount of time it would require for the computer to estimate such models. The most complex models estimated in this study required over three hours to be processed.

Chapter 4

Results

The purposes of this study were to investigate extant expectancy-value motivational profiles of ninth grade students and the relationships of those profiles with occupational choice, high-ability status, mathematics achievement, and demographic variables. The Expectancy Value Model of Achievement-Related Choices (Eccles et al., 1983) was the primary theoretical framework used to examine motivation. Secondary data analysis of the High School Longitudinal Study of 2009 (HSLS: 2009) was conducted. This study investigated the following research questions:

Research Questions

1. What distinct profiles emerge from measures of mathematics self-efficacy and mathematics task values (interest-enjoyment value, utility value, and attainment value)?

2. What distinct profiles emerge from measures of science self-efficacy and science task values (interest-enjoyment value, utility value, and attainment value)?

3. How is cost related to mathematics and science profile membership?

4. How do the memberships of the mathematics and science profiles compare?

5. How do these profiles relate to mathematics ability?

6. How do these profiles relate to STEM occupational choice?

7. How do these profiles relate to giftedness?

8. How does membership in these profiles differ by (a) race-gender group and (b) socioeconomic status?

Data Cleaning

Data cleaning was performed using SPSS 20. The restricted use dataset contained 25,206 cases.

The NCES race variable, X1RACE, originally had eight categories (Table 3a). The eight categories were collapsed into five categories (Table 3b) using variable transformation. The two categories: (1) Hispanic, no race specified and (2) Hispanic, race specified categories were combined into one category called Hispanic. The three categories; (1) American Indian/Alaska Native; (2) more than one race, non-Hispanic; and (3) Native Hawaiian/Pacific Islander, non-Hispanic categories were combined into one category called Other.

Table 3a

Composition of Full Sample by Race (n=25,206)

Race	Frequency
American Indian/Alaska Native	168
Asian, non-Hispanic	2,096
Black/African-American, non-Hispanic	2,648
Hispanic, no race specified	590
Hispanic, race specified	3,410
More than one race, non-Hispanic	1,952
Native Hawaiian/Pacific Islander, non-Hispanic	110
White, non-Hispanic	12,259

3,214 of cases were weighted to zero by NCES because of missing data and were omitted from further analysis, leaving 21,992 cases. The 2,199 cases in the "Other" category were omitted from subsequent analyses, leaving 19,793 cases,

Table 3b

Composition of Analysis Sample by Race (n = 19,793)

Race	Frequency
Asian	1,792
Black	2,293
Hispanic	3,655
White	12,053

Occupation Codes

In HSLS: 2009, ninth grade students were asked to write in the occupation that they saw themselves in at age 30. These occupations were manually coded by NCES staff using the six-digit Occupational Information Network (O*NET) coding system. Although O*NET has categorized these six-digit codes into STEM and non-STEM categories, a modified coding system was used in this study. The US Bureau of Labor and Statistics maintains a database of occupations that was used to determine the level of education typical for that occupation. Occupations that typically required education in science, technology, education, and mathematics (STEM) beyond high school coursework were coded as STEM occupations (Appendix C). Some occupations that were coded by O*NET as non-STEM, but were found to require STEM knowledge beyond high school coursework were manually recoded as STEM occupations. For example, postsecondary science and math educators were indicated as STEM occupations in the O*NET system while high school teachers of those same subjects were coded as non-STEM. Because a Bachelor's degree in the discipline is required to be a high school science or math teacher those occupations were manually recoded as STEM occupations. Occupations were coded as "STEM", "Non-STEM", and "Don't Know" (Table 4). The large group of

students who responded "Don't Know" to this question were included in the profile

analysis process, but were not included in the subsequent occupational choice analysis.

Table 4

Occupation Coding (n = 19,793)

Occupation Type	Frequency	Percentage
STEM	6697	33.8%
Non-STEM	6407	34.4%
Don't Know	5538	28.0%
Missing	1151	5.8%

The NCES variable, X1STUEDEXPCT, was collapsed into one three-level

variable, STUEXPCT, with three possible values: less than BA, BA or higher, and don't

know (Table 5). The two variables STEMOCC and STUEXPCT were used to create the

outcome variable, STEM. Students who identified STEM occupations and indicated that

they planned on achieving a bachelor's degree or higher were coded as "1" in the variable

STEM (Table 6).

Table 5

Students' Educational Expectations

Level	Frequency
Less than BA	3,729
BA or higher	11,362
Don't know	4,168
Missing	534

Table 6

Occupation and Education Classifications

Category	< BA	>=BA	Don't Know	Total
STEM	893 (4.8%)	4859 (26.1%)	945 (5.1%)	6,697 (35.9%)
Non-STEM	1,427 (7.7%)	3698 (19.8%)	1,282 (6.9%)	6,407 (34.4%)
Don't know	1,247 (6.7%)	2489 (13.4%)	1,802 (9.7%)	5,538 (29.7%)
Missing				1,511

The math achievement test score X1TXMSCR was used to identify students who had high ability. Cutoff scores were calculated for each race group separately and the +1Z score for each group was used as the determining score (Table 7). Therefore, students were identified as high ability relative to other students of the same race/ethnicity group. The value of X1TXMSCR had already been imputed by NCES for all valid cases. Of the 19,793 cases in the current sample, 534 were found to be missing values for the math achievement score and these cases were omitted from future analyses, leaving 19,259 cases.

Table 7

Math Achievement Test +1Z Cutoff Score by Race/Ethnicity Group

Race	Cutoff Score	Valid N
Asian	61.375839	1,672
Black	46.430236	2,218
Hispanic	48.695370	3,515
White	53.198261	11,854

A dummy variable called HABILITY was created that had the value of "0" if a student's X1TXMSCR was below the cutoff score and "1" if it was at the cutoff or higher.

Cost Scale

Four items were used to create a scale for cost. Items S1E13A, S1E13B, S1E13C, and S1E13D asked students about the potential effect of time and effort in math and

science on time with friends, time for extracurricular activities, popularity, and being made fun of. Responses were on a four-point Likert scale that was coded such that higher scores indicated more positive perceptions of cost. Principal components analysis with Varimax rotation was used to create factor scores for the cost scale (Table 8). Cronbach's Alpha for this scale was .75, which was indicates acceptable internal consistency for the COST scale. A two-factor solution explained 84.4% of the total variance. Scale reliability analysis showed that the deletion of any of the four items would decrease Cronbach's alpha.

Table 8

Factor Loadings for Cost Scale

Item	Factor 1 Cost-Popular Loading	Factor 2 Cost-Time Loading
S1 E13A Time/effort in math/science means not enough time with friends.		.898
S1 E13B Time/effort in math/science means not enough time for extracurriculars		.901
S1 E13C Time/effort in math/science means 9th grader won't be popular.	.894	
S1 E13D Time/effort in math/science means people will make fun of 9th grader.	.917	
% of explained variance	57.4	27.0

Descriptive Statistics

A table of descriptive statistics was generated that included means, standard deviations, and zero order correlations for each of the nine indicators: mathematics self-efficacy, science self-efficacy, mathematics attainment value, science attainment value, mathematics utility value, science utility value, mathematics interest-enjoyment value, science interest-enjoyment value, and cost. The coefficient alphas for all scales, except

the cost scale, were calculated by NCES. Descriptive statistics for the correlates (race-gender and SES) as well as the dependent variable, occupational choice, were determined (Tables 9, 10, and 11).

Table 9

Descriptive Statistics (N = 19,259)

Variable	Mean (SE)	SD	Alpha
Socioeconomic Status	-0.0718 (.0118)	0.759	N/A
Math Achievement Test Score	38.956 (0.187)	11.920	N/A
Math Self-Efficacy	0.0016 (.0167)	0.997	.90
Math Attainment Value	0.0010 (.0157)	0.999	.84
Math Utility Value	0.0020 (.0166)	0.997	.78
Math Interest-Enjoyment Value	0.0055 (.0168)	0.996	.75
Science Self-Efficacy	-0.0057 (.0174)	0.994	.88
Science Attainment Value	-0.0061 (.0156)	0.996	.83
Science Utility Value	0.0019 (.0174)	0.995	.75
Science Interest-Enjoyment Value	0.0060 (.0175)	0.990	.73
Cost-Time	-0.0059 (.0161)	1.011	.74
Cost-Popular	-0.0166 (.0161)	1.009	

Table 10

Race-Gender Distribution

Race-Gender Group	Frequency	%
Asian Female	824	1.9
Asian Male	848	1.9
Black Female	1,069	8.0
Black Male	1,149	6.9
Hispanic Female	1,751	12.0
Hispanic Male	1,764	12.4
White Female	5,845	27.8
White Male	6,009	29.1
Total	19,259	

Table 11

High Ability Status

Status	Frequency	%
High ability	3,054	15.9
Not High ability	16,205	84.1

Table 12

Bivariate Correlations

	MSE	MAV	MUV	MIV	SSE	SAV	SUV	SIV	COST-TIME	COST-POPULAR	X1TXMSCR	X1SES
MSE	1											
MAV	.572**	1										
MUV	.360**	.290**	1									
MIV	.540**	.547**	.423**	1								
SSE	.401**	.267**	.190**	.180**	1							
SAV	.188**	.274**	.103**	.114**	.493**	1						
SUV	.201**	.190**	.426**	.224**	.414**	.387**	1					
SIV	.141**	.136**	.180**	.194**	.508**	.462**	.492**	1				
COST-TIME	.101*	.065**	.109**	.134**	.106**	.041*	.098**	.118**	1			
COST-POPULAR	.174**	.135**	.105**	.200**	.181**	.107**	.123**	.190**	.004	1		
X1TXMSCR	.306**	.384**	.000	.213**	.225**	.248**	.057**	.123**	.080**	.108**	1	
X1SES	.128**	.117**	-.070**	.039*	.130**	.182**	-.002	.060**	.033**	.080**	.431**	1

** $p < .01$
* $p < .05$

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Results for Research Question #1

Testing Latent Class Models

For each of the five parameterizations (A through E), multiple models were tested. First, a two-class model was estimated, then models with additional classes were estimated until: (1) the model would not converge, (2) the LMR p-value exceeded .05, or (3) the log-likelihood would not replicate. The initial number of starts used in Mplus was initially set to 1000; the number of starts was increased first to 2000, then to 4000 to attempt to reach convergence or log-likelihood replication. If the model did not converge after the starts were changed to 4000, "did not converge" was recorded as the result. The results of the model testing are shown in Table 13 and plots of the class profiles for each tested model are in Appendix E.

Math E-V Models

The next step was to determine which model best represented the latent class structure for the math classes. The list of models was sorted by BIC and the models with the five lowest values of BIC are displayed in Table 13. Model 4D had the lowest value of LL and BIC. The p-value for the model 4D LMR was 0.5172, which indicated that the 4D model was not a statistically significant improvement over the 3D model. The cluster profiles (Figure 2), sample size, and sample statistics were inspected. Profile plots were created for each estimated model (Appendix E). A unique profile (class 3) was revealed in the 4D model that was not visible in the 3D model, which justified retention of the 4D model even though the 4D model was not a statistical improvement. Pastor et al. (2007) has recommended the retention of profiles with an additional class beyond that which is

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indicated by the LMR when the solution reveals a unique profile that would otherwise be subsumed into another class. Model 3E was rejected because the LMR could not be computed. Therefore, model 4D was selected as the best latent class model for the mathematics expectancy-value indicators.

Table 13

Math Model Fit Indicators

Model	LL	No. free parameters	BIC	p LMR	Entropy	Smallest class freq.
2A	-91429	13	182988	.0000	.658	8450 (.441)
3A	-89134	18	178446	.0009	.707	2902 (.151)
4A	-88235	23	176698	.0067	.703	904 (.047)
5A	-87121	28	174518	.0231	.841	604 (.032)
6A	-86195	33	172717	.0122	.741	543 (.028)
7A	-85939	38	172252	.4824	.724	589 (.031)
2B	-88185	19	176558	.1233	.918	408 (.021)
3B	-87147	24	174531	.0002	.788	977 (.051)
4B	-85771	29	171828	.0000	.852	531 (.028)
5B	-85485	34	171306	.2906	.846	553 (.029)
2C	-90980	17	182129	.0000	.658	9508 (.496)
3C	-87190	26	174647	.0000	.751	4186 (.218)
4C	-85769	35	171883	.1215	.753	2126 (.110)
5C	Would not converge					
2D	-87345	23	174917	.0000	.726	4766 (.25)
3D	-85276	32	170867	.0000	.640	3541 (.18)
4D	-84700	41	169804	.5172	.713	2571 (.13)
2E	-87195	29	174676	.0000	.419	5882 (.31)
3E	-84874	44	170181	Could not be computed	.611	4512 (.22)
4E	Not replicated					

Table 14

Math Models with Lowest BICs

No. of groups	LL	No. free parameters	BIC	p LMR	Entropy	Smallest class freq.
4D	-84700	41	169804	.5172	.713	2571 (.13)
3E	-84874	44	170181	NA	.611	4512 (.22)
3D	-85276	32	170867	.0000	.640	3541 (.18)

Next, the probabilities of latent class membership of model 4D were examined for sufficiency (Table 15). The correct class assignment probabilities of .813, .829, .852, and .881 were all above the minimum threshold of acceptability of 0.70 (Wang & Wang, 2012). The entropy statistic for this model was .713, which is considered to be good (Clark, 2010). The size of the classes was good, with the smallest class comprising 13.4% of the sample.

Table 15

Average Latent Class Probability for Most Likely Class Membership (Row) by Latent Class (Column) for Math 4D Model

Class	1	2	3	4
1	.813	.116	.023	.049
2	.126	.829	.011	.034
3	.022	.026	.852	.100
4	.039	.057	.023	.881

Class homogeneity was assessed via comparison of the model-estimated within class variances for each indicator to the overall sampling variance (Table 16). The smaller the within class variance, the more homogeneous the class. The overall sampling variance for each indicator was 1.0 because the indicators are z-scores. Classes 1 and 4 are more homogeneous than classes 2 and 3. Class 2 is less homogeneous with respect to

MUV, and class 3 is less homogeneous with respect to MAV and MIV. Class 3 is typified by high MSE and is very homogeneous with respect to that indicator. Class 4 is typified by a high MUV and is very homogeneous with respect to MUV. Class 1 is typified by average values of MSE and MUV. Class 2, the lowest expectancy-value class, is also the least homogeneous.
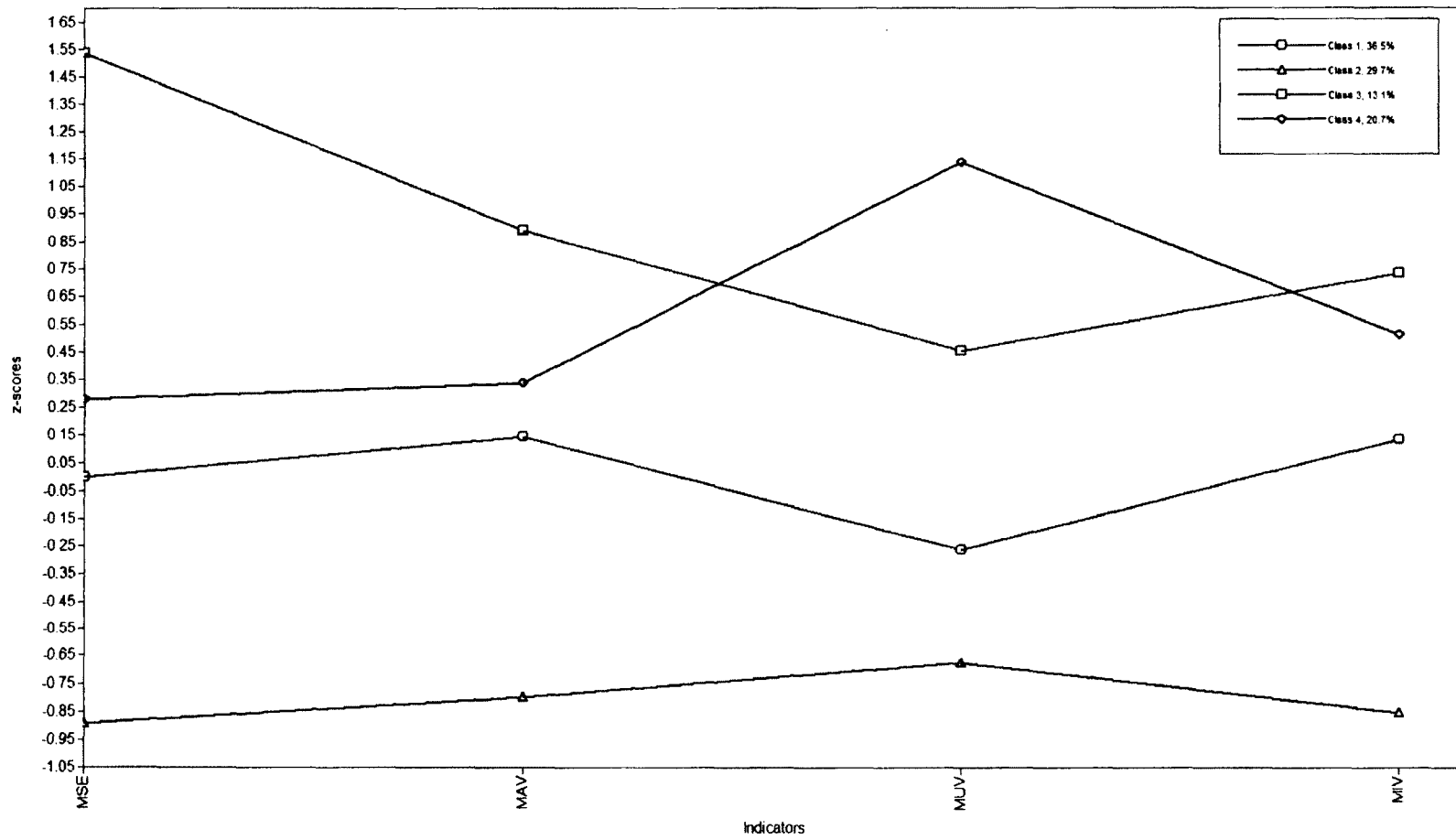
Figure 2

Math Model 4D Profiles

Table 16

Model-estimated Within Class Variances for Math 4D Model

	Class 1	Class 2	Class 3	Class 4
Math Self-Efficacy	0.155	0.924	0.038	0.345
Math Attainment Value	0.568	0.706	0.923	0.676
Math Utility Value	0.218	1.210	0.660	0.051
Math Interest-Enjoyment Value	0.504	0.711	0.987	0.614

The estimated covariances were compared to the parameterization D

specifications (Table 17). In parameterization D, the covariances are constrained to be

equal across the classes, while the variances vary within and between the classes. The

values on the diagonal for each class will be the variances specific to that class.

Table 17

Estimated Covariance Matrix for Math Model 4D

	Math Self-Efficacy	Math Attainment Value	Math Utility Value	Math Interest-Enjoyment Value
Math Self-Efficacy				
Math Attainment Value	.090**			
Math Utility Value	.003	-.002		
Math Interest-Enjoyment Value	.073**	.205**	.041**	

According to the model, MUV does not have a significant relationship with MSE

or MAV, but has a weak positive relationship with MIV. The relationship between MAV

and MIV is the strongest in this set of indicators, while the other statistically significant

relationships are all small.

The class separation is the distance between the classes. The 95% confidence

intervals for estimates were examined to check for overlap. The only overlap occurred

between classes 3 and 4 on the MIV indicator, the two confidence intervals overlap by

0.024. The classes were well separated.

Table 18

Estimated Means, Standard Errors, and Confidence Intervals for Math 4D Model

	Class 1 M (SE) [CI]	Class 2 M (SE) [CI]	Class 3 M (SE) [CI]	Class 4 M (SE) [CI]
Math Self-Efficacy	-0.004 (.016) [-0.035, 0.027]	-0.894 (.066) [-1.023, -0.765]	1.535 (.010) [1.515, 1.555]	0.278 (.073) [0.135, 0.421]
Math Attainment Value	0.144 (.033) [0.079, 0.209]	-0.800 (.039) [-0.876, -0.723]	0.891 (.077) [0.740, 1.041]	0.337 (.057) [0.225, 0.449]
Math Utility Value	-0.263 (.014) [-0.290, -0.236]	-0.676 (.039) [-0.752, -0.560]	0.452 (.073) [0.309, 0.595]	1.139 (.012) [1.112, 1.163]
Math Interest-Enjoyment Value	0.135 (.024) [0.088, 0.182]	-0.855 (.044) [-0.941, -0.769]	0.730 (.063) [0.607, 0.853]	0.511 (.061) [0.391, 0.631]

Results for Research Question #2

The same model testing procedure was used for the science classes. The results

of the model testing are shown in Table 19 and in Appendix G.

Science E-V Models

The next step was to determine which model best represented the latent class

structure for the science classes. The list of models was sorted by BIC and the models

with the five lowest values of BIC are displayed in Table 20. Model 3E had the lowest

value of LL and BIC. The two models with the lowest BIC are nested and can be

compared using the chi-square difference test, which shows that the 3E model is significantly better than the 3D model, $(\chi^2 (12) = 864, p < .001)$. The p-value for the model 3E LMR was 0.4635, which indicated that the 3E model was not a statistically significant improvement over the 2E model. The cluster profiles (Figure 3), sample size, and sample statistics were inspected. A unique profile (class 3) was revealed in the 3E model that was not visible in the 2E model, which justified retention of the 3E model. Pastor et al. (2007) recommended the retention of profiles with an additional class beyond that which is indicated by the LMR when the solution reveals a unique profile that would otherwise be subsumed into another class. Therefore, model 3E was selected as the best latent class model for the mathematics expectancy-value indicators.

Next, the probabilities of latent class membership of model 3E were examined for sufficiency (Table 21). The correct class assignment probabilities of .768, .749, and .834 were all above the minimum threshold of acceptability of 0.70 (Wang & Wang, 2012). However, the classification table indicates that classes 1 and 2 have some overlap. Class 3 has a much higher correct class assignment probability than the other classes. The entropy statistic for this model was .524, which is considered to be low (Clark, 2010). The size of the classes was good, with the smallest class comprising 13.7% of the sample.

Table 19

Science Model Fit Indicators

Model	LL	No. free parameters	BIC	*p* LMR	Entropy	Smallest class freq.
2A	-86025	13	172180	.0000	.578	9311 (.487)
3A	-83920	18	168019	.0008	.680	2685 (.203)
4A	-83390	23	167006	.3251	.648	594 (.031)
2B	-83290	19	166769	.2333	.812	714 (.037)
2C	-85715	17	171597	.0000	.585	8988 (.497)
3C	-83059	26	166374	.1079	.627	3382 (.177)
2D	-82627	23	165480	.0314	.286	5523 (.29)
3D	-81854	32	164023	.2367	.623	2428 (.13)
2E	-82476	29	165239	.0216	.314	5792 (.30)
3E	-81590	44	163614	.4635	.524	2628 (.14)
4E	Did not replicate					

Table 20

Science Models with Lowest BICs

Model	LL	No. free parameters	BIC	*p* LMR	Entropy	Smallest class freq.
3E	-81590	44	163614	.4635	.524	2628 (.14)
3D	-81854	32	164023	.2367	.623	2428 (.13)
2E	-82476	29	165239	.0216	.314	5792 (.30)
2D	-82627	23	165480	.0314	.286	5523 (.29)

Table 21

Average Latent Class Probability for Most Likely Class Membership (Row) by Latent

Class (Column) for Science Model 3E

Class	1	2	3
1	.768	.211	.021
2	.217	.749	.034
3	.078	.088	.834

Class homogeneity was assessed via comparison of the model-estimated within class variances for each indicator to the overall sampling variance (Table 22). The

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smaller the within class variance, the more homogeneous the class. The overall sampling variance for each indicator was 1.0 because the indicators are z-scores. Classes 2 and 3 are more homogeneous than class 1. Class 3 is typified by high SUV and is very homogenous with respect to SUV. Class 3 is more homogeneous with respect to SIV and SSE than the sample. Class 2 is more homogeneous than the sample with respect to all four indicators, and class 1 is less homogeneous with respect to SSE, SUV, and SIV than the sample. Class 1, the lowest expectancy-value class, is the least homogeneous. Class 2, the typical or average class, is the most homogeneous overall.

Table 22

Model-estimated Within Class Variances for Science 3E Model

	Class 1	Class 2	Class 3
Science Self-Efficacy	1.515	0.537	0.694
Science Attainment Value	0.938	0.775	1.099
Science Utility Value	1.173	0.298	0.052
Science Interest-Enjoyment Value	1.030	0.601	0.528

The model-estimated covariances were compared to the parameterization for model E. In model E, the variances and covariances are allowed to vary within and between classes. Thus, each class has its own unique covariance matrix, unlike the D models in which only the diagonal of the covariance matrix differs between classes. The three matrices for the science classes are shown in Tables 23a, b, and c.

Table 23a

Covariance Matrix for Class 1

	Science Self-Efficacy	Science Self-Efficacy	Science Self-Efficacy	Science Self-Efficacy
Science Self-Efficacy	1.5145			
Science Attainment Value	.463**	.938		
Science Utility Value	.394**	.260**	1.173	
Science Interest-Enjoyment Value	.442**	.226**	.276**	1.030

Table 23b

Covariance Matrix for Class 2

	Science Self-Efficacy	Science Self-Efficacy	Science Self-Efficacy	Science Self-Efficacy
Science Self-Efficacy	.694			
Science Attainment Value	.377**	1.099		
Science Utility Value	.018*	-.004	.052	
Science Interest-Enjoyment Value	.291**	.342**	.020**	.528

Table 23c

Covariance Matrix for Class 3

	Science Self-Efficacy	Science Self-Efficacy	Science Self-Efficacy	Science Self-Efficacy
Science Self-Efficacy	0.537			
Science Attainment Value	.333**	.775		
Science Utility Value	.131**	.151**	.298	
Science Interest-Enjoyment Value	.317**	.312**	.156**	.601

The class separation is the distance between the classes. The 95% confidence intervals for estimates were examined to check for overlap (Table 24). No overlaps occurred; the classes were well separated.

Table 24

Estimated Means, Standard Errors, and 95% Confidence Intervals for Indicators by Class for Science 3E Model

	Class 1 M (SE) [CI]	Class 2 M (SE) [CI]	Class 3 M (SE) [CI]
Science Self-Efficacy	-0.304 (.055) [-0.412, -0.196]	-0.034 (.026) [-0.085, 0.017]	0.673 (.034) [0.606, 0.740]
Science Attainment Value	-0.397 (.048) [-0.491, -0.303]	0.078 (.029) [0.021, 0.135]	0.639 (.079) [0.484, 0.794]
Science Utility Value	-0.598 (.069) [-0.733, -0.463]	-0.035 (.026) [-0.086, 0.016]	1.479 (.016) [1.448, 1.510]
Science Interest-Enjoyment Value	-0.599 (.067) [-0.703, -0.468]	0.127 (.024) [0.080, 0.174]	0.889 (.042) [0.807, 0.971]

Figure 3

Science Model 3E Profiles
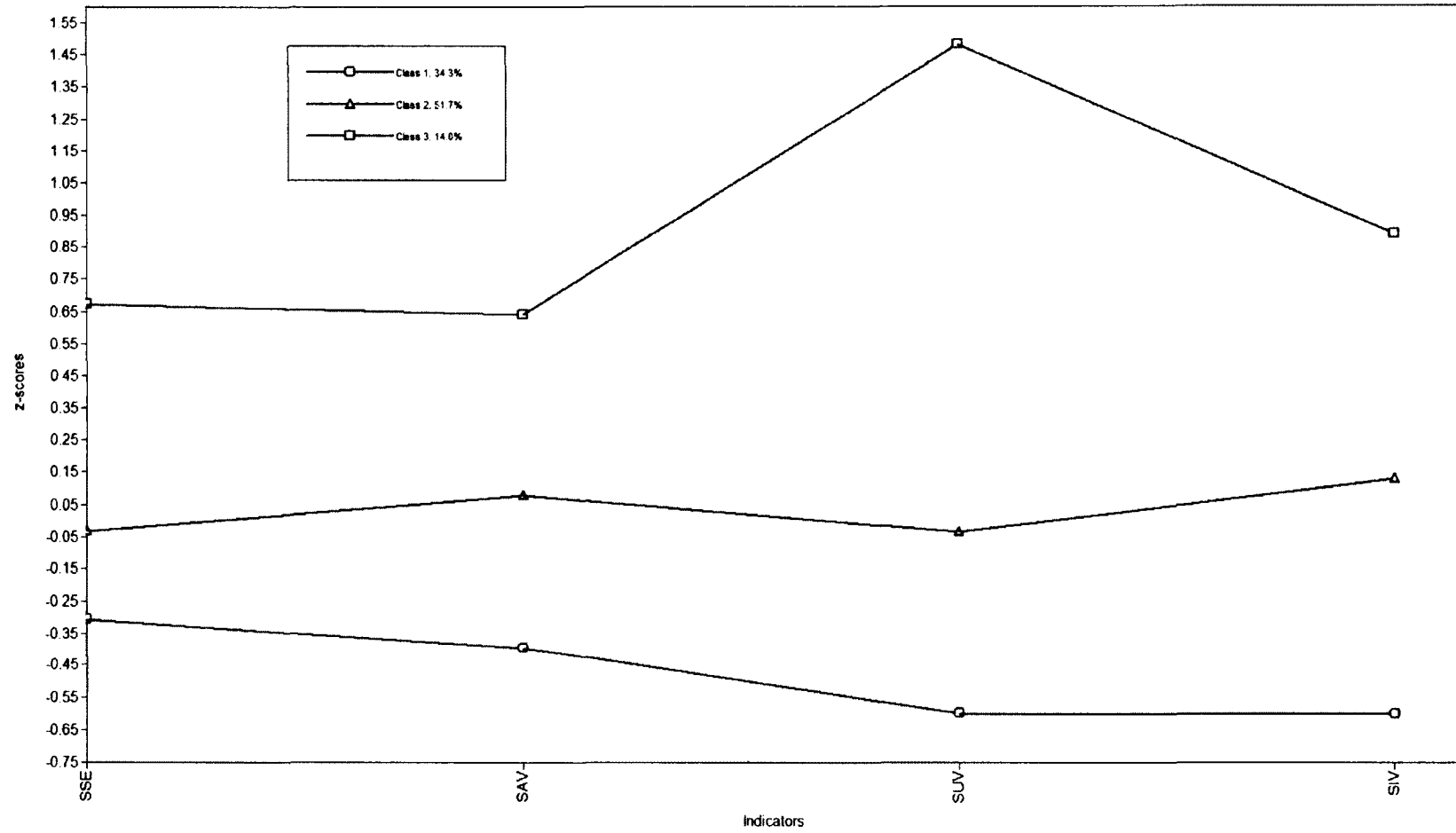
Results for Research Question #3

Question 3 asked how the membership of the math classes compared to the

science classes. To answer this question, each student was assigned to his or her most

probable Math and Science class and a crosstabulation was performed (Table 25). To test

for a relationship between science and math latent class assignment, a chi-square analysis

was conducted. The result of the χ^2 test showed that the fit of the observed frequencies to

the expected frequencies was poor; therefore math class membership was not

independent of science class membership (χ^2 (6) = 1678, p = .000).

Table 25

Comparison of Membership of Science Class 3E and Math Class 4D

	Science Class 1 Low obs (exp)	Science Class 2 Average obs (exp)	Science Class 3 High Science Utility Value obs (exp)	Totals
Math Class 2 – Low	1,889 (1352)	3,016 (3184)	392 (761)	5,297
Math Class 1 – Average	1,588 (1942)	5,346 (4573)	674 (1093)	7,608
Math Class 3 – High Math Self-Efficacy	778 (700)	1,296 (1649)	669 (394)	2,743
Math Class 4 – High Math Utility Value	612 (873)	1,805 (2057)	1005 (492)	3,422
Totals	4,867	11,463	2,740	19,070

A larger number of students from the low science class (class 1) were in the low

math class (class 2) than would be expected by chance. Smaller numbers of students from

science classes 2 and 3 were in math class 2 than would be expected by chance. Both of

these classes are labeled as low; therefore students who had low E-V profiles in science

were more likely to have low E-V profiles in math.

A larger number of the students in the average science class (class 2) were in the average math class (class 1) than would be expected by chance. A smaller number of students in the low and high science classes (classes 1 and 3) were in the average math class (class 1) than would be expected by chance. Therefore students who had average E-V profiles in science were more likely to have average E-V profiles in math.

A larger number of students from the low and high science classes (1 and 3) were in the high MSE math class (class 3) than would be expected by chance, while smaller numbers of students from the average science class (2) were in the high MSE math class (3). Therefore, students who were in the average science class were less likely to be in the high MSE math class, while students who were in the low and high science classes were more likely to be in the high MSE math class.

A larger number of students from the high science class (3) were in the high MUV math class (4) than would be expected by chance, while smaller numbers of students from the low and average science classes (1 and 2) were in the high MUV math class (4). Therefore, students who were in the high science class were more likely to be in the high math utility value class. Notably, the observed number of students from the high MUV class that were in the high SUV class was more than double the expected number of students, and the number of students in the high MSE class that were in the high SUV class was 70% above the expected value. Taken together, students who were in the two high math classes (MSE and MUV) were far more likely to be in the high SUV class.

Results for Research Question #3

To examine the relationship between latent class membership and cost the AUXILIARY (e) function in Mplus 7 was used. The equality of means across latent

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classes was tested using pseudo-class-based multiple imputations (Muthen & Muthen, 2012) for each of the subscales of the cost scale – cost-time and cost-popular.

For math, the overall test found significant differences between the mean values of cost-time for the four math classes ($\chi^2(3) = 75.174$, $p = .000$). Furthermore, the differences in cost-time between class 1 and class 2 were not significant and the differences in cost-time between class 3 and class 4 were not significant (Table 26a). The effect size of the difference in cost-time from the low to the high MSE class was $d = 0.200$. This is a small effect. The overall test found significant differences between the mean values of cost-popular for the four math classes ($\chi^2(3) = 323.571$, $p = .000$). The differences in cost-popular were significant between every pair of math classes. The effect size of the difference in cost-popular from the low to the high MSE class was $d = .330$. This is a small effect.

For science, the overall test found significant difference between the mean values of cost –time for the three science classes ($\chi^2(2) = 76.611$, $p = .000$). The differences between cost-time for the low and average science classes was not significant. The difference between the low and the high class, and between the average and the high class were significantly different, with the most positive sense of cost-time for the high class (.196Z), with a slightly negative sense of cost for both the low and average class. The effect size of the difference in cost-time from the low to the high science class was $d = .239$. The overall test found significant differences between the mean values of cost-popular for the three science classes ($\chi^2(2) = 35.306$, $p = .000$). The differences between all pairs of science classes on cost-popular was statistically significant. The effect size of

the difference in cost-popular from the low to the high science class was d = .167. This is

a very small effect.

Table 26a

Mean Cost-Time Scores for Latent Classes

Math Class	Mean (SE)	Science Class	Mean (SE)
Class 2 – Low	-0.094 (0.018)	Class 1 – Low	-0.024 (0.018)
Class 1 – Average	-0.077 (0.014)	Class 2 – Average	-0.045 (0.012)
Class 3 – High MSE	0.175 (0.027)	Class 3 – High	0.196 (0.027)
Class 4 – High MUV	0.133 (0.023)		

Table 26b

Mean Cost-Popular Scores for Latent Classes

Math Class	Mean (SE)	Science Class	Mean (SE)
Class 2 – Low	-0.216 (0.018)	Class 1 – Low	-0.126 (0.018)
Class 1 – Average	0.002 (0.013)	Class 2 – Average	0.000 (0.013)
Class 3 – High MSE	0.233 (0.028)	Class 3 – High	0.192 (0.028)
Class 4 – High MUV	0.074 (0.021)		

Results for Research Question #4

To examine the relationship between latent class membership and mathematics

ability the auxiliary (e) function in Mplus 7 was used. For math, the overall test found

significant differences among the mean values of the math achievement test score,

X1TXMSCR, for the four math classes ($\chi^2(3)$ = 1307, p = .000). The effect size of the

difference in math achievement score between the lowest and highest math classes was, d

= .68, which is a medium-sized effect. Furthermore, the differences between every pair of

math classes were significantly different (Table 24). For science, the overall test found

significant differences among the mean values of the math achievement test scores for the

three science classes ($\chi^2(2)$ = 14.094, p = .001). The differences between every pair of

science classes were significantly different. The effect size of the difference in math

achievement score between the lowest and highest science classes was $d = .18$, which is a

very small effect. This was not surprising because it was hypothesized that math

achievement score would not be strongly related to science expectancy-value class.

Table 27

Mean Math Achievement Scores for Latent Classes

Math Class	Mean (SE)	Science Class	Mean (SE)
Class 2 – Low	35.391 (0.179)	Class 1 – Low	38.115 (0.208)
Class 1 – Average	40.227 (0.164)	Class 2 – Average	39.357 (0.157)
Class 3 – High MSE	45.111 (0.318)	Class 3 – High	40.293 (0.315)
Class 4 – High MUV	38.335 (0.231)		

Results for Research Question #5

To examine the relationship between latent class membership and high ability the

auxiliary (e) function in Mplus 7 was used. The variable, HABILITY, was a dichotomous

dummy variable that used to indicate gifted status. Students who had math achievement

test scores that were at least one standard deviation above the mean were assigned a "1"

in HABILITY and those who had scores less than that threshold were assigned "0". The

mean score on HABILITY indicates the percentage membership of each latent class by

gifted students.

Table 28

Membership of High-ability Students in Latent Classes

Math Class	M (SE)	Science Class	M (SE)
Class 2 – Low	0.084 (.005)	Class 1 – Low	0.138 (.006)
Class 1 – Average	0.161 (.005)	Class 2 – Average	0.152 (.004)
Class 3 – High MSE	0.312 (.011)	Class 3 – High	0.187 (.009)
Class 4 – High MUV	0.135 (.007)		

As high-ability students were identified using a +1Z cutoff within racial group, 15.9% of the population was identified. An examination of the means showed that high-ability students were significantly underrepresented in the low math class, while significantly overrepresented in the high MSE math class. Representation in the average math class was very close to the representation in the population, while slight underrepresentation in the high MUV class was noted. For the science classes, the distribution of high-ability students among the classes was much more uniform; slight overrepresentation in the high class and slight underrepresentation in the low class were noted.

Results for Research Question #6

To examine the relationship between latent class membership and race-gender category the AUXILIARY (e) function in Mplus 7 was used. Eight dichotomous dummy variables were used to indicate race-gender group. The mean score on this variable indicated the percentage membership of each latent class by that race-gender group.

Each class was examined for over- or underrepresentation by visually inspecting the membership percentages for each race-gender group (Table 29). Asians were slightly underrepresented in the low math class while Hispanic females were overrepresented in the low math class. Hispanic females were greatly underrepresented in the high MSE group; White females were also underrepresented. Asian males and White males were over represented in the high MSE group. Black females, Black males, Hispanic males, and Asian males were overrepresented in the high MUV group, while Hispanic females, and all White students were underrepresented.

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Asians were slightly underrepresented in the low science group, while the representation of other groups was very similar to their representation in the population. In the high science group, Asians were greatly overrepresented, Blacks females were were somewhat overrepresented, Black males were slightly overrepresented, Hispanic Males were underrepresented, and Whites were underrepresented. White students were overrepresented in the average science class while the representation of other groups was close to their representation in the population.

Table 29

Race-gender Group Membership of Latent Classes

Race-gender group	Math – Low (2)	Math – Avg (1)	Math – High MSE (3)	Math – High MUV (4)	Science – Low (1)	Science – Avg (2)	Science – High (3)	Overall %
Asian Female	*.014*	.021	.021	.019	.016	.017	**.030**	.019
	(.002)	(.002)	(.003)	(.003)	(.002)	(.002)	(.004)	
Asian Male	*.010*	.020	**.030**	.025	.016	.019	**.029**	.019
	(.002)	(.002)	(.004)	(.003)	(.002)	(.002)	(.004)	
Black Female	.071	*.062*	.087	**.119**	.079	*.072*	**.110**	.080
	(.005)	(.004)	(.009)	(.008)	(.006)	(.004)	(.009)	
Black Male	*.057*	.061	.071	**.096**	.071	*.061*	.083	.069
	(.004)	(.004)	(.008)	(.006)	(.005)	(.003)	(.007)	
Hispanic Female	**.142**	.123	*.080*	.111	.122	.118	.124	.120
	(.006)	(.005)	(.007)	(.007)	(.006)	(.005)	(.009)	
Hispanic Male	.115	.122	.120	.137	.126	.126	*.106*	.124
	(.006)	(.005)	(.009)	(.007)	(.007)	(.005)	(.008)	
White Female	**.298**	**.303**	*.250*	*.230*	.272	**.292**	.257	.278
	(.006)	(.007)	(.010)	(.008)	(.008)	(.006)	(.011)	
White Male	.289	.292	**.341**	*.262*	.298	.295	*.260*	.291
	(.007)	(.006)	(.012)	(.009)	(.008)	(.006)	(.010)	

Note: Bolded values indicate overrepresentation; italicized values indicate underrepresentation.

Results for Research Question #7

To examine the relationship between latent class membership and socioeconomic status the auxiliary (e) function in Mplus 7 was used. The data showed significant differences in SES by math class ($\chi^2(3) = 206.141, p = .000$). However, the difference in mean SES from the lowest value in Class 4 to the highest value in class 3 only represented an effect size of $d = .27$; a small effect. Only one pair of math classes did not

have a significant difference in SES (Class 2 vs. 4; $\chi^2(1) = 0.490$, $p = .484$); every other

pair of classes were significantly different at the $p = .000$ level. The low math class (Class

2) and the high MUV math class (Class 4) both had low SES values, which were not

significantly different. The high MSE class had the highest SES and the average math

class had an average SES value. There were no significant differences in SES by science

class ($\chi^2(2) = 2.729$, $p = .255$).

Table 30

Mean Socioeconomic Status of Students by Latent Classes

Math Class	M (SE)	Science Class	M (SE)
Class 2 – Low	-0.131 (.012)	Class 1 – Low	-0.092 (.014)
Class 1 – Average	-0.037 (.011)	Class 2 – Average	-0.057 (.010)
Class 3 – High MSE	0.105 (.019)	Class 3 – High	-0.049 (.020)
Class 4 – High MUV	-0.145 (.015)		

Results for Research Question #8

To examine the relationship between latent class membership and STEM

occupational choice the auxiliary (e) function in Mplus 7 was used. The variable STEM

was a dichotomous dummy variable that indicated students expected to be in a STEM-

related occupation at age 30 and to have earned at least a bachelor's degree. The mean

value of this variable indicates the percentage of these students within that class (Table

31).

In math, the overall test indicated a significant difference in the means by class

($\chi^2(3) = 292.821$, $p = .000$) and the differences between every pair of classes were

significant. The high MSE math class had a higher value than the high MUV math class

($\chi^2(1) = 18.17$, $p = .000$). The average math class had a higher value than the low math

class.

In science, the overall test indicated a significant difference in the means by class ($\chi^2(2) = 143.862$, $p = .000$). The high science class had the highest value, and the low science class had the lowest value.

Table 31

STEM Occupational Choice by Latent Class

Math Class	M (SE)	Science Class	M (SE)
Class 2 – Low	0.174 (.006)	Class 1 – Low	0.193 (.007)
Class 1 – Average	0.246 (.006)	Class 2 – Average	0.237 (.006)
Class 3 – High MSE	0.353 (.012)	Class 3 – High SUV	0.413 (.013)
Class 4 – High MUV	0.284 (.009)		

Summary of Mathematics Expectancy-Value Classes

In this section, the characteristics of the classes that were identified through latent class analysis are discussed. Table 32 provides a comparison of the data for each mathematics class.

Mathematics Classes

Typical. In the typical mathematics expectancy-value class all of the EV profile indicators were near the mean. These students had a perception of the cost that was considered average and mathematics achievement scores that were slightly above the mean. High-ability students were represented at the same rate as in the population. The SES of this group was slightly below the mean. These students identified STEM occupations at a rate that was slightly below the mean rate for the population. White females were overrepresented in this group, while Black females are underrepresented.

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Table 32

Summary of Mathematics Expectancy-Value Classes

	Math Self-Efficacy M (SE)	Math Attainment Value M (SE)	Math Utility Value M (SE)	Math Interest Value M (SE)	Cost-Time M (SE)	Cost-Popular M (SE)	Math Ach. M (SE)	High-ability students % of class	SES M (SE)	STEM % of class	Over-rep	Under-rep
M1 – Typical (36.5%)	-.004 (.016)	.144 (.033)	-.263 (.014)	.135 (.024)	-.077 (.014)	.002 (.013)	40.227 (.164)	16.1	-.037 (.011)	24.6	WF	BF
M2 – Low (29.7%)	-.894 (.066)	-.800 (.039)	-.676 (.039)	-.855 (.044)	-.094 (.018)	-.216 (.018)	35.391 (.179)	8.4	-.131 (.012)	17.4	WF, HF	BM, AF, AM
M3 – High MSE (13.1%)	1.535 (.010)	0.891 (.077)	0.452 (.073)	.730 (.063)	.175 (.027)	.233 (.028)	45.111 (.318)	31.2	.105 (.019)	35.3	AM, WM	WF, HF
M4 – High MUV (20.7%)	.278 (.073)	.337 (.057)	1.139 (.012)	0.511 (.061)	.133 (.023)	.074 (.021)	38.335 (.231)	13.5	-.145 (.015)	28.4	BF, BM	WF, WM
Entire Sample	.002 (.017)	.001 (.016)	.002 (.017)	.006 (.017)	.000 (.016)	.000 (.017)	38.956 (0.187)	15.9	-.072 (.012)	26.1		

Low. In the low mathematics expectancy-value class all of the EV profile indicators were below the mean, and ranged from -.676Z to -0.894Z. These students had a perception of cost that was more negative than average and achievement test scores that were below the mean. High-ability students were represented in this group at about half the rate as in the population. The SES of this group was below the mean. These students identified STEM occupations at a rate that was 8.7% less than the mean rate for the population. Hispanic females and White females were overrepresented in this group, while Black males and Asian females were overrepresented.

High MSE. In the high MSE mathematics expectancy-value class, MSE was high (+1.535Z) and the other EV profile indicators were above the mean, ranging from +.452Z to +.891Z. These students had a perception of cost that was the most positive of any of the classes; they also had the highest mean achievement test scores. High-ability students were represented in this group at nearly twice the rate as in the population. The SES of this group was above the mean. These students identified STEM occupations at a rate that was 9% higher than the mean rate for the population. Asian males and White males were overrepresented in this group, while Hispanic females and White females were underrepresented. This class is best described as traditional high math achievers. These students had the strongest sense of mathematics self-efficacy and saw themselves in STEM occupations at greater rates than the population. This class of students fit the stereotype of the gifted math student.

High MUV. In the high MUV mathematics expectancy-value class, MUV was high (+1.139Z) and the other EV profile indicators were above the mean, ranging from .278Z to .511Z, but were lower than the values for the high MSE class. These students

had a perception of cost-time that was the same as the high MSE group but had a more negative perception of cost-popular than the high MSE students. The mean achievement score was the same as the mean for the population. High-ability students were represented in this class at a rate that was 2.4% less than the population. These students had the lowest mean SES of the four classes. These students identified STEM occupations at a rate that was 2.3% higher than the population. Black females and Black males were overrepresented in this class, while White females and White males were underrepresented. This class is best described as math utilitarian. These students had the strongest perception of the usefulness of mathematics for their future careers and college success, however they did not see themselves in STEM occupations at greater rates than the population.

Summary of Science Expectancy-Value Classes

In this section, the characteristics of the science classes that were identified through latent class analysis are discussed. Table 33 provides a comparison of the data for each science class.

Science Classes

Low. In the low science expectancy-value class all of the EV profile indicators were below the mean, ranging from -.304Z to -0.599Z. These students had a perception of cost that was average and achievement test scores that were at the mean. High-ability students were represented in this group at a rate that was 2.1% less than in the population. The SES of this group was at the mean. These students identified STEM occupations at a rate that was 6.8% less than the mean rate for the population. No race-gender groups were under- or over represented in this class.

Typical. In the typical science expectancy-value class all of the EV profile indicators were near the mean. These students had a perception of the cost that was average and mathematics achievement scores that were at the mean. High-ability students were represented at the same rate as in the population. The SES of this group was at the mean. These students identified STEM occupations at a rate that was 2.4% below the mean rate for the population. White females were underrepresented in this class, while Black students were overrepresented.

High. In the high science expectancy-value class, SUV was high (+1.479Z) and the other EV profile indicators were above the mean, ranging from .639Z to .889Z. These students had a perception of cost that was more positive than average, at nearly the same level as the high MSE students. The mean achievement score was slightly above the mean for the population. High-ability students were represented in this class at a rate that was 2.8% greater than the population. The SES of this group was at the mean. These students identified STEM occupations at a rate that was 15.2% higher than the population. Asian students and Black females were overrepresented in this class, while White males and Hispanic males were underrepresented. This class is best described as science motivated. These students had the strongest perception of the usefulness of science to their future careers and college successes, and they saw themselves in STEM occupations at greater rates than the population.

Table 33

Summary of Science Expectancy-Value Classes

	SSE M (SE)	SAV M (SE)	SUV M (SE)	SIV M (SE)	Cost-time M (SE)	Cost-Popular M (SE)	Math ach. (of 70) M (SE)	High-ability students % of class	SES M (SE)	STEM % of class	Over-rep	Under-rep
S1 – Low (34.3%)	-.304 (.055)	-.397 (.048)	-.598 (.069)	-.599 (.067)	-.024 (.018)	-.126 (.018)	38.115 (.164)	13.8	-.092 (.014)	19.3		
S2 – Typical (51.7%)	-.034 (.026)	.078 (.029)	-.035 (.026)	.127 (.024)	-.045 (.012)	.000 (.013)	39.357 (.157)	15.2	-.057 (.010)	23.7	WF	BF, BM
S3 – High (14.0%)	.673 (.034)	.639 (.079)	1.479 (.016)	.889 (.042)	.196 (.027)	.192 (.028)	40.293 (.315)	18.7	-.049 (.020)	41.3	AF, AM, BF	HM, WM
Entire Sample	.002 (.017)	.001 (.016)	.002 (.017)	.006 (.017)	.000 (.016)	.000 (.017)	38.956 (0.187)	15.9	-.072 (.012)	26.1		

CHAPTER 5

DISCUSSION, CONCLUSIONS, IMPLICATIONS

The purposes of this study were to investigate extant expectancy-value motivational profiles of ninth grade students and the relationships of those profiles with occupational choice, high-ability status, mathematics achievement, and demographic variables. This study investigated the following research questions:

Research Questions

1. What distinct profiles emerge from measures of mathematics self-efficacy and mathematics task values (interest-enjoyment value, utility value, and attainment value)?

2. What distinct profiles emerge from measures of science self-efficacy and science task values (interest-enjoyment value, utility value, and attainment value)?

3. How is cost related to mathematics and science profile membership?

4. How do the memberships of the mathematics and science profiles compare?

5. How do these profiles relate to mathematics ability?

6. How do these profiles relate to STEM occupational choice?

7. How do these profiles relate to giftedness?

8. How does membership in these profiles differ by (a) race-gender group and (b) socioeconomic status?

Extant Mathematics and Science Expectancy-Value Profiles

The main objective of this study was to identify mathematics and science motivation latent classes. An exploratory modeling process revealed patterns in the latent profile indicators that were observed in the population of US ninth-grade students in 2009. Separate models were established for mathematics expectancy-value and for science expectancy value. These models differed by the number of distinct classes that were identified and by the parameterization of the covariance matrix. In math model 4D, four distinct classes of mathematics expectancy-value were identified and the best model employed a covariance matrix in which the indicator variances were allowed to vary within clusters and across classes, while the covariances could vary within classes but were constrained to be equal across the classes. The math latent class indicators, MSE, MAV, MUV, and MIV were correlated, but these correlations were the same for each class. The variances of the four indicators were different from each other and varied across the classes. In science model 4E, three distinct classes of science expectancy-value were identified and the best model utilized a covariance matrix in which the indicator variances and covariances were allowed to vary within and across classes. The science latent class indicators, SSE, SAV, SUV, and SIV were correlated and those correlations differed for each class. The variances of the four indicators were different from each other and varied across the classes. Thus the best science model had a more complex covariance matrix than the best math model, while the best math model had more classes than the best science model. The latent profile indicators for science had more complex interrelationships while the cases were categorized into fewer distinct classes than the math model.

The classes that were identified partially supported the hypothesis that a number of subgroups would be identified with high, low and mixed levels of expectancy-value. The high and low classes were identified for mathematics and for science, while mixed levels were only identified for mathematics. Based on Conley (2012), who found seven distinct clusters in her analysis of mathematics expectancies and values, it was expected that the latent class models would have had several classes. However, Conley used cluster analysis and model selection was affected more by the researcher's opinion than objective measures. Therefore, direct comparisons between the cluster solutions in Conley (2012) and the latent profile solutions in the current study may not be valid.

Comparison of Math and Science Profiles

The latent class expectancy-value models that were obtained in this study revealed information about students' comparative self-efficacies and subjective task values in mathematics and science. While the math model had four classes, the science model only had three classes. However, both models were selected based on the model-selection guidelines of Pastor et al. (2007). Thus, there was more differentiation in the ways that students viewed their mathematics expectancies and values than their science expectancies and values. First, in the math model the high MSE class (class 3) depicted a class of students who had a mean math self-efficacy that was at the 94th percentile with a math utility value that was around the 67th percentile. However, a similar profile was not seen in the science classes. Second, the high MUV class (class 4) described a class of students who had a mean math utility value that was at the 87th percentile with a math self-efficacy that was around the 60th percentile. A similar high SUV profile was identified in the science classes. The high SUV class described a class of students who

had a mean science utility value that was at the 93rd percentile with an average science self-efficacy that was at the 75th percentile. The high math and science classes had the highest correct class assignment probabilities, which indicated that the high classes are better defined than the low and average classes where greater probabilities of incorrect assignment were observed. The math profiles reflected a wider range of all constructs between classes, except for utility value, than the science profiles.

Class Size and Membership

The size of the two high math classes combined (66.2%) far exceeded the size of the high science class (14.0%), the size of the low science class (34.3%) was slightly larger than the size of the low math class (29.7%), and the size of the average science class (51.7%) was much greater than the size of the average math class (36.5%). Fewer students had high science expectancy-value profiles than had high mathematics expectancy-value profiles. Although a class of students who placed a high utility value on science was identified, a class typified by high science-self-efficacy was not identified. Classes had a wider range of math self-efficacies than science self-efficacies; a relatively low MSE was observed in the high MUV class. A possible cause may be that students have had a greater number of and more frequent experiences with mathematics than with science prior to high school because of US testing mandates that place much greater emphasis on mathematics than science in the K-8 curriculum (Berliner, 2009, 2011; McMurrer, 2008). Thus, students may have not developed a strong sense of what science is or of their abilities in science by the ninth grade. If the current trend of increased emphasis on STEM education continues, more differentiation of students' science expectancy-value profiles may result.

Some dependency between math and science class membership was identified because students who were in the two high math classes were in the high science class, those in the average math class were in the average science class, and those in the low math class were in the low science class more frequently than would have been expected by chance. However, a surprising finding was that students who were in the high MSE class were in both the low and high science classes more frequently than would have been expected by chance and in the average science classes less frequently than would have been expected by chance. For some students, there was a negative relationship between math expectancy-value and science expectancy-value.

Representation of High-Ability Students

In this study, high-ability was operationalized as students who scored +1Z (84.1%) on the mathematics achievement test within the respective race/ethnicity group. This is a much broader conception of giftedness than is generally seen in practice because typical threshold scores are closer to 95% for selection, and it reflects a strategic effort to identify equal proportions of gifted students in every race/ethnicity group through the use of group-specific thresholds. It was hypothesized that expectancy-value profiles would not be strongly related to giftedness; the findings of this study supported this hypothesis. The representation of high-ability students varied considerably between the math classes and the science classes. While the high MSE class had nearly twice the level of high-ability students as in the population, high-ability students were represented in the high MUV class at a rate proportional to the population. High-ability students had a significantly greater chance of belonging to the high MSE class, but their chances of belonging to the high MUV classes or low math classes were not different than their

chances of belonging to the average class. However, there was a positive relationship between mathematics ability and math self-efficacy, as would be expected. Interestingly, in the science classes the distribution of high-ability students was much more uniform, with little difference in the chance of high-ability students belonging to the low or high science group compared to the average group. There was a much smaller relationship between high-ability and science expectancy-value class membership than the relationship between high-ability and math expectancy-value class membership. Thus, high-ability status based on mathematics achievement was a poor predictor of expectancy-value class membership in science. However, this difference may be attributable to the fact that the identification of high ability was a mathematics achievement measure because no science achievement measure was administered in HSLS. Furthermore, the more inclusive operationalization of high ability means that many students who were included in this group have not been formally identified as having high ability by their schools. The lack of formal identification may cause these students to have lower self-efficacy and attainment value in the domain because they have not received the affirmation of their teachers. These lower expectancies and values would result in a lower expectancy-value class membership than the students' abilities might warrant.

Representation of Race-Gender Groups

It was hypothesized that males (Black and White) would be overrepresented in the high expectancy-value profiles. The findings only partially support this hypothesis. White males were only overrepresented in the high MSE class, while Black males were only overrepresented in the high MUV class. Furthermore, neither group was overrepresented

in the high science class. However, several other instances of over- and underrepresentation were identified in the mathematics classes and some in the science classes. Asian males and White males were overrepresented in the high MSE group, while Black females and Black males were significantly overrepresented in the high MUV group. Hispanic females and White females were overrepresented in the low math class. The high rate of representation of Black females in the two high math classes implies that these girls have not internalized common negative stereotypes about mathematics. However, the low rate of representation for Hispanic females and White females implies that these girls may have been more affected by negative stereotypes. This supports the findings of Simpkins and Davis-Kean (2005) that the gap between females mathematics self-concepts has narrowed, while contradicting the findings of Riegle-Crumb et al. (2011) who found that Black females had lower math self-concepts than other students. The findings of this study indicated that gender gaps in mathematics expectancy-value class assignment are much smaller for Black students than for other students. This phenomenon should be investigated further.

Black females were the only group overrepresented in the high MUV group. This finding is interesting because it implies that Black female students view mathematics as important for their future careers and college entrance at greater rates than other students. However, like other members of the high MUV group, these students selected STEM occupations at rates that were only slightly higher than the overall population. This finding implies that these students saw mathematics as important for entrance into college, success in college, and for future careers, but not necessarily for a STEM career. The prominence of utility value in both the mathematics and science profiles is supported

by previous research (e.g. Andersen & Ward, in press; Maltese & Tai 2011), which supported utility value as predictive of persistence plans or the completion of a STEM bachelor's degree. However, in this study the high MSE profile had a stronger association with STEM occupational choice than the high MUV profile.

The distribution of Black females among the motivation classes was surprising because the overrepresentation of these students in the high math and science classes implies that these girls do not personally endorse prevalent stereotypes about minorities or females and mathematics and science ability. This is a contrast to the underrepresentation of Hispanic females and White females in the high math and science classes, which indicates that Hispanic females and White females are more susceptible to gender stereotyping than Black females. However, the continued underrepresentation of Black females in STEM occupations may indicate that events that happen after ninth grade may deflate these girls' sense of efficacy and value and reduce their motivation to persist.

The science classes had fewer instances of over- or underrepresentation. In the high SUV group, Hispanics males and Whites males were underrepresented, while Asian females, Asian males, and Black females were overrepresented. An interesting finding was that Hispanic females were not underrepresented in the high science profile, nor were Black males which ran counter to research on identity-based motivation (e. g. Carlone & Johnson, 2007; Kao, 2000; Oyserman & Destin, 2010) that claims lower science identities for these students. However, none of the science classes was typified by a high science self-efficacy.

In general, White students were underrepresented in both high utility value classes (math and science), which indicated that majority status tends to be correlated to lower utility value. Of minority students, only Hispanic males were underrepresented in the high SUV profile indicating that minority status tended to correlate to higher utility value. Surprisingly, even though White males are the modal gifted for science these students were underrepresented in the high science class.

Representation of SES

Students of different SES were distributed quite differently in the mathematics classes than in the science classes. The high MSE class had the highest mean SES, the average class had an average value of SES, and both the high MUV and low classes had the same and lowest mean SES. Lower SES students tended to have a higher utility value for mathematics. Although the differences in SES were statistically significant, they were relatively small. These findings imply that there was not a relationship between SES and science expectancy-value class. It was surprising that science class membership was independent of SES while math class membership had a relationship with SES, albeit a small one. In the math classes, the high MUV class had the lowest SES and the highest utility value for mathematics, which implies that students in this class may view mathematics coursetaking as a means to pull themselves up from a lower SES group to a higher one. Science does not appear to be viewed in this way.

STEM Occupational Choice

Overall, 26.1% of ninth-grade students planned to be in a STEM occupation at age 30 and have earned a bachelor's degree. It was hypothesized that high expectancy-value classes would have stronger relationships to STEM occupational choice. The

results support this hypothesis. Both the math and science latent classes had relationships with STEM occupational choice, but the science classes better predicted choice than the math classes. Among the math classes, the high MSE class had the highest rate of STEM occupational choice (35.3%), while the high MUV profile had a lower rate (28.4%). This finding implies that high math self-efficacy is a better predictor of choice than high math utility value. The high MUV class had only a slightly higher rate of choice than the average math class (24.6%). This implies that although students in the high MUV class hold a high utility value for mathematics, this is not as influential in the decision to pursue a STEM career as high values of mathematics self-efficacy. Among the science classes, the high SUV profile had the highest rate of STEM occupational choice (41.3%); however, there was not a high SSE profile for comparison. The average science class (23.7%) had a rate that was comparable to the average math class (24.6%). These findings imply that science-expectancy value class membership is a better predictor of STEM occupational choice than math expectancy-value membership. The high SUV class had the highest SSE of the three science classes; therefore this finding is somewhat similar to the findings of Andersen and Ward (in press), that SSE was a better predictor of choice than MSE. However, the lack of separate high SSE and high MUV classes clouds this issue. Most extant research relies on mathematics expectancies and values to predict STEM outcomes (e. g. Maltese & Tai, 2011; Mau, 2003) and this practice may be less valuable than using science expectancies and values.

STV Components

In this study, a person-centered approach was taken that considered the relationship of profiles of the STV variables that naturally occurred with correlaten and

an outcome, rather than the mean levels of the STV variables. These two approaches are different methods of looking at the same set of data and each provides useful information. Previous research has shown that the STV variables are highly correlated and has combined the multiple constructs into a composite variable (e. g. Eccles et al., 1984; Simpkins & Davis-Kean, 2005; Watt et al., 2006). In this study, profiles of the STV variables showed that the variables are somewhat related but do not always occur at the same levels. In the science profiles, the low, average, and high groups all had low, average, or high values of each of the EV constructs, respectively; no mixed profiles were observed. In the mathematics profiles, the low and average profiles each contained low or average values of the EV constructs. However, the two high mathematics profiles were mixed. In the high MUV class (class 4) the value of MUV was higher than in the high MSE class (class 3). However, MAV was higher in class 3 than class 4, while there was no significant difference in MIV between the two classes. The differences between these two math classes justify the use of a person-centered approach because these differences would not be observed if the STV variables were combined into a composite. However, no mixed classes were observed in the science profiles. The C, D, and E, parameterizations of the science profiles would not converge for models with larger than three classes. Mixed profiles were observed in the A parameterization, but these models did not fit as well as the other parameterizations.

Cost

The cost scale was somewhat of an enigma in this study. Initially, attempts were made to include cost in the set of science latent class indicators, but the models would not converge due to a problem in the covariance matrix involving the cost variable.

Therefore, the method was modified to test science latent class models that did not include cost and to use cost as a correlate.

The math classes had nearly the same relationship with cost-time as the science classes. In math, the range of mean cost-time from the lowest to the highest group was 0.227 which is an effect size of $d = 0.200$. The high MSE and high MUV groups had equivalent, positive perceptions of cost ($z = 0.175$ and 0.133). There was no difference in the high MUV and high MSE group beliefs that exerting effort in math and science would have a negative impact on their time with friends and for activities. This analysis showed a significant relationship between math expectancy-value class and cost-time. In science the range of cost-time from the lowest to the highest group was 0.220 which is an effect size of $d = 0.239$.

The effect on cost-popular was smaller for the science classes than for the math classes. The effect size of the difference in cost-popular from the lowest to the highest math class was $d = 0.330$. In science, the effect size was 0.167. The relationship between cost-popular and science class membership is much smaller than the relationship between cost-popular and math class membership. This implies that there is much less difference between the perceptions of cost for members of different science classes than for members of different math classes.

This study addressed problems in the extant literature with external validity because a large, nationally representative sample was used. Previous studies of STEM occupational choice lacked sufficient representation of underrepresented minority students. This provided a chance to examine students' expectancies and values to see if stereotypical patterns existed. The only previous study that separated STV components

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and included cost was Conley (2012). However, her sample consisted of predominantly Vietnamese and Latino children of working class parents. Conley (2012) found that mathematics utility value was uniformly high and cost had either high or low values with no average values across the seven-cluster solution. In this sample that had proportional representation to the US population of ninth-grade students in 2009, classes with high and low utility value were identified. However, no classes with extreme values of cost were identified. An explanation for this may be that the subpopulations in which extreme values of cost might be found were relatively small portions of this sample.

Motivation Profiles and Gifted Potential

The classification of students into motivation profiles has potential to facilitate the identification of high-ability students who may exhibit gifted behavior. The Three Ring Conception of Giftedness (Renzulli, 1978) describes giftedness as the intersection of three traits: above-average ability, task-commitment or motivation, and creativity. Cross and Coleman (2005) described gifted adolescent children as those who "demonstrated consistent engagement in activities" (p. 59). Production and consistent involvement are indicators of high levels of motivation. In this study, a $+1Z$ cutoff was used to define the high-ability group and latent profile analysis was used to identify the high motivation groups. Through this process, students who possessed the first two traits were identified. In the Three Ring Conception of Giftedness (Renzulli, 1978), motivation is a key component that must be combined with above average ability and creativity to produce gifted behavior. In the School-Based Conception of Giftedness, Cross and Coleman (2005) asserted that if a child does not exhibit such indicators of motivation, the child should not be labeled gifted.

Expectancy-value profiles could provide a means to identify those students within the high-ability group who have the greatest potential for creative productivity within that domain. In the math profiles, the students in the high MSE class (class 3) would be identified as highly motivated. This class had 31.2% of its membership from high-ability students; this represents 4.1% of the population, which could be considered mathematically gifted based on two of the three rings. This elite group represented 25.8% of the high-ability students. If the high MUV class (class 4) is included in the highly motivated group, the percentage of the population that would be identified as mathematically gifted increases to 6.9%, or 43.3% of the high-ability students. In the science profiles, the students in the high SUV class had 18.7% of its membership from high-ability students; this represents 2.6% of the population and 16.4% of the high-ability students. These two groups have some overlap in membership. The finding that a minority of high-ability students also exhibited high motivation is supported by previous research with small samples (e. g. Gottfried, Cook, Gottfried, & Morris, 2009; Gottfried & Gottfried, 2004).

This approach demonstrates a way to cast a wider net for identification of students who are potentially gifted because within group norms were used to identify high-ability students and motivation was considered. The use of within group norms has been recommended by Lohman (2005, 2006) as a method to alleviate underrepresentation in gifted programs, while motivation has been identified in the gifted education literature as vitally important to the development of talent and creative productivity (Coleman & Cross, 2005; Subotnik et al., 2011). Thus, attempts to identify the concomitance of high-

ability and high motivation could be useful in gifted education to select those students who would benefit most from gifted education services.

Motivation Profiles and Underachievement

Expectancy-value profiles could also be used to identify high-ability, but undermotivated students who are likely to be underachieving academically. Contemporary methods used in schools generally compare expected school achievement, as indicated by achievement or IQ tests, to actual school achievement; underachievement is indicated by a large disparity between the two. However, by broadening the field of view to include above-average students and measuring motivation a larger number of underachieving, undermotivated, high-ability students could be identified. An examination of the rate at which high-ability students populated the lowest motivation profiles in this study exemplifies this point. The low math class (class 2) was comprised of 8.4% high-ability students and this represented 2.5% of the population, or 15.7% of high-ability students. The low science class (class 1) consisted of 13.8% high-ability students and this represents 4.7% of the population, or 29.6% of high-ability students. The size of the low-motivation, high-ability group in science was larger than the high-motivation, high-ability group. The high occurrence of high-ability students in low motivation profiles is a topic that should be investigated further to ascertain the causes of this undermotivation, as this condition is likely to result in underachievement and hamper the development of potential. However, this group of high-ability students may be less likely to benefit from gifted education services than the group of high-ability students who exhibit high motivation. Thus, considerations of relative motivation could prevent the placement of students who are unlikely to benefit from gifted education services in

such programs over placements of students who are more likely to benefit. This view is advocated by Cross and Coleman (2005) in the School-Based Conception of Giftedness. Given the omnipresent fiscal concerns of public schools it seems prudent to reserve placement in gifted education programs to those students who are most likely to benefit. Historically, these placements have been reserved for students who scored very high on achievement or IQ measures without consideration of motivation. Perhaps, talent development outcomes of gifted education could be improved if motivation was considered along with measures of intellectual potential.

Some evidence was found of disidentification among high-ability students. In general, the students with higher self-efficacies had higher utility, attainment, and interest values. This analysis may not have revealed groups of student with high self-efficacy and low subjective task values because the high-ability group was less than 16% of the total sample; if the latent profile analysis was conducted using the high-ability group alone, perhaps this class may have been detected. However, substantial numbers of high-ability students were found in the low motivation classes, which means that many high-ability students exhibited low self-efficacy in mathematics or science. This contradicted the findings of Dai, Moon, and Feldhusen (1998) in their review of the literature on gifted students and self-efficacy that claimed invariant findings of higher self-efficacy among gifted students. The relationships of self-efficacy and giftedness in this sample should be investigated further.

Future Research

It remains to be analyzed how the classes and the groups of students who chose STEM occupations were populated in detail. Although the correlates of race-gender

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group, high-ability status, and SES were included, interactions were not tested. Extant literature on the differences between minority and modal gifted children has raised many questions that could be answered with further analysis of these data. For example, questions in the literature concerning differentiated views of cost among race-gender groups could shed light on the reasons why some groups are underrepresented in STEM occupations. These data could also be used to answer questions about the potential stigma of STEM and how it is perceived by students of different race/ethnicity, gender, and SES. The future waves of data that will be collected from this sample will also provide an opportunity to explore longitudinal person-centered approaches.

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competence and motivation* (pp. 222–239). New York, NY: Guilford Press.

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expectancy/value and disidentification models for understanding ethnic group

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Appendix A

HSLS: 2009 Variables Used

Variable	Description	Use
X1TXMSCR	Mathematics IRT-estimated number right score. Maximum of 72 possible.	To identify above-average mathematics ability within each race group and as a correlate.
X1STU30OCC6	Occupation expected at age 30, specified by six digit O*NET code	Used to create outcome variable, STAYIN
X1RACE	NCES composite variable designating race (8 values)	To select the Black, Hispanic, and White students who will be included in this study.
X1SEX	NCES composite variable designating gender	Used with X1RACE to create dummy variables for race-gender groups
X1SES	NCES composite variable indicating SES.	Correlate
S1TEFRNDS, S1TEACTIV, S1TEPOPULAR, and S1TEMAKEFUN	Asked students about the impact of spending a lot of time and effort in math and science classes on the amount of time for friends/activities and peer responses	Dimension reduction and factor analysis used to create scale scores for COST.
X1MTHEFF (S1MTESTS, S1MTEXTBOOK, S1MSKILLS, S1MASSEXCL)	NCES created scale score representing mathematics self-efficacy, 4 items, α = .90	Latent Class Indicator MSE
X1SCIEFF (S1STESTS, S1STEXTBOOK, S1SSKILLS, S1SASSEXCL)	NCES created scale score representing science self-efficacy, 4 items, α = .88	Latent Class Indicator SSE

X1MTHID (S1MPERSON1, S1MPERSON2)	NCES scale of student's math identity. Used as indicator of math attainment value. 2 items, α = .84	Latent Class Indicator MAV
X1SCIID (S1SPERSON1, S1SPERSON2)	NCES scale of student's science identity. Used as indicator of science attainment value. 2 items, α = .83	Latent Class Indicator SAV
X1MTHINT (S1FAVSUBJ, S1LEASTSUBJ, S1MENJOYING, S1MENJOYS, S1MWASTE, S1MBORING)	NCES scale of math interest-enjoyment value, 6 items, α = .75	Latent Class Indicator MIV
X1SCIINT (S1FAVSUBJ, S1LEASTSUBJ, S1SENJOYING, S1SENJOYS, S1SWASTE, S1SBORING)	NCES scale of science interest-enjoyment value, 6 items, α = .73	Latent Class Indicator SIV
X1MTHUTI (S1MUSELIFE, S1MUSECLG, S1MUSEJOB)	NCES scale of math utility value, 3 items, α = .78	Latent Class Indicator MUV
X1SCIUTI (S1SUSELIFE, S1SUSECLG, S1SUSEJOB)	NCES scale of science utility value. 3 items, α = .75	Latent Class Indicator SUV

Appendix B

Researcher-created Variables Used

Variable	Description	Use
CM	Researcher-created variable to represent class membership	Latent Class
CS	Researcher-created variable to represent class membership	Latent Class
HABILITY	Researcher-created dummy variable for ability status; Students who have scores on X1TXMSCR that are 1 SD above the mean.	Correlate
STEM	Researcher-created dummy variable for STEM occupational choice defined as students who planned to be in a STEM occupation at age 30 and have at least a Bachelor's degree	Outcome Variable
WM, WF, BM, BF, HM, HF, AM, AF	Researcher-created dummy variables for race-gender group membership	Correlates
COST-Time COST-Popular	Researcher-created scale score to represent perceived cost.	Correlate

Appendix C

List of STEM Occupations

O*NET Code	Description
131041	Coroner/Medical Examiner
150000	Computer Sci/Technology
151000	Computer Sci/Tech
151021	Computer Programmer
151031	Computer Programmer
151032	Software Design
151041	IT Support
151051	Computer systems analyst
151071	Computer network specialist
151099	Computer engineer, video game designer
152000	Math
152011	Actuary
152021	Mathematician
152041	Statistician
170000	Computer Business
171011	Architect
171012	Landscape Architect
172000	Engineer
172011	Aerospace Engineer
172021	Agricultural Engineer
172031	Biomedical Engineer
172041	Chemical Engineer
172051	Civil Engineer
172061	Computer Engineer
172071	Electrical Engineer
172072	Electronic Engineer
172112	Industrial Engineer
172121	Naval/Marine/Technician/Engineer
172131	Materials Engineering
172141	Automotive/Mechanical/Robotic Engineer
172161	Nuclear Engineer
172171	Petroleum Engineer
172199	Engineering, All Others
173011	Architectural & Civil Drafters
173012	Technology Design
173023	Electronic technician, vehicle engineer
190000	Scientist

191000	Astronaut, Biologist, Scientist
191013	Plant biologist
191021	Geneticist, biochemist
191022	Microbiologist
191023	Marine biologist, ornithologist, herpetologist, zoologist
191029	Biotechnology, physiologist
191031	Park ranger, conservationist
191032	Forestry
191041	Epidemiologist
191042	Medical research scientist
192000	Physics
192011	Astronomy
192012	Physics (Astro, Nano, Nuclear)
192021	Meteorology/Space
192031	Chemist & Psychotherapist
192041	Environmental Science
192042	Geology
193000	Psychology (Social Science)
193011	Economist (Social Science)
193030	Psychologist (Social Science)
193039	Psychologist (Social Science)
193041	Sociologist (Social Science)
193051	Urban Planner (Social Science)
193091	Anthropologist and Archaelogist (Social Science)
193094	Political Scientists (Social Science)
194000	Forensic Science
194021	Biotechnologist
194031	Chemical Technician
194091	Environmental Scientist
194092	Forensic Science Technician
251000	Math or Science Professors
251071	Health Specialties Teachers, postsecondary
251072	Nursing Instructor, post secondary
252000	STEM High School Teachers
252031	Math or Science High School Teacher
271021	Engineering (Car design, weapons research, inventor)
290000	Medical
291000	Doctor/Medical
291011	Chiropractor
291021	Dentist
291023	Orthodontist
291031	Dietician
291041	Optometrist

291051	Pharmacist
291061	Anesthesiologist
291062	General Practitioner
291063	Internal Medicine
291064	OB GYN
291065	Pediatrician
291066	Psychiatrist
291067	Surgeon
291069	Physicians and Surgeons
291071	Physician Assistant
291111	Nurse
291122	Occupational Therapist
291123	Physical Therapist
291126	Respiratory Therapist
291127	Speech-Language Pathologist
291129	Therapists
291131	Veterinarian
291199	Health Diagnosing and Treating Practitioners
292000	Medical
292011	Medical Lab Director
292021	Dental Hygienists
292031	Cardiovascular tech
292032	Ultrasound technician
292034	X-ray tech
292041	EMT, Paramedic
292052	Pharmacy Tech
292055	Surgical Tech
292056	Veterinarian Tech
299011	Occupational Health Tech
299091	Athletic Trainer
310000	Geriatrics/NICU
311012	Nurses Aide
312000	Occupational therapy assistants
319011	Massage Therapists
319092	Medical Assistant
319096	Veterinary Assistant
492011	Computer technician
493011	Aviation mechanic/technician
493023	Automotive technician
514041	Machinist
514061	Model designer
553019	Military STEM jobs

Appendix D

Missing Data Analysis

A large number of cases had missing values on some of the latent profile

indicators because these students were not enrolled in math or not enrolled in science,

which resulted in a legitimate skip of the section of questions that pertained to the math

or science course respectively. If this was a random effect, the cases with missing data

could be omitted without biasing the sample. Ultimately, the decision was made to

include students who were not enrolled in a mathematics or science class in Fall 2009 in

subsequent analyses. The following data and analyses are provided to substantiate this

decision.

Two dummy variables were created that indicated students who were not enrolled

in math (F09Math) or not enrolled in science (F09Science). A third dummy variable

(MathSci) was the sum of F09Math and F09Science. Table 34 displays the frequency

distribution of MathSci and the SES for those groups. A one-way ANOVA was used to

compare the mean SES for each of the three groups and was significant ($F(2) = 248.037$,

$p = .000$). A Tukey test was used to conduct a post hoc analysis and the differences

between each pair of groups was significant at the $p = .000$ level. The students who were

not enrolled in math or science had significantly lower SES than the students who were

enrolled math or science as well as the students who were enrolled in math and science in

Fall 2009.

Table 34

Student Enrollment in Math or Science in Fall 2009

Status	N	SES M (SD)
Not enrolled in Math or Science	1,152	-0.356 (.696)
Enrolled in Math or Science	2,859	-0.106 (.747)
Enrolled in Math and Science	15,782	0.101 (.789)

Another analysis was conducted to examine the differences in these groups separated by math and science (Table 35)

Table 35

Student Enrollment in Math and Science in Fall 2009

Status	Frequency	SES M (SD)	t	df	p	d
Enrolled in Math	17,883	0.0388 (1.003)				
Not enrolled in Math	1,910	-0.3634 (0.933)	16.829	1	.000	0.42
Enrolled in Science	16,540	0.0619 (1.00)				
Not enrolled in Science	3,325	-0.3150 (0.935)	19.846	1	.000	0.39

The SES of the enrolled students was compared to that of the students who were not enrolled using an independent samples t-test and the groups were found to be significantly different for math. The effect size was determined by calculating Cohen's d; the effect is a medium-sized effect. This is the same as saying that enrolled group mean SES is at approximately the 65th percentile of the non-enrolled group. Therefore, the omission of the non-enrolled students would bias the sample in favor of higher SES.

The enrolled and non-enrolled groups were also compared by race-gender group distribution (Table 36). Examination of this data showed that Hispanic and Black

students were overrepresented in the not enrolled groups while Asian and White students were underrepresented. Therefore, the omission of the non-enrolled students would also bias the sample in favor of Asian and White students.

Table 36

Math and Science Fall 2009 Non-Enrollment by Race-Gender Group

Race-Gender Group	Not enrolled in Math	Not enrolled in Science
Asian Female	.0764	.1129
Asian Male	.0995	.1388
Black Female	.1245	.2309
Black Male	.1308	.2079
Hispanic Female	.1149	.1840
Hispanic Male	.1371	.2152
White Female	.0788	.1425
White Male	.0866	.1551
All Females	.0905	.1576
All Males	.1023	.1709

Examination of these data led to the decision to retain the cases for students who were not enrolled in math or science in Fall 2009. Mplus has excellent capabilities for dealing with missing data (Wang & Wang, 2012); MLR estimation was used to handle missing data. Models were tested with three different datasets: (1) all cases, (2) all cases minus the students who were not enrolled in math, and (3) all cases minus the students who were not enrolled in science. The models were compared and found to be equivalent; the only difference that was noted was that the entropy was typically .05 higher for the models built from datasets without missing data. Thus, the decision was made to proceed with all subsequent analyses using the dataset that included the students who had not taken math or not taken science in Fall 2009.

Appendix E

Math Latent Class Profile Plots

Math Model 2A

Math Model 3A

z-score

Indicators

MSE   MAV   MUV   MIV

Class 1 15 1%
Class 2 57 7%
Class 3 27 1%

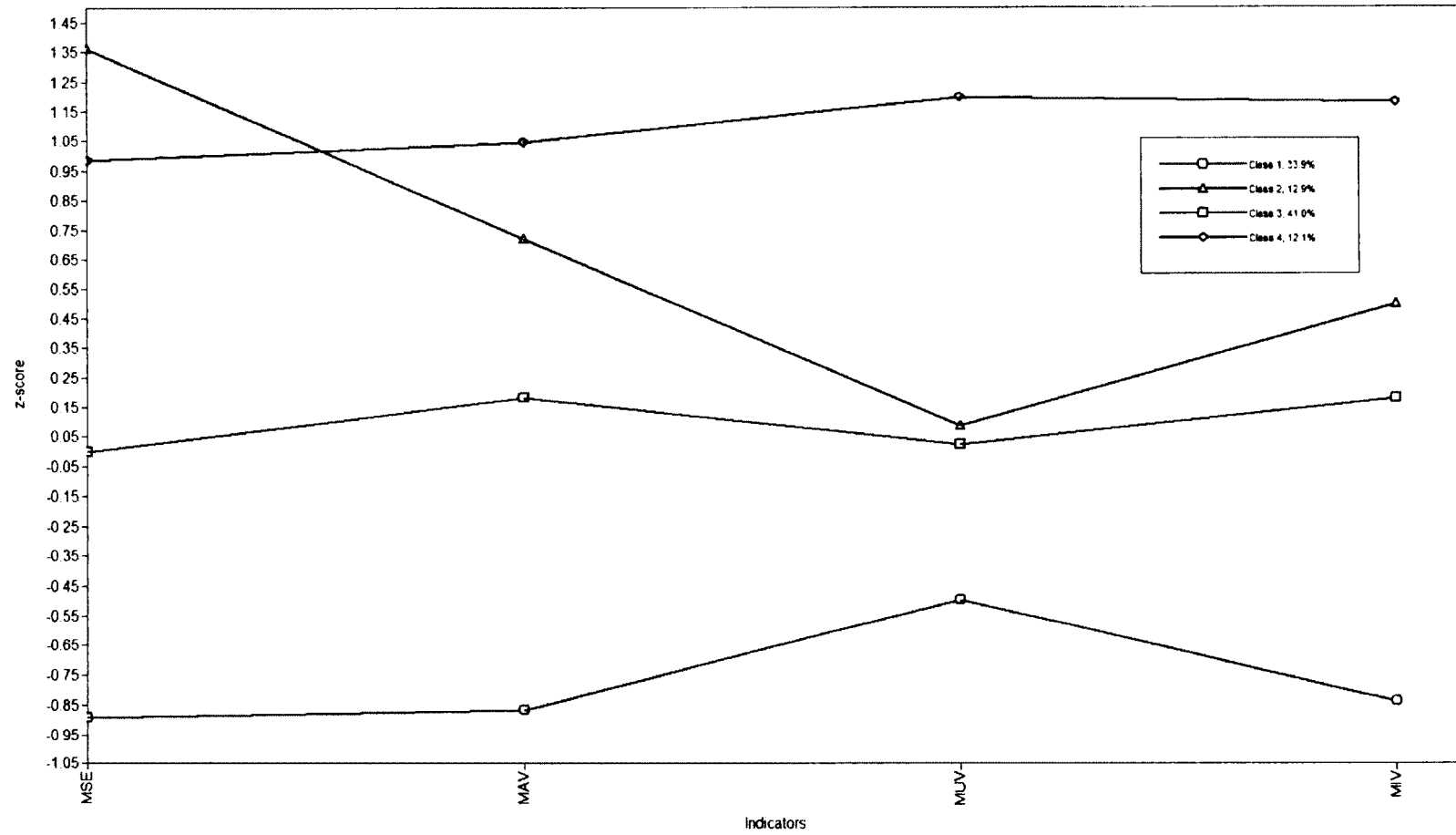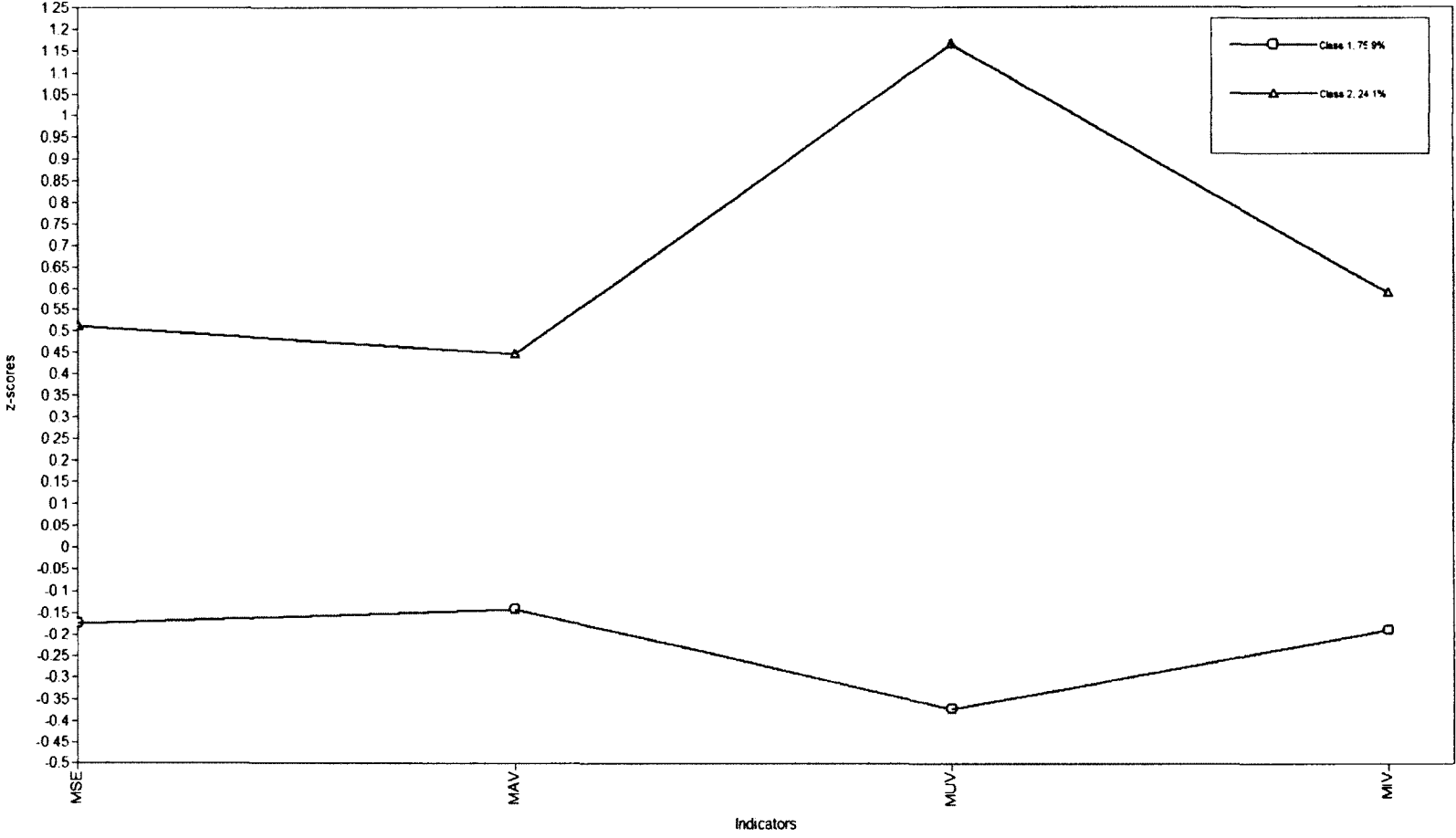Math Model 4A

169
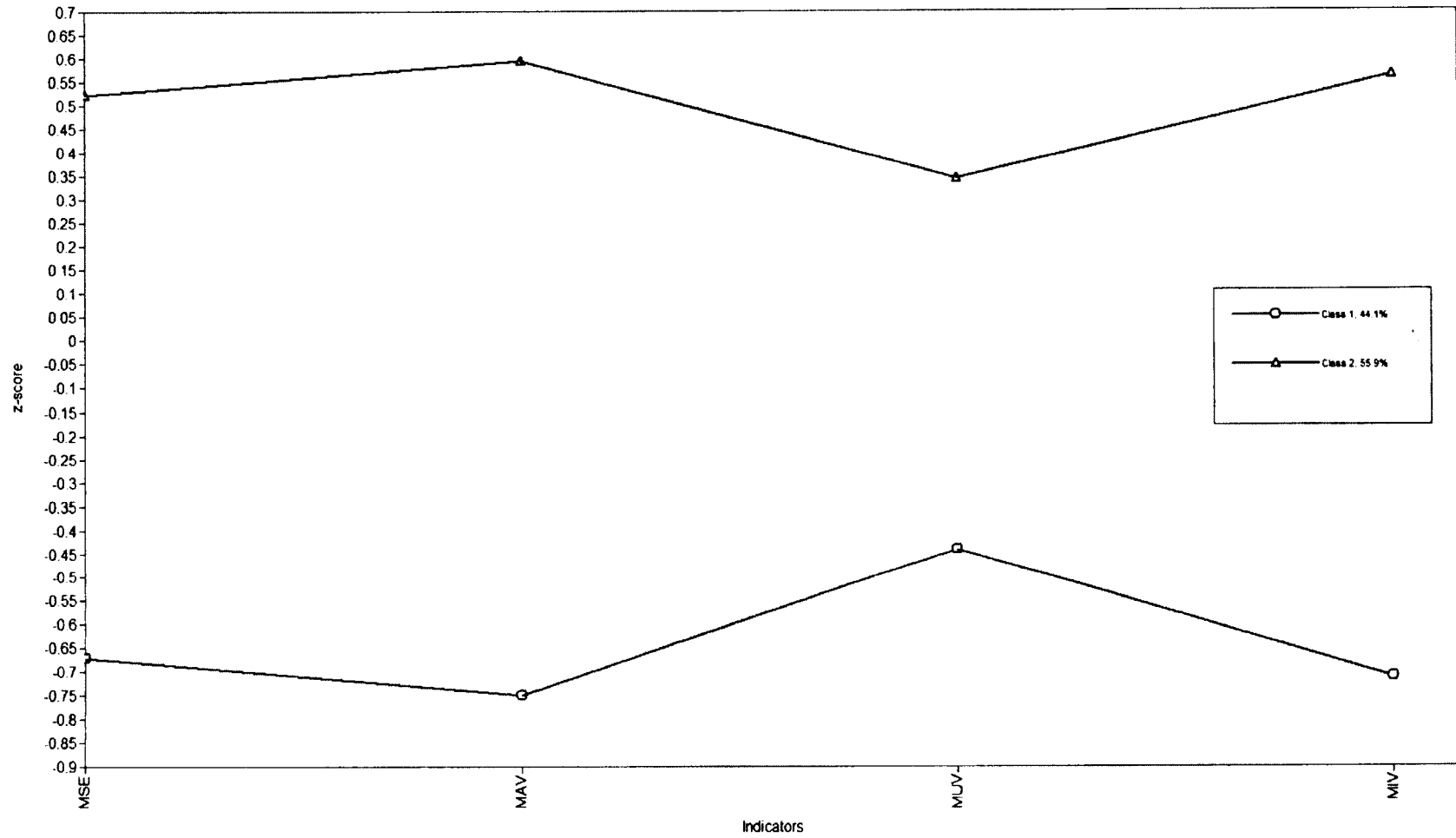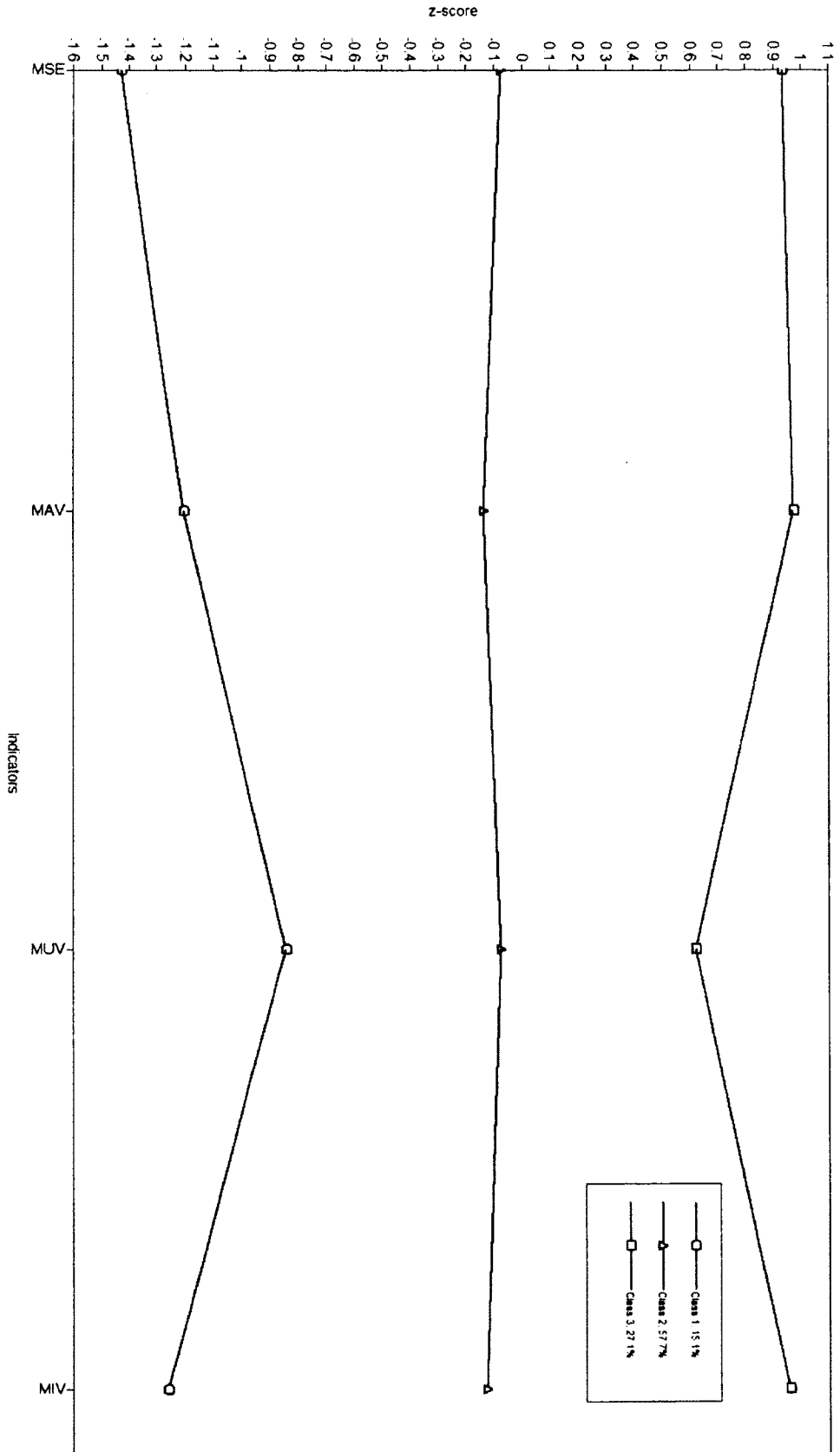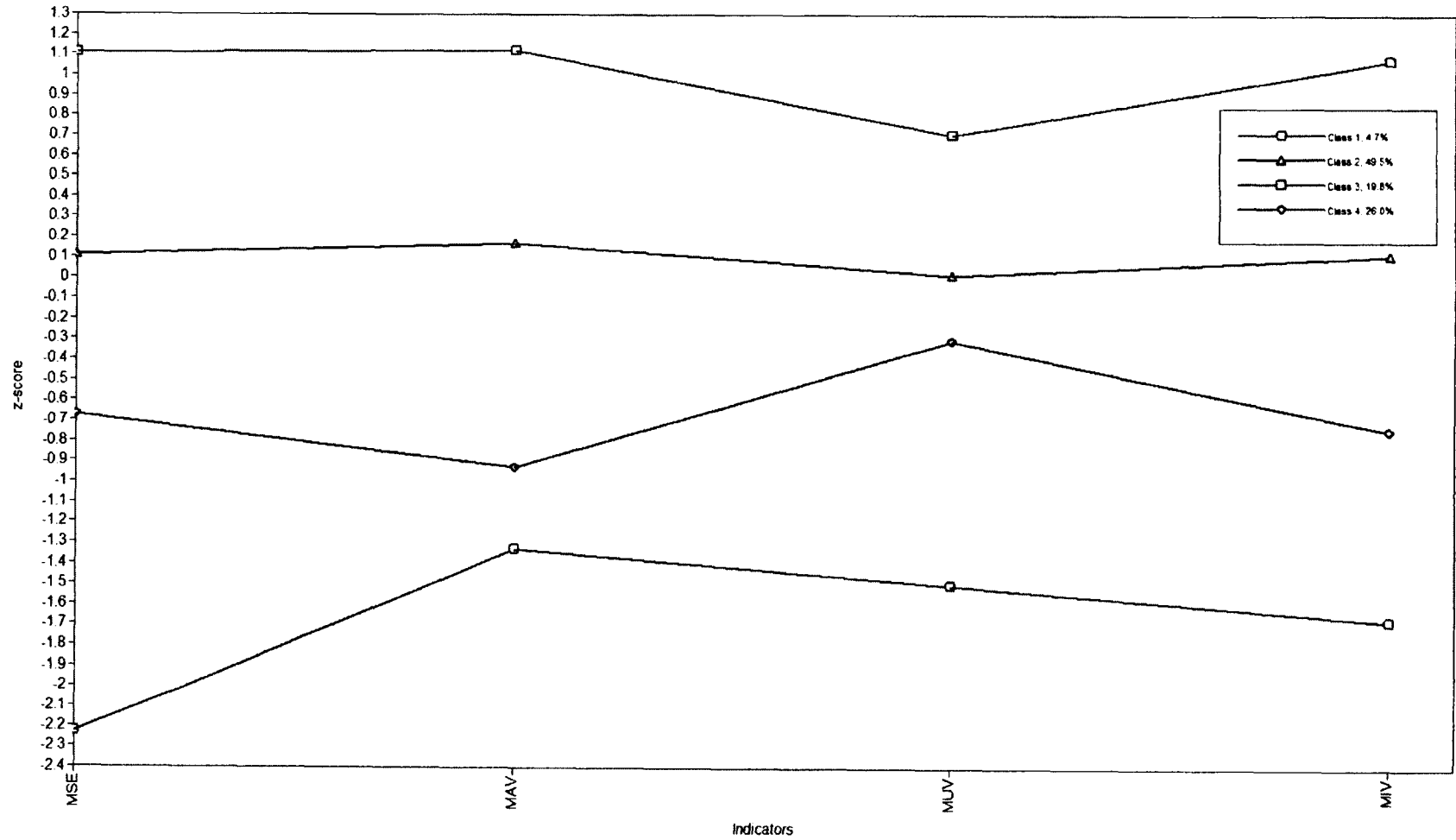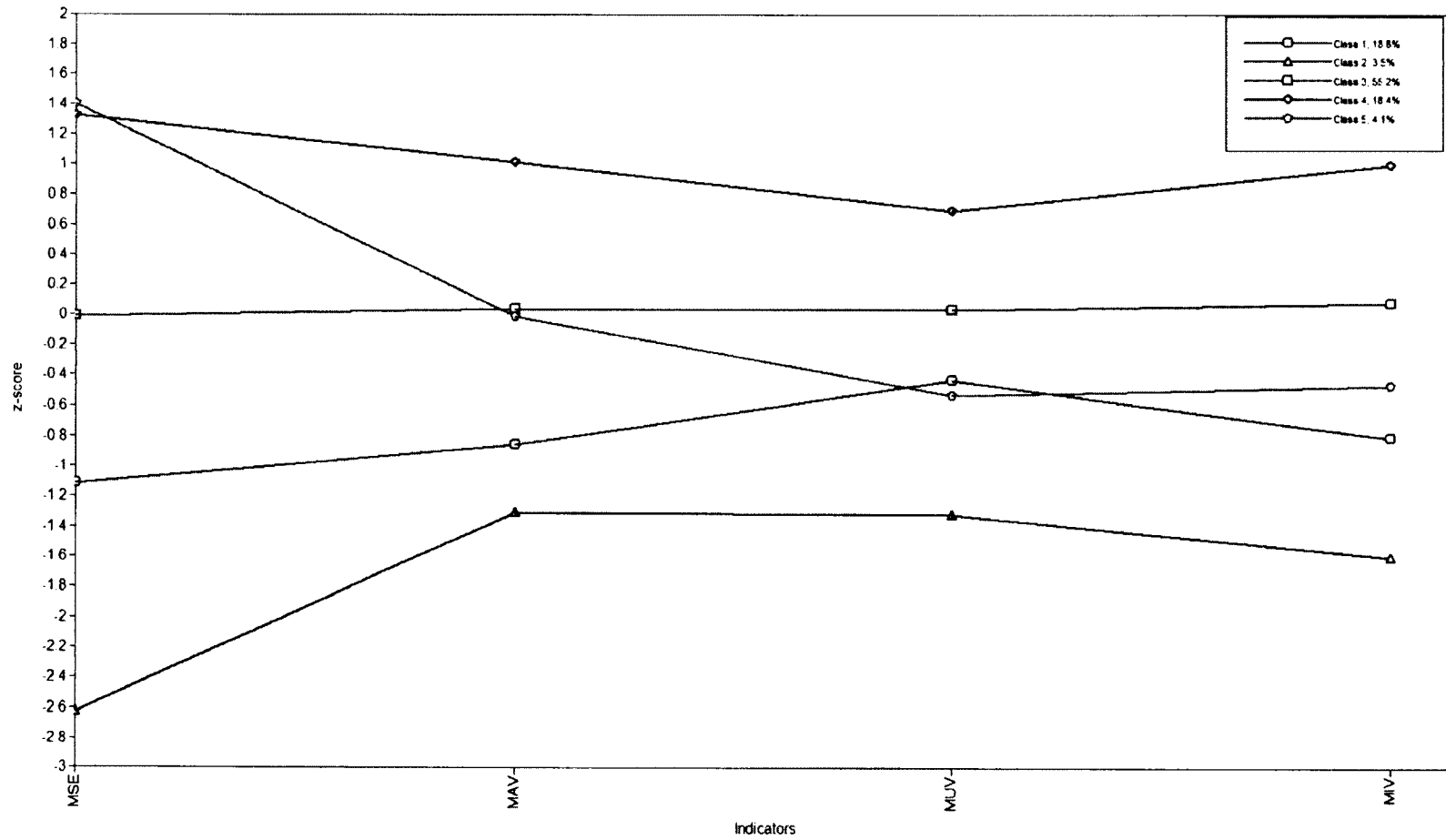
Math Model 5A

Math Model 6A
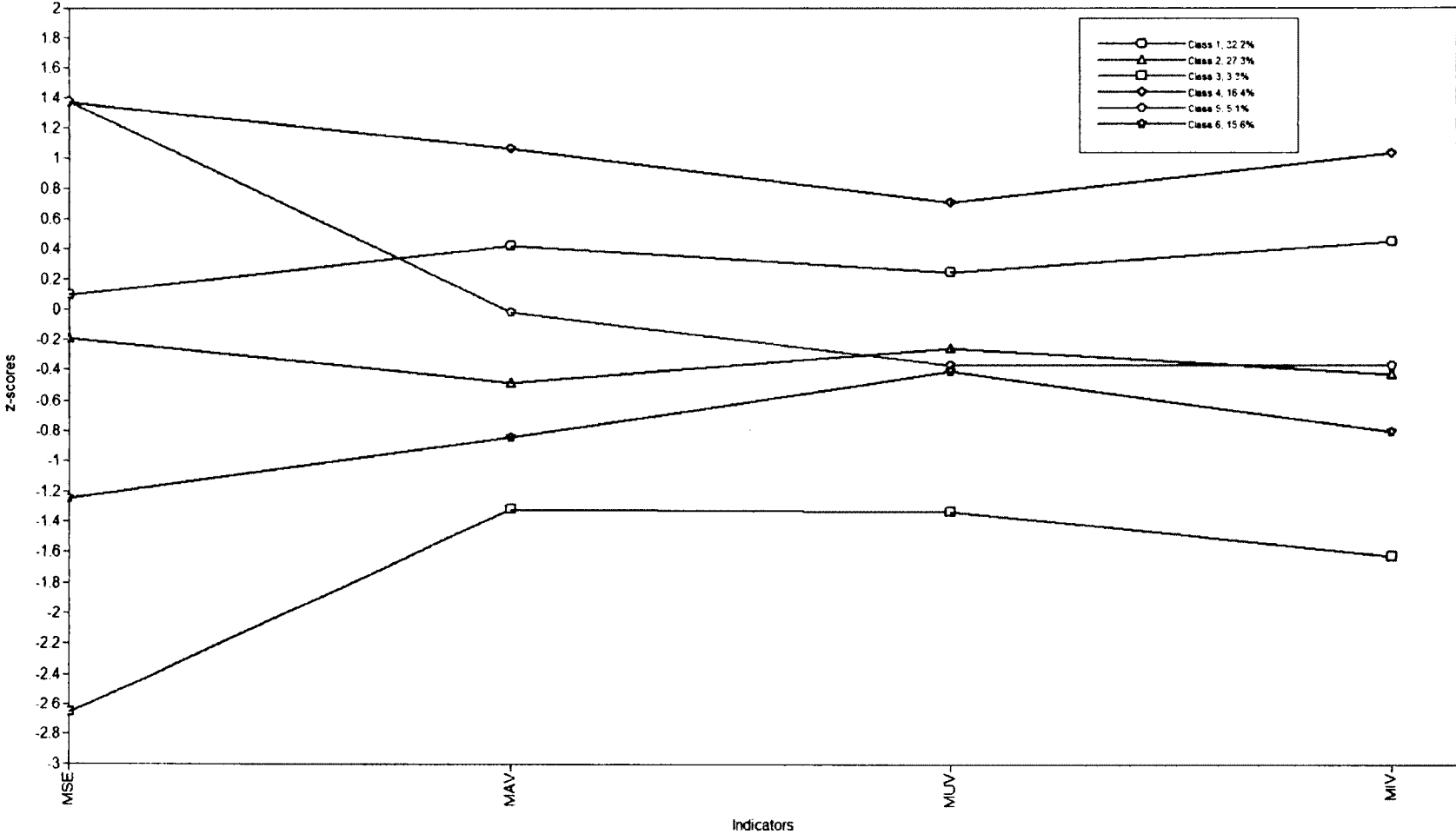
Math Model 7A

Math Model 2B
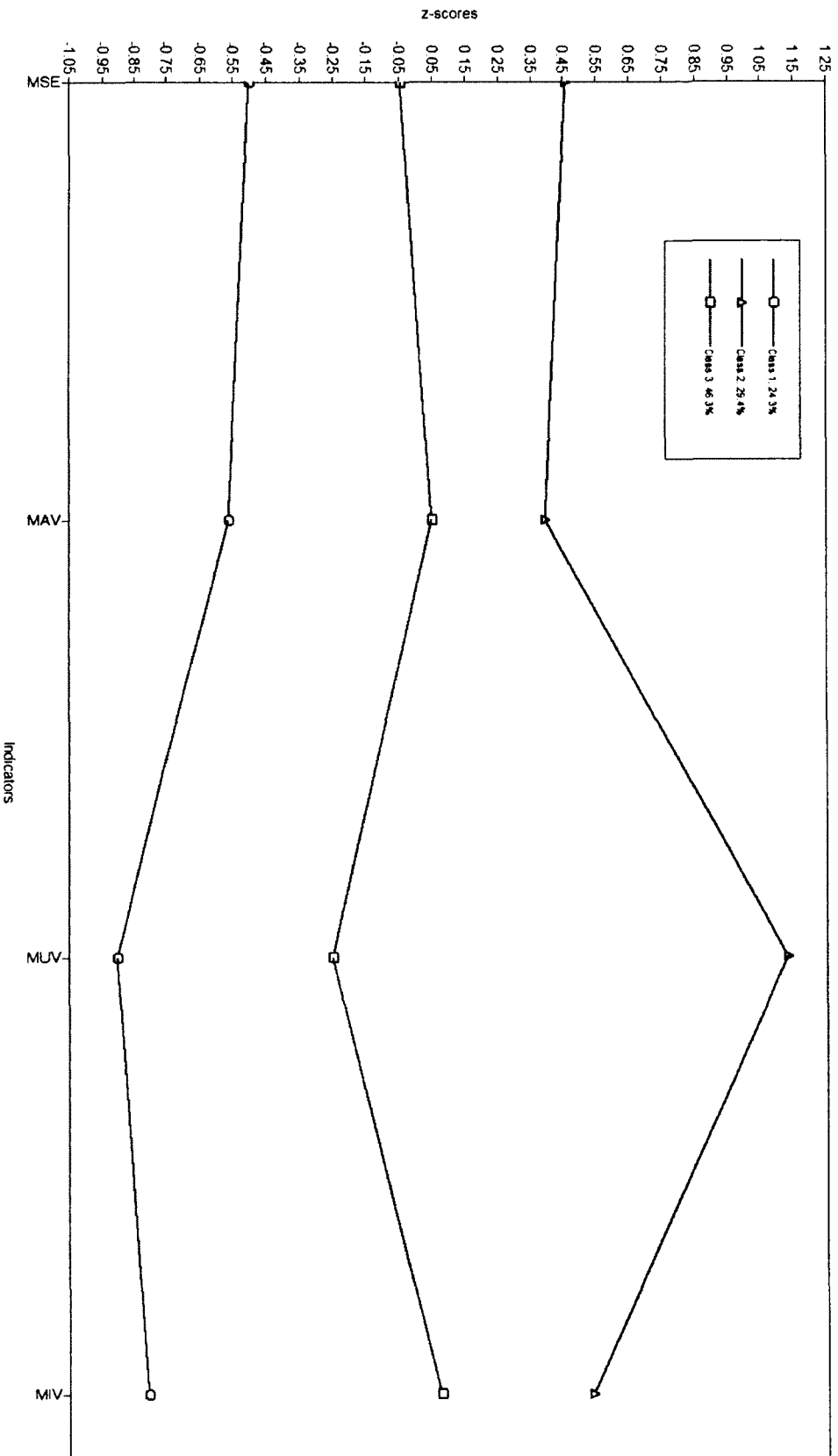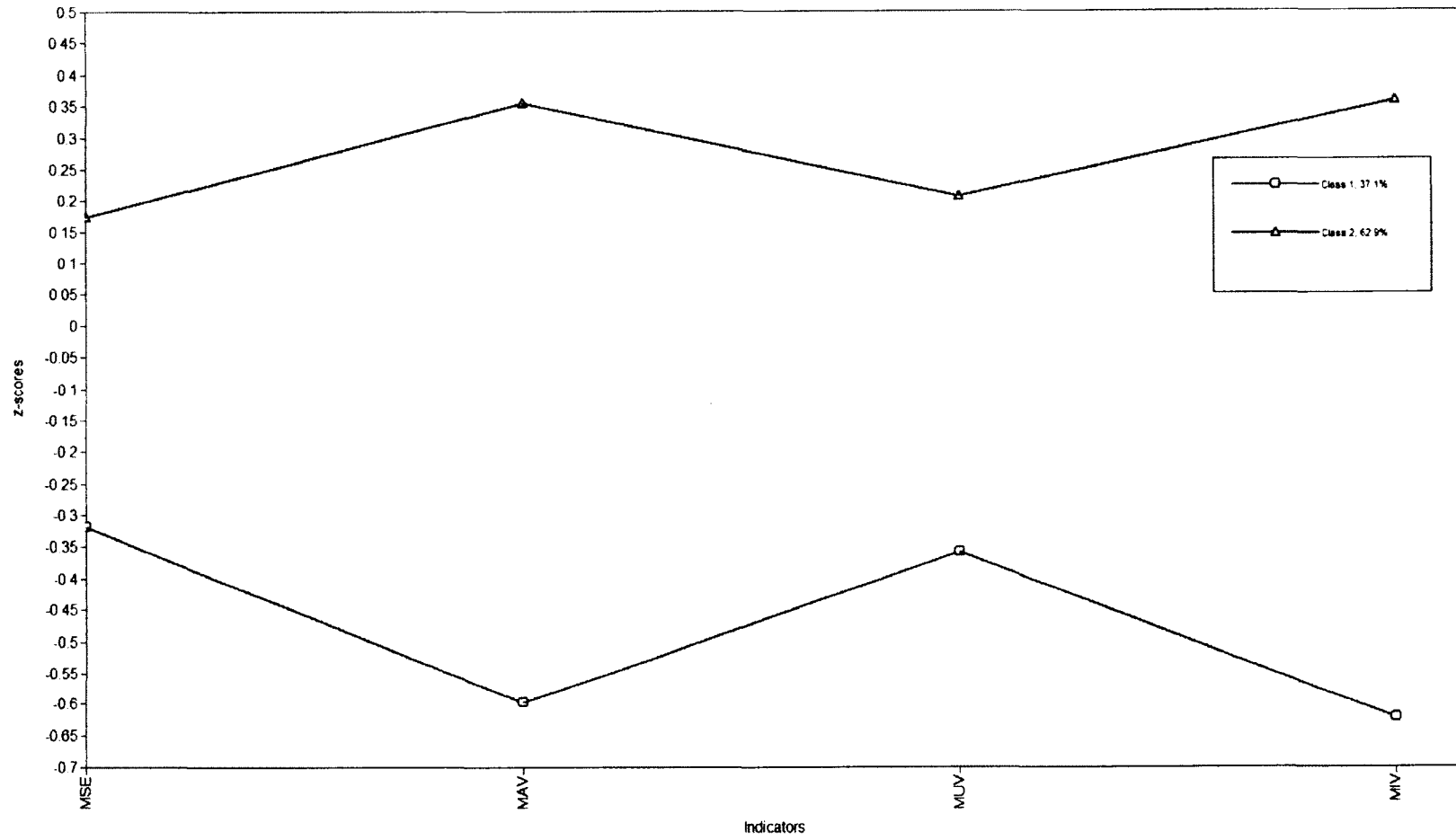
z-scores

Indicators

MSE   MAV   MUV   MIV

Class 1 1.3%
Class 2 2.96 7%

173
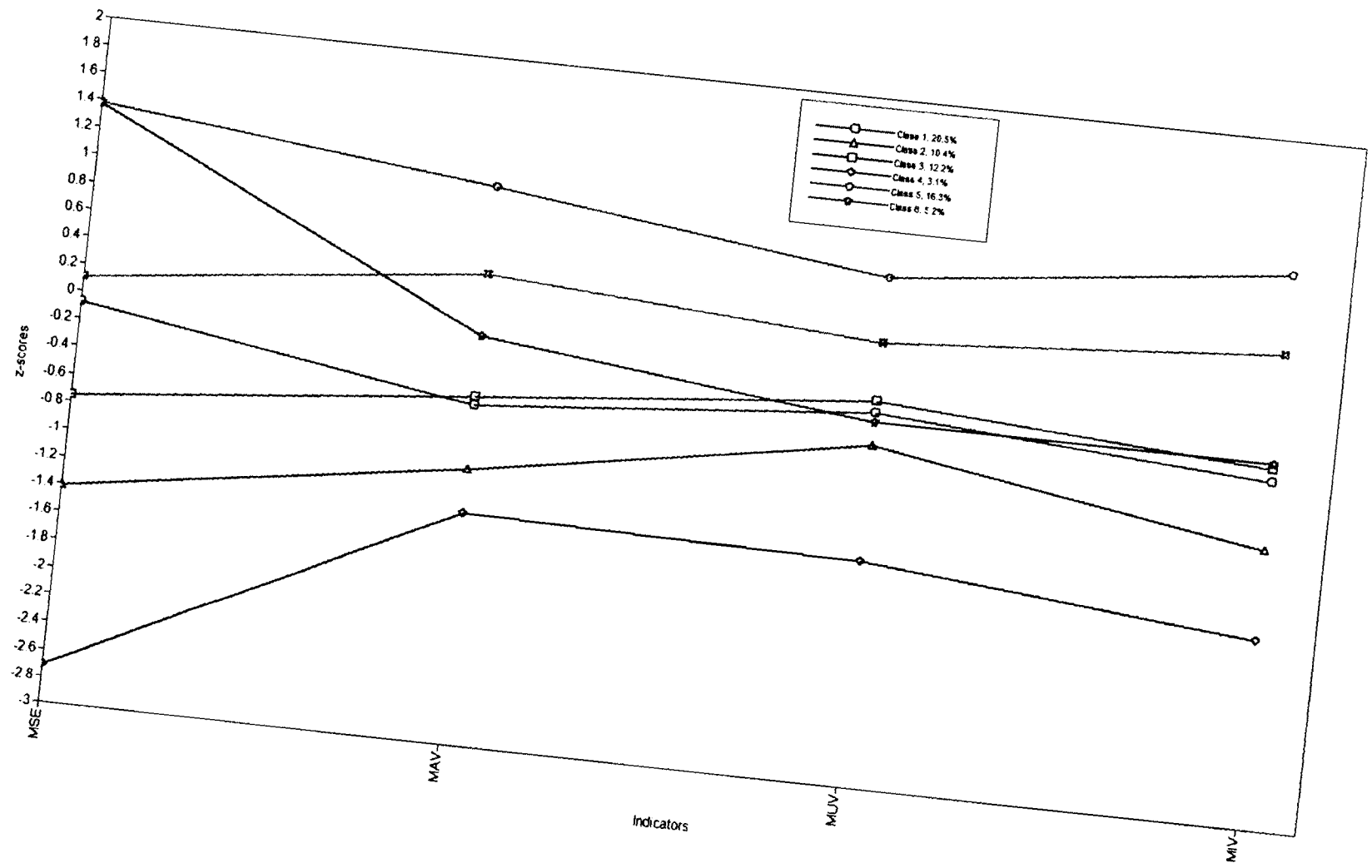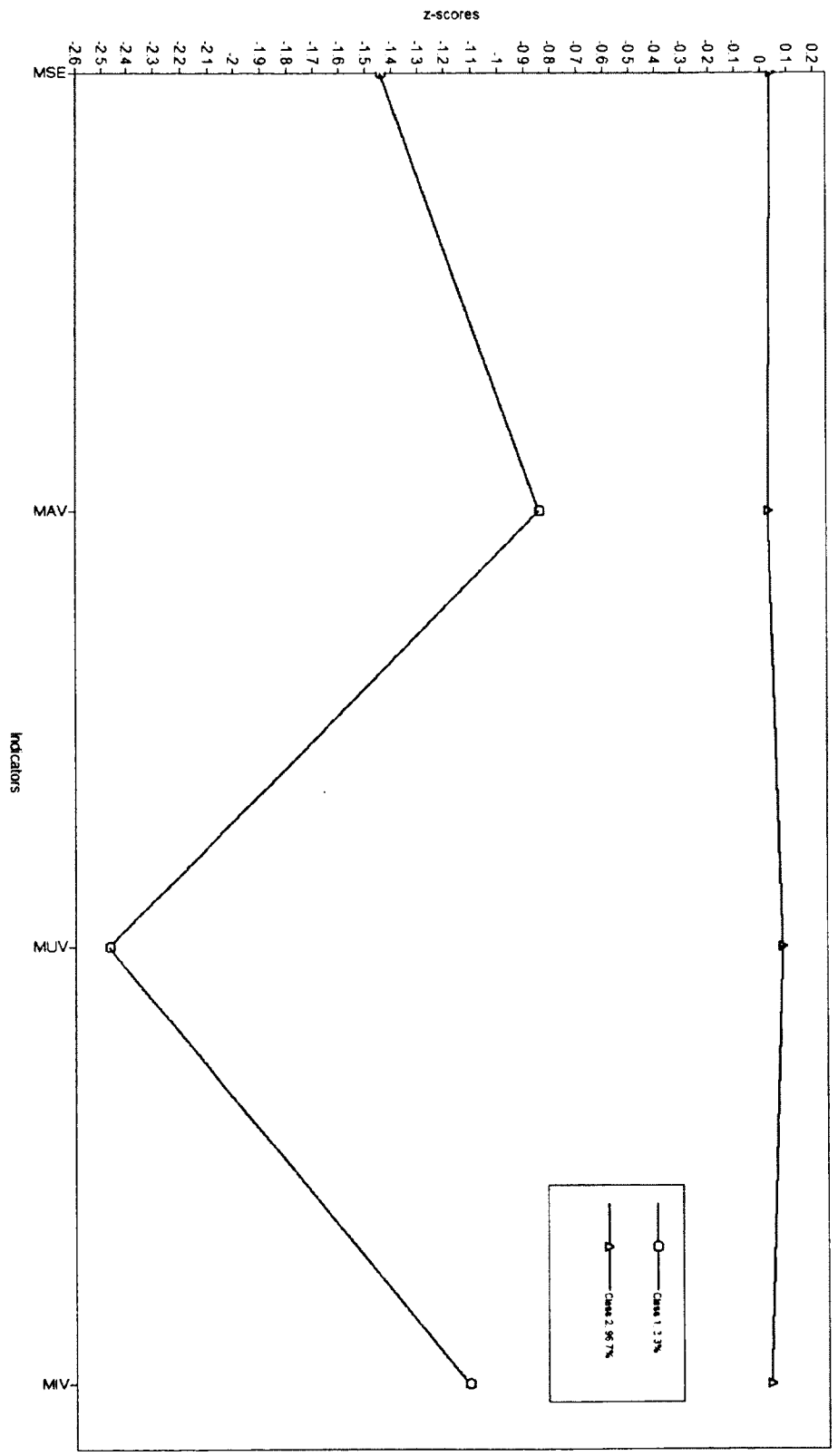
Math Model 3B

Math Model 4B

Legend:
- Class 1, 3.3%
- Class 2, 17.0%
- Class 3, 21.7%
- Class 4, 58.1%

Y-axis: z-scores
X-axis: Indicators (MSE, MAV, MUV, MIV)

Math Model 5B

z-scores

Indicators

| MSE | MAV | MUV | MIV |

Class 1: 3%
Class 2: 16.9%
Class 3: 2.9%
Class 4: 16.9%
Class 5: 58.0%

176
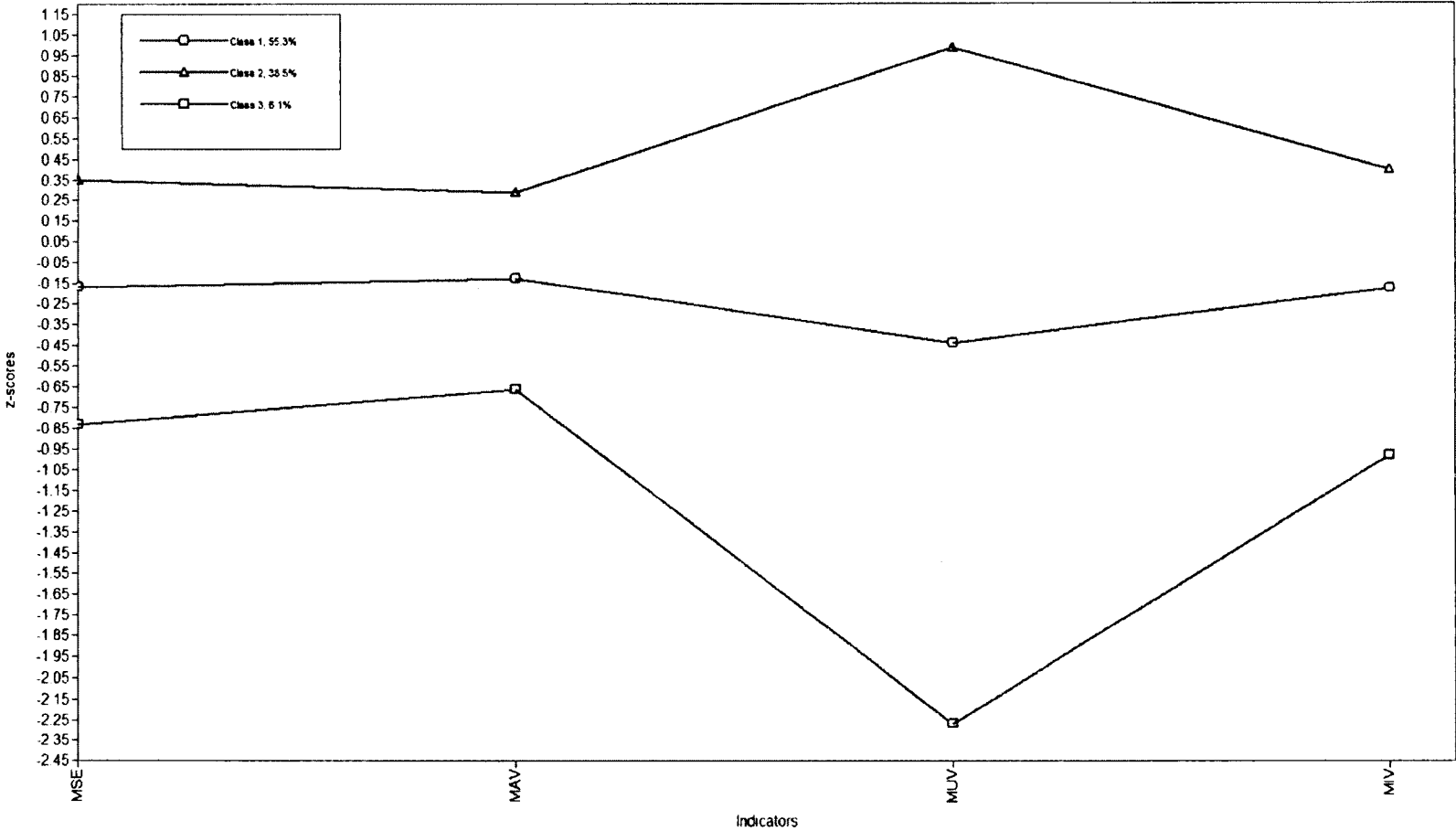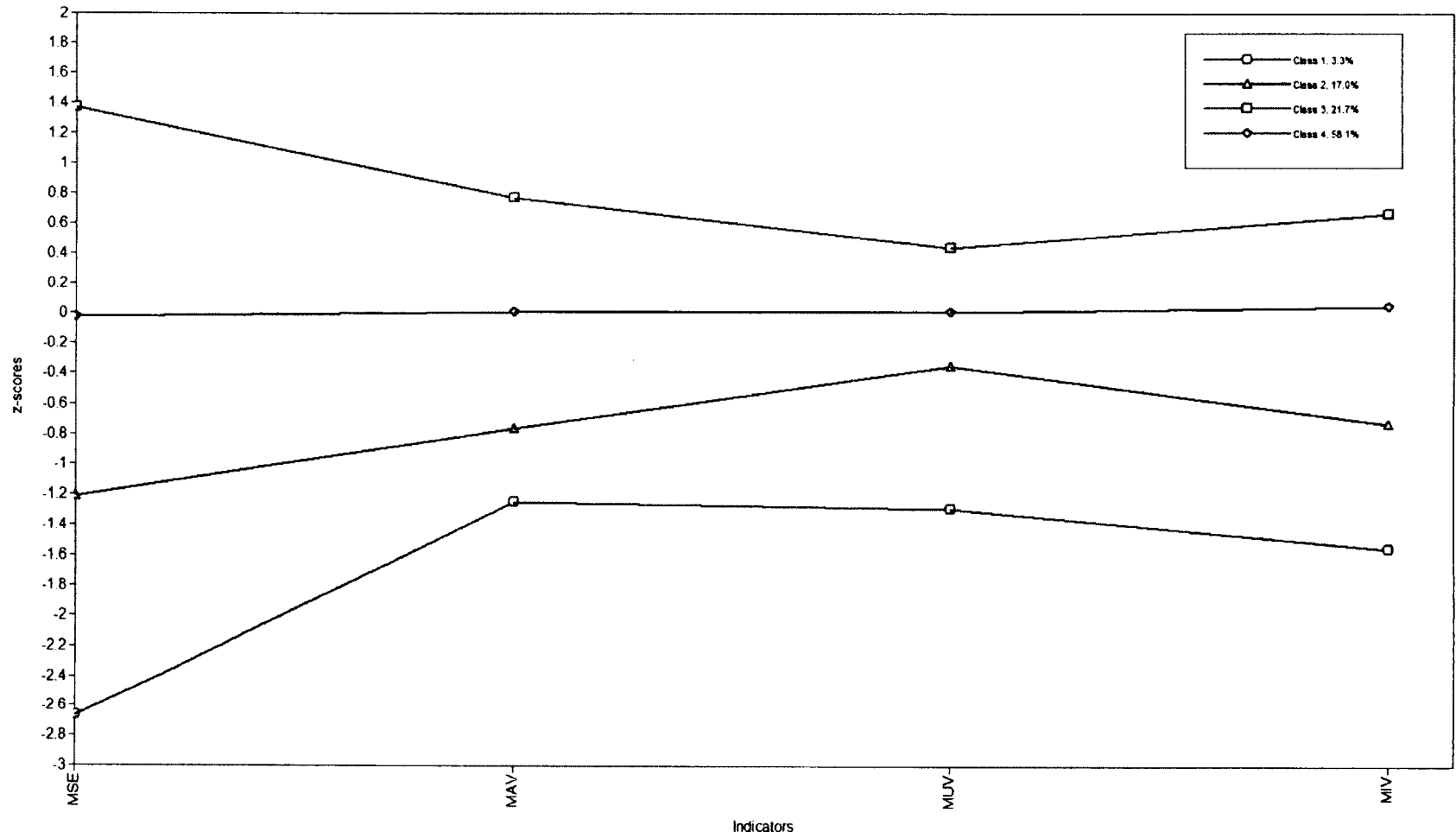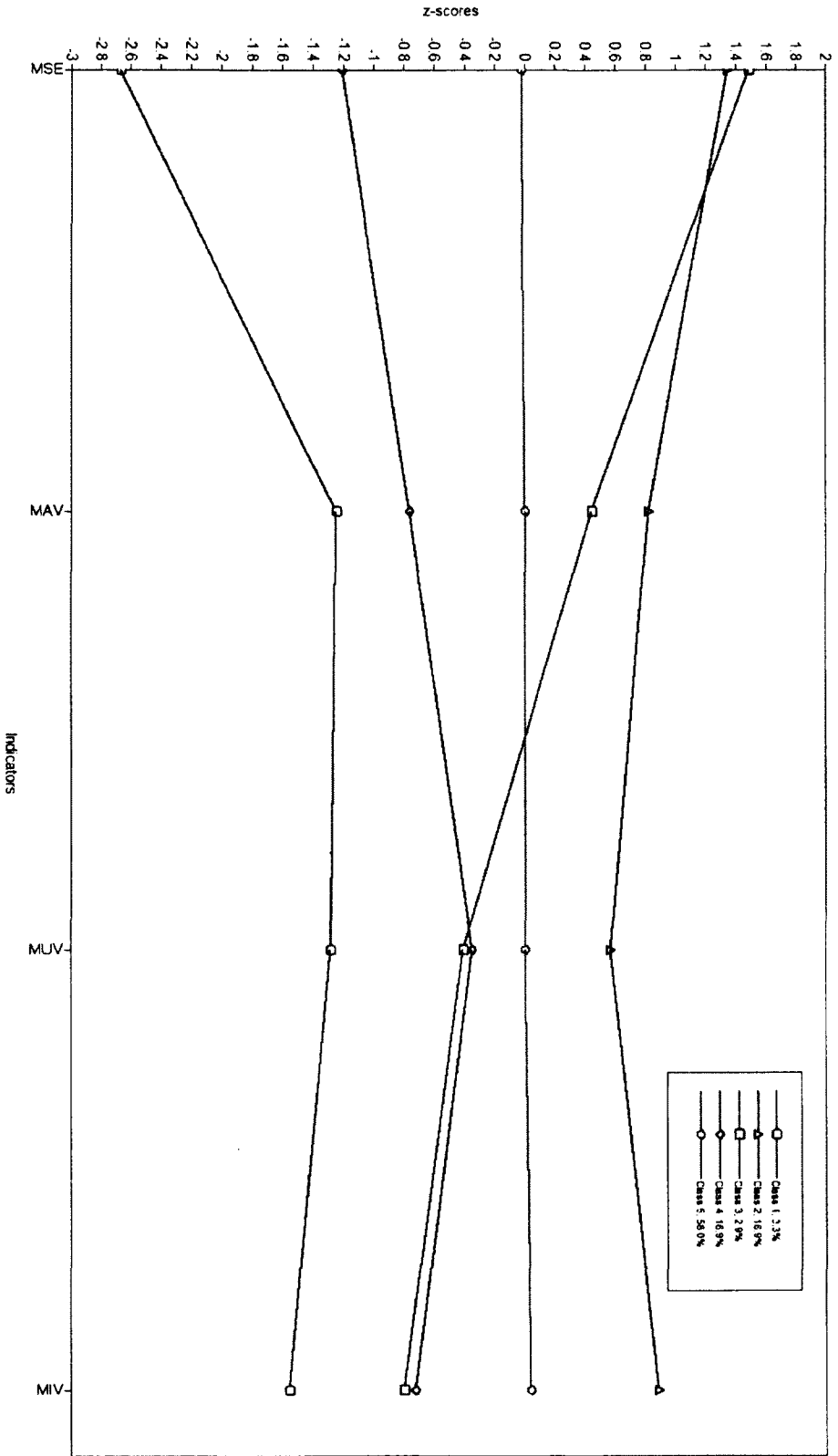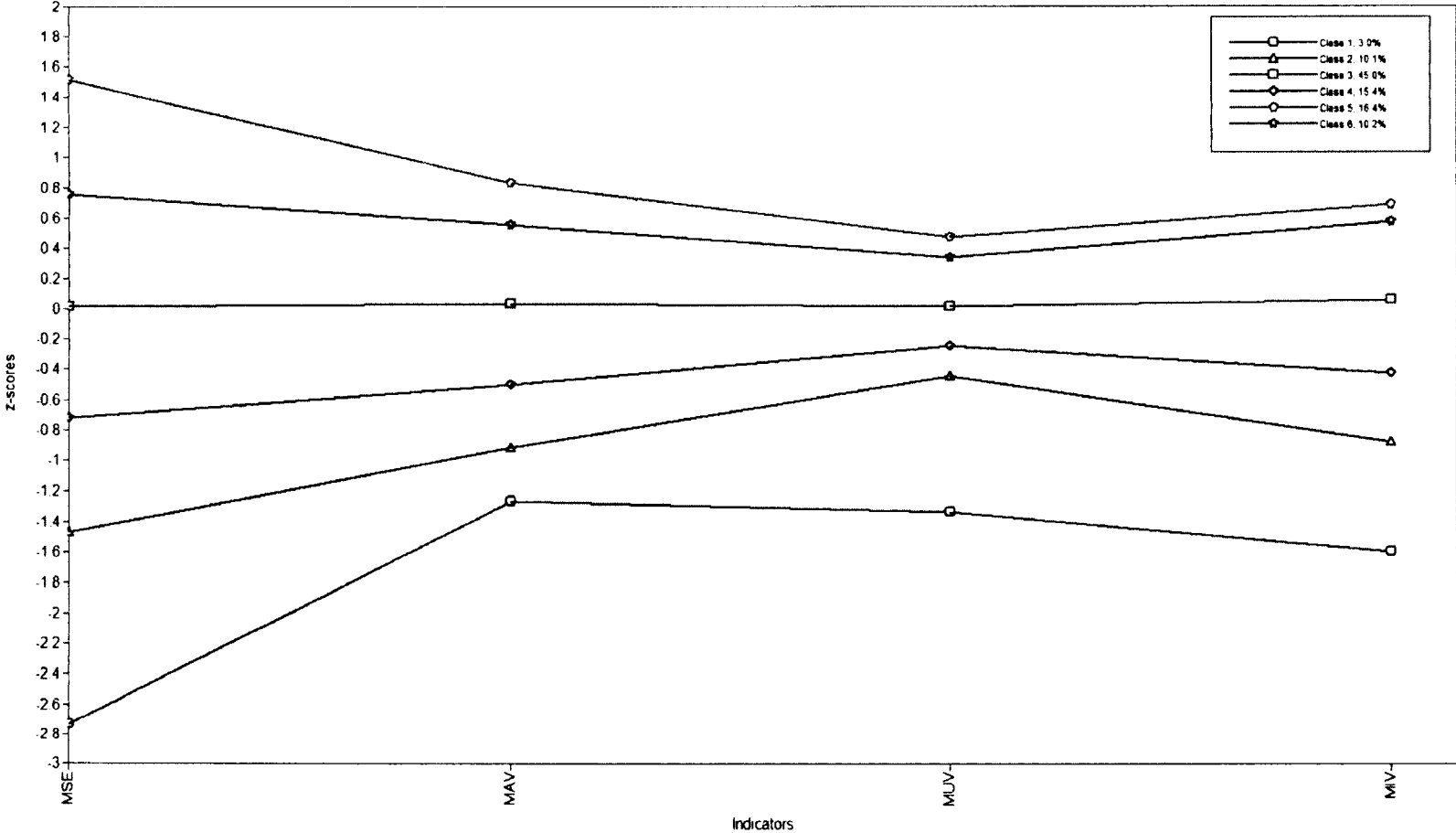
Math Model 6B

Math Model 2C
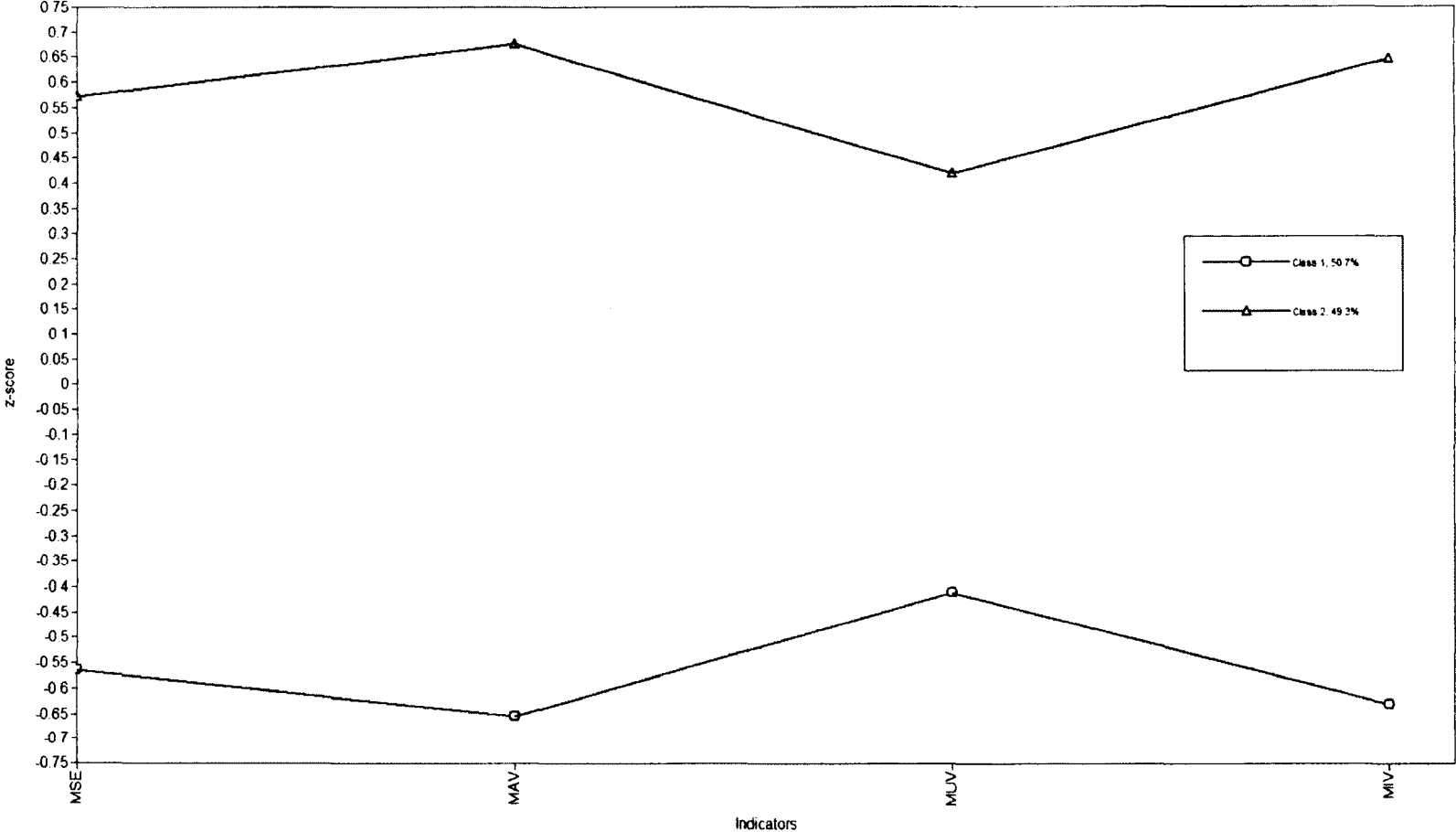
Math Model 3C

Math Model 4C

180
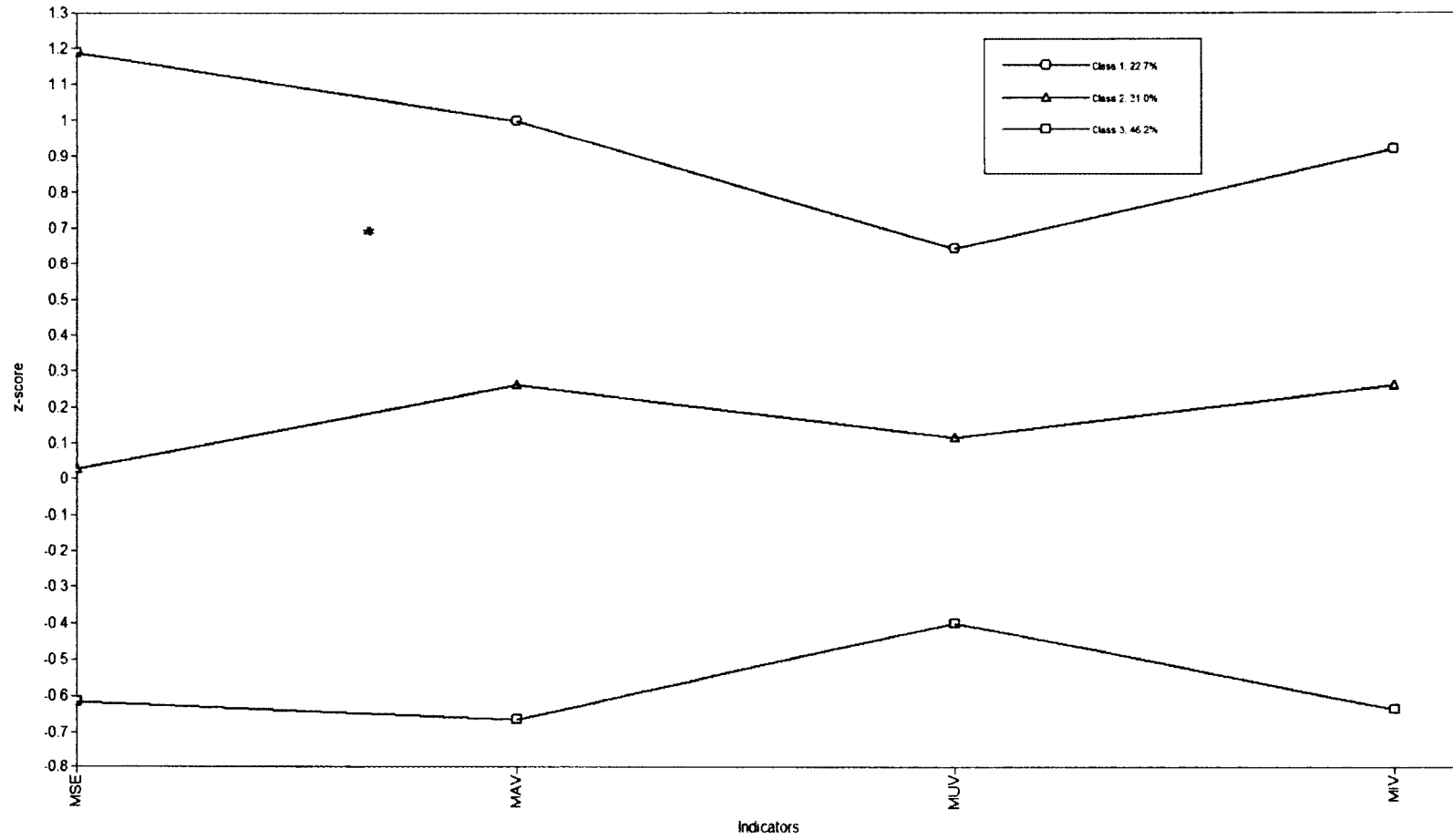
Math Model 2D

Math Model 3D

182

Math Model 4D

183
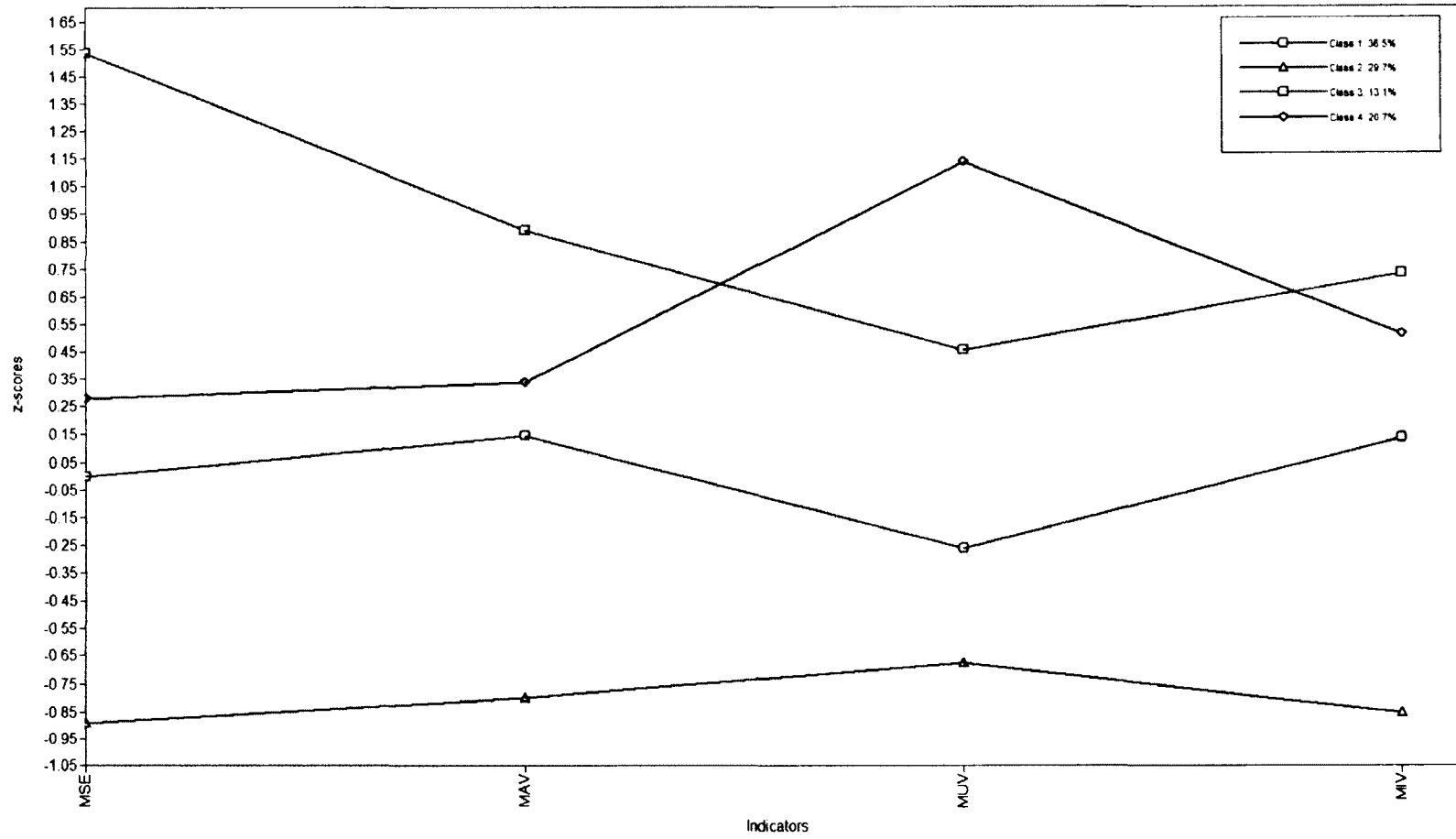
Math Model 2E

Math Model 3E
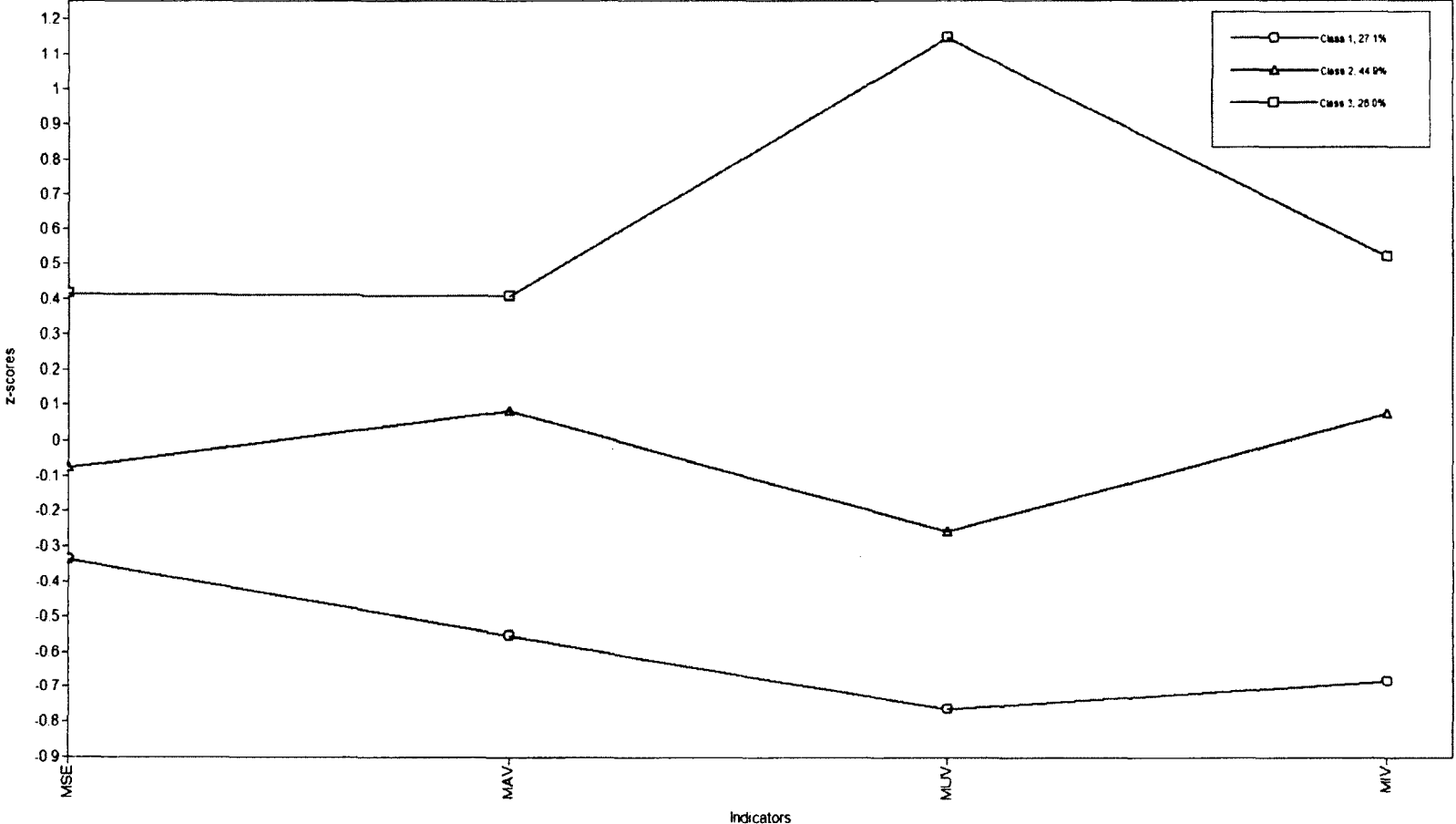
Appendix F

Mplus VERSION 7
MUTHEN & MUTHEN
04/10/2013   4:26 PM

INPUT INSTRUCTIONS

 TITLE: LATENT CLASS ANALYSIS LORI ANDERSEN

DATA:
     FILE IS hslsnew.dat;
     FORMAT IS free;
     TYPE IS individual;

VARIABLE:
   names = Stu_ID Sch_ID W1STUDEN x1txmscr X1SES
       MAV MUV MSE MIV SAV SUV SSE SIV
       STRAT_ID PSU choice hability
       WM WF BM BF HM HF AM AF stem costtime costpop;
       USEVARIABLES ARE MAV MUV MSE MIV;
   AUXILIARY = X1TXMSCR (E) X1SES (E)
     HABILITY (E)
     WM (E) WF (E) BM (E) BF (E) HM (E)
     HF (E) AM (E) AF (e) STEM (E)
     costtime (E) costpop (E);
   MISSING= ALL(-99);
       CLUSTER IS Sch_ID;
       STRATIFICATION IS STRAT_ID;
       WEIGHT IS w1studen;
   classes = cm(4);

ANALYSIS:
   TYPE IS mixture;
   TYPE IS COMPLEX;
   starts = 1000 100;
   stiterations = 50;
   ESTIMATOR = MLR;
   OPTSEED = 638977;

SAVEDATA:
   FILE = 4dCm.DAT;
   SAVE = CPROBABILITIES;

MODEL:
   %OVERALL%

```
MAV; MUV; MSE; MIV;
MAV WITH MUV MSE MIV;
MUV WITH MSE MIV;
MSE WITH MIV;
%Cm#1%
MAV; MUV; MSE; MIV;
%Cm#2%
MAV; MUV; MSE; MIV;
%Cm#3%
MAV; MUV; MSE; MIV;
%Cm#4%
MAV; MUV; MSE; MIV;

plot:
   series = MSE mav muv miv(*);
   type = plot3;

output:
    TECH1 TECH2 TECH8 TECH7 TECH11 TECH12 MODINDICES SVALUES;
```
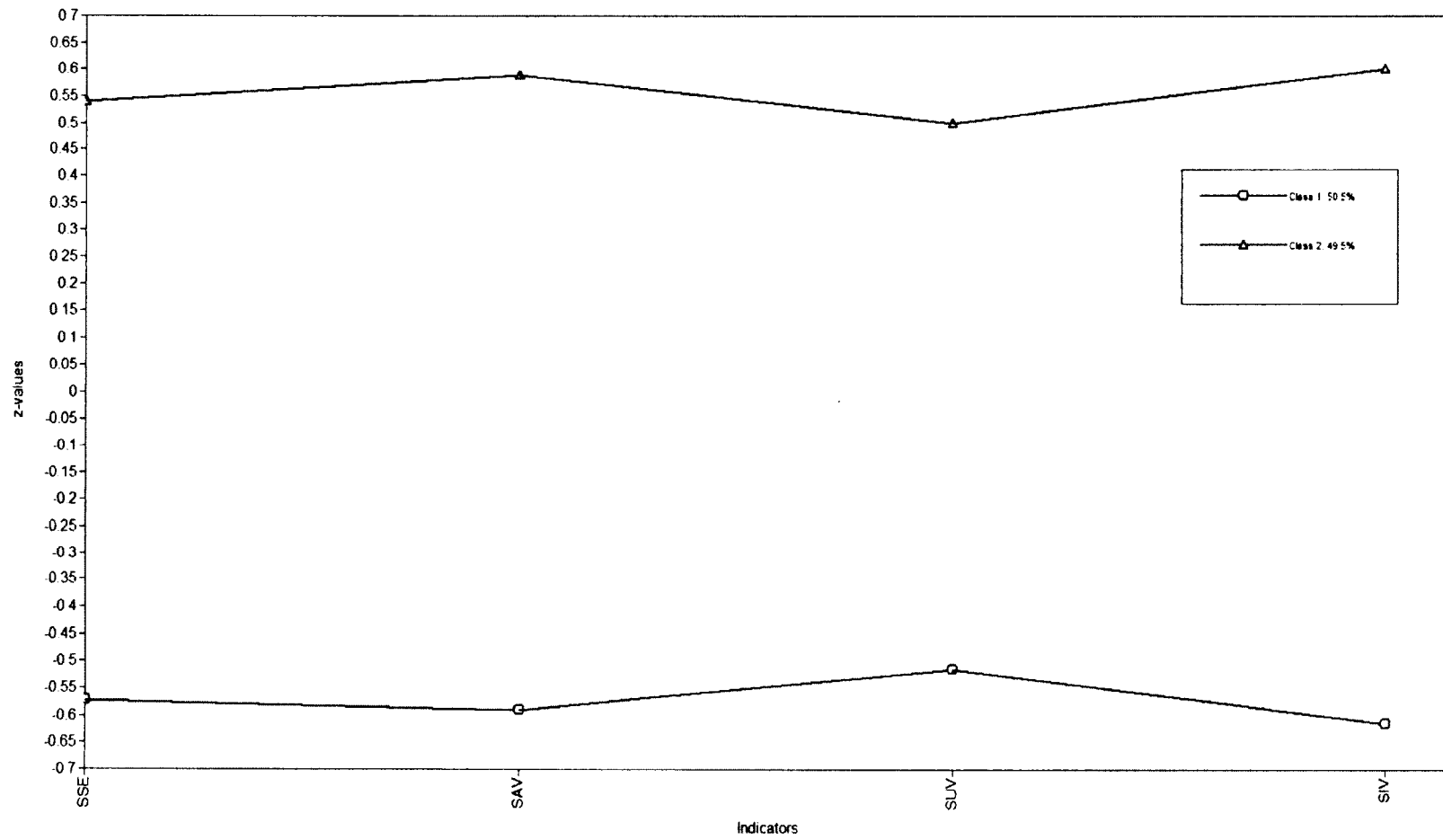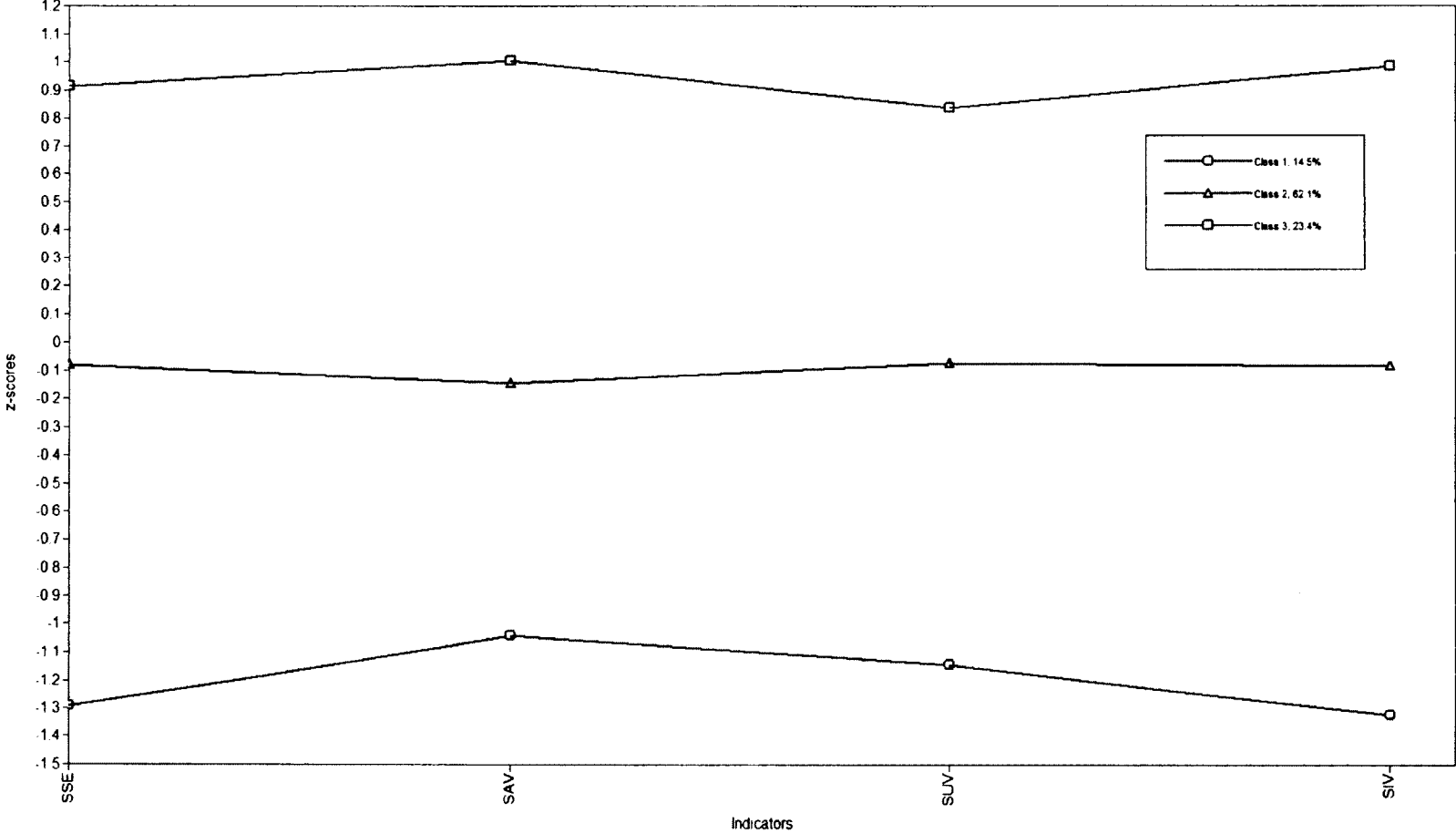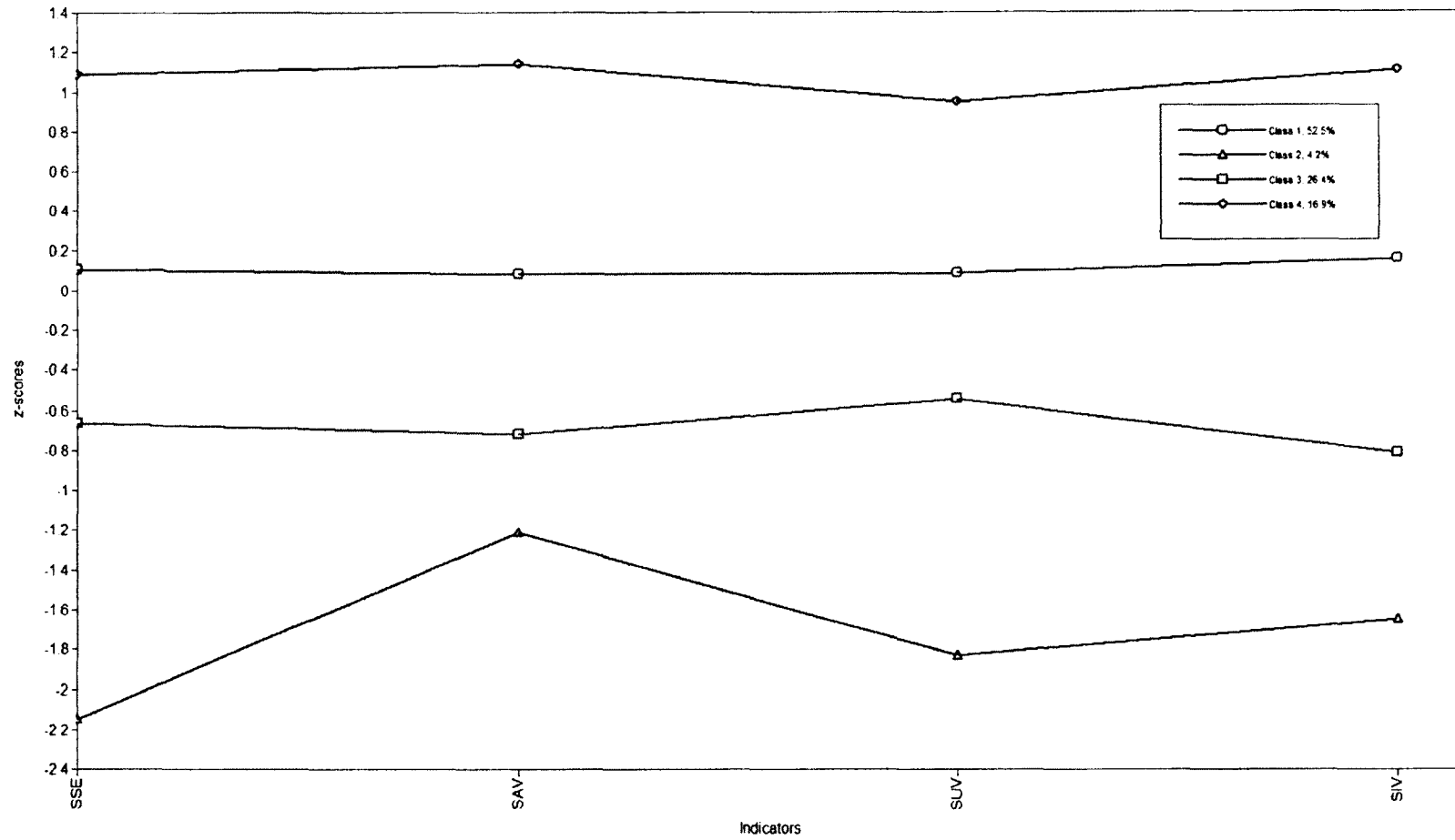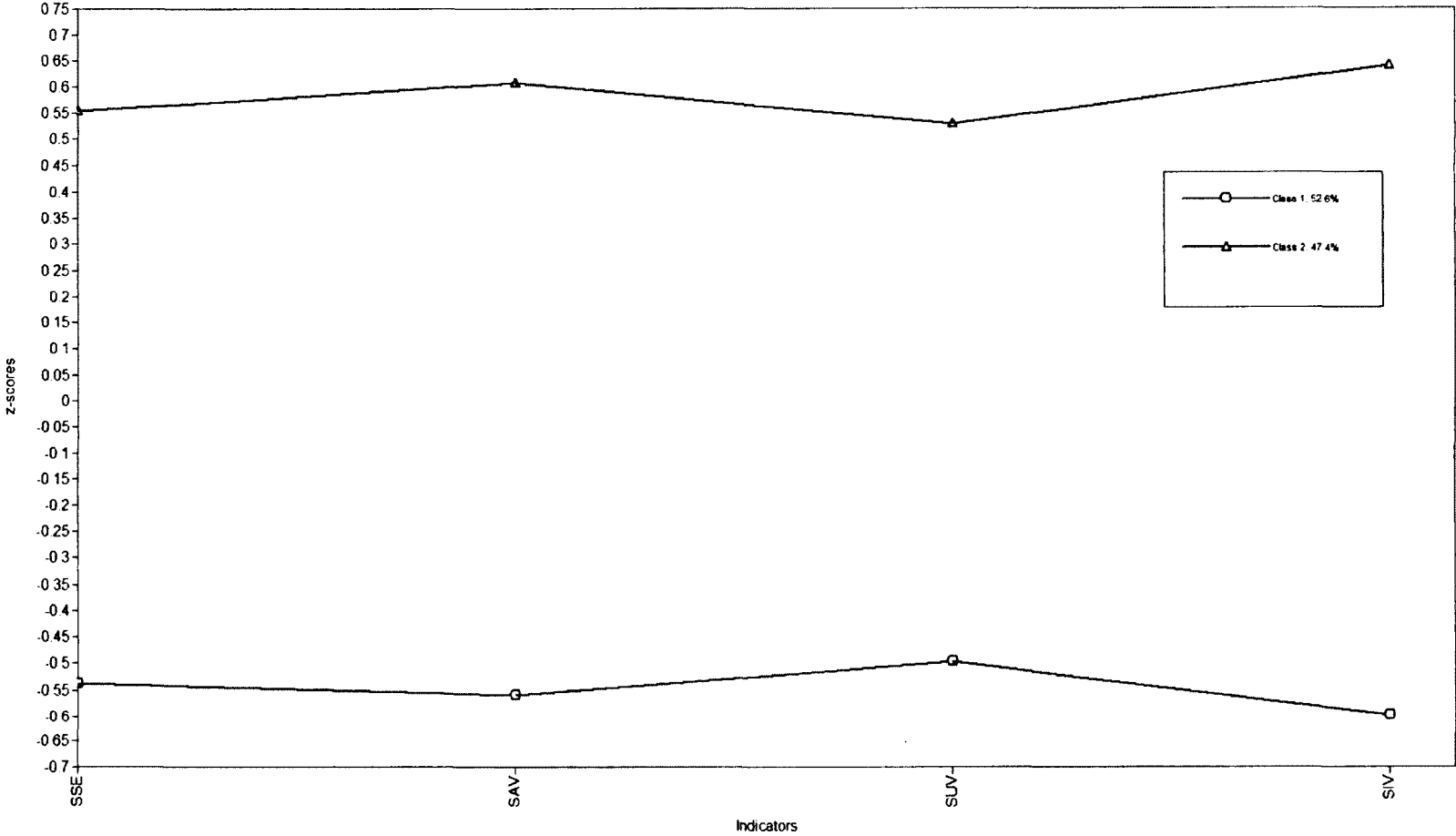
Appendix G

Science Class Latent Profile Plots

Science Model 2A
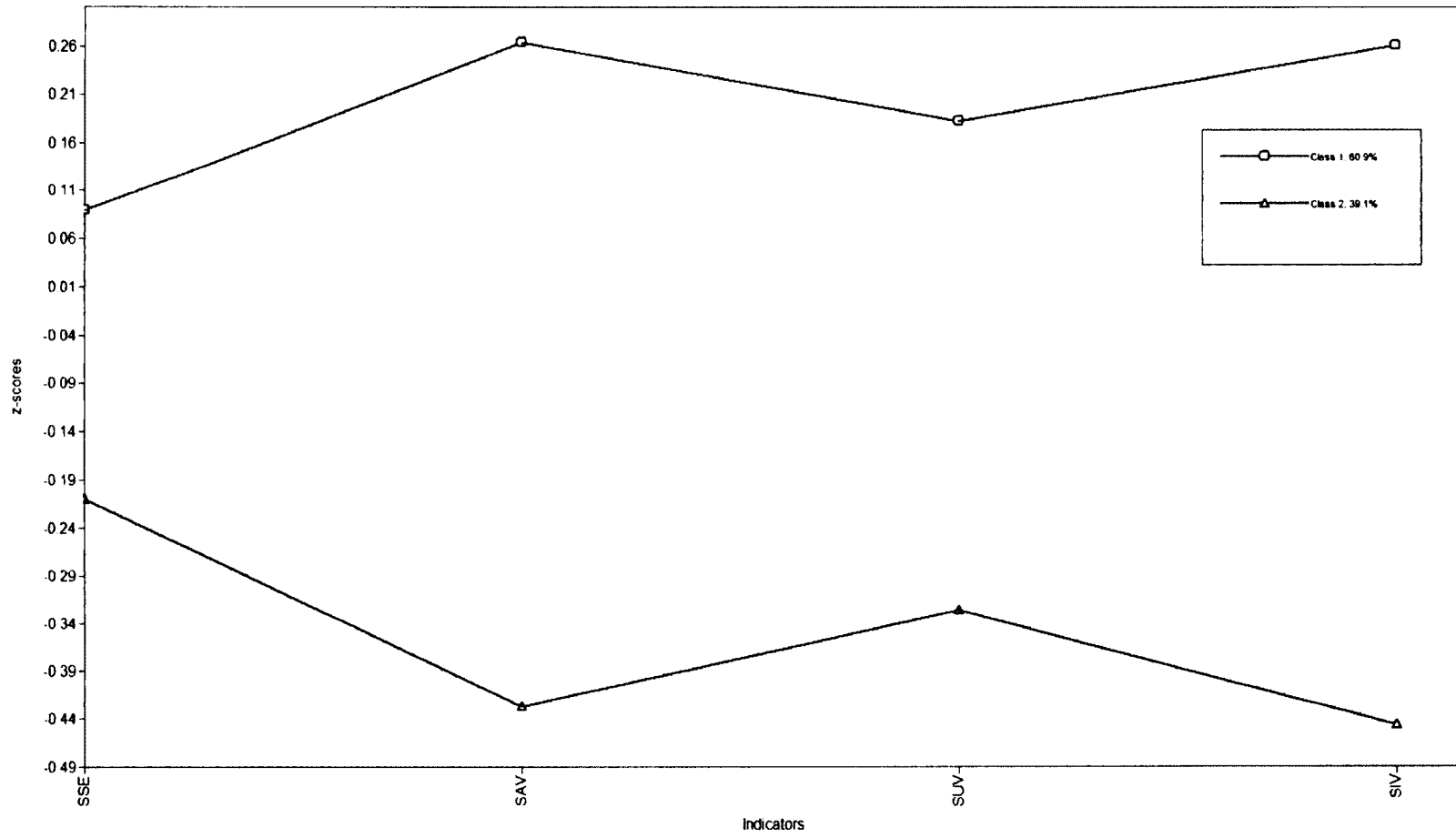
Science Model 3A
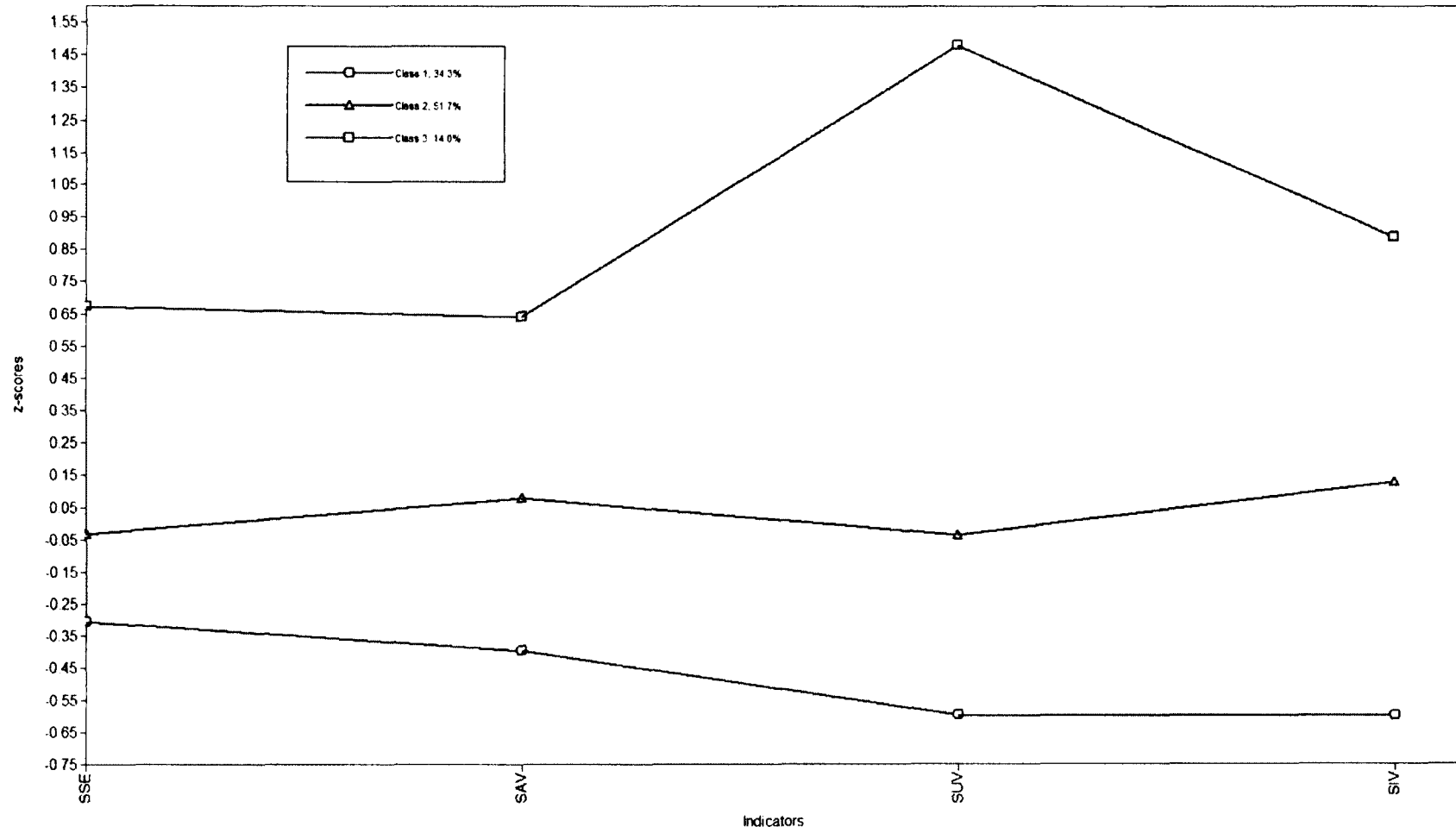
Science Model 4A

Science Model 2C

Science Model 3C
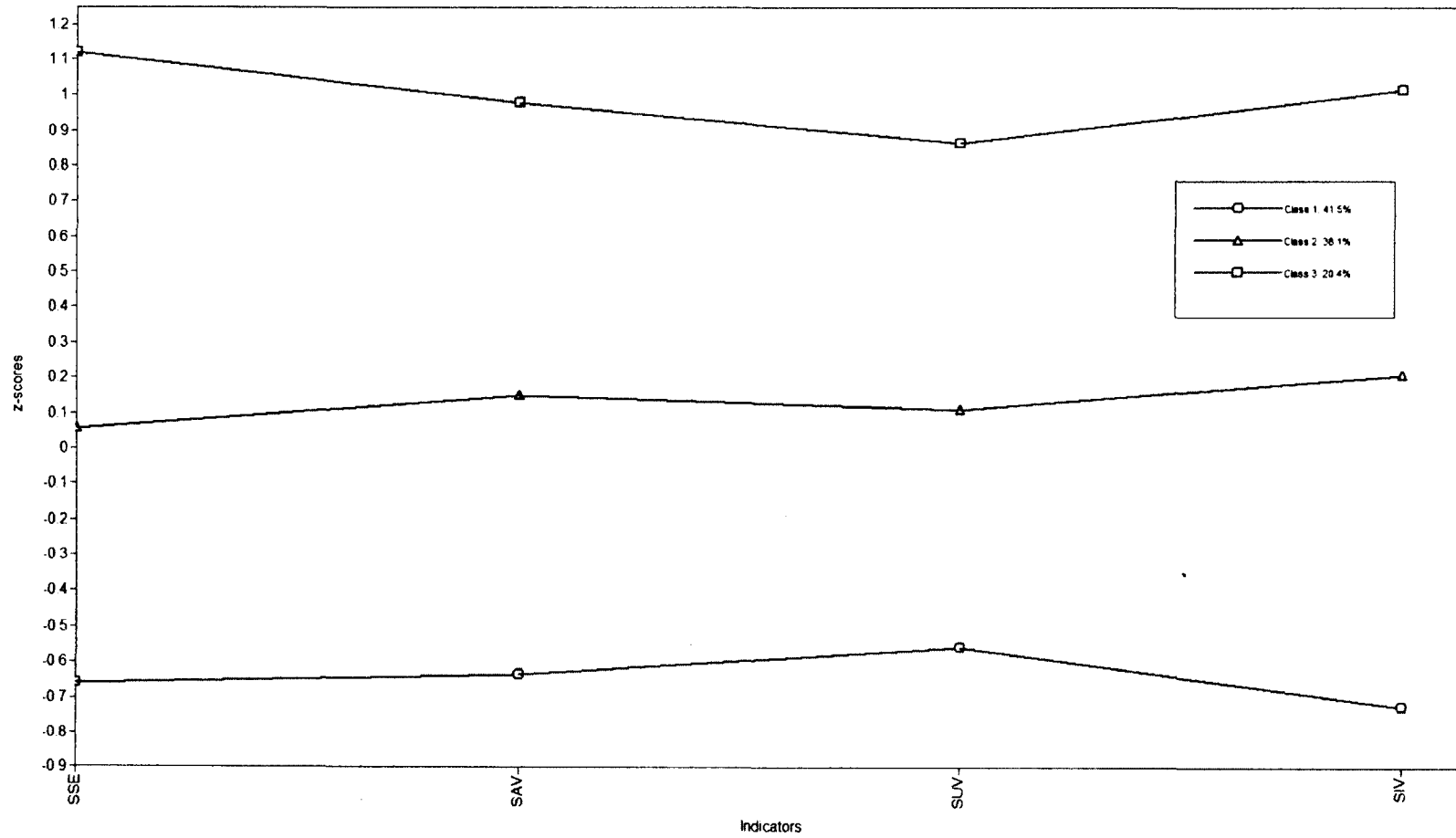
Science Model 2E

Science Model 3E

Appendix H

Mplus VERSION 7
MUTHEN & MUTHEN
04/10/2013   4:19 PM

INPUT INSTRUCTIONS

   TITLE: LATENT CLASS ANALYSIS LORI ANDERSEN

DATA:
      FILE IS hslsnew.dat;
      FORMAT IS free;
      TYPE IS individual;
VARIABLE:
      names = Stu_ID Sch_ID W1STUDEN x1txmscr X1SES
   MAV MUV MSE MIV SAV SUV SSE SIV
   STRAT_ID PSU choice hability
   WM WF BM BF HM HF AM AF stem costtime costpop;
      USEVARIABLES ARE SAV SUV SSE SIV;
   AUXILIARY = X1TXMSCR (E) X1SES (E)
    HABILITY (E)
    WM (E) WF (E) BM (E) BF (E) HM (E)
    HF (E) AM (E) AF (e) STEM (E)
    costtime (E) costpop (E);
      MISSING= ALL(-99);
      CLUSTER IS Sch_ID;
      STRATIFICATION IS STRAT_ID;
      WEIGHT IS w1studen;
   IDVARIABLE = STU_ID;
   classes = cS(3);

ANALYSIS:
      TYPE IS mixture;
   TYPE IS COMPLEX;
   starts = 2000 200;
   stiterations = 50;
      ESTIMATOR = MLR;
   OPTSEED = 715561;

SAVEDATA:

   FILE = 3E-SCIENCE-NOCOST-FEB26.DAT;
   SAVE = CPROB;

```
FORMAT = FREE;

MODEL:
  %OVERALL%
  SAV SUV SSE SIV;
  sav with suv sse siv;
  suv with sse siv;
  sse with siv;
  %CS#1%
  SAV SUV SSE SIV;
  sav with suv sse siv;
  suv with sse siv;
  sse with siv;
  %CS#2%
  SAV SUV SSE SIV;
  sav with suv sse siv;
  suv with sse siv;
  sse with siv;
  %CS#3%
  SAV SUV SSE SIV;
  sav with suv sse siv;
  suv with sse siv;
  sse with siv;

plot:
  series = SSE SAV SUV SIV(*);
  type = plot3;

output:
  TECH1 TECH2 TECH8 TECH7 TECH11 TECH11 TECH14 MODINDICES
SVALUES
```