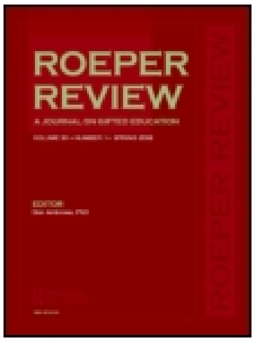

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Are Students With High Ability in Math More Motivated in Math and Science Than Other Students?

Lori Andersen and Tracy L. Cross

Expectancy-value motivation profiles were identified in a sample of US ninth-grade students in 2009 (n = 19,259) using latent profile analysis. Of four distinct profiles, two were high, one typical, and one low in math and in science. In each area, the two high profiles were distinguished by (1) high self-efficacy with lower utility value and (2) high utility value with lower self-efficacy. High-ability was identified by a math score at least one standard deviation above the mean within the race/ethnicity group. Forty-one percent of high-ability students had high math motivation, while only 27% had high science motivation. Evidence of disidentification was observed. Some high-ability students had low motivation in math (15%) and science (28%). Implications for talent development and gifted education are discussed.

Keywords: disidentification, expectancy-value model, giftedness, latent profile analysis, math, motivation, science, secondary data analysis

High-school students who have high ability or demonstrate superior performance in math and science form a talent pool from which the future scientists, mathematicians, and engineers of our nation should come. However, of the large number of individuals who form this pool of talent, relatively few are motivated to develop their abilities in science, technology, engineering, and mathematics (STEM) disciplines (National Science Board, 2010). If the motivation of high-ability students was better understood, interventions could target the specific aspects of motivation that promote talent development. In this study, the domain-specific motivations of high-ability students were explored.

The expectancy-value (EV) model of achievement-related choices (Eccles et al., 1983) has been used extensively in education research but not as much with high-ability populations. This article begins with a description of the expectancy-value model of achievement-related choices, followed by an examination of each of the key constructs in the model. The importance of motivation to giftedness and issues particular to high-ability students are discussed.

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EXPECTANCY-VALUE

In the EV model, individuals choose among options they perceive to be available, and this perception is affected by cultural stereotypes and parental, familial, or peer influences. The immediate considerations that motivate decisions about achievement tasks include (a) the expectations for success; (b) how well the choice aligns with goals, with one's identity, and with basic psychological needs; and (c) the individual's role schema based on gender, race, or ethnicity (Wigfield & Eccles, 2000). The first of these considerations is called *expectancy* and the remaining two collectively comprise *subjective task value*. Choice, persistence, and performance are explained by an individual's expectation of success and the subjective task value held for the activity. 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, Eccles, & Durik, 2006).

Expectancy

Expectancy is the confidence in one's ability to successfully perform a task (Wigfield & Eccles, 2000). Expectancy is very similar to *self-efficacy*. Bandura (1994) defined self-efficacy as "people's beliefs about their capabilities to produce designated levels of performance" (p. 71). According to the EV model (Eccles et al., 1983), individuals who have higher expectancies for success in mathematics or science will be more likely to study STEM disciplines. The EV model explains that prior achievement predicts 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, expectancy is positively related to ability, but even high-ability students who internalize stereotypes about abilities or who adopt familial or cultural views about who can be successful at certain activities are likely to have reduced expectancies in the STEM domains.

Subjective Task Value

Subjective task value (STV) is the net value ascribed to a task by an individual (Wigfield, Tonks, & Klauda, 2009). Value is affected by how interesting an activity was, how much it was liked, and the nature of feedback as to the importance or usefulness of a task. In this way, cultural expectations and peer expectations influence the values of activities. Cultural norms or stereotypes and how much these have been internalized affect the perceived personal cost of an activity. In general, STV is a better predictor of choice than ability or expectancy. Each of the four constructs that comprise STV will be described next.

Interest–Enjoyment Value

This value is the degree of interest in the activity, which is often operationalized as how much the task is liked or enjoyed (Wigfield & Eccles, 2000). Those who like or enjoy math or science are more motivated to take courses and pursue STEM careers (Jacobs, Finken, Griffin, & Wright, 1998; Lent, Lopez, Lopez, & Sheu, 2008; Lent, Paixão, Silva, & Leitão, 2010; Miller, Lietz, & Kotte, 2002; Watt et al., 2006).

Attainment Value

This value describes how much the task confirms salient aspects of one's identity (Wigfield et al., 2009). Thus, STEM course taking will be influenced by identification with math or science; the greater the identification, the more likely those options will be selected. Factors that affect attainment value include individual perceptions of the domains of math 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 math identity aligns with other components of the individual's identity.

Identity Incongruence

When the perception of a math or science identity conflicts with what is believed appropriate for one's gender, race, or ethnicity, STEM-related choices will have lower attainment value (Eccles, 2009). Research on students' perceptions over the past 50 years 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, Olszewski-Kubilius, & Worrell, 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 United States (Coleman & Cross, 1988; 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 for persistence (Carlone & Johnson, 2007; Kao, 2000; Oyserman & Destin, 2010).

Utility Value

This value is the degree of alignment with 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 related goals will place higher utility value on math or science courses. Utility value is a significant predictor of STEM career choice (Andersen & Ward, 2013, 2014; Maltese & Tai, 2011).

Components of STV versus Composite STV

Subjective task value predicted choice after controlling for prior achievement (Eccles et al., 1984; Simpkins & Davis-Kean, 2005; Watt et al., 2006), but these studies 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. Most studies that have shown relationships between STV and choice focused on the subjective task value of math and how it predicted math course taking or career choice. Few studies 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 three constructs and have neglected science.

In most EV-based studies, external validity was limited by the use of samples that lacked adequate representation of racial or ethnic diversity. Thus, little is known about how EV theory functions to predict choices for minority students. In response to this concern, several studies have been conducted using national data sets (e.g., Maltese & Tai, 2011; Mau, 2003; Riegle-Crumb, Moore, & Ramos-Wada, 2011).

However, problems exist with these secondary data analyses, such as:

- studies that are not grounded in strong theoretical frameworks (e.g., Maltese & Tai, 2011; Maple & Stage, 1991; Miller et al., 2002);
- constructs that are only weakly supported by individual survey items (e.g., Maltese & Tai, 2011; Riegle-Crumb et al., 2011; Shaw & Barbuti, 2010);
- overcapitalization on chance through the testing of many variables and retaining only significant predictors in models (e.g., Maltese & Tai, 2011);
- conflation of constructs, particularly self-efficacy and self-concept (e.g., Mau, 2003; Riegle-Crumb et al., 2011); and
- the use of poorly defined constructs, such as science attitude (Blalock et al., 2008).

Each of these concerns was addressed in the present study.

GIFTEDNESS

Subotnik et al. (2011) emphasized the importance of motivation to the talent development process. "[G]eneral ability is necessary but not sufficient to explain optimal performance or creative productivity. It remains a component of talent development along with . . . motivation" (p. 14). Thus, to successfully navigate the talent-development process requires a nominal level of ability but also requires motivation. 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 present study, giftedness was 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. In the TRCG (Renzulli, 1978), above-average ability is used rather than the more typical 95th percentile designation because research has shown that for IQ scores above 120 (91st percentile), 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 versus bottom quartile of the upper 1% for those 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 also had higher subjective task value and were more motivated; motivation variables were not measured in these studies. Furthermore, the top 1% 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 1% 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 programs (Ford, 2010). A persistent gap exists between the achievement test scores of White and minority (Black and Hispanic) 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. However, 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 was taken in the present study.

Task Commitment

The task commitment component of the TRCG (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). Another way that motivation is incorporated into the TRCG is through *Operation Hounds Tooth.* Renzulli placed the three rings atop a hounds tooth background that represents a set of cocognitive factors, which are personal characteristics that are related to commitment. These factors include sensitivity to human concerns, optimism, courage, romance with a topic, physical and mental energy, vision and a sense of destiny, and a sense of power to change things (Renzulli, 2012). According to Renzulli, "Giftedness in the new century will have to be redefined in ways that take these co-cognitive components into account" (Renzulli, 2012, p. 156). This provides further support to the idea that ways for quantifying student motivation are needed.

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) stated this was 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*, which describes 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 math and science would be expected to have higher STV (attainment, utility, and interest–enjoyment values) for those domains than students who are not gifted in these domains. On the other hand, school subjects may not be 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 attainment, utility, and interest–enjoyment values.

The findings of Fredericks et al. (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. The information management model (Coleman & Cross, 1988; Cross & Coleman, 2005) 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 lower levels of attainment value. No research has been done on gifted students' disidentification with the STEM domains specifically.

In studies of highly gifted students, educational–occupational interests have been shown to have 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 these studies 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. However, identity-incongruence is a barrier to 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). Thus, interest–enjoyment value and attainment value are likely to affect science choices for gifted students.

Gifted Students and STV

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. 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 in a study that used a small ($N = 111$), nondiverse, 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 math and science depend on domain-specific STVs and expectancies (Eccles, 2011; Maltese & Tai, 2011; Zarrett & Malanchuk, 2005). The students with the highest abilities or prior performance within the domains of math and science are thought to be the best candidates for talent development in that domain. However, domain-specific STV (attainment, utility, and interest–enjoyment values) may be more important than ability to the development of talent. Students who are motivated to pursue STEM talent development must value the domain.

Each gifted student 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. More empirical research is needed to study the actual expectancy value patterns of above average ability students. 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.

PERSON-CENTERED APPROACH

The extant literature suggests that occupational choice is a result of interactions that occur within individuals among expectancies and values. This suggests that a person-centered approach should be taken in which the level of a variable for that person is compared to the levels of the other variables for that person. In the present study, such an approach was used to find profiles of variable configurations present in individuals. 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 active agents who take intentional actions as they interact with the environment in a dynamic, complex, and adaptive process. In the present study, a person-centered approach was used because (a) EV variables function in constellations instead of singly, (b) relationships between variables within the EV model are different for each individual, and (c) methodological constraints of the general linear model are removed.

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. In the present study, classes of people are identified by the patterns of variables that exist within the population.

Differential Functioning of Variables

A variable-centered analysis 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. 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.

Constraints of the General Linear Model

In EV research, the collinearity of the STV constructs has been noted (Wigfield & Eccles, 2000). Researchers have handled this concern by using a composite variable that represented the three STV constructs of attainment, utility, and interest–enjoyment values. However, this combination may have masked differences in the relative contributions to outcomes or how the constructs worked together. In a person-centered approach, patterns of expectancies and values are used to identify classes within the population. Thus, the function of each of the STV constructs within classes of individuals can be examined. Such an approach permits the use of collinear variables and facilitates study of the components of STV.

The present study identifies expectancy value profiles. The extant literature supports the hypothesis that there exist multiple profiles that promote math and science-related choices and other profiles that do not promote those choices. Profile analysis has the potential to reveal how expectancy-value constructs function together in individuals.

Research Questions

1. What distinct profiles emerge from measures of math-specific expectancies and values: math self-efficacy (MSE), math attainment value (MAV), math utility value (MUV), and math interest–enjoyment (MIV)?
2. What distinct profiles emerge from measures of science-specific expectancies and values: science self-efficacy (SSE), science attainment values (SAV), science utility value (SUV), and science interest–enjoyment value (SIV)?
3. How does profile membership relate to high-ability status? It is hypothesized that expectancy value profiles will not be strongly related to high-ability status. 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.

METHOD

Subjects and Sample Selection

The High School Longitudinal Study (HSLS) of 2009 (Ingels et al., 2011) is a longitudinal study from the National Center for Education Statistics (NCES) that tracks a nationally representative sample of secondary students. The data come from the base year. 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 representative of ninth-grade students in public and private schools in the United States in 2009. Schools in 10 states were selected; 944 schools participated. Within each school, a stratified random sample of students was selected based on race/ethnicity. An average of 27 students per school were selected and the total number of students who participated in the study was 21,444 (Ingels et al., 2011).

Instrumentation

The design of HSLS: 2009 differs from previous studies because it was 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). By NCES design, the questionnaire items support the important constructs of EV theory (Ingels et al., 2011). Scale reliability analyses were conducted for each scale (Table 1).

Variables

The scales that were used in this study had been created by NCES (see Ingels et al., 2011). Descriptive statistics and Cronbach's alphas for each scale are summarized in Table 1.

TABLE 1
Descriptive Statistics ($N = 19{,}259$)

Variable	*Mean (SE)*	*SD*	*Alpha*
Math achievement test score	38.956 (0.187)	11.920	N/A
Math self-efficacy (MSE)	0.0016 (0.0167)	0.997	.90
Math attainment value (MAV)	0.0010 (0.0157)	0.999	.84
Math utility value (MUV)	0.0020 (0.0166)	0.997	.78
Math interest–enjoyment value (MIV)	0.0055 (0.0168)	0.996	.75
Science self-efficacy (SSE)	−0.0057 (0.0174)	0.994	.88
Science attainment value (SAV)	−0.0061 (0.0156)	0.996	.83
Science utility value (SUV)	0.0019 (0.0174)	0.995	.75
Science interest–enjoyment value (SIV)	0.0060 (0.0175)	0.990	.73

Note. All measures except for the Math Achievement Test Score are *z*-scores. The Math Achievement Test Score had a maximum of 70.

Expectancies

Self-efficacy scales for science and math were created by NCES. Expectancies were operationalized as self-efficacies or the confidence that the student has in her or his ability to be successful at specific math or science tasks (Ingels et al., 2011).

Subjective Task Values

Subjective task values represent the degree that the student valued math or science. Separate scales for three of the STV constructs (attainment, utility, and interest–enjoyment values), for each of the two domains (math and science), were created by NCES.

Math/science attainment values (MAV/SAV). Math or science attainment value describes how well the domain of math or science fit with the student's identity. Two sets of *z*-scores were created by NCES derived from factor analysis of two items for each scale (Ingels et al., 2011).

Math/science utility values (MUV/SUV). Math or science utility value describes how much the student thinks math or science will be useful in life, for college, or for a future career. Two sets of *z*-scores were created by NCES derived from factor analysis of three items for each scale (Ingels et al., 2011).

Math/science interest–enjoyment values (MIV/SIV). Math or science interest–enjoyment value describes how much the student is interested in or enjoys the respective subject. Two sets of *z*-scores were created by NCES derived from factor analysis of six items for each scale (Ingels et al., 2011).

High Ability

In alignment with recommendations for the identification of underrepresented groups (e.g., Lohman, 2005), within-group norms were used to identify students who scored at least one standard deviation above the mean within their racial group (Asian, Black, Hispanic, or White) on the math achievement score were identified as having high ability (Table 2). The math achievement test score is an acceptable proxy for above-average ability (J. Renzulli, University of Connecticut, personal communication, November 2, 2012).

In each analysis, the complexity of the sample was taken into account and standard errors were adjusted for the clustering of students within schools using the complex sample features in MPlus 7 (Muthén & Muthén, 2012).

TABLE 2
Math Achievement Test +1Z Cutoff Scores

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

RESULTS

Data cleaning was performed using SPSS 20. The restricted-use data set contained 25,206 cases. The following cases were omitted from further analyses: 3,214 that were weighted to zero by NCES because of missing data, 2,199 in the "Other" race/ethnicity category, and 534 cases missing the mathematics achievement score. This left 19,259 cases.

Results for Research Question #1

In accordance with the latent class analysis procedures recommended by Pastor, Barron, Miller, and Davis (2007), a one-class model was estimated, then models with additional classes were estimated until (a) the model would not converge; (b) the Lo-Mendel-Rubin p-value exceeded .05; or (c) the log-likelihood would not replicate. The initial number of starts used in Mplus was increased to attempt to reach convergence or log-likelihood replication. If the model did not converge after the starts were changed to 4,000, "did not converge" was recorded as the result. Models were structured such that profile indicator variances were allowed to vary within and between classes and covariances were constrained to zero.

The models were compared using procedures recommended by Pastor et al. (2007). To determine which model best represented the latent class structure for the mathematics classes, the values of the Bayesian information criterion (BIC) were examined (Table 3). The five-class model had the lowest BIC value (Figure 1). However, the five-class model split the typical class into two classes that were not theoretically distinguishable from the typical class in the four-class model; thus, the four-class model was selected. The elbow in the plot of BIC versus number of classes occurred at 3, indicating less improvement in model fit when additional classes were added. However, a unique profile (high math self-efficacy profile) was revealed in the four-class model (Figure 2) that was not visible in the three-class model, which justified retention of the four-class model (Pastor et al., 2007). The four classes were labeled as *low, typical, high MSE,* and *high MUV* based on the characteristics that typified each.

TABLE 3
Math Models

Classes	*LL*	*No. Free Parameters*	*BIC*	*Entropy*	*Smallest Class Freq.*
1	−97,711	8	195,501		
2	−90,981	17	182,129	0.658	9,508 (0.50)
3	−87,190	26	174,637	0.751	4,186 (0.22)
4	−85,769	35	171,883	0.753	2,126 (0.11)
5	−84,220	43	168,865	0.708	2,325 (0.12)
6			Did not converge		
7			Did not converge		

Note. LL = Log Likelihood.

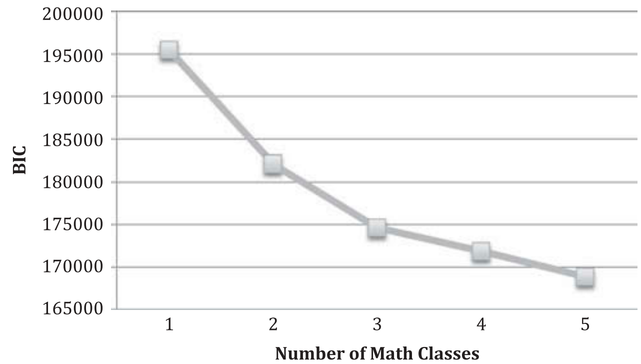

FIGURE 1 Plot of BIC vs. number of math classes.

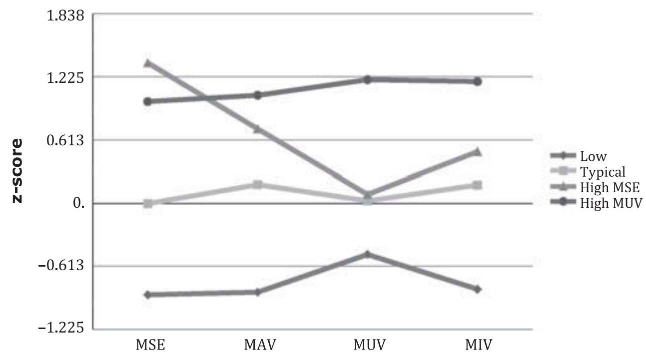

FIGURE 2 Mathematics four-class model profiles.

Results for Research Question #2

The same model testing procedure was used for the science classes (Table 4). The four-class model had the lowest value of BIC. The graph of BIC vs. number of classes reached a minimum at four classes (Figure 3). A unique profile (high science self-efficacy profile) was revealed in the four-class model (Figure 4) that was not visible in the three-class model. The four classes were labeled as *low, typical, high SSE,* and *high SUV* based on the characteristics that typified each.

TABLE 4
Science Models

Classes	*LL*	*No. Free Parameters*	*BIC*	*Entropy*	*Smallest Class Freq.*
1	−91,171	8	182,421		
2	−85,715	17	171,597	0.585	8,988 (0.47)
3	−83,059	26	166,169	0.627	3,382 (0.18)
4	−82,189	35	164,723	0.704	1,470 (0.08)
5			Did not converge		
6			Did not converge		
7			Did not converge		

Note. LL = Log Likelihood.

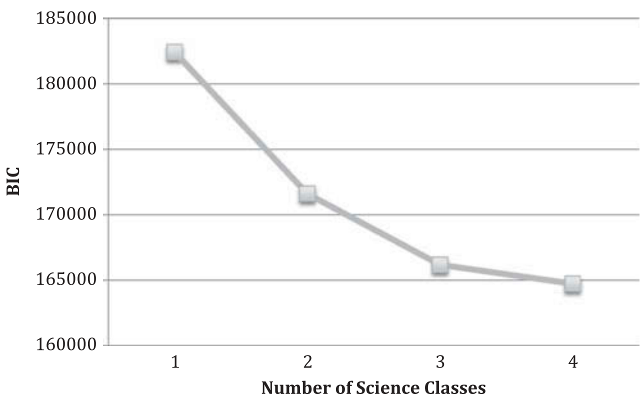

FIGURE 3 Plot of BIC vs. number of science classes.

Results for Research Question #3

To examine the relationship between latent class membership and high ability status the AUXILIARY (e) function in Mplus 7 was used. Because high-ability students were identified using a +1Z cutoff within racial group, 15.9% of the population was identified. High-ability students were significantly underrepresented in the *low* math class and significantly overrepresented in the *high math self-efficacy* (HMSE; 31%) and *high math utility value* (HMUV; 22%) classes (Table 5). Representation in the *typical* math class (15%) was very close to the representation in the population.

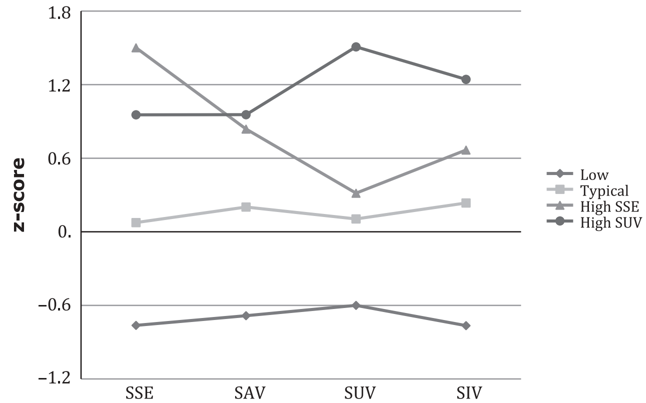

FIGURE 4 Science four-class model profiles.

SUMMARY OF MATH EXPECTANCY-VALUE CLASSES

Math Classes

- Typical. All profile indicators were near the mean (Figure 2). Forty-four percent of high-ability students were members of this class.
- Low. All profile indicators were below the mean (Figure 2). Fifteen percent of high-ability students were members of this class.
- HMSE. In this class, MSE was high and the other profile indicators were above the mean, except for math utility value, which was average (Figure 2). High-ability students were represented in this group at nearly twice the rate as in the population. These students had the strongest sense of MSE, fitting the stereotype of the gifted math student. However, these students had relatively low MUV and MIV. Twenty-three percent of high-ability students were members of this class.
- HMUV. In this class, all indicators were high, but MSE was lower than the value for the high MSE class (Figure 2). These students had the strongest perception of the usefulness of math for their future careers and college success and the highest level of interest in math. Eighteen percent of high-ability students were members of this class.

TABLE 5
Summary of Science Classes

Class (% of Sample)	*SSE M (SE)*	*SAV M (SE)*	*SUV M (SE)*	*SIV M (SE)*	*High-Ability Students (% of Class)*
Low (40%)	−0.763 (0.060)	−0.684 (0.041)	−0.600 (0.050)	−0.765 (0.057)	10.3
Typical (43%)	0.075 (0.022)	0.202 (0.031)	0.105 (0.023)	0.235 (0.027)	15.4
High SSE (8%)	1.501 (0.045)	0.838 (0.109)	0.315 (0.062)	0.667 (0.077)	27.8
High SUV (9%)	0.954 (0.056)	0.955 (0.112)	1.508 (0.020)	1.243 (0.054)	21.8
Entire sample (100%)	0.002 (0.017)	0.001 (0.016)	0.002 (0.017)	0.006 (0.017)	15.9

Note. All scale scores are *z*-scores.

SUMMARY OF SCIENCE EXPECTANCY-VALUE CLASSES

Science Classes

- Low. All of the profile indicators were below the mean (Figure 4). Twenty-eight percent of high-ability students were members of this class.
- Typical. All of the profile indicators were near the mean. Forty-five percent of high-ability students were members of this class.
- HSSE. In this class, SSE was high and the other profile indicators were above average but below the values for the HMUV class. Fourteen percent of high-ability students were members of this class.
- HSUV. In this class, SUV and SIV were high and the other profile indicators were above the mean. These students had the strongest perception of the usefulness of science to their future careers and college successes and the highest levels of interest in science. However, attainment value was not distinguishable from the level in the HSSE class and self-efficacy was below the level in the HSSE class. Thirteen percent of high-ability students were members of this class.

DISCUSSION, CONCLUSIONS, IMPLICATIONS

Limitations and Delimitations

First, a limitation was the lack of a standardized measure of science achievement. The math achievement test score was a proxy for high ability in science. The nature of the EV questionnaire items was a limitation because the questions were asked specifically about the Fall 2009 math and sciences courses in which the students were enrolled. Students' expectancies and values about a specific math or science course may be different from their expectancies and values about the domains of math and science in general. Furthermore, expectancies and values for technology and engineering were not addressed in the HSLS, 2009 questionnaire. In this study, high-ability was defined as a score greater than or equal to +1Z within a race group on the math achievement test. This definition may differ from other definitions because it is used within group norms instead of global norms. The bulk of studies on gifted students have used identification standards that are more stringent than this standard.

EXTANT MATH AND SCIENCE EXPECTANCY-VALUE PROFILES

The main objective was to identify math and science motivation profiles. An exploratory modeling process revealed patterns in the latent profile indicators within the population of U.S. ninth-grade students in 2009. Separate models were established for math expectancy-value and for science-expectancy value.

The classes supported the hypothesis that a number of subgroups would be identified with high, low, and mixed levels of expectancy-value. High, low, and mixed classes were identified for math and for science. Based on Conley (2012), who found seven distinct clusters in her analysis of math expectancies and values, it was expected that the latent class models would have had several classes. However, Conley used cluster analysis and different model selection criteria. Therefore, direct comparisons between Conley (2012) and the latent profile solutions in the current study may not be relevant.

Comparison of Math and Science Profiles

The models revealed information about students' comparative self-efficacies and subjective task values in math and science. Both the math and science models had four classes (see Figures 2 and 4). Both models show high self-efficacy classes, which depict groups who had relatively high self-efficacies but much lower utility values than the high utility value classes. Another similarity between the models was that both the math and science models had a high utility value class. These classes described students who had relatively high utility and interest values combined with relatively lower self-efficacies.

Class Size and Membership

The sizes of the classes in each model (Tables 5 and 6) revealed that fewer students were in the high science classes (17%) than in the high math classes (33%). This trend was also observed for high-ability students; 41% of high-ability students were in the high math classes and 27% were in the high science classes. A possible cause may be that students have had a greater number of and more frequent experiences with math than with science prior to high school because of U.S. testing mandates that place much greater emphasis on math than science in the K–8 curriculum (Berliner, 2009, 2011; McMurrer, 2008). Thus, students may not have 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.

Representation of High-Ability Students

In this study, high ability was operationalized as students who scored +1Z on the math 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

TABLE 6
Summary of Math Classes

Class (% of Sample)	*MSE M (SE)*	*MAV M (SE)*	*MUV M (SE)*	*MIV M (SE)*	*High-Ability Students (% of Class)*
Low (33%)	−0.890 (0.051)	−0.864 (0.030)	−0.497 (0.032)	−0.836 (0.036)	7.0
Typical (44%)	−0.003 (0.010)	0.182 (0.029)	0.023 (0.038)	0.178 (0.022)	15.1
High MSE (11%)	1.360 (0.021)	0.719 (0.098)	0.086 (0.039)	0.498 (0.067)	30.8
High MUV (12%)	0.984 (0.093)	1.045 (0.138)	1.197 (0.021)	1.179 (0.098)	22.2
Entire sample (100%)	0.002 (0.017)	0.001 (0.016)	0.002 (0.017)	0.006 (0.017)	15.9

Note. All scale scores are *z*-scores.

TABLE 7
Bivariate Correlations

	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*
MSE	1								
MAV	0.572*	1							
MUV	0.360*	0.290*	1						
MIV	0.540*	0.547*	0.423*	1					
SSE	0.401*	0.267*	0.190*	0.180*	1				
SAV	0.188*	0.274*	0.103*	0.114*	0.493*	1			
SUV	0.201*	0.190*	0.426*	0.224*	0.414*	0.387*	1		
SIV	0.141*	0.136*	0.180*	0.194*	0.508*	0.462*	0.492*	1	
X1TXMSCR	0.306*	0.384*	0.000	0.213*	0.225*	0.248*	0.057*	0.123*	1

$^*p < .01$.

proportions of gifted students in every race/ethnicity group through the use of group-specific thresholds. The representation of high-ability students varied considerably between the math classes and the science classes. Though the high MSE class had nearly twice the level of high-ability students (30.8%) as in the population, high-ability students were represented in the high MUV class at a rate larger than in the population (22.2%). However, there was a positive relationship between math ability and MSE (Table 7; $r = 0.306$, $p < .01$), as would be expected. Similarly, high-ability students were represented in the high SSE class at a rate of 27.8% and at a rate of 21.8% in the high SUV class. Equal proportions of high-ability students were in the high SUV group and the high MUV group. The more inclusive operationalization of high ability means that many students who were included in the high-ability 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.

Subjective Task Value Components

A person-centered approach was taken that considered the relationship of profiles of the STV variables that naturally occurred with correlates, rather than the mean levels of the variables. Both approaches are different methods of looking at the same data and each is useful. 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, the variables were somewhat related but did not always occur at the same levels. In the math and science profiles, the low and typical profiles each contained low or average values of the profile indicators (see Figures 2 and 4). However, the two high profiles were mixed. In the high utility-value classes, the value of utility value was higher than in the high self-efficacy classes. However, interest and attainment values were higher in the high utility-value classes than the high self-efficacy classes. The differences between these 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.

This study addressed problems in the literature with external validity because a large, nationally representative sample was used. Previous studies lacked sufficient representation of minority students. The only previous study that separated STV components was Conley (2012). However, her sample consisted of predominantly Vietnamese and Latino children of working-class parents. Conley (2012) found that math utility value was uniformly high across the seven-cluster solution. In this sample that had proportional representation to the U.S. population of ninth-grade students in 2009, classes with high and low utility value were identified.

An explanation for this may be that the subpopulations in which high utility value 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, in accordance with the TRCG (Renzulli, 1978). 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 qualities, above-average ability and task commitment or motivation, were identified.

The findings of this study show that the majority of high-ability students were not part of the high motivation groups. In the math profiles, the students in the high self-efficacy class would be identified as highly motivated. This class represents 23% of the high-ability students. If the high utility class is included in the highly motivated group, the percentage of the population that would be identified as mathematically gifted increases to 41% of the high-ability students. In the science profiles, the high self-efficacy class represents 14% and the high utility class represents 13% of the high-ability students, which sum to 27%. These two groups (mathematically and scientifically gifted) have some overlap in membership. The finding that a minority of high-ability students also exhibited high motivation is supported by previous research (e.g., Gottfried et al., 2009; Gottfried & Gottfried, 2004). Importantly, this finding has serious implications for talent development in the science and math disciplines. Students who have lower motivation are less likely to choose and persist in the study of these subjects. Possible reasons for the lower motivation of high-ability students may be that academic coursework in math and science are not perceived as useful for future careers or college course-taking because these students do not consider careers in STEM disciplines as viable options for their futures. Further, low values of interest–enjoyment value indicate that these students generally do not find school math or science interesting or enjoyable. This lack of interest and enjoyment negatively affects potential interest in STEM occupations and future coursework.

This approach demonstrates a way to cast a wider net for identification of students who are potentially gifted because lower threshold scores and within group norms were used to identify high-ability students and motivation was considered. Thus, attempts to identify the concomitance of high ability and high motivation could be useful to select those students who would benefit most from gifted education services.

Motivation Profiles and Underachievement

Expectancy-value profiles could 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 represented 15% of high-ability students. The low science class represents 28% of high-ability students. The size of the low-motivation, high-ability group was larger than the high-motivation, high-ability group in science. The high occurrence of high-ability students in low motivation profiles should be investigated further, because this condition is likely to result in underachievement and hamper the development of potential. This group may be less likely to develop domain-specific talents than the group of high-ability students who exhibit high motivation. Perhaps talent development outcomes of gifted education could be improved if motivation was considered and ability threshold scores were lowered.

Some evidence was found of disidentification. In general, students with higher self-efficacies had above-average subjective task values (attainment, utility, and interest values). However, students in the high self-efficacy groups had lower attainment, utility, and interest values than the students in the high utility value groups. Furthermore, 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 math and/or science. This contradicts the findings of Dai, Moon, and Feldhusen (1998) that claimed invariant findings of higher self-efficacy among gifted students.

FUTURE RESEARCH

It remains to be analyzed how the classes were populated in detail. 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. In particular, 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.

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