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Do High Ability Students Disidentify With Science?
A Descriptive Study of U. S. Ninth Graders in 2009

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Abstract

The present study describes science expectancy-value motivation classes within a nationally representative sample of students who were U. S. ninth-graders in 2009. An expectancy-value model was the basis for science-specific profile indicators (self-efficacy, attainment value, utility value, interest-enjoyment value). Using exploratory latent class analysis, a four-class model was identified as the best model, based on model fit and interpretability. Although the *Low* and *Typical* profiles had uniform levels of indicators, the two high motivation profiles (*High Self-Efficacy* and *High Utility Value*) had mixed levels. The profile characterized by very high self-efficacy had lower values, while the profile characterized by high utility value had lower self-efficacy. The differences in math achievement between profiles were small. High-ability students disidentified with science; only 29% of high-ability students had high science expectancy-value profiles. The implications for science talent development are discussed.

How Motivated are 9th Graders in Science? A Descriptive Study of Science Motivation Profiles

in U. S. Ninth-Graders in 2009

High-ability high school students form a talent pool from which future scientists and engineers should come. However, relatively few members of this large talent pool develop their abilities in the STEM disciplines (National Science Board, 2010). The question of why this might be happening is important to consider as the United States is engaged in a national effort to strengthen the science and engineering workforce by actively recruiting all Americans, especially students who have been identified as having high ability in math. One factor that has been neglected for the most part in efforts to understand students' participation in STEM disciplines is knowing what motivates these students. Exploration of students' STEM motivation is the focus of the present study.

Because the construct of motivation is quite broad and multidimensional, we begin by outlining the theory that undergirds our study, with a specific focus on how motivation plays out in science. Although there are numerous models of motivation, we focus on Expectancy-Value Theory because we view beliefs about competence (i.e., the expectancy component of the model) and beliefs about the *value* of a subject to be especially salient in science—a subject in which students typically struggle (Drew, 2011; National Academies of Science, 2011) and find irrelevant for what they want to do in the future (Basu & Barton, 2007; Hannover & Kessels, 2004).

We posit that a students' expectancy-value profile in the ninth grade has a relationship with his or her plans to pursue later STEM occupations. In the present study, we identify four

distinct profiles that have different relationships with occupational plans. Further, we believe that

the characteristics of this profile provide information about what motivates the student towards

STEM occupations. The identified profiles have distinctive features and provide information

about students' motivations that has not previously been studied. In the present study, some basic

assumptions about students and STEM were scrutinized. For example, it is widely accepted that

mathematics ability is a good indicator of who should pursue STEM occupations. However, prior

research with small samples of gifted students suggests that the students with the highest

academic ability are not the most highly motivated in an academic domain. Thus, we

investigated the possibility that motivation profile may have a stronger relationship with

occupational plans than ability. Our evidence supports the idea that motivation has a stronger

relationship with STEM occupational plans than mathematics ability.

Expectancy-Value

In the expectancy-value model, students choose among viable options with their

perception of viability being affected by cultural stereotypes and parental, familial, or peer

influences (Wigfield & Eccles, 2000). The considerations that drive decisions include one's

expectations for success and the alignment of the choice with three components: personal goals,

identity, and interests. Each of these considerations is influenced by cultural role schemas based

on race, gender, or ethnicity. (Wigfield & Eccles, 2000). The first of these considerations is

expectancy and the remaining three components collectively comprise *subjective task value.*

Through this model, choice, persistence, and performance are causally linked to the individual's

expectation for success and the subjective task value of the activity. Sociocultural contexts shape

beliefs and directly affect expectancies and values, which in turn affect the choices, how much

effort is exerted, and performance. 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).

Science Expectancy

Generally, expectancy is the belief that one can succeed in future tasks (Wigfield & Eccles, 2000). Science expectancy is positively related to prior achievement and to interest in science (Denissen, Zarrett, & Eccles, 2007; Navarro, Flores, & Worthington, 2007; Rottinghaus, Larson, & Borgen, 2003). However, expectancy can also be influenced by sociocultural factors. Gender differences in expectancy beliefs often favor males in gender-role stereotyped domains, such as science (Riegle-Crumb, Moore, & Ramos-Wada, 2011; Simpkins & Davis-Kean, 2005). Expectancy may not align well with actual ability or achievement. For example, if high-ability students have internalized negative stereotypes about their science abilities or adopted negative views about their potentials to be successful in science, they are likely to hold relatively lower expectancies for success. For example, gifted girls are more responsive to social-evaluative feedback and stereotype threat than gifted boys (Dai, 2002) and therefore may have lower expectancies. Most studies of science-related choices have used math self-efficacy as a proxy for science self-efficacy (e.g., Mau, 2003; Moakler, 2011; Zarrett & Malanchuk, 2005), while a few have used latent variables that combined math and science expectancy (e.g., Navarro et al., 2007). The alignment of the expectancy domain with the choice domain may have affected prior findings; Andersen and Ward (2014) found that science expectancy was a predictor of STEM-related plans, while math expectancy was not. Overall, the effect of expectancy was smaller than the effect of subjective task value on choice (Andersen & Ward, 2014; Watt et al., 2006).

Science Subjective Task Value

Subjective task value (STV) can be defined as students' beliefs about how interesting science activities are, how enjoyable they are, and how personally important or useful the science activities are (Wigfield, Tonks, & Klauda, 2009). Individuals make these value judgments based on their memberships in multiple cultural or social groups, therefore cultural expectations and peer expectations influence the value of science. In the next section, each of the four constructs that comprise STV will be described.

Science attainment value. Science attainment value is how important science is to self, or how well aligned one's own identity is with a science identity (Wigfield et al., 2009). Science course taking is positively related to attainment value and identification with science. When the perception of a science identity conflicts with what is believed appropriate for one's gender, race, or ethnicity, science will have lower attainment value (Eccles, 2009). Negative stereotypes are often associated with a science identity. Fifty years of research on students' perceptions of scientists has revealed persistent and pervasive stereotypes that include descriptors such as: exceedingly clever, amoral, insensitive, obsessive, unemotional, unsocial, unkempt, and uncaring (Barba, 1998; Finson, 2002; Seymour & Hewitt, 1997). *Scientist* is 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; Howley, Howley, & Pendarvis, 1995). Recent 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 and personal identities for persistence (Carlone & Johnson, 2007; Hannover & Kessels, 2004; Kao, 2000; Oyserman & Destin, 2010; Taconis & Kessels, 2009).

Science utility value. Utility value is the degree of the alignment between science courses and future goals, such as college or career. For example, students may perceive a science class as being useful to their lives because it is required for their career goals. Students who pursue science-related goals tend to place higher utility value on science courses. Utility value is a significant predictor of STEM career choice (Andersen & Ward, 2013, 2014; Maltese & Tai, 2011).

Science interest-enjoyment value. Interest-enjoyment value is the degree to which students like science or find it fun (Wigfield & Eccles, 2000). Interest-enjoyment value is positively related to decisions about taking STEM-related courses and pursuing 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).

Prior Research on STV. Although 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), these studies operationalized STV as a single score that represented interest-enjoyment, attainment, and utility values. This is problematic because motivation is a multidimensional construct such that students can certainly view a subject as being very useful to their lives yet derive very little enjoyment from it. There are numerous configurations in which the different constructs contained within expectancy-value theory can be arranged. We claim that these different configurations of expectancy-value constructs can result in quite different motivational and achievement outcomes. Past studies that collapse the various dimensions of motivation into one overarching construct miss out on nuanced questions such as this: What differences exist, if any, between students who see science as useful but not interesting compared to students who view science as interesting but not useful? Few studies of STV have examined

the motivational and achievement outcomes of various configurations of the four main constructs within expectancy-value theory, and few have examined these issues with science.

In most expectancy-value based studies, external validity was limited by the use of samples that lacked adequate racial or ethnic diversity. Thus, it is not known if the expectancy-value theory functions in the same way for minority students as it does for other students. Although studies have been conducted using national datasets (e.g., Maltese & Tai, 2011; Mau, 2003; Riegle-Crumb et al., 2011), 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). This study addresses each of these concerns.

Motivation and Talent Development in the Sciences

Subotnik, Olszewski-Kubilius, and Worrell (2011) emphasized the importance of motivation to the talent development process. "General 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 both a nominal level of ability as well as substantial motivation. Talent development has also been conceptualized as the demonstration of gifted behavior. Renzulli's (1978) Three Ring Conception of Giftedness (TRCG) defines *giftedness* as creative

productive behavior arising from the interaction between above-average ability, task

commitment, and creativity. Above-average ability is used instead of high ability 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).

Motivation as 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" (Renzulli, 2005, 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) cites identification with the talent

domain as the cause of this intense engagement. In STV terminology, task commitment is

represented by a combination of high interest-enjoyment value and high attainment value.

Evidence of this intense engagement is seen in the *deliberate practice* of the talent development

process*,* 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 and is undertaken because it holds utility

value for the individual. Individuals who are gifted in science would be expected to have higher

STV (attainment, utility, and interest-enjoyment values) for science than students who are not

gifted in science. 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 students showed that none of these students were passionate about schoolwork 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.

         Disidentification. The findings of Fredericks, Alfeld, and Eccles (2010) raise the question of 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) states that high-ability students may disidentify with academics because they encounter mixed messages in different contexts and often must decide between achievement and social acceptance (Cross & Coleman, 1995; Cross, Coleman, & Stewart, 1993; Swiatek, 2001). In the typical American high school, passion about academics is viewed as socially unacceptable or stigmatizing, but high-ability students desire popularity and social acceptance just as other children do (Coleman & Cross, 1988). Most high-ability children feel different from their non-high-ability peers, and some of those who feel different engage in social-coping strategies to manage their identities at school and feel less different (Cross & Coleman, 1995; Swiatek, 1998). Some of the most common strategies are to hide their abilities or to disidentify (Cross, 1997; Swiatek, 2001). In terms of the EV model, students who have disidentified with science are likely to report lower levels of attainment, utility, and interest-enjoyment value, while reporting relatively high levels of self-efficacy. Most research has focused on disidentification associated with general academic ability and academics (e.g. Cross & Coleman, 1995; Cross et al., 1993; Swiatek, 2001). One study has focused on high-ability students' disidentification with science specifically (Andersen & Cross, 2014).

Ability and STV. Students with high expectancy are more likely to have high interest in those domains (Denissen et al., 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, and the high intrinsic motivation group had higher levels of achievement than the high-ability group. However, the sample for this study was a small, non-diverse, convenience sample, which limits the generalizability of this finding and general academic ability and motivation were the outcome measures. Studies are needed that include diverse populations and that focus on science. In the present study, a diverse sample was used to examine the relationship between ability and science-specific motivation.

Summary

Adolescents' decisions to study science depend on their science expectancies and values (Eccles, 2011; Maltese & Tai, 2011). Students with above-average ability in science are thought to be good candidates for talent development in science. However, science values (attainment, utility, and interest-enjoyment values) may matter more than ability in the development of talent. Students with above-average ability and high motivation are likely to be the best candidates for talent development. In order for students to be motivated to pursue talent development in science, they must value science.

Each student feels a different degree of dissonance between his or her cultural norms and the norms of science culture. For females, gender-role expectations may conflict with STEM career expectations and negative STEM-related gender stereotypes are abundant (Arnold, 1993; Jacobs, 2005; Weisgram, Bigler, & Liben, 2010). For African Americans and Hispanic students, negative STEM-related racial or ethnic stereotypes may discourage participation (Kao, 2000; Oyserman & Destin, 2010; Steele, 1997). In addition to these cultural considerations, above-average ability students may also feel stigmatized to some degree due to their differentness from other students (Cross & Coleman, 1995; Coleman et al., 1993; Swiatek, 2001). Science identities are stigmatizing due to negative stereotypes that directly oppose the characteristics and traits that adolescents desire and threaten their potential for popularity and peer acceptance (Hannover & Kessels, 2004; Kessels, 2005). It is hypothesized that these sociocultural phenomena affect students' expectancies and values as well as their plans for future occupations. Little is known about the science-specific expectancy value patterns of high school students. This large-scale study of students' expectancies and value will provide some baseline data to guide further research into why some students choose science and others do not.

Research Questions

1. What distinct profiles emerge from measures of science expectancies and values: science self-efficacy (SSE), science attainment values (SAV), science utility value (SUV), and science interest-enjoyment value (SIV)?

2. Do the profiles provide evidence of disidentification?

3. How is profile membership related to STEM occupational plans?

Method

Participants

Subjects and Sample Selection

The High School Longitudinal Study of 2009 is a longitudinal study from the U. S. National Center for Education Statistics (NCES) that tracks a nationally representative sample of secondary students (Ingels et al., 2011). These data came from the base year. The sample design was 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 US in 2009. Schools in ten 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).

Research Design

Person-Centered Approach

The extant literature suggests that occupational choice is a result of interactions that occur within individuals among expectancies and values. This implies 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 this study, such an approach was used to identify

profiles of expectancy-value variable configurations. Person-centered approaches are 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). In this study, a person-

centered approach was used because: (1) EV variables function in constellations instead of

singly, (2) relationships between variables within the EV model are different for each individual,

and (3) methodological constraints of the general linear model are removed.

Focus on constellations of variables. Individuals make choices based on combinations

of expectancies and values (Wigfield & Eccles, 2000). Thus considerations of single variables in

isolation, examined out of context from other relevant variables that are operating

simultaneously, are not important psychologically (Bergman et al., 2003). Classes of people will

be identified by the patterns of variables that exist within the population.

A variable-centered analysis uses group means to predicting outcomes for individuals in

the group. The relationships that are found are used to make inferences about individuals. In such

an approach, an observed statistical relationship may appear to be small because a small group

within the sample has little influence on the group mean. This is a concern for this study because

a relatively small percentage of students choose STEM careers. Previous variable-centered

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, it has been noted that the STV

constructs are often highly correlated (Wigfield & Eccles, 2000). Researchers have handled this

concern using a composite variable for attainment, utility, and interest-enjoyment values (e.g.

Eccles et al., 1984, Simpkins & Davis-Kean, 2005; Watt et al., 2006) and found that composite

STV predicted choice. However, this mathematical combination of the three values masked

differences in the individual contributions of each value and does not permit investigation of how

the three values are related to each other in people. In a person-centered approach, patterns of

expectancies and values will be used to identify classes within the population and each construct

within classes of individuals will be examined. This study explored expectancy value profiles

using latent class analysis. The extant literature supports the hypothesis that there exist multiple

science motivation profiles that promote science-related choices and other profiles that do not

promote those choices (Wigfield & Eccles, 2000, Bergman et al., 2003).

Measures

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). The

questionnaire items support the important constructs of EV theory, and this study, very well.

Variables

Scales had been created by NCES (see Ingels et al., 2011). Descriptive statistics and

Cronbach's Alphas for each scale are summarized in Tables 1 and 2.

INSERT TABLES 1 AND 2 ABOUT HERE

Expectancy. A science self-efficacy scale measures the confidence that the student has in

his or her ability to be successful at specific science tasks (Ingels et al., 2011). These z-scores

were created by NCES from four items.

Subjective task values. Subjective task values represent the value a student has for science. Separate scales for three of the STV constructs (attainment, utility, and interest-enjoyment values) had been created by NCES.

Science attainment values (SAV). Science attainment value describes how well the domain of science fits with the student's identity. These z-scores had been created by NCES from two items (Ingels et al., 2011).

Science utility values (SUV). Science utility value describes how much the student thinks science will be useful in life, for college, or for a future career. These z-scores had been created by NCES from three items (Ingels et al., 2011).

Science interest-enjoyment value (SIV). Science interest-enjoyment value describes how much the student is interested in or enjoys science. These z-scores had been created by NCES from six items (Ingels et al., 2011).

Math achievement. An assessment of algebraic reasoning was given to all students in Fall 2009 over six domains of algebraic content and four algebraic processes (Ingels et al., 2011). The assessment had two stages and was delivered by computer. Student performance on the first stage determined the questions that student would receive in the second stage. The scores were based on IRT, which uses information from student response patterns and assessment item information to compute a student ability estimate. The estimated number right score was used as the math achievement score in the present study. The IRT-estimated reliability of the HSLS:09 test was 0.92 (Ingels et al., 2011). No other measures of ability or achievement were available in these data. The math achievement test score was determined to be an acceptable proxy for ability (J. Renzulli, personal communication, November 2, 2012). The +1z cutoff score for above-average ability was computed to be 53.057 out of 70. All students who had math achievement

scores above this threshold were identified as above-average ability. This effectively

operationalized the level of above-average ability as equivalent to an IQ cutoff score of 115,

based on mathematics ability only.

STEM occupational plans. Students were asked to write in the name of the occupation

that they thought they would have at age 30. These were coded by NCES with six-digit codes

based on the Occupational Information Network Standard Occupational Classification (O*NET-

SOC; http://www.onetcenter.org/overview.html) database. The researcher recoded these

occupations as STEM if the occupation required postsecondary STEM education according to

the Bureau of Labor and Statistics descriptions of each occupation and non-STEM if it did not

require postsecondary STEM education.

Procedure

In each analysis, the complex samples features in MPlus 7 (Muthén & Muthén, 2012)

were used to account for the complexity of the sample and the clustering of students within

schools. SPSS 20 was used for data cleaning. The restricted use dataset contained 21,992 cases.

The following cases were omitted from further analyses: 2,199 in the "Other" race/ethnicity

category and 534 cases missing the mathematics achievement score. Cases in the "other"

race/ethnicity group represented groups that were too small to provide adequate power for

examination of patterns across groups. This left 19,259 cases.

Research Question #1. Research Question 1 asked what distinct profiles would emerge

based on the four profile indicators. 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: (1) the model would not converge or

(2) the best log-likelihood value was not replicated. The initial number of starts used in Mplus 7

(Muthén & Muthén, 2012) was increased to attempt to reach convergence or log-likelihood replication. If the model did not converge after the starts were changed to 8000, "did not replicate" was recorded as the result. In the models, indicator variances were allowed to vary within and between classes while covariances were constrained to zero. The models were compared using procedures recommended by Pastor et al. (2007) and the best model was selected based on absolute fit, relative fit, and theoretical interpretability.

Research Question #2. Research Question 2 was investigated by comparing: (a) the mean abilities of each expectancy-value class, (b) the representation of above-average ability within each expectancy-value class compared to its representation in the population, and (c) the distribution of the group of above-average ability students among the expectancy-value classes. To assess differences in mean ability between science expectancy-value classes, the auxiliary (E) function in MPlus 7.0 was used. This function tested the equality of means across latent classes using posterior probability-based multiple imputations (Muthén & Muthén, 2012) for math achievement scores. Above-average ability was a dummy variable that was assigned to students who had math achievement scores above the +1z cutoff. The mean value of this variable for each expectancy-value class provided the percentage of students within that class who had above-average ability.

Research Question #3. Research Question 3 asked how science expectancy-value class membership was related to STEM occupational plans. Each case was assigned the value 0 or 1 to the variable STEM based on the occupational plans that were indicated. The means of this dummy variable within each class provide the percentage of class members who planned STEM occupations at age 30.

Results

Results for Research Question #1

Research Question 1 asked what distinct profiles would emerge based on the four profile indicators. To determine which model best represented the latent class structure for the science classes, the values of BIC were examined (Table 3). The 4-class model had the lowest value of BIC and the graph of BIC vs. number of classes reached a minimum at four classes (Figure 1), which supported selection of this model. The four profiles were labeled as *Low, Typical, High Self-Efficacy* (HSE)*,* and *High Utility Value* (HUV).

INSERT TABLE 3, FIGURE 1, AND FIGURE 2 ABOUT HERE

Summary of science expectancy-value profiles. Four distinct profiles were observed in the best model (Figure 2). Two profiles displayed consistent levels of all four indicators, and taken together, represented 83% of all students – a *Low* and a *Typical* class. Forty percent of all students fit the *Low* science expectancy-value profile, in which all indicators were below the mean. Forty-three percent of all students fit the *Typical* profile in which all indicators were near the mean. Two high-level profiles indicated mixed levels of the indicators, and taken together, represented 17% of all students – *High Self-Efficacy* and a *High Utility Value*. Eight percent of all students had the *High Self-Efficacy profile* in which self-efficacy was very high, but the levels of the three value indicators were relatively low. Nine percent of all students had the *High Utility Value* profile, which had: a very high level of SUV, levels of SAV and SIV that were above those observed in the High Self-Efficacy profile, and a level of SSE that was below the level observed in the High Self-Efficacy profile.

INSERT TABLE 4 ABOUT HERE

Low. All indicators were below the mean (Figure 2; Table 4).

Typical. All of the indicators were near the mean (Figure 2; Table 4). This profile is

characterized by an average level of SSE (z = .075). The levels of the other indicators (SAV,

SIV, SUV) are slightly above the mean (.202, .235, and .105 respectively).

High self-efficacy (HSE). In this profile, SSE was high (z = 1.501; Figure 2; Table 4)

and the other indicators (SUV and SIV; z = 0.315 and z = 0.667 respectively) were above

average but significantly below the values of these indicators for the High Utility Value profile

(z = 1.508 and z = 1.243 respectively). The mean level of SAV in this class (z = 0.838) was not

distinguishable from the mean level in the High Utility Value profile (z = 0.955). This profile is

characterized by very high SSE and above average values of SUV and SIV, which are lower than

those who had the High SUV profile.

High Utility Value (HUV). In this profile, SUV (z = 1.508) and SIV (z = 1.243) were

high and the other indicators (SSE and SAV) were above the mean (Figure 2; Table 4). 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, SAV (z = .955, SE =

0.112) was not statistically different from the level in the HSE class (z = .838, SE = 0.109) and

self-efficacy (z = .954) was significantly below the level in the HSE class (z = 1.501). This class

is characterized by very high SUV and SIV.

Results for Research Question #2.

Mean ability of classes. The overall equality of means test found statistically significant

differences between math achievement in all four profiles (χ^2 (3) = 211, *p* = .000) and between

every pair of profiles at the *p* = .000 level. However, the effect sizes were not large. The

difference between the Low profile and the HSE profile was a medium effect (*d* = 0.542) and the

difference between the Low profile and the HUV profile was a small effect (*d* = .337). The

differences between the Typical profile and both the HSE and HUV profiles were small ($d = .306$

and .119, respectively). This was not surprising given the correlation between math achievement

and science self-efficacy of $r = .228$.

Representation of above-average ability in profiles. In this study, above-average

ability was operationalized as students who scored +1z on the math achievement test, comprising

15.9% of the population. The percentage of each profile group that was identified as above-

average ability was calculated (Table 5). Above-average ability students comprised 25.6% of the

HSE group and 19.1% of the HUV group. The HSE profile configuration describes a group of

students who have very high science self-efficacy with low science utility value and science

interest-enjoyment value. This profile is evidence of the disidentification of some above-average

ability students with science. Above-average ability students were also represented in the Typical

(13.4%) and the Low profiles (8.1%), but at rates lower than their representation in the total

sample.

<div align="center">INSERT TABLE 5 ABOUT HERE</div>

Distribution of above-average ability group. The distribution of the subsample of

above-average ability students among the four profiles was calculated. Only 29.0% of all above-

average ability students belonged to the high science expectancy-value profiles (13.5% in HUV

and 15.5% in HSE). Therefore, the majority (71%) of above-average ability students did not

belong to high science expectancy-value profiles (45.4% in Typical and 25.6% in Low), which is

another indicator of the disidentification of these students.

Results for Research Question #3

Each science motivation profile had a different percentage of students who planned

STEM occupations at age 30 (Table 4). The HUV profile members planned STEM occupations

at the highest rate (45.6%), followed by the HSE profile (36.9%), Typical profile (25.3%) and

Low profile (15.8%).

Discussion

Research Question #1: Four Distinct Profiles

An exploratory modeling process revealed four distinct science expectancy-value profiles

in the population of US ninth-grade students in 2009. The four-class model supports the

hypothesis that subgroups would be identified with high, low and mixed levels of expectancy-

value. 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 studied math and used cluster analysis. Her model selection was

driven by a different set of criterion than the relative model fit indicators that latent class analysis

provides. Therefore, direct comparisons between Conley (2012) and the latent profile solutions

in the current study are limited. The distinct profiles — Low, Typical, High Utility Value

(HUV), and High Self-Efficacy (HSE) — indicate that these four groups of ninth-grade students

had unique constellations of science expectancy and value indicators.

The differences in the HSE and HUV profiles have implications for talent development in

science. The HSE profile was characterized by relatively low science value. The development of

science expertise depends on processes such as deliberate practice, which are motivated by

strong utility and interest-enjoyment value. Therefore, the observation that the class with the

highest self-efficacy had lower levels of these values implies that these individuals lack the

internal drive to engage in talent development. Furthermore, the HUV class had the highest

utility and interest-enjoyment value combined with lower self-efficacy. Individuals in the HUV

class may be more likely to engage in deliberate practice and talent development despite having

lower self-efficacy because science is more interesting to them and holds more value for their

future college and career. This situation represents a potential loss of science talent of those with

the highest expectancies, while supporting the notion that individuals with above-average

abilities and high motivation should be provided talent development opportunities.

The person-centered approach, taken in the present study, examined expectancy-value

profiles, rather than the mean levels of profile indicators. These findings provide a different

perspective on expectancy-value and provide information that complements typical variable-

centered methods. Previous research has shown that the STV variables are highly correlated.

Previous researchers have also combined the multiple STV constructs into a composite variable

(e. g. Eccles et al., 1984; Simpkins & Davis-Kean, 2005; Watt et al., 2006). In the present study,

the value variables were somewhat related but did not always occur at the same levels. The two

high profiles had mixed levels of indicators. For example, students who had high science

expectancy tended to have lower interest in science and lower science utility value. The

differences between these profiles support the use of a person-centered approach because these

differences would not be observed if the value variables were combined into a composite. The

person-centered approach complements prior variable-centered studies. Andersen and Ward

(2014) found science attainment value to be a strong predictor of occupational plans for all

students, while STEM utility value was a strong predictor only for Hispanic students. In the

present study, utility value distinguishes the two high motivation classes, but attainment value is

not distinguishable. The different methods use the same data, but allow different relationships to

be identified. In the logistic regression models presented in Andersen and Ward (2014),

attainment value was a strong predictor of occupational plans, along with utility value. In the

present study, utility value distinguishes the two high motivation classes, but attainment value is

not distinguishable. Furthermore, the rates of STEM occupational plans were substantially

different in the two high motivation classes, even though the attainment values were not.

therefore, utility value has more discriminant power than attainment value.

The present 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 value 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 difference may be that the subpopulations that had high utility

value were relatively small portions of this sample or that students' patterns of science utility

value differ from their patterns of math utility value.

Research Question #2: Evidence of Disidentification

One important finding was that the math achievement levels of each profile group were

statistically different from each other. Students were assigned to profile groups based on

patterns of science expectancies and values, which ensures that each group has the largest

differences in science expectancies and values. It seemed logical that students who had the

highest science expectancies and values would have also had the highest math achievement

levels. However, this was not the case. Differences in math achievement between profile groups

were small and did not have practical importance. Considering the wide range of math

achievement scores in this sample (ranging from 16 to 70) it is remarkable that the difference in

mean ability between the highest and lowest profiles is only 6 points. This relatively small

difference, combined with the low correlation between math achievement and science self-efficacy show that differences in ability between profiles were smaller than differences in expectancies and values. In other words, the groups of students did not differ much by ability, but differed much more in their profiles of expectancies and values.

Only a minority of above-average ability students were members of the high science expectancy-value profiles. This implies that, in this sample, above-average students have disidentified with science. In other words, students who had high potential in science had low expectancy and value for science. The finding that a minority of high-ability students exhibited high motivation is supported by previous research (e. g. Gottfried et al. 2005; Gottfried & Gottfried, 2004). Importantly, this finding has serious implications for talent development in the science disciplines. Students who have lower motivation are less likely to persist in the study of science. This implies that factors other than ability are influencing expectancies and values. Future research should attempt to identify such factors. An alternative explanation may be that that math achievement is not a good indicator of potential science ability and the group of students who have high science potential is substantially different than the group of students who are high achievers in math. It is recommended that science achievement be assessed directly in future NCES surveys.

Above-average ability students had low science expectancy-value profiles. The low science class represented 25.6% of above-average ability students. This low-motivation, above-average ability group was only slightly smaller than the high-motivation, high-ability group (29%). The large number of above-average ability students in low motivation profiles should be investigated further, as this condition is likely to hamper the development of potential. This group is less likely to develop science-specific talents than the group of above-average ability

students who had high motivation. Perhaps, talent development outcomes of science education could be improved if motivation was addressed through intervention strategies. Schools could strategically address motivation to engage these above-average ability students in learning and encourage talent development in science.

Research Question #3: Profiles and STEM Occupational Plans

Another important finding was that the percentage of profile group members who planned STEM-related occupations was different in each profile group, which demonstrates a connection between students' science expectancy-value profile and STEM-related occupational plans. An implication of this finding is that profiles of science expectancies and values matter more for occupational plans than their math achievement. Science utility and interest enjoyment values may be more important to STEM occupational plans than science self-efficacy. This contradicts previous findings by Simpkins & Davis-Keen (2005) that science expectancy had a stronger relationship to occupational plans than students' value for science. However, Simpkins & Davis-Keen (2005) used a composite score for value.

At face value, the finding that 26% of the overall student sample indicated a plan for a STEM-related occupation seems promising. However, it is important to remember that these students were in the ninth grade and must successfully navigate multiple transitions before entering the STEM workforce. For example, 34% of U. S. 25 to 29 year olds have attained a bachelor's degree (U. S. Census Bureau, 2014) and 31% of these bachelor's degrees were in the science and engineering fields (NSF, 2013). Thus, only 11% of U. S. 25 to 29 year olds (in 2013) have attained bachelor's degrees in the science and engineering fields. This rate is much lower than the ninth-grade occupational plans measured in HSLS: 2009, implying that events may occur between ninth grade and college graduation that negatively affect degree completion.

Conclusions

A possible cause of students' low expectancies and values for science is that students have a limited number of experiences with science prior to high school. Since 2002, U. S. education mandates have had unintended consequences, such as curriculum narrowing (Berliner, 2009, 2011) and decreased science instructional time in the K-8 curriculum (McMurrer, 2008). For example, since the enactment of the *No Child Left Behind* legislation in 2002, 62% of all school districts have increased the amount of instructional time for language arts and/or math. Of these schools (that increased instructional time for language arts and math), the average decrease in science instructional time was 75 minutes per week, or 33% of the total science instructional time (McMurrer, 2008). Thus, this cohort of 2009 ninth-grade students have had fewer science experiences and have not developed as strong a sense of what science is or of their abilities in science.

Indeed, history is an important consideration for this cohort. Future cohorts may have greater science expectancies and values because in 2013, new and more rigorous *Next Generation Science Standards* (Achieve Inc., 2013) were published that may help reverse the trend of decreased emphasis on science in elementary schools. There is a presidential push for increased national attention to science education (The White House, 2010), but it is left to each U.S. State to decide whether or not the new standards will be adopted. As of August 2014, fewer than 25% of states have adopted the new standards. As adoptions continue and science education reforms are implemented, future cohorts of students may have larger-sized high science motivation classes.

The findings of the present study suggest that interventions are necessary to increase students' science expectancies and values. Elementary students should be provided with a wide

variety of science experiences so that they can develop strong expectancies and values for science before entering secondary school. Furthermore, strategic efforts should be made to counter the negative stereotypes that are associated with science by providing examples of scientists who break the stereotype.

Another possible explanation for students' low expectancies and values could be that these students hold a performance orientation for schoolwork. Particularly in the contemporary high-stakes test culture that exists in K-12 education in the U. S., students have been trained that educational success is measured by how well you perform on multiple-choice tests. This promotes a performance orientation, in which effort is valued only for the immediate reward (the grade), compared to a mastery orientation in which effort is valued because of the knowledge that is gained in the process of learning. Students who hold a performance orientation would be more likely to have low utility value than those who hold a mastery orientation. Unfortunately, the HSLS: 09 questionnaires did not contain items that assessed performance or mastery orientations. Future questionnaires should include such items.

Yet another possible explanation for above-average ability students' low science expectancies and values could be that expectancy is highly domain specific (Marsh & Hau, 2004). It may be that students' expectancies in science are not related to math achievement, but are more related to science achievement. Furthermore, a student with high math achievement may not view him or herself as a "science person". In other words, the relationship between math achievement and how much the student identifies with science is small. This explanation is supported by a lower correlation between math achievement and science attainment value of than between math achievement and math attainment value in a prior study that used HSLS: 09 (Andersen, 2013).

Limitations

First, a limitation of this study was that multiple measures of ability and achievement were not available within the HSLS: 09 data. Therefore, the math achievement score was used as a proxy for above-average ability. Above-average ability was operationalized as a score greater than or equal to $+1z$ on the math achievement test. This operationalization may differ from other definitions because it is based solely on math achievement. It may be that some of these students have higher abilities in non-STEM domains than in mathematics and this could explain low science expectancies and values. A lack of measures of ability in non-STEM domains within the HSLS: 2009 data limited the researchers' ability to evaluate the effect of such ability profiles on science expectancies and values.

The nature of the expectancy-value questionnaire items was a limitation because the questions were specifically about the Fall 2009 science courses. Students' expectancies and values about a specific science course may be different than their expectancies and values about science in general. Furthermore, expectancies and values for math, technology, and engineering were not included in the present study.

Future Research

The demographics of the expectancy-value profiles have not yet been explored. The sociocultural aspects of the expectancy-value model and the cultural differences between minority and majority high-ability students raise 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 stigma of a science identity and how it is perceived by students of different race/ethnicity, gender, and SES.

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Table 1

Descriptive Statistics (N = 19,260)

Variable	Mean (SE)	SD	Alpha
Math Achievement Test Score	38.956 (0.187)	11.920	N/A
Science Self-Efficacy (SSE)	-0.0057 (.0174)	0.994	.88
Science Attainment Value (SAV)	-0.0061 (.0156)	0.996	.83
Science Utility Value (SUV)	0.0019 (.0174)	0.995	.75
Science Interest-Enjoyment Value (SIV)	0.0060 (.0175)	0.990	.73
STEM	0.2456 (.0130)		N/A

Note: All measures except for the Math Achievement Test Score and STEM are z-scores. The Math Achievement Test Score had a maximum of 70. STEM was a dichotomous variable with values of 0 or 1. All *n* are rounded to the nearest 10.

Table 2

Bivariate Correlations

	1	2	3	4	5
Science Self-Efficacy (SSE)	1				
Science Attainment Value (SAV)	.493**	1			
Science Utility Value (SUV)	.414**	.387**	1		
Science Interest-Enjoyment Value (SIV)	.508**	.462**	.492**	1	
Math Achievement	.225**	.248**	.057**	.123**	1

** *p* < .01

Table 3

Science Models

Number of Classes	LL	Number free parameters	BIC	Smallest class frequency
1	-91171	8	182421	
2	-85715	17	171597	8990 (.47)
3	-83059	26	166169	3380 (.18)
4	-82189	35	164723	1470 (.08)

Notes: LL = Log Likelihood, BIC = Bayesian Information Criterion

Table 4

Summary of Science Classes

Class (n; % of sample)	SSE M (SE)	SAV M (SE)	SUV M (SE)	SIV M (SE)	Math Achievement	SES M (SE)	STEM % of class (SE)	Above-Average Ability (% of class; SE)
Low (7,680; 40%)	-0.763 (0.060)	-0.684 (0.041)	-0.600 (0.050)	-0.765 (0.057)	48.190 (.131)	-0.161 (.011)	0.158 (.006)	0.081 (.004)
Typical (8250; 43%)	0.075 (0.022)	0.202 (0.031)	0.105 (0.023)	0.235 (0.027)	50.594 (.138)	-0.054 (.010)	0.253 (.006)	0.134 (.004)
High SSE (1470; 8%)	1.501 (0.045)	0.838 (0.109)	0.315 (0.062)	0.667 (0.077)	54.430 (.343)	0.156 (.024)	0.369 (.014)	0.256 (.012)
High SUV (1720; 9%)	0.954 (0.056)	0.955 (0.112)	1.508 (0.020)	1.243 (0.054)	52.085 (.344)	0.015 (.024)	0.456 (.016)	0.191 (.012)
Entire Sample (19,120; 100%)	0.002 (0.017)	0.001 (0.016)	0.002 (0.017)	0.006 (0.017)				

Note: All scale scores (SSE, SAV, SUV, SIV, SES) are z-scores. Math achievement is out of 70. SSE = Science Self-Efficacy, SAV = Science Attainment Value, SUV = Science Utility Value, SIV = Science Interest-Enjoyment Value, SES = Socioeconomic status.

Table 5

Profiles Membership of Above-Average Ability Group

Profile	Number of above-average ability students with profile	Percentage of all above-average ability students
Low	620	25.6
Typical	1110	45.4
High Utility Value	330	13.5
High Self-Efficacy	380	15.5

Note: Numbers are rounded to the nearest 10.

Figure 1

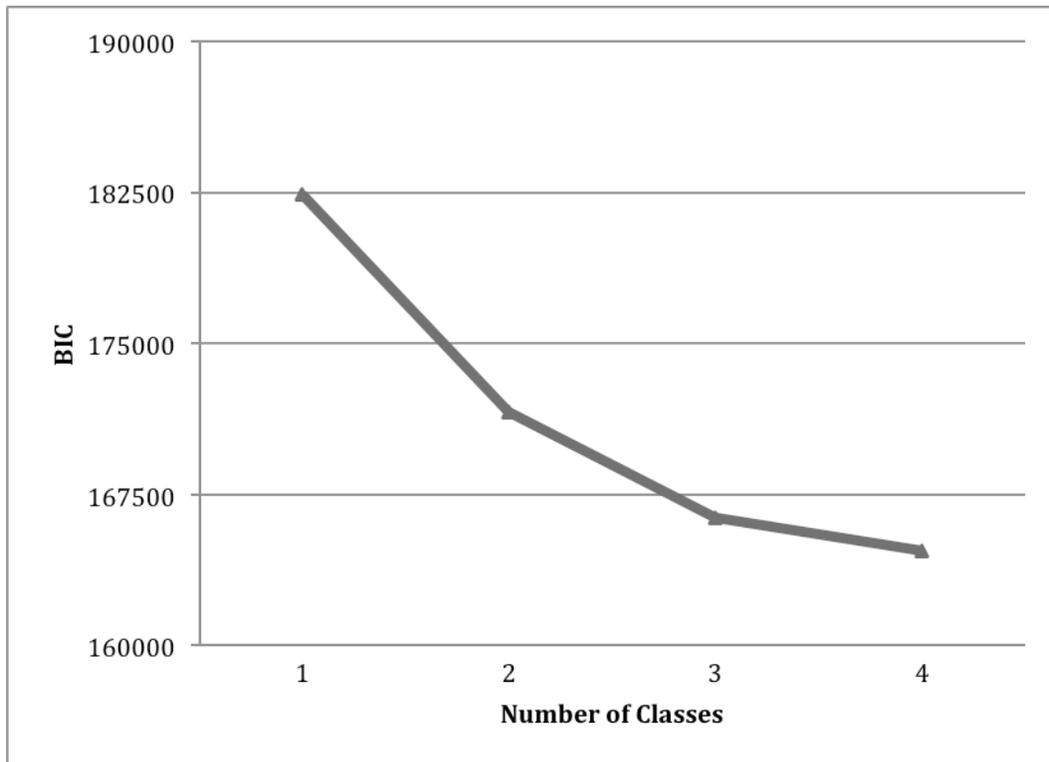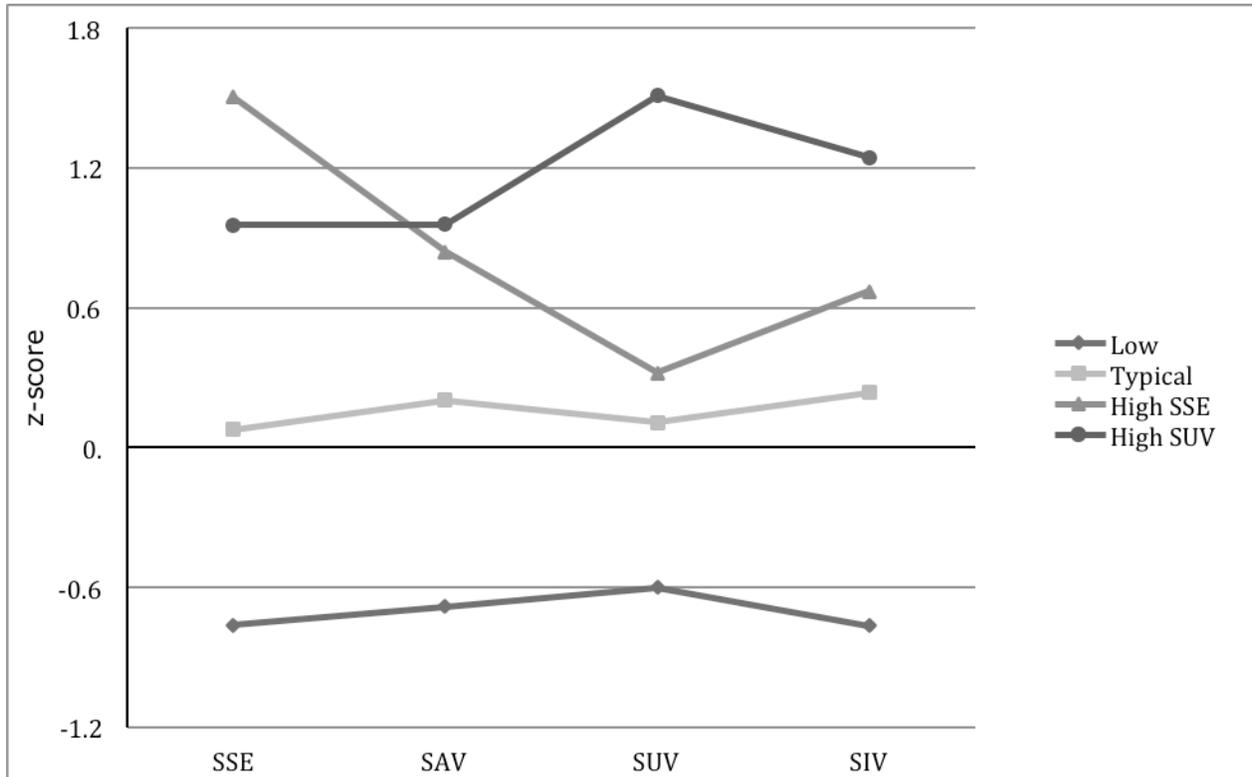*Plot of BIC vs. Number of Science Classes*

Figure 2

Science 4-Class Model Profiles

Note: SSE = Science Self-Efficacy, SAV = Science Attainment Value, SUV = Science Utility Value, SIV = Science Interest-Enjoyment Value.