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Science expectancy, value, and cost profiles and their proximal and distal relations to undergraduate science, technology, engineering, and math persistence

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Abstract

Despite efforts to attract and maintain diverse students in the science, technology, engineering and math (STEM) pipeline, issues with attrition from undergraduate STEM majors persist. The aim of this study was to examine how undergraduate science students' competence beliefs, task values, and perceived costs in science combine into motivational profiles and to consider how such profiles relate to short and long-term persistence outcomes in STEM. We also examined the relations between underrepresented group membership and profile membership. Using latent profile analysis, we identified three profiles that characterized 600 participants' motivation during their first semester in college: *Moderate All, Very High Competence/Values-Low Effort Cost,* and *High Competence/Values-Moderate Low Costs.* The *Moderate All* profile was associated with the completion of fewer STEM courses and lower STEM GPAs relative to the other profiles after one year and after four years of college. Furthermore, underrepresented minority students were overrepresented in the *Moderate All* profile. Findings contribute to our understanding of how science competence beliefs, task values, and perceived costs may coexist and what combinations of these variables may be adaptive or deleterious for STEM persistence and achievement.

Keywords

Science Motivation; Expectancy-Value Theory; Perceived Costs; STEM persistence; Latent Profile Analysis

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Despite the proliferation of programs geared toward attracting and maintaining undergraduate students in science, technology, engineering, and math (STEM) fields over

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the past several decades (Schultz et al., 2011), college STEM majors are still plagued by high attrition rates, particularly in retaining women and underrepresented minorities (National Science Foundation, 2011). Compared to White and Asian students, African American, Native American, and Hispanic/Latinx students earn fewer STEM degrees and continue to be underrepresented in the STEM workforce (National Science Foundation, 2017). While women are more well represented in the biological sciences, they remain underrepresented in fields such as engineering, computer science, and physics (National Science Foundation, 2017). Given the investment of resources by many universities and funding agencies to meet the goals of broadening participation and retaining students in STEM disciplines, it is important to understand the various factors that shape students' decisions to pursue STEM majors. Students' STEM-specific motivational beliefs are critical to this understanding.

Prior studies have demonstrated that factors related to student motivation, such as students' interest, perceived value, and feelings of competence in STEM disciplines, are important for explaining persistence in STEM (Andersen, Chen, 2016; Chow, Eccles, Salmela-Aaro, 2012; Cromley, Perez, Kaplan, 2016; Dai, Cromley, 2014; Perez, Cromley, Kaplan, 2014; Nagengast et al., 2011; Seymour, Hewitt, 1997; Simpkins, Davis-Kean, Eccles, 2006; Strenta, Elliot, Adair, Scott, 1994; Watt, 2006; Watt et al., 2012). This research suggests that students who feel competent in a STEM discipline (i.e., competence beliefs) and view the STEM discipline as interesting, important, or useful (i.e., task value) are more likely to pursue a major or career in a STEM discipline. There is comparatively less work on how students' perceptions of the drawbacks of pursuing a STEM discipline (i.e., perceived costs) relate to STEM achievement and persistence (Barron, Hulleman, 2015; Wigfield, Cambria, 2010). For example, if students view a major in a STEM discipline as requiring too much time and effort, they may be less likely to persist in the STEM major (Perez et al., 2014). Factors such as the perception of a highly competitive institutional context among STEM majors (Hurtado, Newman, Tran, Chang, 2010) and demanding workloads may contribute to students perceiving high costs in STEM disciplines. Thus, students' perceived costs in STEM disciplines may be particularly important for understanding their decisions to leave the STEM pipeline (Barron, Hulleman, 2015; Flake, Barron, Hulleman, McCoach, Welsh, 2015; Perez et al., 2014).

Theory and research indicate that competence beliefs, task values, and perceived costs are each important individual predictors of STEM persistence and achievement (Perez et al., 2014; also see Barron, Hulleman, 2015 and Wigfield, Cambria, 2010 for reviews). Beyond that, these motivational factors likely work together to influence students' decisions to persist in or leave STEM fields. Indeed, students often hold multiple motivational beliefs simultaneously (e.g., Andersen, Chen, 2016; Bøe, Henriksen, 2013; Conley, 2012; Linnenbrink-Garcia et al., 2018). For example, it is possible that a student may have a high interest in pursuing a STEM career but may also perceive high costs associated with pursuing such a career. How would such a combination of beliefs impact this student's achievement and decision-making in STEM? Most quantitative research examining motivational beliefs uses a variable-oriented approach that isolates the effect of a single variable on an outcome, which cannot answer such a question. Rather, a person-oriented approach that considers how combinations of beliefs predict behavior is needed.

Understanding how various types of motivation jointly relate to STEM persistence can provide insights into how to retain more well-qualified students in STEM disciplines, including students from traditionally underrepresented groups. Given limited prior research examining such a question, a study examining how competence beliefs, task values, and perceived costs in science jointly influence STEM outcomes seems timely and necessary.

Accordingly, the current study, which was situated within an expectancy-value framework (Eccles et al., 1983), investigated the relation of undergraduate students' early (first semester of college) science motivation profiles to short-term (after 1 year of college) and longterm (after 4 years of college) STEM outcomes using latent profile analysis (LPA). By doing so, we were able to examine how various combinations of competence beliefs, task values, and perceived costs in science related to proximal and distal STEM outcomes, including achievement and course completion, which extends our understanding of how these important variables jointly affect STEM outcomes. Moreover, we considered whether the motivational profiles differed across gender and underrepresented minority (URM) status, as overall lower science motivation may be one mechanism that helps to explain differential patterns of persistence among underrepresented groups. As such, we were particularly interested in whether or not students from groups traditionally underrepresented in STEM were overrepresented in profiles characterized by lower overall science motivation.

Expectancy-Value Theory

Eccles and colleagues' (Eccles et al., 1983; Wigfield, Eccles, 2000) contemporary *Expectancy-Value Theory* focuses on two fundamental motivational questions that individuals ask themselves before engaging in a particular task: "Can I do this?" and "Why do I want to do this?" According to this theory, individuals will be optimally motivated when they feel competent and expect success in a domain (expectations for success or their *competence beliefs;* e.g., I can be successful in science) and also highly value the domain (*task value;* e.g., I want to do this because it is interesting). Expectations for success fall under a broader umbrella of similar beliefs related to one's feelings of competence such as self-efficacy and self-concept of ability, which have been used interchangeably with expectations for success in prior expectancy-value research (e.g., Andersen, Chen, 2016; Guo et al., 2016; Nagengast et al., 2011). In this study, we operationalize the expectancy side of the theoretical model as *science competence beliefs,* which are beliefs in one's ability to successfully master science skills and coursework.

In terms of task values, three different kinds of positive task values are included in the expectancy-value model: (1) *interest value,* the anticipated enjoyment of a task or interest in a domain; (2) *attainment value,* the perceived importance of a task to one's identity; and (3) *utility value,* the subjective value of a task for attaining an extrinsic goal such as a career goal. A fourth factor, *perceived cost,* has also traditionally been included under the task value umbrella (Eccles, Wigfield, 2002; Wigfield, Eccles, 2000). Perceived cost can be thought of as answering the question, "why *don't* I want to do this?" In other words, costs represent the perceived drawbacks of engaging in a task and are thought to be particularly important for decision making (Eccles et al., 1983). Perceived costs were originally conceptualized by Eccles and her colleagues along three dimensions (Eccles et al.), including (1) *effort cost,* perceptions of whether the time and effort needed to be successful on a task is worthwhile; (2) *opportunity cost,* perceptions of lost opportunities to engage in other valued activities; and (3)*psychological costs,* perceptions related to fear of failure and anxiety associated with engaging in the task. With the increased interest in perceived cost as an important component of contemporary expectancy-value theory (Barron, Hulleman, 2015), we focus on all three components (expectancies, task values, and perceived cost) as predictors of STEM persistence. An individual who feels competent in science, values science, *and* perceives minimal costs in science would be more likely to choose and persist in a STEM major or career.

Associations Between Expectancies, Values, Costs, and STEM Outcomes

Researchers using variable-oriented approaches (e.g., regression, structural equation modeling, correlation analysis) have demonstrated the unique relations of competence beliefs, task values, and perceived costs to various outcomes in STEM disciplines (e.g., Bathgate, Schunn, Correnti, 2013; Bryan, Glynn, Kittleson, 2011; Gaspard et al., 2018; Guo et al., 2016; Lauermann, Tsai, Eccles, 2017; Perez et al., 2014; Watt et al., 2012). In a recent example, Lauermann and her colleagues (Lauermann, Tsai, Eccles, 2017) found that math competence beliefs (self-concept of ability), math utility value, and math interest value in 9th grade were related to 9th grade math-related career plans. Furthermore, math competence beliefs, utility value, and interest value in 9th grade were indirectly related to math-related career attainment via 12th grade career plans. In other words, 9th grade students with higher competence beliefs in math, higher value for math in attaining future goals, and with higher math interest were more likely to have math-related career goals in 12th grade. Those with 12th grade math-related career goals were more likely to have a math career as an adult. While research has demonstrated that both competence beliefs and task values relate to achievement (e.g., GPA) and choices (e.g., career aspirations), findings indicate that competence beliefs are typically more strongly related to achievement while task values are more strongly related to choice behaviors (see Wigfield, Tonks, Klauda, 2009 for a review).

Compared to the corpus of research examining the effects of competence beliefs and task values on academic outcomes, there has been much less research on perceived cost (Barron, Hulleman, 2015; Wigfield, Cambria, 2010); however, the research on perceived cost has been growing. For example, perceived cost has been found to be an important factor in undergraduates' intentions to leave a STEM major (Perez et al., 2014) and has also been associated with high school math achievement (Trautwein et al., 2012). Few studies have examined perceptions of cost in science specifically and the relations of such beliefs to outcomes in STEM. An important open question about perceived costs also relates to whether multiple kinds of costs should be considered (as with values). While Eccles and her colleagues (Eccles et al., 1983) described three different sources of perceived costs, research has often incorporated only a single cost dimension (e.g., Bøe, Henriksen, 2013; Conley, 2012; Luttrell et al., 2010; Trautwein et al. 2012). Recent research has demonstrated the utility of examining multiple dimensions of perceived cost (Flake, Barron, Hulleman, McCoach, Welsh, 2015; Gaspard, Dicke, Flunger, Schreier, et al., 2015; Perez et al., 2014) and suggests that different cost dimensions may be more or less important for STEM outcomes with undergraduates (Perez et al., 2014).

In the current study, we included measures of perceived cost associated with lost opportunities to engage in other valued activities (i.e., opportunity cost; What do I have to give up for science?) and time and effort (i.e., effort costs; Is the time and effort required to be successful in science worth it?) in addition to science competence beliefs and science task values (i.e., attainment, utility, interest). Both opportunity cost and effort cost are likely to be salient for science undergraduates since STEM courses are often characterized by heavy workloads and students often need to sacrifice other activities to be successful in STEM courses (Hurtado et al., 2010). Both kinds of cost have also been found to relate to STEM outcomes in prior research (Perez et al., 2014) such that higher perceived effort and opportunity cost were associated with higher intentions to leave a STEM major. Therefore, effort and opportunity costs are both likely meaningful and important for science undergraduates in particular.

Person-Oriented Versus Variable-Oriented Approaches to Studying Science Motivation

Most prior research examining the role of competence beliefs, task values, and perceived cost in explaining STEM achievement outcomes relied on variable-oriented approaches like analysis of variance, multiple regression, or structural equation modeling. These approaches typically investigate the unique contribution of a particular variable to an outcome after controlling for the other variables in the model. Variable-oriented approaches have yielded useful findings but have primarily focused on main effects (and potentially interactions) rather than considering complex patterns among variables. Yet, the complexity may be key for understanding more fully how motivation shapes engagement, learning, and persistence. For example, it is possible that having high competence beliefs alongside high task values in science may mitigate the potential negative effects of simultaneously perceiving high costs in science. In response to the need to identify more complex ways in which variables combine to predict outcomes, some researchers have examined interactive effects of these motivation variables (e.g., Nagengast, Marsh, Scalas, Xu, Hau, Trautwein, 2011; Trautwein, Marsh, Nagengast, Ludtke, Nagy, Jonkmann, 2012). Examining interactions in variable-oriented models has also been fruitful, as these studies suggest that it is important to simultaneously consider levels of task value and competence beliefs. For instance, Guo et al. (2015) found that ability self-concept in math was more strongly related to math course selection when interest value was also high in a representative sample of Australian high school students. However, studying interactions in this way has a number of limitations and challenges. First, very large samples are often required to achieve sufficient power to detect such interactions. Second, variables like competence beliefs and task values are often highly correlated creating issues with multicollinearity in regression based models. Third, it is challenging to study complex interactions among more than two variables. For instance, prior work by Nagengast, Trautwein, and their colleagues (2011; 2012) only considered two-way interactions between competence beliefs and each type of task value individually, leaving it unclear how multiple forms of task value and perceived costs combine with competence beliefs and how such combinations of beliefs relate to key outcomes. Fourth, interpreting patterns within interactions (e.g., low perceived competence, high task value) runs the risk that there may be very few people who actually endorse such a pattern of motivational beliefs – a point explicitly noted by Trautwein and his colleagues (2012).

Person-oriented approaches address many of the aforementioned challenges with variable-oriented interaction analyses (Bergman, Trost, 2006; Wormington, Linnenbrink-Garcia, 2017). Specifically, one can use profile analysis (e.g., cluster analysis, latent profile analysis) to identify combinations of motivational beliefs—or motivational profiles—within a sample. Profile analysis allows for an examination of common profiles within a given sample and of how various profiles of beliefs relate to particular outcomes (Bergman, El Khouri, 2003; Bergman, Trost, 2006). While any analytic approach has both strengths and weaknesses, a person-oriented approach such as latent profile analysis holds several potential advantages over variable-oriented methods of examining interactions, particularly when dealing with multiple constructs. Specifically, profile-oriented analyses do not always require as large of a sample size as is typically needed in variable-oriented analyses to have sufficient power to detect two and three-way interactions. Additionally, interpreting profiles of multiple beliefs is usually not as challenging as interpreting patterns from higher-order interactions involving four or more variables in variable-oriented analyses. By identifying common combinations of variables that represent individuals in a given sample, one also avoids the concern about interpreting aspects of the interaction that rarely occur in the sample.

Person-oriented research findings.

Although still relatively rare, researchers have increasingly been investigating how expectancy-value beliefs combine into motivational profiles and how such profiles relate to academic outcomes in STEM (Andersen, Chen, 2016; Bøe, Henriksen, 2013; Conley, 2012; Chow, Eccles, Salmela-Aro, 2012; Rosenzweig, Wigfield, 2017; Viljaranta, Nurmi, Aunola, Salmela-Aro, 2009; Wang, Eccles, Kenny, 2013). These studies have found that variable expectancy-value profiles can be identified across a variety of samples and that profiles of beliefs are differentially related to achievement and career choices in STEM disciplines. Thus, extant research highlights the value of using a person-oriented approach to investigate how science motivation relates to important STEM outcomes. For example, using data from the High School Longitudinal Study of 2009, Andersen and Chen (2016) identified four expectancy-value profiles in science using latent profile analysis. They found variability in levels of task value and competence beliefs across the four profiles indicating that competence beliefs and task values do not simply combine into all high and all low profiles of beliefs. Furthermore, the profile labeled high utility value (very high utility value with variably high scores on the other variables) had the greatest percentage of participants who planned to pursue STEM careers (45.6%) while the low profile (below average scores on all measures) had the lowest percentage of students who planned to pursue a STEM career (15.8%). Andersen and Chen also found differences among the profiles in math achievement. In a different study with Norwegian high school physics students,[1] Bøe and Henriksen (2013) found that students with a motivational profile that included high science interest value, attainment value, and competence beliefs with low utility value and cost or a

[1]The researchers also included a sample of undergraduate students, but they did not conduct profile analyses with the undergraduate students.

profile with high science interest value, attainment value, and utility value with low competence beliefs and cost were more likely to indicate that they would like to study physics as an undergraduate compared to students with a motivational profile that was high on utility value and relatively low on the other variables. This study highlights that various combinations of motivational beliefs (combinations of high task value and low competence beliefs) can have similar outcomes with regard to STEM career intentions. Overall, various studies have demonstrated that profiles of expectancy-value beliefs are differentially related to persistence and achievement outcomes in STEM. However, most of these studies did not include measures of perceived cost.

While the inclusion of perceived cost measures is relatively rare in expectancy-value studies, two relevant studies included perceived cost as a variable in person-oriented analyses. First, in her study with 7th grade math students, Conley (2012) included measures of competence beliefs, task values, and a single measure of cost (opportunity cost) in addition to achievement goal orientations in a cluster analysis. Results suggested that students in profiles with high cost had less positive feelings toward math than students in profiles with lower cost. However, Conley did not include choice-based outcomes in her study. Furthermore, Conley's study included variables from a second theoretical model (achievement goals), which would have an important impact on the final profile solution. Second, Bøe and Henriksen (2013), which was already discussed above, included a measure of relative cost in their study. While the authors identified three profiles of expectancy, value, and cost beliefs, all profiles included similarly low levels of relative cost. Importantly, it is unclear what specific dimension of cost was measured in the study. Furthermore, the survey questions were retrospective and asked students about what was most important in their decision to study physics, which may explain why perceived cost was low in all profiles. In this study, we included measures of opportunity cost and effort cost in our analyses and we examined how profiles of expectancy, value, and cost beliefs in students' first-semester of their first year related to STEM achievement and total STEM course completion at the end of one year of college and at the end of four years of college. Thus, we are examining how profiles of science motivation beliefs relate to STEM outcomes prospectively rather than retrospectively.

Representation of women and underrepresented minorities in motivational profiles.

An important aim of this study is adding to the literature on broadening participation in STEM disciplines. Contemporary expectancy-value theory is well-suited to this task given Eccles' and her colleagues' desires to better understand gendered STEM career choices in developing the model (Eccles, 2011; Eccles et al., 1983). Indeed, Eccles' expectancy-value model highlights the critical role of contextual factors, such as the cultural milieu and important socializers, in the development of expectancy-value beliefs (Eccles, 2011). As the most proximal predictors of choice, expectancy-value beliefs are believed to mediate the relations between contextual factors and academic and career choices. Empirical work examining the underrepresentation of women and racial/ethnic minorities in STEM disciplines suggests that these groups may not see the relevance (i.e., utility value) of science curriculum to their own lives (Barton, Yang, 2000; Basu, Barton, 2007; Thoman, Brown, Mason, Harmsen, Smith, 2015) due to a lack of alignment between the dominant cultural values embedded in science disciplines and the cultural values of underrepresented students. In fact, interventions designed to highlight culturally aligned values in science have been successful in enhancing underrepresented students' motivation for science (Brown, Smith, Thoman, Allen, Muragishi, 2015; Thoman et al., 2015). Furthermore, due to structural inequalities, many students from underrepresented groups are more likely to face barriers not encountered by many majority groups in STEM, such as inadequate STEM preparation in high school (Seymour, Hewitt, 1997) and implicit or explicit racism or sexism (Hill, Corbett, St Rose, 2010; McGee, Bentley, 2017). Such barriers and potential discrimination faced by underrepresented groups may lead to reduced motivation in school (Wong, Eccles, Sameroff, 2003). Thus, such barriers may lead underrepresented undergraduate science students to become less motivated in science as represented by a variety of motivational beliefs.

Using person-oriented methods, it is possible to examine the underrepresentation or overrepresentation of particular groups in various science motivation profiles, which may further understandings of why certain groups are underrepresented in STEM disciplines more broadly. However, there have been a few person-oriented studies that have taken such an approach. In one study, results indicated that females were overrepresented in motivation profiles with lower task value for math and science relative to profiles with higher task value for math and science (Chow et al., 2012) indicating that men and women may differ in their profiles of science motivational beliefs, which has consequences for their future career aspirations. Furthermore, few studies have examined the representation of students who identify with different races/ethnicities in motivational profiles. However, one study indicated that underrepresented minority middle school students were overrepresented in less adaptive profiles of expectancy-value beliefs (Rosenzweig, Wigfield, 2017), which had consequences for comprehension of science information text. Thus, patterns of motivational beliefs may at least partially explain differences in STEM achievement and persistence between underrepresented and non-underrepresented groups. Examining the representation of underrepresented groups in different science expectancy, value, and cost profiles is an important aim of this study, particularly given the likelihood that such groups face barriers that may impact their science motivation.

In sum, more research is needed to understand how competence beliefs, task values, and perceived costs combine in science and to understand how such motivational profiles relate to STEM outcomes. A handful of researchers have examined expectancy-value beliefs using person-oriented methods (Andersen, Chen, 2016; Bøe, Henriksen, 2013; Chow et al., 2012; Conley, 2012; Linnenbrink-Garcia et al., 2018; Viljaranta et al., 2009; Wang, Eccles, Kenny, 2013) and only two of these studies included competence beliefs and task values along with a measure of perceived costs (Bøe, Henriksen, 2013; Conley, 2012) in the profile analysis. Furthermore, only a few studies focused on science expectancy-value beliefs in particular (Andersen, Chen, 2016; Bøe, Henriksen, 2013; Chow et al., 2012; Linnenbrink-Garcia et al., 2018). Finally, more research is needed examining the representation of underrepresented groups in various expectancy-value profiles.

Current Study

In this study, we assessed science motivation profiles using measures of science competence beliefs, all three task values, and two perceived costs with undergraduate students enrolled in gateway chemistry courses during their first semester of college. Our study aimed to build on extant person-oriented, expectancy-value research (e.g., Andersen, Chen, 2016; Bøe, Henriksen, 2013) by incorporating two measures of perceived costs-important constructs for understanding attrition from STEM disciplines-in a latent profile analysis and examining how the science motivation profiles predict proximal (after one year of college) and distal (after four years of college) outcomes in STEM. Thus, we were able to examine how undergraduates' first year science motivation related to their achievement and persistence in STEM over most, if not all, of their college career. Furthermore, we aimed to add to the broadening participation in STEM literature by examining the prevalence of women and underrepresented minorities (URMs) in the different profiles. Specifically, we asked the following research questions in this study:

1. How do science competence beliefs, task values, and perceived costs combine into motivational profiles for undergraduate science students?
2. Do students' science motivational profiles differentially predict short-term and long-term STEM academic achievement and STEM course completion?
3. Are there differences in profile membership based on gender and URM status?

Considering theory and prior research, we hypothesized that profiles with high science competence beliefs, high science task values, and low perceived costs in science would relate to a higher GPA in STEM courses and completing more STEM courses while profiles with low competence beliefs and task values but high perceived costs would be the least adaptive in terms of the STEM GPA and STEM course completion outcomes. Additionally, we speculated that there may be other combinations of competence beliefs, task values, and perceived costs (e.g., high values and high costs or high effort cost and low opportunity cost); however, the specific profiles identified and the relations of such profiles with the outcomes were less clear. Therefore, we did not make specific hypotheses about the relations of such profiles to the outcomes. Finally, we hypothesized that women and URMs would be more represented in less adaptive science motivational profiles (e.g., low competence beliefs, low task values, and high costs in science) given prior research and theory surrounding the prevalence and impact of contextual barriers on the persistence and motivation of underrepresented groups in STEM disciplines. Furthermore, the context of this study is a predominately white and Asian university (approximately 72% are white or Asian) with relatively few URM students. Such a context may impact underrepresented students' perceptions of threat and belonging leading to reduced science motivation (Murphy, Steele, Gross, 2007).

Method

Participants

Participants included 600 undergraduate students enrolled in first-year gateway chemistry courses at a highly selective university in the United States. The participants were drawn from a larger four-year study that involved a summer instructional intervention designed to support undergraduates' interest in pursuing science careers. A sub-sample of participants who did not receive the intervention and completed a baseline survey in their first-year college chemistry course were included in this study.[2] The sample was 50.5% female, 30.6% Asian, 48.0% White, 7.6% African American, 7.1% Latino, and 6.2% multiracial. Approximately 4% of students in the sample were first-generation college students. The mean age of the sample was 18.13 years old (*SD* = .36) and the mode family salary range was over $250,000 (25.6% of respondents; range *Below* $25,000 to $250,000+).

Procedure

Seven weeks into the fall 2012 semester, students were invited to participate in the larger study. A member of the research team made an announcement about the study during the last 15 minutes of class in all first-year chemistry courses. Students were informed that participation was voluntary and that their responses to the survey would be kept confidential. Participants completed the paper-and-pencil surveys in approximately 15 minutes and were compensated with $10. Absent students were emailed an electronic version of the survey and were also compensated $10 for completing the survey. The course instructor was not present during survey administration. The survey consent also asked students for permission to release their academic records to the research team; these records were collected at the end of the first and fourth year of college.

Measures

The in-class survey included a variety of measures related to students' beliefs and behaviors in science, which were relevant for the larger study; however, only the scales assessing science competence beliefs, science task values (attainment, utility, interest), and science perceived costs (opportunity, effort) were used for this study. All items were rated on a 5-point Likert response scale ranging from 1 (*Strongly disagree*) to 5 (*Strongly agree*). We used confirmatory factor analysis (CFA) to analyze the factor structure of the competence beliefs, task values, and perceived costs measures. We inspected the comparative fit index (CFI), root mean square error of approximation (RMSEA), and the standardized root mean square residual (SRMR) to assess model fit using conventional standards for good model fit (Hu, Bentler, 1999). Good model fit is indicated when CFI ≥ .95, RMSEA ≤ .08 and SRMR ≤ .10. A six-factor CFA resulted in a good model fit to the data (χ^2 [215] = 511.61, $p < .001$, CFI = .96, RMSEA = .05, SRMR = .04), which supports the construct validity of the variables. All scales had good reliability with Cronbach's alpha above .75 (see Table 1 for information on the reliability of each of the measure). We averaged the scores on each subscale to create the relevant variable. Higher scores on each variable indicate higher endorsement of the construct. Each measure is described in detail below.

Competence beliefs.—We adapted the five Academic Efficacy items from the Patterns of Adaptive Learning Survey (Midgley et al., 2000) to assess science competence beliefs. An example item read, "I'm certain I can master the skills taught in science classes."

[2]This sample was drawn from Cohort 3 of the larger project.

Task Values.—Twelve items from Conley (2012) were adapted to assess science task values. Each of the task value subscales was measured including science attainment value (4 items), science utility value (3 items), and science interest value (5 items). Example items included: attainment value: "Being good in science is an important part of who I am."; utility value: "Being good in science will be important for my future (like when I get a job or go to graduate school)."; interest value: "I enjoy doing science."

Perceived costs.—We adapted perceived cost items used in prior research (Battle, Wigfield, 2003; Conley, 2012; Perez et al., 2014) to assess science opportunity cost and science effort cost. Two items were adapted for science undergraduates from Conley (2012) to assess perceived opportunity costs (i.e., costs associated with forgone opportunities). A sample item was, "Success in science requires that I give up other activities I enjoy." Perceived effort cost (i.e., perceptions of whether the time and effort in science are worthwhile) was assessed using 4 items adapted from (Perez et al., 2014); a sample item was, "Studying science requires more effort than I'm willing to put in."

STEM GPA and STEM Courses Completed.—We collected from the university's institutional records office students' course grades in all STEM courses after the end of the first year of college and after the end of four years of college. We calculated their cumulative STEM GPA at the end of one year and at the end of four years using a 4.0 GPA scale. Thus, the first-year STEM GPA represents students' cumulative STEM GPA for the first year of college and students' fourth-year cumulative GPA is their STEM GPA including all courses over four years of college.

We also collected data from intuitional records on the total number of STEM courses completed after the first year of college and the total number of STEM courses completed at the end of four years of college. Total STEM courses completed included any course in a science (e.g., biology, chemistry, physics), technology (computer science), engineering, or mathematics discipline. We counted any course that received a passing grade as having been completed (i.e., we did not count a grade of W or F as having been completed). Thus, first-year total STEM courses include all courses completed in the first year of college and fourth-year total STEM courses completed includes all courses completed from students' first year through their fourth year of college.[3]

Data Analyses

To identify motivational profiles among our sample, we used a model-based approach known as latent profile analysis (LPA; Collins, Lanza, 2010) using Mplus version 7. LPA relies on a number of fit indices for non-nested models—including Akaike Information Criteria (AIC), Bayesian Information Criterion (BIC), adjusted BIC, and entropy—to select the profile solution that best characterizes the data overall. Lower values of AIC, BIC, and adjusted BIC, along with higher levels of entropy, indicate improved model fit when comparing models to one another (Collins, Lanza, 2010), with BIC often considered the most reliable indicator for model fit (Nylund, Asparouhov, Muthén, 2007). LPA also takes

[3]The majority of students in the sample (92%) graduated within four years.

into consideration membership in each profile; if a profile in one solution is empty or only characterizes a small proportion of the sample, it may not represent the most parsimonious profile solution. We used raw scores on each of the variables as input variables for the LPA analysis. Before performing the LPA, Grubbs' test (1950) was used to identify outliers. Outliers were replaced with the next closest score (Field, 2013)—rather than deleted—in order to maintain the maximum sample size and accurately represent the original distribution of data. We conducted a multivariate analysis of variance to determine whether final profiles differed on mean levels of motivational variables.

To determine whether students' individual characteristics (i.e., gender, underrepresented minority status) predicted profile membership, we utilized the R3STEP command for auxiliary variables in MPlus (Asparouhov, Muthen, 2014). The R3STEP approach determines whether predictor variables—in this case, gender and underrepresented minority status—are significantly associated with a greater likelihood of being categorized into one profile versus being categorized into another profile. More specifically, this procedure automatically creates the most likely profile as an outcome and compares the likelihood of individuals being categorized into one profile versus another based on the covariate of interest (e.g., gender or underrepresented status). To explore whether individuals' profile membership predicted STEM outcomes of interest (i.e., first-year total STEM courses completed and STEM GPA, total STEM courses completed and STEM GPA at the end of the fourth year), we employed the automatic BCH approach in MPlus. The BCH approach estimates differences between latent profiles in outcome variables of interest (Asparouhov, Muthen, 2014).

Results

Descriptive Statistics and Correlations

Descriptive statistics for the entire sample and correlations among the observed variables are presented in Table 1. Correlations were consistent with what would be expected from theory and prior research. For example, the significant correlations between competence beliefs scores and all three task value scores were positive while scores on both cost variables were negatively correlated with competence beliefs. Effort cost and opportunity cost scores were also negatively correlated with all task values scores. Opportunity cost and effort cost scores were significantly and positively correlated with each other. The motivation variables were all correlated with all outcomes with the exception of opportunity cost and STEM GPA. Importantly, these results support the validity of the competence beliefs, task values, and perceived costs measures and suggest the motivation variables are related to the outcome variables. Finally, the number of STEM courses completed and STEM GPA were correlated with each other at both time points, Year 1 and Year 4 STEM courses completed were correlated with each other, and Year 1 and Year 4 STEM GPA was highly correlated.

How Do Science Competence Beliefs, Task Values, and Perceived Costs Combine into Motivational Profiles for Undergraduate Science Students?

Fit indices for potential profile solutions are displayed in Table 2. A three-profile solution best fit the data from the current sample. Results from a Lo-Mendell-Rubin Likelihood Ratio

Test and Parametric Bootstrap Likelihood Ratio test both indicated that a three-profile solution better characterized the data than a two-profile solution. The AIC, BIC, and Adjusted BIC values were also lower for a three-profile solution than the two-profile solution, and each of the three profiles best characterized a substantial proportion of the sample (smallest profile = 16% of the sample). Although the entropy for the three-profile solution was lower than that of the two-profile solution, indicating that the profiles were less distinct from one another, all other fit indices suggested that a three-profile solution best fit the data. Despite having lower AIC and adjusted BIC values, a four-profile solution was not determined to be a better fit for the data than a three-profile solution due to a nonsignificant likelihood ratio test, one profile that only characterized 2% of the sample, and a lower entropy value. A four-profile solution also failed to replicate a loglikelihood value, indicating that the profile solution may have been over specifying to the data based on a small number of cases (i.e., settling on a local maxima).

To help label the profiles, we considered the relative scores (i.e., z-scores) and raw scores on the input variables as well as their mean-level differences among the profiles. Table 3 presents the means, standard deviations, and z-scores for the motivation variables in each profile and Figure 1 presents the raw mean scores for each profile. A multivariate analysis of variance and follow-up univariate analyses of variance indicated that profiles differed on the motivation variables (Wilk's $\lambda = 96.65$, $p < .001$; $Fs = 44.14–359.31$, $ps < .001$; $\eta^2s = .13–.55$). Follow up Tukey HSD tests indicated that profiles differed significantly on all motivational variables; the only exception is that students in the *Very High Competence/Values-Low Effort Cost* profile and *High Competence/Values- Moderate Low Costs* profile (described below) did not differ in reported opportunity cost.

Description of profiles.—The first profile was the smallest ($n = 96$; 16.00% of sample) and was characterized by the lowest levels of competence beliefs and all three task values and the highest levels of both costs relative to the other two profiles. The raw scores on all variables ranged between 3.21 and 3.88. This profile had, on average, significantly higher opportunity cost and effort cost than all other profiles. The z-scores on the task value and competence beliefs variables were ≥ 1 *SD* below the sample mean. While raw scores on all variables were moderate for this profile, relative scores were below average on task values and competence beliefs and above average on both costs. We labeled this profile *Moderate All* to reflect the moderate raw scores across all motivation variables.

The second profile was characterized by very high raw scores on competence beliefs and task values, low raw scores on opportunity cost, and very low raw scores on effort cost. This profile included 24.33% of the total sample ($n = 146$) when examining students' most likely classified profile. Scores on competence beliefs and task values were significantly higher than the other two profiles, scores on effort cost were significantly lower than the other two profiles, and opportunity cost scores were significantly lower than the *Moderate All* profile. Compared to the entire sample, students most likely classified in this profile were approximately 1 *SD* above mean levels of task values, about .75 *SD* above mean levels of competence beliefs, were slightly below the mean on opportunity cost, and approximately .75 *SD* below the mean on effort cost. We labeled this profile *Very High Competence/Values-Low Effort Cost* (see Table 2).

The third profile was the largest (59.67% of the sample; $n = 358$) when considering students' most likely classified profile and was characterized by high raw scores on competence beliefs and task values and moderately-low raw scores on both perceived costs. This profile was similar to the *Very High Competence/Values-Low Effort Cost* profile but with lower raw scores on all variables except effort cost, which was higher compared to the *Very High Competence/Values-Low Effort Cost* profile. Relative to the overall sample, students most likely classified in this profile had approximately average scores on all variables. Given that students most likely classified in the profile had high raw scores on competence beliefs and the three task values with scores below 3.00 on the two cost variables, we labeled this profile *High Competence/Values-Moderate Low Costs.*

Overall, the LPA results suggested that when raw scores on competence beliefs and task values were higher ($M \geq 4.0$ on a 5-point scale), perceptions of cost were lower ($M < 3.0$ on a 5-point scale). When raw scores on task values and competence beliefs were more moderate ($M > 3.00 < 4.00$ on a 5-point scale), perceived cost scores were also moderate ($M > 3.00 < 4.00$ on a 5-point scale).

Do Students' Science Motivational Profiles Differentially Predict Short-Term and Long-Term STEM Academic Achievement and Course Completion?

First-year STEM outcomes.—The profiles were associated with differences in STEM GPA and total STEM course completion at the end of the first year of college (see Table 4). Students most likely classified into the *Moderate All* profile had a significantly lower STEM GPA than students most likely classified into the *Very High Competence/Values-Low Effort Cost* profile **(**$d = .48$) and a significantly lower GPA than the students most likely classified into the *High Competence/Values- Moderate Low Costs* profile **(**$d = .31$). However, there was no significant difference in STEM GPA between the *Very High Competence/Values-Low Effort Cost* and *High Competence/Values-Moderate Low Costs* profiles ($d = .17$).

Students most likely to belong to the *Moderate All* profile completed significantly fewer STEM courses than students most likely to belong to the *Very High Competence/Values-Low Effort Costs* profile ($d = .78$) and significantly fewer STEM courses than the students most likely to belong to the *High Competence/Values-Moderate Low Costs* profile ($d = .54$). There was also a statistically significant difference between the *Very High Competence/Values-Low Effort Costs* and *High Competence/Values-Moderate Low Costs* profiles in the total number of STEM courses completed such that students most likely classified into the *Very High Competence/Values-Low Effort Costs* profile completed significantly more STEM courses than students most likely classified into the *High Competence/Values-Moderate Low Costs* profile ($d = .20$).

Fourth-year STEM outcomes.—As with the first-year outcomes, the profiles were associated with differences in STEM GPA and total STEM course completion after four years of college (see Table 4). Specifically, students most likely to belong to the *Moderate All* profile had a significantly lower STEM GPA than students most likely to belong to the *Very High Competence/Values-Low Effort Cost* profile **(**$d = .54$) and a significantly lower STEM GPA than students most likely to belong to the *High Competence/Values-Moderate*

Low Costs profile *(d* = .41). However, students most likely to belong to the *Very High Competence/Values-Low Effort Cost* profile and to the *High Competence/Values- Moderate Low Costs* profile had a similar STEM GPA at the end of four years (d = .05, p > .05).

Students most likely to belong to the *Moderate All* profile completed significantly fewer STEM courses at the end of four years compared to students most likely to belong to the *Very High Competence/Values-Low Effort Cost* profile. The effect size of this difference was large (d = .96). Indeed, students most likely classified into the *Very High Competence/Values-Low Effort Cost* profile completed almost eight more STEM courses than students most likely classified into the *Moderate All* profile. Students most likely classified into the *Moderate All* profile also completed significantly fewer STEM courses over four years than students most likely classified into the *High Competence/Values- Moderate Low Costs* profile (d = .65). Students most likely classified into the *Moderate All* profile completed approximately five fewer STEM courses over four years than students most likely classified into the *High Competence/Values- Moderate Low Costs* profile. Finally, students most likely to belong to the *Very High Competence/Values-Low Effort Cost* profile completed approximately 2 more courses over four years than students most likely to belong to the *High Competence/Values- Moderate Low Costs* profile, which was a significant difference in course completion (d = .30).

Are there Differences in Profile Membership Based on Gender and URM Status?

We examined whether or not gender and URM status related to profile membership in our LPA models. Although a greater percentage of women were more likely to be classified into the *Moderate All* profile, gender was not statistically significantly related to profile membership (Ests. = 0.029–0.514, *ps* = .067-.892). Indeed, the distribution of women within the profiles (*Moderate All* profile: 61.05% female; *High Competence/Values- Moderate Low Costs* profile: 48.88% female; *Very High Competence/Values- Moderate Low Effort Cost* profile: 47.95% female) mirrored that of the whole sample (50.5% female). However, URM status was significantly related to profile membership. Specifically, 18.7% students identified as a URM in the current sample and these URM students were most likely to be classified into the *Moderate All* profile (29.47%). This proportion was marginally greater when compared to the *High Competence/Values-Moderate Low Costs* profile (19.55%; Est. = 0.551, *SE* = 0.312, p = .078) and significantly greater when compared to the *Very High Competence/Values-Low Effort Cost* profile (9.59%; Est. = −1.423, *SE* = 0.404, p < .001). Students who identified as URM were also significantly more likely to be classified into the *High Competence/Values- Moderate Low Costs* profile than the *Very High Competence/Values-Low Effort Cost* profile (Est. = 0.872, *SE* = 0.353, p = .014). Thus, in this sample, URM students were more likely to belong to the profile with the lowest levels of science task values and competence beliefs and highest levels of perceived costs than would be expected by chance given the overall sample of URM students. Furthermore, URM students were less likely to belong to the profile with the highest levels of science task values and competence beliefs and lowest levels of effort cost in science than would be expected by chance given the overall sample of URM students.

Discussion

Undergraduate students' achievement and choices in STEM disciplines are driven by a variety of factors, many of which interact to synergistically affect their behaviors. In this study, we identified profiles of first-year undergraduates' science competence beliefs, science task values, and science perceived costs and examined how these profiles of beliefs related to two important STEM persistence outcomes: (1) students' achievement in their STEM courses and (2) the number of STEM courses completed. We examined the relations of first-year motivational profiles to the STEM outcomes after one year of college and then at the end of four years of college to determine the extent to which early science motivation in college was related to STEM persistence outcomes throughout college. Each of these outcomes is critical for students' persistence in the STEM pipeline because students need to both select and then be successful in STEM courses to persist in STEM majors and, ultimately, STEM careers. Finally, we examined how gender and underrepresented minority status related to profile membership. Women and racial/ethnic minorities are underrepresented in many STEM fields; therefore, it is important to examine factors that lead to attrition of underrepresented groups from the STEM pipeline.

The findings indicated that science expectancy, value, and cost beliefs combined into three motivational profiles. The levels of perceived cost, particularly effort cost, varied with levels of task values and competence beliefs across the three profiles such that effort cost tended to be lower when task values and competence beliefs were higher. However, opportunity cost was less variable across the profiles. Importantly, the first-semester science motivation profiles differentially related to the STEM persistence outcomes over four years of college. The *Moderate All* profile was least adaptive in terms of STEM outcomes while the *Very High Competence/Value-Low Effort Cost* profile was the most adaptive and there were large differences in STEM GPA and total STEM courses completed after four years between these two profiles. The *Moderate All* profile also had significantly lower STEM GPA and total STEM course completion than the *High Competence/Value-Moderate Low Costs* profile. While there were differences in total STEM course completion between the *Very High Competence/Value-Low Effort Cost* and the *High Competence/Value-Moderate Low Costs* profiles, these differences were generally small. There were no differences between these profiles in terms of STEM GPA. Thus, students' first-semester science motivation profile has implications for STEM achievement and persistence through four years of college, with potentially large effects. We also found that URM students were most likely to be classified into the *Moderate All* profile and were least likely classified into the *Very High Competence/Value-Low Effort Cost* profile suggesting that URM students may be more likely to develop a profile of science motivation beliefs that is less conducive to persisting in STEM, perhaps as a result of systemic barriers faced by URM students in their early college experiences (Seymour, Hewitt, 1997).

The results of this study contribute to expectancy-value theory and to research on broadening participation in STEM by adding new empirical evidence for the ways in which undergraduate science students' competence beliefs, task values, and perceived costs may combine and how such combinations of beliefs relate to more proximal and distal STEM persistence outcomes. While there have a been a few studies that have examined profiles of science competence beliefs and task values (e.g., Andersen, Chen, 2016), perceived costs in science have rarely been included in profiles of science beliefs (Conley, 2012 and Bøe, Henriksen, 2013 are exceptions). Our inclusion of the understudied perceived cost component provided a more comprehensive picture of students' science-related motivational experience and allowed us to explore whether or not students may experience high task values and competence beliefs along with high costs in science. Furthermore, there have been few studies that have taken a person-oriented approach with college students' science motivation beliefs and examined how such profiles of beliefs relate to STEM persistence outcomes over four years of college. Finally, few studies have examined the prevalence of underrepresented groups (racial/ethnic minorities and women) in more and less adaptive science motivation profiles. We discuss the contributions of this study in further detail below.

Profiles of Expectancy, Value, and Cost Beliefs

There has been little prior research examining how science expectancy-value variables combine and how such beliefs relate to important STEM persistence outcomes in college. Using LPA, we identified three profiles of expectancy-value beliefs among a sample of highly capable undergraduate science students who demonstrated at least some initial interest in STEM disciplines (i.e., they were enrolled in a gateway chemistry course for science majors). The profiles identified in this study were generally consistent with what would be expected from theory. First, expectancy-value theory and research suggest that individuals will tend to value domains in which they feel competent (Wigfield et al., 2009) and competence beliefs and task values tended to fluctuate together in this study. In other words, profiles with higher competence beliefs also had higher task values. While this finding is consistent with the premise that competence beliefs and task values are correlated, this differs from findings in studies with younger students (Andersen, Chen, 2016; Bøe, Henriksen, 2013) that identified profiles with more variability between their measures of competence beliefs and task values. These differences may be due to differences in samples. For example, Andersen and Chen's (2016) study was with high school students who were likely more diversified in their motivation for science. Expectancy-value theory suggests that students will choose a domain of study when they feel competent in the domain *and* value the domain (Eccles et al., 1983), and the undergraduates in our study self-selected into a science course for science majors. Students coming into college with a combination of high perceived competence in science and very low value for science, for example, may be less likely to select into an undergraduate gateway science course. Indeed, none of the profiles identified in this study had low levels (< 3.00) of science competence beliefs or task values. Second, competence beliefs and task values tended to be inversely related to perceptions of cost. Students most likely to belong to the *Very High Competence/Values-Low Effort Cost* profile held the highest levels of competence beliefs and task values for science, with ratings approximately one standard deviation above the mean on both variables. These students also endorsed the lowest level of effort cost, with ratings approximately a half of a standard deviation below the sample mean. Conversely, the *Moderate All* profile had the lowest average competence beliefs and task values with the highest levels of cost. While the *High Competence/Values-Moderate Low Costs* profile also had high raw scores on competence beliefs and task values, this profile was more moderate than the *Very High Competence/*

Values-Low Effort Cost profile and the *High Competence/Values-Moderate Low Costs* profile also had higher effort costs than the *Very High Competence/Values-Low Effort Costs* profile. Thus, effort cost in particular seemed to fluctuate with the levels of competence beliefs and task values. It may be that perceiving the effort required to be successful in science as worthwhile is more closely connected to one's perceived competence and task value in science. For example, if a student views science as an important part of her identity (attainment value) and as important for her future career goals (utility value) then the effort to be successful may not feel as costly. Furthermore, if one simultaneously feels competent in one's science ability, then expended effort may also not feel as costly. Opportunity cost, on the other hand, may not fluctuate as much with competence beliefs and task values because success in STEM courses requires sacrifice. Therefore, students are giving up other valued activities regardless of their perceptions of value for science. These results highlight the importance of measuring different kinds of cost perceptions in science.

Unlike prior profile-oriented studies that included cost (Conley, 2012) we did not find a high task value-high perceived cost profile. However, the *Moderate All* profile was interesting because students' perceptions of task values and costs were around the same level. Raw task value scores for this profile ranged from 3.35 to 3.88 and perceived cost scores ranged from 3.21 to 3.58. These results suggest that college students can hold similar levels of science task values and perceived costs simultaneously. There are several factors that may explain differences in Conley's and our findings. First, our study included undergraduate students from an elite university, while Conley's study included middle school students from urban, public-school districts. The university students in this study selected into a gateway chemistry course and those who highly value science but also experience higher costs may be less likely to take a gateway chemistry course for science majors. In other words, students with a high value-high cost profile may have selected themselves out by this point. Second, the variables were measured in different domains, math in Conley's study and science in our study. Third, Conley also included achievement goals in her profile analyses making it more difficult to compare her findings to ours. It should be noted however, that if one were to simply subtract cost scores from value scores, this obscures the fact that some students do at least moderately value science while also perceiving science as moderately costly. However, these results do lend some support to Eccles et al.'s (1983) original conceptualization that the overall value for a task or domain will be dependent on perceptions of cost.

LPA also revealed that a majority of students in the sample were likely to belong to the *High Competence/Values-Moderate Low Cost* profile. Specifically, approximately 60% of the sample was classified into this profile. This indicates that, unsurprisingly, most students in this sample were motivated for science. The smallest group was the *Moderate All* profile (16% of the sample). Again, these results make sense since most students who are not at least initially motivated to pursue science would likely have selected out of a gateway chemistry course. There have been few studies that have examined profiles of science competence beliefs and task values. Andersen and Chen (2016) did examine profiles of science motivation from an expectancy-value framework using variables similar to those used in this study, but they did not include perceptions of costs. Furthermore, their sample included high school students whereas the sample in this study included undergraduates. However, similar to the results of this study, Andersen and Chen identified a low motivation profile (below average science task values and competence beliefs; similar to the *Moderate All* profile) and a typical motivation profile with task value and competence belief scores at the mean (similar to the *High Comptence/Values-Moderate Low Costs* profile in this study).[4] They also found two additional profiles of beliefs that were more variable in terms of the profiles of beliefs (e.g., high science efficacy and high science utility value). Furthermore, while Andersen and Chen found similar profiles to profiles identified in this study (low and typical), the "low" profile in our study had a smaller proportion of the sample (16% vs. 40% in Andersen and Chen) and our "average" profile included a larger proportion of the sample (60% vs. 43% in Andersen and Chen). These differences are likely partly explained by the fact that our sample included college students who selected into a gateway chemistry course. Future studies should replicate this study with the same input variables using various samples (e.g., high school students vs. college students) to investigate the similarities and differences in science expectancy, value, and cost profiles across age groups.

Relations of Profile Membership to STEM-related Outcomes

After identifying science expectancy, value, and cost profiles, a central question in this study was whether different motivational profiles were related to short-term and long-term STEM academic outcomes in college. Results suggested that students most likely to belong to the *Moderate All* profile had the lowest academic achievement in STEM and completed the fewest STEM courses. Not only did students most likely to belong this profile complete significantly fewer STEM courses and had a lower STEM GPA than students most likely to belong to the other two profiles by the end of the first year, they were also lowest on the STEM outcomes at the end of four years of college. At the end of the first year, the size of the differences between the *Moderate All* profile and the other profiles ranged from small to medium for GPA (.31 and .48) and ranged from medium to large for STEM course completion (.54 and .78). The size of the effects for the differences between the *Moderate All* profile and the other two profiles only increased at the end of four years (.41 - .54 for STEM GPA and .65 - .96 for STEM course completion). These results likely reflect attrition from STEM disciplines between the first and fourth year of college for the students in the *Moderate All* profile. Indeed, on average, at the end of four years, students in the *Very High Competence/Values-Low Effort Cost* profile completed almost 8 more STEM courses than students in the *Moderate All* profile. Eight courses represent nearly an entire year of STEM courses completed. The *Moderate All* profile also completed approximately 5 fewer courses over four years compared to the *High Competence/Values-Moderate Low Costs* profile or approximately a semester's worth of STEM courses. As a reminder, *all* students in the sample were taking a gateway chemistry course for STEM majors, thus demonstrating an initial interest in pursuing a STEM major.

In addition to the differences between the *Moderate All* profile and the other profiles, there were also differences in STEM achievement and course completion between the *High Competence/Values-Moderate Low Costs* profile and the *Very High Competence/Values-Low Effort Cost* profile. However, the differences between these profiles were not as large.

[4]It is important to note that Andersen and Chen (2016) reported and used *z*-scores in their analyses and students' raw scores on the measures are not reported.

At the end of the first year of college and after fourth years of college, there was no difference in STEM GPA between students in these profiles. However, there were significant differences in total STEM course completion at the end of the first year and after four years of college. While the effect size differences in total STEM course completion grew over time (d = .20 after year 1 and d = .30 after year 4), the differences remained small. At the end of four years of college, students in the *Very High Competence/Values-Low Effort Cost* profile completed approximately two more STEM courses than the *High Competence/Values-Moderate Low Costs* profile. Such a difference is likely less meaningful in terms of students' persistence in STEM disciplines.

These results align with expectancy-value theory, suggesting that those who perceive relatively low science competence beliefs along with relatively low science task value and relatively high science perceived cost will also have lower achievement and persistence in the domain. Importantly, the results of this study demonstrate that science motivational beliefs formed in the first semester of the first year of college may have long-term effects on STEM achievement and persistence. This study adds to the literature by also including two different kinds of perceived costs in the profile analysis and lends empirical evidence to the notion that task values are a function of the perceived costs, which combine to affect achievement outcomes. An important question is whether and how to intervene with students who start college with moderate levels of competence beliefs, task values, and perceived costs. It is possible that such a profile of beliefs reflects other interests outside of the STEM disciplines and, therefore, the attrition from STEM may be appropriate for these students. On the other hand, if we are aiming to broaden participation in STEM, it may be important to intervene on motivation early with students who show initial interest in STEM (i.e., by selecting a gateway science course early in college) in order to maintain at least some in the STEM pipeline. This is particularly important to consider given the results related to the relations between underrepresented minority status and profile membership, which we discuss next.

Gender and Race Representation Across Profiles

In addition to identifying how science expectancy, value, and cost beliefs combine into motivational profiles, we examined whether women and URM students were over or underrepresented in the different profiles. While gender was not related to profile membership, URM status was significantly related to profile membership. Specifically, URM students were more likely to be classified into the *Moderate All* profile than in the other two profiles than would be expected by chance. URM students were also more likely to be classified into the *High Competence/Values-Moderate Low Costs* profile than in the *Very High Competence/Values-Low Effort Cost* profile. These results are important given the lack of representation of URMs in many STEM disciplines and that fact that students in the *Moderate All* profile had a lower average STEM GPA and also completed fewer STEM courses than students in the other two profiles. The results suggest that students who are underrepresented in STEM–even those who are highly qualified and show an initial interest in STEM by selecting a chemistry course for majors-may be more likely to develop moderate science competence beliefs and task values and relatively high perceptions of cost in science early in college. Furthermore, developing more moderate science motivation may have long-term consequences for STEM persistence.

Unfortunately, our data cannot speak to *why* URM students are more likely to develop moderate science motivation early in college and identifying the factors that shape these motivational beliefs for URM students will be important for creating interventions that aim to broaden participation in STEM disciplines. It is possible, that early experiences that suggest underrepresented students do not belong in science (Murphy, Steele, Gross, 2007) may result in more moderate overall science motivation. Indeed, the institution itself is a predominantly white and Asian institution. Numerical underrepresentation in students' classrooms may lead URM students to perceive that they do not belong in science. An important direction for future research is understanding the structural mechanisms that may explain why students who identify with underrepresented groups in science are more likely to exhibit moderate science motivation. While the long-term implications for STEM persistence of such a motivational profile may partially explain the lack of representation of URM students in STEM careers, understanding how sociocultural views of race or ethnicity play into the messages students receive both prior to and during college and how these messages influence students' motivation is crucial (Eccles, 2009; Mutegi, 2013). For example, the expectancy-value model (Eccles et al., 1983) highlights the importance of stereotypes in the formation of expectancy-value beliefs. Prior research further suggests that factors such as stereotype threat may lead to lower perceptions of value and higher perceptions of cost in science (Smith, Brown, Thoman, Deemer, 2015). Our results may be indicative that URM students' early experiences in gateway science courses at a predominately white and Asian institution coupled with their prior experiences in science may account for reduced motivation for science. In future research, it will be important to explore the question of why, during the first semester of college, URM students have relatively lower overall motivation and relatively higher costs for science than their peers.

Limitations and Future Directions

There are limitations to this study that should be considered as one interprets the findings. First, the participants in this study were students attending an elite, private university. Therefore, the sample was comprised of students who started college with a particularly strong academic background and are not representative of the larger population of college students. However, the results demonstrate that even among high-achieving students, one's motivational profile at the beginning of college can have long-lasting effects on STEM achievement and persistence. In future research, it will be important to examine expectancy, value, and cost profiles with more diverse samples of science students from colleges and universities with various levels of selectivity. As Andersen and Chen (2016) found, more variable profiles of science competence beliefs, task values, and perceived costs may be identified in more academically diverse samples.

A second important limitation concerns the perceived cost measures. While we assessed two dimensions of cost, research suggests three or more cost dimensions may be important (Flake et al., 2015; Gaspard, Dicke, Flunger, Schreier, et al., 2015; Perez et al., 2014). Furthermore, the opportunity cost measure included only two items. However, both cost measures were adapted from previously published research (Conley, 2012; Perez et al., 2014) and the results still provide empirical support for theorized relations among different perceived costs, competence beliefs, and task values. Future research should examine profiles of students using a more expanded cost measures. For example, it would be important to examine how psychological costs (Perez et al., 2014) or emotional costs (Flake et al., 2015; Gaspard, Dicke, Flunger, Schreier, et al., 2015) combine with effort costs and opportunity costs. Others have also noted the importance of external time and effort costs (Flake et al., 2015). Such costs may be particularly important for science students who are required to take lecture courses, labs, participate in internships, etc. and therefore have many external demands on their time.

We were unable to examine differences in profile representation for students who identify with different racial and ethnic groups. For example, there may be differences between Latinx students and African American students in terms of representation in profiles. Furthermore, the intersectionality of gender and race/ethnicity also needs to be considered. Unfortunately, we did not have the sample size to make these comparisons. Future research should focus on examining whether there are more nuanced differences. Additionally, we were not able to examine how or why racial/ethnic differences in science motivation profile membership materialized in this study, which is a very important yet often overlooked question (Mutegi, 2013). Indeed, a variety of barriers exist that may hinder the development of science motivation beliefs for groups that are underrepresented in science and STEM more broadly.

As a future direction for this research, it would be very interesting to examine how students' profiles of science expectancies, values and costs beliefs change over an academic career and how such changes relate to STEM outcomes. It is likely that some students' motivational profiles will change over time and that such changes may be associated with achievement and choice in STEM disciplines. It would also be important to examine factors that influence changes in profiles of beliefs. Future studies could examine the prevalence and predictors of shifts in expectancy-value profiles over the college career. Such predictors could indicate targets for interventions designed to broaden participation in STEM disciplines.

Finally, a limitation of any data examined at a single time point is that we were not able to examine how expectancies, values, and perceived cost changed in tandem over time. For instance, it would be interesting to examine the temporal and reciprocal relations among expectancies, values, and costs to understand how these beliefs shape each other. Future longitudinal studies—utilizing both variable-oriented and person-oriented techniques—should further investigate such questions, particularly given the limited research on factors that shape perceived costs and their relation to expectancies and values over time.

Conclusion

In this study, we identified three expectancy, value, and cost motivational profiles and examined how the profiles related to achievement and course completion in STEM at the end of the first year of college and after four years of college. We also examined whether gender and URM status related to profile membership. The three identified profiles provided empirical evidence for theoretical relations among competence beliefs, task values and perceived costs. This study was unique in that we examined how science expectancy-value beliefs combined into profiles among a sample of college students, including multiple dimensions of perceived costs. We then examined how first-year profiles related to proximal and distal STEM outcomes. We found that the most deleterious profile for STEM achievement and persistence in this sample was the profile with below average competence beliefs and task values and above average perceived costs, relative to the sample. The relations of first-year profiles-assessed in the first semester of college-to the STEM outcomes held after four years. Finally, URM students were most likely to be in the profile characterized by relatively low motivation for science. Future research should continue to examine how motivational beliefs in science combine to form various profiles of beliefs, examine the factors that lead to the development of particular profiles of beliefs, and examine how motivational profiles relate to important academic and career outcomes.

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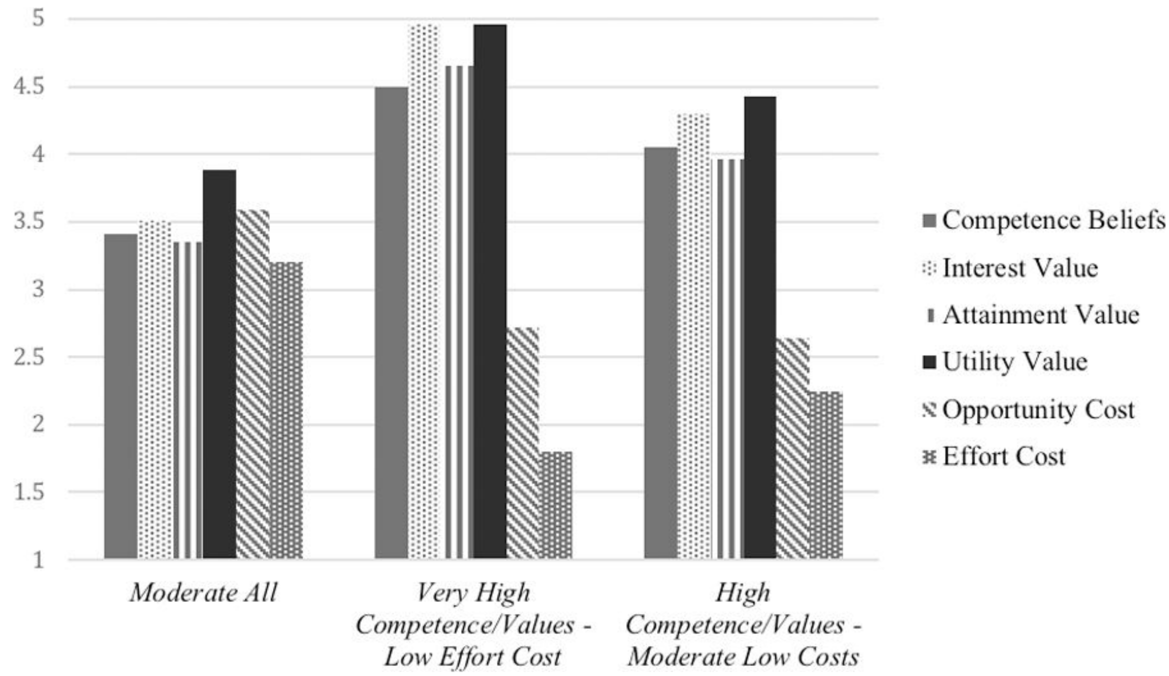

Figure 1.
Raw cluster centroids for motivation profiles. All items assessed on a 1–5 Likert scale.

Table 1

Correlations and Descriptive Statistics for the Sample

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.
1. Comp. Beliefs	–									
2. Interest Value	.42**	–								
3. Attainment Value	.48**	.59**	–							
4. Utility Value	.39**	.57**	.57**	–						
5. Opportunity Cost	−.30**	−.19**	−.09*	−.15**	–					
6. Effort Cost	−.37**	−.46**	−.30**	−.49**	.42**	–				
7. STEM Courses – 1 Year	.19**	.22**	.24**	.11**	−.08*	−.17**	–			
8. STEM GPA – 1 Year	.10*	.18**	.14**	.11**	−.03	−.09*	.22**	–		
9. STEM Courses – 4 Years	.17**	.28**	.28**	.12**	−.11*	−.22**	.60**	.33**	–	
10. STEM GPA – 4 Years	.08*	.16**	.12**	.12**	−.06	−.11*	.15**	.84**	.40**	–
M	4.04	4.32	4.02	4.45	2.82	2.31	4.28	3.17	18.49	3.30
SD	0.66	0.64	0.67	0.51	1.00	0.79	1.50	0.62	7.24	0.54
Cronbach's α	.87	.91	.79	.79	.78[1]	.75	–	–	–	–

Note. N = 586 Listwise; Comp. Beliefs = Competence Beliefs; STEM Courses – 1 Year = Total STEM courses completed through the first year; STEM GPA – 1 Year = Grade point average in STEM courses at the end of the first year; STEM Courses – 4 years = Total STEM courses completed at the end of four years; STEM GPA – 4 Years= Grade point average in STEM courses at the end of the four years.

[1] Interitem Spearman-Brown correlation between the two opportunity cost items, which is more appropriate for two-item measures than Cronbach's alpha (Eisinga, te Grotenhuis, Pelzer, 2012).

* $p < .05$

** $p < .01$.

Table 2

Fit Indices for Different Latent Profile Solutions

Number of profiles	AIC	BIC	Adjusted BIC	Entropy	Profile Sizes	Smallest Class Size	−2 Log Likelihood Difference
1	10873.89	10944.29	10893.50	--	600	600 (100%)	--
2	6621.95	6731.87	6652.50	.93	166, 434	166 (27.57%)	983.76
3	**6175.43**	**6342.51**	**6221.87**	**.86**	**96, 146, 358**	**96 (16.00%)**	**466.91**
4	6119.49	6343.73	6181.82	.83	140, 273, 13, 174	13 (2.16%)	80.97 *(ns)*

Note: AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion; Adjusted BIC = Adjusted Bayesian Information Criterion; Log Likelihood Difference = Result from Lo-Mendell-Rubin Adjusted Likelihood Ratio Test (comparing X profile solution to solution with X-1 profiles). The 3-profile solution (in bold) was selected as the best fitting solution.

Table 3

Latent Profile Analysis of Expectancy, Value, and Cost Variables

Expectancy-Value Variables	*Moderate All*	*Very High Competence/Values-Low Effort Cost*	*High Competence/Values-Moderate Low Costs*
Total *n*	96	146	358
(%)	(16.00%)	(24.33%)	(59.67%)
Competence Beliefs			
M	3.41[a]	4.49[b]	4.05[c]
(*SD*)	(0.52)	(0.30)	(0.25)
z-score	−1.06	0.67	0.01
Interest Value			
M	3.51[a]	4.96[b]	4.30[c]
(*SD*)	(0.50)	(0.01)	(0.18)
z-score	−1.36	1.01	−0.05
Attainment Value			
M	3.35[a]	4.66[b]	3.97[c]
(*SD*)	(0.35)	(0.14)	(0.29)
z-score	−1.08	0.94	−0.10
Utility Value			
M	3.88[a]	4.96[b]	4.43[c]
(*SD*)	(0.35)	(0.01)	(0.13)
z-score	−1.24	0.98	−0.07
Opportunity Cost			
M	3.58[a]	2.72[b]	2.64[b]
(*SD*)	(0.75)	(1.21)	(0.78)
z-score	0.82	−0.10	−0.18
Effort Cost			
M	3.21[a]	1.80[b]	2.25[c]
(*SD*)	(0.42)	(0.59)	(0.35)
z-score	1.21	−0.63	−0.07

Note. Different subscripts denote significantly different means between profiles.

Table 4

Differences Among Profiles on the Outcome Variables

Outcome	*Moderate All*	*Very High Competence/Values-Low Effort Cost*	*High Competence/Values-Moderate Low Costs*
	M (*SE*)	*M* (*SE*)	*M* (*SE*)
End of One Year			
STEM GPA	2.91[a] (.10)	3.32[b] (.06)	3.19 [b] (.04)
STEM Courses	3.46[a] (.18)	4.68[b] (.12)	4.38[c] (.09)
End of Four Years			
STEM GPA	2.95[a] (.11)	3.40[b] (.05)	3.36[b] (.05)
STEM Courses	13.47[a] (.90)	21.12[b] (.59)	18.88[c] (.42)

Note. Different subscripts across rows indicate statistically significant differences between groups on the outcome variable; STEM = science, technology, engineering, and math; STEM GPA = STEM grade point average; STEM Courses = Total number of STEM courses completed after 1 year and 4 years of college; all significant differences are at $p < .05$.