Published in final edited form as:

Ann N Y Acad Sci. 2023 August ; 1526(1): 73–83. doi:10.1111/nyas.15031.

Patterns, predictors, and outcomes of situated expectancy-value profiles in an introductory chemistry course

Tony Perez[1], **Kristy A. Robinson**[2], **Stacy J. Priniski**[3], **You-kyung Lee**[4], **Delaram A. Totonchi**[5], **Lisa Linnenbrink-Garcia**[6]

[1]Department of Educational Foundations and Leadership, Old Dominion University, Norfolk, Virginia, USA

[2]Department of Educational & Counseling Psychology, McGill University, Montreal, Canada

[3]The Hope Center for College, Community, and Justice, Temple University, Philadelphia, Pennsylvania, USA

[4]Division of Education, Sookmyung Women's University, Seoul, South Korea

[5]Center for Advanced Study of Teaching and Learning, University of Virginia, Charlottesville, Virginia, USA

[6]Department of Counseling, Educational Psychology and Special Education, Michigan State University, East Lansing, Michigan, USA

Abstract

Using latent profile analysis, we identified profiles of expectancy beliefs, perceived values, and perceived costs among 1,433 first- and second-year undergraduates in an introductory chemistry course for STEMM majors. We also investigated demographic differences in profile membership and the relation of profiles to chemistry final exam achievement, science/STEMM courses completed, and graduating with a science/STEMM major. Four motivational profiles were identified: *Moderately Confident and Costly* (profile 1), *Mixed Values-Costs/Moderate-High Confidence* (profile 2), *High Confidence and Values/Moderate-Low Costs* (profile 3), and *High All* (profile 4). Underrepresented students in STEMM were more likely to be in profile 2 relative to profile 3. First-generation college students were more likely to be in profile 4 than profile 3. Finally, students likely to be in profile 3 had higher final exam grades than the other profiles and were more likely to graduate with a science major compared to profile 1. There were no differences in graduating science major between profile 3 and the other two profiles. Thus, profile 3 was most adaptive for both proximal (final exam) and distal (graduating with a science major)

Correspondence Tony Perez, Old Dominion University, 5115 Hampton Blvd., Education Building Suite 2300, Norfolk, VA 23529 USA, acperez@odu.edu.

AUTHOR CONTRIBUTIONS

T.P. drafted the manuscript and contributed to the conceptualization and design of the study, and interpretation of the findings. K.R. and S.P. contributed to data analyses and interpretation of findings with further analysis support from Y-k.L. K.A.R. also drafted sections of the method and results sections, contributed to data collection, and read and edited the manuscript. Y-k.L., D.A.T., and S.J.P. read and edited the manuscript and contributed to the interpretation of findings. L.L-G. contributed to the conceptualization and design of the study, interpretation of the findings, and read and edited the manuscript. All authors reviewed the manuscript and approved its content.

COMPETING INTERESTS

The authors declare no competing interests.

outcomes. Results suggest supporting motivation early in college is important for persistence and ultimately the talent development of undergraduate STEMM students.

Keywords

costs; expectancy; motivation profiles; STEMM persistence; values

INTRODUCTION

Many undergraduates aspiring to pursue science, technology, engineering, math, and medical science (STEMM) majors end up leaving the major or college entirely.[1] From a STEMM talent development perspective, these students lose the opportunity to continue to develop their emerging talents in the STEMM domain, which contributes to a loss of talent in the STEMM workforce. This is especially concerning for students who identify with minoritized racial/ethnic and gender groups, as well as first-generation college students, since they are historically underrepresented in many STEMM fields.[2,3] For example, in the US, Black students earn 6% of physical sciences degrees versus 10% of all bachelor's degrees. While women earn 57% of all bachelor's degrees, only 41% and 21% of students earning physical science and computer science degrees are women, respectively.[2] This loss of STEMM talent negatively impacts the advancement of diverse scientific ideas, the scientific literacy of the population, and the advancement of individuals' STEMM talents, well-being, and economic stability. Therefore, identifying and supporting students at risk of leaving STEMM early in their undergraduate pathway is critical for mitigating the loss of STEMM talent.

According to Situated Expectancy-Value Theory (SEVT) students who expect success, perceive high value, and perceive low costs in their STEMM discipline should be the most academically successful and persistent.[4] Importantly, students' SEVT motivation beliefs in introductory STEMM courses can be a gauge for their risk of leaving; students with lower success expectancy or value in STEMM disciplines may be at risk.[5] Many students experience challenges that destabilize their motivation in the transition from high school to college.[6] Moreover, prior research suggests there are differences in levels of motivation based on demographic characteristics, which are likely a result of additional barriers faced by underrepresented groups and may contribute to demographic variations in persistence.[7,8] Thus, examining students' motivation beliefs earlier in their undergraduate career is critical for understanding future enrollment and persistence decisions.

While researchers frequently focus on the unique effects of STEMM motivation variables on academic outcomes, SEVT motivation beliefs are hypothesized to function synergistically.[4] Students must value, feel confident, and perceive few costs in STEMM to maximize their engagement, persistence, and ultimately the development of their talents. Thus, examining profiles of multiple beliefs, rather than the unique effects of individual motivation variables, is more consistent with the theoretical underpinnings of SEVT and provides a more holistic picture of the role of motivation in STEMM persistence.

In this study, we identified synergistic intra-individual motivation profiles of expectancy, perceived values, and perceived costs among undergraduates in an introductory chemistry course for STEMM majors. Furthermore, we investigated demographic differences in profile membership to explore whether students from historically underrepresented groups were more likely to endorse varying patterns of motivation since these students may be underserved leading to destabilization in motivation. Finally, we examined the relations of early profiles with proximal course achievement and graduating major. This approach allowed us to identify adaptive patterns of motivation early in college that predicted proximal and distal STEMM persistence outcomes, which can facilitate the development of targeted interventions to support students and diversify STEMM talent development. We operationalized talent development based on the idea that students who enter college intending to pursue a STEMM degree have already demonstrated talent within their K-12 academic careers. We adopt the view that talent is not strictly a fixed entity, that individuals can develop domain-specific talents over time,[9] and contend that students' decisions to pursue an undergraduate STEMM degree represents the opportunity to continue to develop their STEMM talent.

Situated Expectancy-Value Theory

Our study is grounded in SEVT,[4] a prominent motivation theory well suited to understanding STEMM persistence and talent development.[10] SEVT posits that achievement outcomes are proximally driven by students' perceived task value and success expectancy for a given task. Success expectancies are individuals' beliefs about whether they will succeed on a future task and are closely tied to their ability beliefs in the domain. Perceived value for a task is important in individuals' selection, persistence, and achievement in the task and is conceptualized in terms of its connection to identity (*attainment value*), because it is enjoyable or interesting (*interest value*), and for its usefulness for meeting one's goals (*utility value*).[4]

These values may lead students to persist in a STEMM major; however, perceived costs may lead students to avoid the task and diminish the overall perceived task value.[11] Costs are the perceived drawbacks of the task, including *effort cost* (perceptions that the effort required to be successful on a task are not worthwhile), *opportunity cost* (perceptions that other valued activities have to be given up by selecting the task), and *psychological cost* (anxiety and harm to one's ego associated with potential failure)[a].[4] While there are some distinctions in how scholars operationalize costs,[12] research suggests that they are an important factor in achievement, persistence, and other STEMM outcomes.[5,13–15] Notably, there is less research on costs than the well-established research on expectancies and values.

Motivation profiles, talent development, and persistence

Talent development researchers highlight the importance of motivation for developing talent,[10,16,17] but this research mainly focuses on K-12 students with more limited research on talented undergraduates.[18] Generally, this research suggests that a lack of motivation

[a]Researchers[5,12,13,43] have conceptualized cost in other ways including emotional cost, outside effort cost, and ego cost. We adopted measures from Perez et al.,[5] which are closely aligned to the original conceptualization in Eccles et al.[11] to operationalize costs in our study.

can lead to underachievement of talented K-12 students and undergraduates.[18–20] For example, gifted underachieving elementary students experienced declining self-concept (similar to expectancy) and value from 1st to 6th grade. Sustained underachievers also reported increased psychological cost followed by a decline in psychological costs starting in fourth grade.[20] A recent review of research on talented undergraduates highlighted that motivation is also an important factor in their underachievement, adjustment to college, and academic success.[18] Relevant to this study, research with undergraduates enrolled in the honors college[b] of a US university found strong correlations between science interest and perception of science ability (operationalized as self-efficacy in the study), highlighting the close relationship between interest and ability perceptions.[21] Rea[10] highlights that the students who frequently experience optimal combinations of motivation (i.e., high expectancy, high value, and positive emotions) are more likely to persist in their talent domain. Thus, students who experience more optimal profiles of STEMM motivation early in college should be more likely to persist in STEMM over the long-term.

The majority of prior SEVT research investigates unique effects of expectancies and values, or interactions of these variables using a variable-oriented approach, on academic outcomes and does not consider the synergistic functioning of multiple variables at the intra-individual level. Furthermore, costs are hypothesized to diminish the value of a task,[11] but there is less understanding of how costs function alongside values and expectancy. An important question, for example, is whether some individuals simultaneously endorse high expectancy, values, and costs and how such a profile would impact persistence and talent development. It is possible that perceived costs may sometimes be an additional motivating factor,[22] or at least may be less detrimental when coupled with high values and expectancy, possibly because high costs may signal that students care.[23] SEVT profile research has demonstrated important links between distinct motivation profiles and academic outcomes.[23–29] For example, high value and expectancy profiles predicted future math-related career plans for high school students.[30,31] Further, prior research has revealed complex relations between demographic characteristics and SEVT profiles.[28,29,31] However, most SEVT profile research does not include costs and has been carried out with younger students.

Two prior studies with undergraduates are particularly relevant for this study because they used similar measures, including costs. In one study with science undergraduates at an elite US university, three profiles of expectancy, values (interest, attainment, utility), and costs (effort, opportunity) were identified.[25] The results included a profile in which all variables were moderate (between 3.00 and 4.00 on a 5-point scale) and two profiles in which expectancy and values were high relative to costs. Students in the profile with moderate scores across all SEVT beliefs had a lower STEMM grade point averages than students in the other profiles. The second study examined undergraduates' expectancy, values, and costs in an undergraduate chemistry course at an elite Canadian university and identified four profiles.[23] Profiles with higher values and expectancy relative to costs as well as

[b]Honors colleges are embedded within many US universities. They typically require an additional admissions process and are highly selective. Honors colleges offer an advanced curriculum to highly talented students.

"moderate-low all" and "moderate-high all" profiles were identified. Students most likely to be in the "moderate-low all" profile received the lowest grades in the chemistry course.

We extend this prior SEVT profile research in several ways. First, we examine SEVT motivation profiles in a different context (undergraduate vs. high school; public US university vs. elite university), which may reveal unique motivation profiles. Second, we consider how motivation profiles early in college relate to both short-term achievement and to long-term persistence, which allows us to identify profiles of motivation early in the students' STEMM career that may relate to their long-term persistence and are a prerequisite for continued development of their STEMM talent. Identifying motivation profiles early in the major that relate to persistence may help practitioners and researchers identify talented students that need support earlier and implement contextual supports to help build students' adaptive motivation. However, to do so, it is important to understand which patterns of motivation beliefs are adaptive for undergraduates' STEMM persistence, including cost perceptions, which have rarely been included in SEVT profile studies. Including costs may reveal unique patterns for underserved STEMM students who may be highly motivated but also experiencing challenges.

Current study

We identified profiles of science SEVT motivation—self-efficacy (a proxy for expectancy), perceived values, and costs—in a sample of first- and second-year students enrolled in an introductory chemistry course at a large, public university in the mid-western United States. Based on prior SEVT profile research,[23,25] we expected to identify a profile of high self-efficacy and values with low costs. We further expected to identify a profile with more moderate levels of self-efficacy and values and relatively high costs. There have been few profile studies that have included multiple cost variables with undergraduates, therefore we expected there may be additional profiles with mixed levels of self-efficacy, values, and costs identified.

Next, we examined the extent to which likely profile membership varied based on first-generation college student status and gender and racial/ethnic identities. Prior research suggests that there are differential patterns in the representation of students from underrepresented groups in motivational profiles,[23,25,31] and such patterns may be indicative of the extent to which the context is supportive of these groups. Furthermore, college is a time when talented STEMM students have the opportunity to deepen their skills and expertise in a STEMM discipline. Understanding which profiles of beliefs support persistence will inform interventions designed to retain talented and diverse undergraduates in STEMM. To study persistence, we examined the relation of the motivation profiles to achievement on the cumulative final exam in a gateway chemistry course as a proximal indicator of persistence. We also examined how the motivation profiles related to the proportion of science credits completed during the second half of college and graduating major as distal indicators of long-term persistence in science.

METHODS

Data were collected in an undergraduate gateway chemistry course as part of an ongoing longitudinal study examining undergraduate students' persistence in STEMM fields. The chemistry course was a prerequisite for students pursuing majors in the natural sciences and some engineering majors, and it was designed to support students' development of chemistry knowledge through a reformed curriculum titled *Chemistry, Life, the Universe, and Everything* (CLUE).[32]

Participants

Participants were 1,433 first- or second-year undergraduates from the gateway chemistry course. The sample was 87% first-year students (13% second-year); 56% female; 16% first-generation college students; 73% White, 14% Asian/Asian American, 6% Black/African American, 3% Hispanic/Latino/a, <1% American Indian/Alaska Native, <1% Native Hawaiian/Pacific Islander, and 4% multiracial. The sample's mean SAT math score was 640.94 on an 800-point scale (SD = 72.89).

Procedure

Surveys were administered online during week eight of a 15-week semester and were completed for homework credit. Students aged 18 and older provided informed consent for the use of their survey responses and academic records in the study with no penalties for opting out of the study. The study was deemed exempt by the university's Institutional Review Board (IRB No. x16–881e).

Measures

Motivation survey items used a 5-point scale, from 1 = *Strongly disagree* to 5 = *Strongly agree*. Variables were created by calculating the mean of the item scores. Higher scores on a variable indicated greater endorsement of the construct. All survey items are included in the Appendix.

Self-efficacy—We assessed science academic self-efficacy as a proxy for students' expectancy beliefs given their similarity[33] and because this approach is often employed in SEVT research.[15,25,34] Expectancy beliefs are typically operationalized as individuals' beliefs about their ability in a task and whether they will succeed. Self-efficacy is defined as individuals' perceptions of their ability to succeed on tasks. Thus, these beliefs are highly similar. Self-efficacy for academic tasks in science was assessed using five items (α = 0.85) adapted from Patterns of Adaptive Learning Scales,[35] which has been frequently adapted to reliably measure science self-efficacy.[15,25,34]

Perceived value—Three types of science perceived value were measured using scales adapted from prior research[36] including interest value (five items, α = 0.91), utility value (three items, α = 0.84), and attainment value (four items, α = 0.82).

Perceived cost—Three types of science perceived cost were assessed using scales adapted from prior research,[5,36] including opportunity cost (two items, α = 0.77), effort cost (four items, α = 0.73), and psychological cost (three items, α = 0.80).

Predictors and outcomes—Demographic characteristics, including gender (male = 0; female = 1), underrepresented minority status (not underrepresented = 0; underrepresented = 1), and first-generation (FG) college student status (non-FG = 0; FG = 1), were gathered from the survey and institutional data. Cumulative final exam scores were obtained from the course instructor. Finally, distal outcomes obtained from institutional records included science major (e.g., biology, chemistry, biochemistry, and physics; non-science = 0, science = 1) and STEMM major (i.e., inclusive of science majors plus technology, engineering, and math majors) at graduation and the proportion of credits completed in years three and four that were in science and STEMM.

Data Analysis

We used latent profile analysis (LPA)[37,38] in Mplus (v.8)[39] to identify subgroups of students with distinct profiles of science self-efficacy, three perceived values, and three perceived costs. We estimated 2- to 8-class models, successively allowing parameters (e.g., means, variances, covariances) to be class-specific[c]. We followed recommendations by Nylund and colleagues for model selection.[40] Specifically, we used theoretical interpretability and fit indices including Bayesian Information Criteria (BIC), which were supplemented by likelihood ratio tests to distinguish between candidate models. Demographic characteristics (gender, underrepresented racial/ethnic minority, and first-generation status) and achievement/persistence (final exam grade, credits completed, and graduating major) were modeled as predictors and outcomes of profile membership, respectively, using automated three step procedures (Mplus's R3STEP command for predictors, BCH command for continuous outcomes, and DCATEGORICAL for major outcome) that minimize bias in estimates by taking into account the uncertainty of class memberships.[41]

RESULTS

Correlations among the variables are in Table 1. We identified four motivation profiles (see Figure 1, Figure S1, Table S1; Table 2 includes model fit indices). Following Nylund et al.,[40] we relied on BIC and theoretical interpretability for model selection, supplemented by likelihood ratio tests to refine (i.e., distinguish between candidate models). As shown in Table 2, BIC continued to decline with an increasing number of classes and free parameters; however, declines in BIC appeared to level off in Model 2 around three or four classes. Thus, we examined the meaning of the three- and four-class solutions, along with the likelihood ratio tests comparing these two models. In particular, the four-class solution revealed a

[c]Traditional latent profile analysis assumes equal variances across classes (profiles) and no within-class correlations among the profile variables. However, these are often not tenable assumptions, particularly when examining highly correlated variables and when class sizes differ, and they are testable assumptions given the flexibility of mixture modeling techniques. Thus, following Masyn[37], we tested models allowing various parameters (means, variances, and covariances) to be class specific. As expected, models allowing covariances to be estimated showed improved fit and classification quality over models with covariances set to 0, and models allowing covariances to be class-specific also performed better than models with equal variances across classes (see Table 2).

profile with “shape effects,” characterized by differentiated levels of specific variables that in other profiles were very similar to each other. In this profile, self-efficacy and utility value were particularly high compared to interest value and attainment value—this was a unique pattern compared to the profiles present in the three-class solution. In addition, the Vuong-Lo-Mendell-Rubin and Lo-Mendell Rub adjusted likelihood ratio tests indicated significantly better fit for the four-class model as compared to the three-class model (*p*s = 0.01), as did the parametric bootstrapped likelihood ratio test ($p < 0.001$).

Profile 1, *Moderately Confident and Costly* (2% of sample), was the smallest profile and was characterized by moderate-low values ($M = 2.17–2.53$) with moderate self-efficacy ($M = 3.27$) and costs ($M = 2.78–2.89$). Importantly, costs exceeded values in profile 1. Profile 2, *Mixed Values-Costs/Moderate-High Confidence* (6%), was also relatively small and was characterized by high utility value scores ($M = 4.06$), moderate-high self-efficacy ($M = 3.76$) and psychological cost ($M = 3.50$), and moderate scores on other values and costs ($M = 2.52–3.31$). Profile 3, *High Confidence and Values/Moderate-Low Costs* (86%), was the largest profile and was characterized by moderate-high to high values and academic self-efficacy ($M = 3.83–4.24$), with low to moderate costs ($M = 2.34–3.04$). Finally, profile 4, *High All* (6%), was relatively small and was characterized by high scores on self-efficacy and values ($M = 4.31–4.49$) and moderate-high cost scores ($M = 3.61–3.96$), which were the highest levels of all variables across the four profiles. Thus, overall, most participants were most likely to be in what would be considered an adaptive motivational profile based on SEVT (i.e., high self-efficacy and values relative to low-moderate perceived costs).

Representation within profiles

We also examined whether women, students from minoritized racial/ethnic groups, and first-generation college students were more likely to be in particular motivation profiles (see Table 3). Results indicated that women and students from minoritized racial/ethnic groups were overrepresented in the *Mixed Values-Costs/Moderate-High Confidence* profile relative to *High Confidence and Values/Moderate-Low Costs* and, for women only, relative to *High All*. First-generation college students were overrepresented in the *Moderately Confident and Costly* and *High All* profiles versus *High Confidence and Values/Moderate-Low Costs*.

Role of profiles in persistence-related outcomes

Next, we examined the relations of the motivation profiles to proximal and distal persistence-related outcomes (see Table 4). First, we investigated how motivation profiles related to students’ cumulative final exam scores in the introductory chemistry course. Students most likely to be in the *High Confidence and Values/Moderate-Low Costs* profile had significantly higher exam scores ($M = 72.91$) than students most likely to be in *Mixed Values-Costs/Moderate-High Confidence* ($M = 67.49$), *Moderately Confident and Costly* ($M = 65.75$), and *High All* ($M = 66.65$), which did not differ from each other. Thus, different motivation profiles were differentially related to students’ success in this important introductory gateway course. Predictably, the students with the most adaptive profile of beliefs, according to theory, also had the most success.

Regarding distal persistence outcomes, we examined the relations of motivation profiles with the proportion of science course credits completed in students' third and fourth years and with their major at graduation (supplemental Table S2 provides initial majors by profile). Results indicated statistically significant differences in the proportion of science course credits taken as a function of most likely profile membership. Students most likely to be in *High Confidence and Values/Moderate-Low Costs* (M = 0.366) or *High All* (M = 0.369) completed significantly more science course credits in their third and fourth years relative to students most likely to be in *Moderately Confident and Costly* (M = 0.207). There were also statistically significant differences among profiles in terms of graduating major. Students most likely to be in the *High Confidence and Values/Moderate-Low Costs* profile were more likely to graduate with a science major (45%) than those most likely to be in *Moderately Confident and Costly* (20%). There were no other significant differences in major among the other profiles.

Given that students enrolled in the chemistry course might have pursued a variety of STEMM majors, we conducted ancillary analyses to investigate the relations between motivation profiles and STEMM major and STEMM course-taking. There were no statistically significant differences in the likelihood of graduating with a STEMM major. However, students most likely to be in *High Confidence and Values/Moderate-Low Costs* completed a greater proportion of STEMM credits in their third and fourth years relative to those most likely to be in *Mixed Values-Costs/Moderate-High Confidence* (See Table 4).

DISCUSSION

In this study, we identified undergraduate science students' SEVT motivation profiles and examined the relations of profiles to proximal and distal persistence-related outcomes. We also examined representativeness within profiles based on demographic characteristics. The results highlight the value of examining synergistic motivation profiles and have implications for undergraduates' STEMM talent development.

Motivation profiles and their role in STEMM persistence

We identified four motivation profiles in this study, which we labeled *Moderately Confident and Costly*, *Mixed Values-Costs/Moderate-High Confidence, High Confidence and Values/ Moderate-Low Costs*, and *High All.* As might be expected from undergraduates who self-selected into a chemistry course for STEMM majors, the *High Confidence and Values/ Moderate-Low Costs* profile was most common. Thus, most students felt confident in their ability to succeed in science, valued science, and perceived only moderate science costs. According to SEVT, such a motivation profile would lead to STEMM persistence,[4] which was supported by our results since this profile was the most adaptive in terms of proximal achievement and long-term persistence. The results build on prior research by highlighting that motivation profiles early in college may have long-term consequences for STEMM persistence and, potentially, STEMM talent development. Therefore, supporting undergraduates' STEMM motivation early is important for maintaining talent development in STEMM.

We also identified three other interesting profiles. While these profiles were relatively small, the findings for these other profiles highlight important contributions of this study to STEMM talent development. A particularly interesting profile identified in this study was the *Mixed Values-Costs/Moderate-High Confidence* profile. First, women and ethnic/racial minoritized students were overrepresented in this profile. While likely membership in this profile was associated with lower final exam performance relative to *High Confidence and Values/Moderate-Low Costs*, there were no significant differences in long-term science persistence between this profile and the others. Thus, the *Mixed Values-Costs/Moderate-High Confidence* motivation profile was not clearly detrimental to science persistence. However, when considering the broader patterns of STEMM course taking, students most likely to be in the *Mixed Values-Costs/Moderate-High Confidence* profile completed a lower proportion of STEMM credits than students likely to be in *High Confidence and Values/Moderate-Low Costs*. This could undermine STEMM talent development, as students have fewer opportunities to develop their talent through advanced coursework. These findings are a novel contribution to theory and suggest a complicated story when it comes to persistence in STEMM domains. Students who are often underrepresented in STEMM disciplines were significantly more likely to be in a motivation profile that may be harmful for early achievement but is not clearly harmful for long-term science persistence. This is important since these results suggest students with this profile may need more contextual support to help mitigate costs and increase some kinds of value (e.g., attainment value) and expectancy. These findings may be particularly useful for developing interventions to support students historically underrepresented in STEMM.

Findings around the *Mixed Values-Costs/Moderate-High Confidence* profile also extend prior research from Lee and colleagues.[23] Our study utilized similar measures as theirs, also with undergraduate science students; however, a similar *Mixed Values-Costs/Moderate-High Confidence* profile was not identified by Lee et al. Our findings are, however, similar to Bøe and Hanriksen[24] who identified an “extrinsic” SEVT profile, which was similar to our *Mixed Values-Costs/Moderate-High Confidence* profile (i.e., the profiles in both studies had high utility value relative to other values). Bøe and Henriksen also included a single measure of relative time and effort cost and found that the extrinsic-profile students endorsed low relative cost. However, students in the *Mixed Values-Costs/Moderate-High Confidence* profile in the current study endorsed relatively high psychological costs along with low effort cost. These differences across studies highlight the importance of including differentiated cost indicators, something that is rarely included in prior profile analysis studies. Results also highlight the advantages of profile analysis. The findings in this study suggest that students with a *Mixed Values-Costs/Moderate-High Confidence* profile were highly motivated in terms of the value of science for their career goals, yet they may have also been experiencing motivational challenges. The overrepresentation of minoritized students in this profile may be reflective of the fact that such students often face additional barriers such as stereotype threat.[42] Variable-oriented approaches would not reveal such nuanced findings.

We also identified a *High All* profile, where students endorsed the highest levels of costs along with the highest levels of value and self-efficacy. Similar to prior research,[23,25] this profile provides further evidence that students may experience moderately-high to high costs and values simultaneously. The adaptiveness of such a profile for STEMM talent development is unclear. According to SEVT, high perceived costs would reduce the overall value of a task. Therefore, motivation for a task is most adaptive when expectancy beliefs and values are high and costs are low. Thus, theoretically, students with both high values and higher costs should perceive science as less valuable overall, which may lead to STEMM attrition. However, the findings suggest that such a profile may not be detrimental for some persistence indicators. Experiencing higher costs may be mitigated by high values and expectancy for more distal outcomes (e.g., later course-taking), or these students may be more likely to shift to more adaptive profiles later in college. However, it is also important to note that values outweighed costs in the *High All* profile suggesting the relative balance of values and costs may be more important than a particular threshold of beliefs. In other words, what may be critical for persistence is that values outweigh costs, which aligns with conceptualizations of how values and costs manifest to determine the overall value of a task.[11]

Notably, first-generation students were overrepresented in the *Moderately Confident and Costly* and *High All* profiles relative to *High Confidence and Values/Moderate-Low Costs*, which may provide further evidence of the challenges first-generation students experience. For some, they may experience more moderate levels of self-efficacy and values for science, which impacts their long-term persistence. Further, our results indicate that even first-generation students who are highly motivated may experience challenges manifesting as perceived costs. For example, if first-generation students have less support with navigating college, they may experience compounding challenges that lead to feeling like science is more costly. While a *High All* motivation profile was not necessarily detrimental to long-term persistence, it may still be important to find ways to mitigate these students' perceived costs to further enhance their science motivation.

It is also clear from this study, and other similar research,[23] that a motivational profile characterized by moderate to low-moderate levels of self-efficacy, values, and costs (*Moderately Confident and Costly*) is disadvantageous for science achievement and long-term persistence. These results are not surprising given that this profile had the lowest levels of value/self-efficacy relative to other profiles and costs outweighed values, which may indicate a relative lack of value for science. This was the smallest profile (2%), which makes sense since it seems unlikely that students with such a profile would select into a chemistry course for STEMM majors. However, a similar motivation profile was found in prior research with a larger proportion of students likely to be in the profile.[13] Thus, while we might expect to find few students with this motivational profile in a gateway chemistry class, this may not always be the case across contexts.

Overall, the findings suggest that potentially talented STEMM students are variably motivated in science, even within an introductory chemistry course for STEMM majors, and their motivation profiles have implications for proximal and distal persistence-related outcomes. This overall finding is an important contribution to the role of motivation profiles in undergraduate STEMM talent development and highlights the importance of supporting undergraduates' STEMM motivation in gateway science courses. While other studies have reported similar profiles as this study,[23–25] there is variability in the profiles identified across research contexts and the relative proportions of students likely to be in different profiles. Thus, our results highlight the unique constellations of profiles of motivation that may emerge for talented students in different contexts (e.g., a highly selective Canadian university vs. a less selective US public university), which highlights the situatedness of motivational beliefs. Our results also suggest that there are students in introductory courses who may not be getting the support they need based on their motivation profile. Finally, the results highlight that profile analyses can reveal nuanced patterns of beliefs that would be obscured in variable-centered analyses. For example, relatively high costs may not necessarily be as detrimental when accompanied by higher self-efficacy and value.

Limitations and future directions

There are limitations to this study that should be considered. First, while motivation profiles may be indicators of support (or lack of) in the context, we did not examine environmental support directly. Therefore, we do not know the extent to which the motivation profiles are indicative of individual differences in motivation early in students' college career versus indicative of their early experiences as a STEMM student. There is likely a mix of both. Second, we cannot make causal claims regarding the relations between profile membership and outcomes. Students likely to be in the *Moderately Confident and Costly* profile may have been less likely to start college as a science major (see Table S2). Third, despite the strengths of profile analysis highlighted previously, profiles may not emerge consistently across samples, making it challenging to generalize to different settings. Fourth, the profiles may in part represent bias or error that may impact any survey research. For example, the *High All* profile may be indicative of respondents who tend to endorse high scores on most survey items. Fifth, we could not explore more nuanced questions around the intersection of race/ethnicity and gender. Future profile analysis research should explore such questions with more diverse samples to increase the number of students who identify within different subgroups (e.g., Black female). Finally, we examined how SEVT motivation profiles related to proximal achievement in a chemistry course and distal persistence in science and STEMM. Such analyses indicate how early motivation profiles impact persistence, which has important implications for students' STEMM talent development. While the findings did support such relations, students' motivation profiles may shift over time.[36] Future research should examine shifts in profile membership, into more or less adaptive profiles, over time.

CONCLUSION

In this study, we identified science motivation profiles of talented undergraduate students in an introductory chemistry course and examined the relations of profiles to STEMM persistence outcomes. We further examined the representation of students with different demographic characteristics in the profiles. The results align with and extend prior motivation profile research since they highlight the importance of motivation profiles early in college for both proximal STEMM achievement and long-term behavioral indicators of STEMM persistence. The results suggest that supporting adaptive motivation early in college may have long-term benefits for students and, therefore, have implications for interventions designed to support students' persistence and talent development in STEMM. The results also have implications for theory as they highlight that perceiving both high values and costs may not necessarily have completely negative consequences for STEMM persistence if the values outweigh the costs. Future research should explore how motivational profiles shift over time, especially in relation to contextual experiences of talented students in STEMM disciplines.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

ACKNOWLEDGMENTS

Research reported in this publication was supported by the National Institute of General Medical Sciences of the National Institutes of Health under award numbers R01GM094534 and R35GM136263. The content is solely the responsibility of the authors and does not necessarily represent the official views of the National Institutes of Health.

APPENDIX

All items used a 1 (*Strongly disagree*) to 5 (*Strongly agree*) scale

Academic Self-Efficacy

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

Perceived value

Intrinsic value

1. I enjoy the subject of science.
2. I enjoy doing science.
3. Science is exciting to me.
4. I am fascinated by science.
5. I like science.

Utility value

1. Science concepts are valuable because they will help me in the future.
2. Science will be useful for me later in life.
3. Being good in science will be important for my future (like when I get a job or go to graduate school).

Attainment value

1. It is important for me to be a person who reasons scientifically.
2. It is important for me to be someone who is good at solving problems that involve science.
3. Being someone who is good at science is important to me.
4. Being good in science is an important part of who I am.

Perceived cost

Opportunity Cost

1. I have to give up a lot to do well in science.
2. Success in science requires that I give up other activities I enjoy.

Effort Cost

1. When I think about the hard work needed to be successful in science, I am not sure that studying science is going to be worth it in the end.
2. Studying science requires more effort than I'm willing to put into it.
3. Considering what I want to do with my life, studying science is just not worth the effort.
4. I worry that I will waste a lot of time before I find out that I do not want to continue in science.

Psychological Cost

1. I am concerned about being embarrassed if I don't do well in science.
2. I am concerned that my self-esteem will suffer if I am unsuccessful in science.
3. I worry that others will think I am a failure if I do not do well in science.

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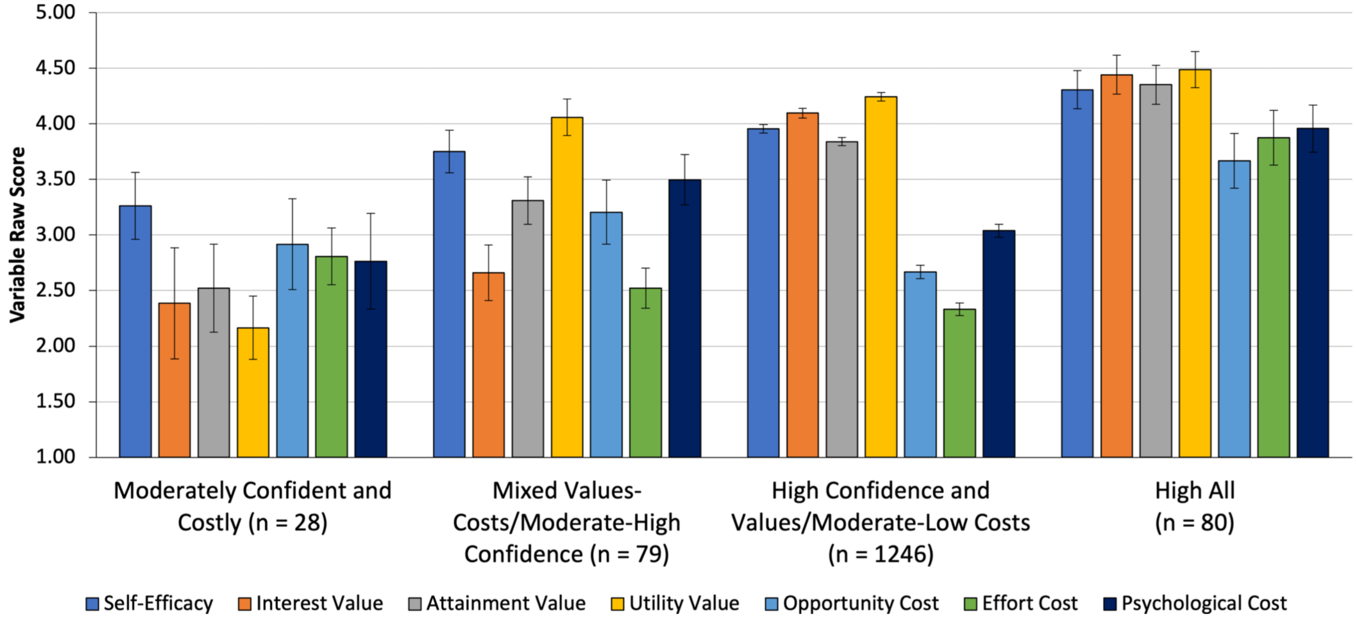

FIGURE 1.

Situated expectancy-value belief profiles using means.

Note. All variables were rated on a 1 (*Strongly Disagree*) to 5 (*Strongly Agree*) response scale.

TABLE 1

Correlations among profile input variables, predictors of profiles, and outcomes

	Interest value	Attainment value	Utility value	Opportunity cost	Effort cost	Psychological cost	Science Self-efficacy	Final Exam score	SCI Grad Major	STEMM Grad Major	Prop. STEMM credits	Prop. SCI credits	URM status	Gender	First Gen
Interest value	-														
Attainment value	0.68^{***}	-													
Utility value	0.64^{***}	0.65^{***}	-												
Opportunity cost	-0.18^{***}	<0.01	-0.07^{**}	-											
Effort cost	-0.33^{***}	-0.25^{***}	-0.37^{***}	0.47^{***}	-										
Psychological cost	−0.03	0.18^{***}	0.10^{***}	0.47^{***}	0.34^{***}	-									
Science SE	0.57^{***}	0.52^{***}	0.50^{***}	-0.26^{***}	-0.36^{***}	-0.11^{***}	-								
Final Exam	0.14^{***}	0.08^{**}	0.05^{*}	-0.19^{***}	-0.16^{***}	-0.08^{**}	0.15^{***}	-							
SCI Grad Major	0.17^{***}	0.16^{***}	0.26^{***}	0.01	-0.17^{***}	0.06^{*}	0.05	0.10^{**}	-						
STEMM Grad Major	0.12^{***}	0.13^{***}	0.12^{***}	-0.09^{**}	-0.09^{***}	−0.03	0.12^{***}	0.30^{***}	0.47^{***}	-					
Prop. STEMM creditss	0.15^{***}	0.16^{***}	0.13^{***}	-0.10^{***}	-0.10^{***}	−0.03	0.14^{***}	0.32^{***}	0.29^{***}	0.80^{***}	-				
Prop. SCI credits	0.17^{***}	0.15^{***}	0.26^{***}	<.01	-0.15^{***}	0.06^{*}	0.04	0.10^{**}	0.88^{***}	0.35^{***}	0.40^{***}	-			
URM status	-0.06^{*}	−0.05	0.02	0.04	0.02	<0.01	<0.01	-0.18^{***}	0.01	-0.11^{***}	-0.10^{***}	0.02	-		
Gender	-0.05^{*}	−0.03	0.12^{***}	0.03	-0.09^{**}	0.09^{**}	-0.08^{**}	-0.08^{**}	0.27^{***}	−0.05	-0.08^{**}	0.31^{***}	0.08^{**}	-	
First Gen	-0.06^{*}	−0.04	-0.06^{*}	0.04	0.08^{**}	0.02	-0.08^{**}	-0.13^{***}	0.01	-0.07^{**}	-0.07^{*}	<0.01	0.12^{***}	0.04	-

Note. Prop. SCI credits = Proportion of all credits taken in years 3 and 4 that were in science coursework; Prop. STEMM credits = Proportion of all credits taken in years 3 and 4 that were in STEMM coursework; Science SE = Science self-efficacy; URM status = Underrepresented Minority Status (0 = non-URM, 1 = URM); First Gen = First Generation College Students Status (0 = non-First Gen; 1 = First Gen); SCI Grad Major = Science Major at Graduation (0 = non-SCI major, 1 = SCI major); STEMM Grad Major = Science, Technology, Engineering, Math, and Medical Science Major at Graduation (0 = non-STEMM major, 1 = STEMM major); Gender is 0 = Male, 1 = Female.

*** $p<0.001$

** $p<0.01$

$^{*}p<0.05$

TABLE 2

Model fit indices for latent profile analysis

Model	Class-Invariant and Class-Specific Parameters	# of Parameters Estimated	Classes	BIC	delta BIC	% of Sample	Entropy
1	Class-invariant means and variances; covariances set to 0; Class-specific means	22	2	21232.02	−1562.66	44, 56	0.72
		30	3	20363.57	−868.45	14, 59, 26	0.84
		38	4	19943.89	−419.68	42, 21, 17, 20	0.80
		46	5	19608.03	−335.86	2, 41, 21, 20, 16	0.83
		54	6	19334.33	−273.70	2, 38, 18, 20, 20, 3	0.84
		62	7	19181.36	−152.97	1, 16, 9, 15, 36, 21, 2	0.84
		70	8	19060.87	−120.49	2, 15, 9, 21, 35, 3, 14, 2	0.85
2	Class-invariant means, variances, and covariances; Class-specific means	43	2	18981.42	−150.79	94, 6	0.91
		51	3	18803.88	−177.54	7, 6, 87	0.89
		59	**4**	**18724.23**	**−79.65**	**2, 6, 87, 6**	**0.91**
		67	5	18662.92	−61.32	2, 4, 82, 6, 6	0.88
		75	6	18608.29	−54.63	2, 6, 7, 4, 76, 6	0.86
			7	Did not converge to an interpretable solution			

Note. Bolded model was selected. We also tested models with class-specific means, variances, and covariances, along with models with class-specific means and variances and covariances set to be equal across classes. None of these converged to interpretable solutions, and so are excluded from this table.

TABLE 3

Covariates predicting latent profile membership via latent variable multinominal logistic regressions using the three-step procedure

Variable	***Moderately Confident and Costly*** **vs.** ***Mixed Values-Costs/ Moderate-High Confidence***	***Moderately Confident and Costly*** **vs.** ***High Confidence and Values/Moderate-Low Costs***	***Moderately Confident and Costly*** **vs.** ***High All***	***Mixed Values-Costs/ Moderate-High Confidence*** **vs.** ***High Confidence and Values/Moderate-Low Costs***	***Mixed Values-Costs/ Moderate-High Confidence*** **vs.** ***High All***	***High Confidence and Values/Moderate-Low Costs*** **vs.** ***High All***
	OR(SE)	**OR(SE)**	**OR(SE)**	**OR(SE)**	**OR(SE)**	**OR(SE)**
Minoritized ethnicity						
URM	2.599 (1.869)	1.191 (0.760)	1.526 (1.249)	**0.458 (0.171)**	0.587 (0.385)	1.281 (0.735)
non-URM	--	--	--	--	--	--
p	0.184	0.784	0.606	**0.036**	0.416	0.667
Gender						
Female	1.515 (0.888)	0.657 (0.319)	0.391 (0. 218)	**0.434 (0.146)**	**0.258 (0.113)**	0.594 (0.183)
Male	--	--	--	--	--	--
p	0.478	0.387	0.093	**0.013**	**0.002**	0.091
First-gen college student status						
Yes	0.451 (0.244)	**0.307 (0.137)**	0.697 (0.382)	0.681 (0.228)	1.545 (0.708)	**2.269 (0.804)**
No	--	--	--	--	--	--
p	0.140	**0.008**	0.510	0.251	0.342	**0.021**

Note. Odds ratios are presented for each paired comparison. **Bold** statistically significant at $p<0.05$. The first group represents the baseline group. Statistically significant findings are in bold. Abbreviations: OR, odds ratio; SE, standard error; URM, underrepresented minority status (0 = non-URM, 1 = URM)

TABLE 4

Relations of latent profiles to outcomes

Continuous Outcomes	Profile 1: *Moderately Confident and Costly*	Profile 2: *Mixed Values-Costs/Moderate-High Confidence*	Profile 3: *High Confidence and Values/ Moderate-Low Costs*	Profile 4: *High All*
	$\bar{x}$(SE)	$\bar{x}$(SE)	$\bar{x}$(SE)	$\bar{x}$(SE)
Final Exam	65.749_{a} (2.903)	67.491_{a} (2.317)	72.913_{b} (0.519)	66.654_{a} (2.781)
Prop. SCI credits	0.207_{a} (0.055)	$0.309_{a,b}$ (0.042)	0.366_{b} (0.010)	0.369_{b} (0.050)
Prop. STEMM credits	0.506_{a} (0.061)	$0.544_{a,b}$ (0.043)	$0.641_{a,c}$ (0.009)	$0.661_{a,c}$ (0.043)
Categorical Outcomes	OR (SE)	OR (SE)	OR (SE)	OR (SE)
SCI Grad Major				
Yes	0.423_{a} (0.274)	$0.860_{a,b}$ (0.389)	1.400_{b} (0.448)	$1.00_{a,b}$ (0.00)
No	--	--	--	--
STEMM Grad Major				
Yes	0.508_{a} (0.286)	0.576_{a} (0.269)	1.063_{a} (0.385)	1.00_{a} (0.00)
No	--	--	--	--

Note. Values in parentheses represent standard error values. Continuous outcomes presented as means by profile; categorical outcomes presented as odds ratios. OR = odds ratio; SE = Standard error. Prop. SCI credits = Proportion of all credits taken in years 3 and 4 that were in science coursework; Prop. STEMM credits = Proportion of all credits taken in years 3 and 4 that were in STEMM coursework. Values with different subscripts in the same row represent significantly different values based on equality tests.