2018

Multiple Pathways to Success: An Examination of Integrative Motivational Profiles Among Upper Elementary and College Students

Lisa Linnenbrink-Garcia
Michigan State University

Stephanie V. Wormington
University of Virginia

Kate E. Snyder
University of Louisville

Jan Riggsbee
Duke University

Tony Perez
Old Dominion University, acperez@odu.edu

See next page for additional authors

Original Publication Citation

Linnenbrink-Garcia, L., Snyder, K. E., Perez, T., Wormington, S. V., Riggsbee, J., Ben-Eliyahu, A., & Hill, N. E. (2018). Multiple pathways to success: An examination of integrative motivational profiles among upper elementary and college students. *Journal of Educational Psychology*, *110*(7), 1026-1048. https://doi.org/10.1037/edu0000245

Authors
Lisa Linnenbrink-Garcia, Stephanie V. Wormington, Kate E. Snyder, Jan Riggsbee, Tony Perez, Adar Ben-Eliyahu, and Nancy E. Hill

HHS Public Access

Author manuscript

J Educ Psychol. Author manuscript; available in PMC 2019 October 01.

Published in final edited form as:

J Educ Psychol. 2018 October ; 110(7): 1026–1048. doi:10.1037/edu0000245.

Multiple Pathways to Success: An Examination of Integrative Motivational Profiles Among Upper Elementary and College Students

Lisa Linnenbrink-Garcia[1], **Stephanie V. Wormington**[2], **Kate E. Snyder**[3], **Jan Riggsbee**[4], **Tony Perez**[5], **Adar Ben-Eliyahu**[6], and **Nancy E. Hill**[7]

[1]Michigan State University

[2]University of Virginia

[3]University of Louisville

[4]Duke University

[5]Old Dominion University

[6]University of Haifa

[7]Harvard University

Abstract

Two studies were conducted with distinct samples to investigate how motivational beliefs cohere and function together (i.e., motivational profiles) and predict academic adjustment. Integrating across motivational theories, participants ($N_{\text{Study 1}}$ = 160 upper elementary students; $N_{\text{Study 2}}$ = 325 college students) reported on multiple types of motivation (achievement goals, task value, perceived competence) for schooling more generally (Study 1) and in science (Study 2). Three profiles characterized by *Moderate-High All, Intrinsic and Confident,* and *Average All* motivation were identified in both studies. Profiles characterized by *Very High All* motivation (Study 1) and *Moderate Intrinsic and Confident* (Study 2) were also present. Across studies, the *Moderate-High All* and *Intrinsic and Confident* profiles were associated with the highest academic engagement and achievement. Findings highlight the benefit of integrating across motivational theories when creating motivational profiles, provide initial evidence regarding similarities and differences in integrative motivational profiles across distinct samples, and identify which motivational combinations are associated with beneficial academic outcomes in two educational contexts.

Keywords

motivation; person-oriented; achievement goals; perceived competence; task value

Correspondence concerning this article should be addressed to Dr. Lisa Linnenbrink-Garcia, Department of Counseling, Educational Psychology, & Special Education, Michigan State University, 620 Farm Lane, Room 513E Erickson Hall, East Lansing, MI 48824-1034. llgarcia@msu.edu.

For the last several decades, social cognitive models have dominated motivational research in education, with a large number of studies investigating how various types of motivation such as competence beliefs, achievement goal orientations, and task value relate to students' learning and engagement in school using a variable-oriented approach (Linnenbrink-Garcia & Patall, 2016; Wigfield et al., 2015). This body of research provides extensive evidence on how different types or components of motivation uniquely and independently predict educational outcomes. Yet, the field continues to be plagued by inconsistent findings that may limit the translation of this research into practice (see Linnenbrink-Garcia & Wormington, 2017). Moreover, a variable-oriented approach focuses on individual variables rather than patterns of multiple variables, and thus may not accurately describe motivation as it functions for students in daily life.

To address these concerns, researchers have begun to use a *person-oriented* approach (also called a *person-centered* or *profile-oriented* approach) to examine how multiple types of motivation combine and cohere into motivational profiles and relate to academic outcomes (e.g., Bråten & Olaussen, 2005; Conley, 2012; Lau & Roeser, 2008; Shell & Husman, 2008). Person-oriented research is promising because it allows researchers to consider how students use multiple motivational resources to support engagement and achievement (Pintrich, 2003). However, this approach is also criticized because the profiles identified are, by design, unique to each sample raising concerns about the generalizability of the profiles identified (see Pastor, Barron, Miller, & Davis, 2007). Moreover, much of the extant person-oriented research is conducted within a single theoretical tradition, an approach that may not adequately capture the wide array of motivational beliefs typically held by students. Thus, current study employed a person-oriented analytic approach to identify motivational profiles based on constructs from both Expectancy-Value Theory and Achievement Goal Theory, and examined how the profiles related to academic engagement and achievement. We conducted this research with two samples (upper elementary school and college) varying in age, demographic make-up, academic context, and domain-specificity in order to explore the existence of common integrative motivational profiles.

Theoretical Background

The current study builds on prior research from two prominent achievement motivation theories: Expectancy-Value Theory (Eccles et al., 1983) and Achievement Goal Theory (Ames, 1992; Dweck & Leggett, 1988). We selected these two theories for several reasons. First, prior research highlights the importance of constructs from these two theories in predicting a range of academic outcomes (e.g., Linnenbrink-Garcia & Patall, 2016; Wigfield & Cambria, 2010). Second, both theories share a common basis in social cognitive models of motivation, where the emphasis is on students' beliefs, values, and goals, and motivation is thought to be "cognitive, conscious, affective, and often under the control of the individual" (Wigfield, A., Eccles, J. S., Schiefele, U., Roeser, R. W., & Davis-Kean, P., 2006, p. 933). Both theories drawn upon the key concepts within Social Cognitive Theory including reciprocal determinism and agency (Bandura, 2006). As such, integrating across these two theories is more reasonable than considering either theory alongside a motivational framework that does not share this common theoretical grounding (e.g., Self-Determination Theory; Ryan & Deci, 2000). Third, Achievement Goal Theory and

Expectancy-Value Theory jointly measure aspects of motivation that align with the two major types of motivational constructs identified by Wigfield et al. (2006): (1) “Can I do this task?” and (2) “Do I want to do this task and why?” (p. 934).[1] The consideration of both questions is critical because these different types of motivation differentially predict academic outcomes.

Fourth, Achievement Goal Theory and Expectancy-Value Theory overlap with other major motivational theories. For instance, expectancies share many similarities with self-efficacy from Social Cognitive Theory (Schunk & Pajares, 2005). Similarly, task value is quite similar to individual interest from Interest Theory given that individual interest is often conceptualized as including both a feeling competent (e.g., enjoyment) and a value component (e.g., valuing the importance of the domain for the self, Krapp, 2002; Schiefele, 2009), aligning with the intrinsic and attainment dimensions of task value (Linnenbrink-Garcia & Wormington, 2017; Wigfield & Eccles, 2000). Thus, the selection of constructs from Achievement Goal Theory and Expectancy-Value Theory overlaps with four of the six major theories of motivation identified in Linnenbrink-Garcia and Patall’s (2016) recent review of motivation research. Fifth, prior person-oriented research provides preliminary evidence regarding the utility of integrating across the two theories (Conley, 2012).

Finally, unresolved debates within both theories regarding the optimal combination of motivational beliefs (e.g., whether the most beneficial academic outcomes are observed when mastery goals are endorsed alone or alongside performance-approach goals, Midgley, Kaplan, & Middleton, 2001; the interaction between expectancies and values, Trautwein et al., 2012) may be addressed using a person-oriented approach. Moreover, the consideration of competence beliefs in understanding the function of performance goals (e.g., Dweck & Elliott, 1983) may provide further insights in the relation of performance goals to educational outcomes. Thus, a person-oriented approach to create profiles using these two theories may help to address unresolved theoretical questions. Below, we briefly describe each theory and the relations between constructs from these theories to key educational outcomes.

Expectancy-Value Theory

Modern Expectancy-Value Theory focuses on two aspects of motivation: expectancies for success (i.e., subjective judgments about the likelihood for completing a task successfully) and task value (i.e., perceived worth associated with a domain or task; Eccles et al., 1983). Task value encompasses interest (i.e., engaging in a task due to interest or enjoyment), attainment (i.e., engaging in a task to support one’s identity), utility (i.e., engaging in a task due to usefulness), and cost (i.e., considering sacrifices associated with a task) dimensions (Wigfield & Eccles, 2000). Although both expectancies and task value relate to a range of outcomes, expectancies are more strongly linked with academic achievement and value with achievement-related choices and task persistence (Wigfield, Tonks, & Klauda, 2009). Recent research suggests that expectancies and values interact to predict school-related outcomes such as engagement and achievement (Nagengast et al., 2011; Trautwein et al., 2012), with

[1]Wigfield et al. (2006) also include, “What do I have to do to succeed on this task?” However, this draws on the broader literature related to the regulation of achievement behavior and is beyond our focus on motivational beliefs.

more beneficial outcomes when both expectancies and values are high and less adaptive outcomes when value is high but expectancies are low. Indeed, the latter pattern (high value but low expectancies) was more detrimental for achievement than having low values *and* low expectancies. This recent research highlights the need to investigate varying patterns of both expectancies and values and to determine the proportion of students who endorse less adaptive patterns of motivation (e.g., high value and low expectancies).

Achievement Goal Theory

Achievement goal orientations refer to the general underlying reasons why individuals engage in achievement-related situations (Ames, 1992; Dweck & Leggett, 1988). Two primary types of goal orientations focus on developing competence (mastery) or demonstrating competence (performance). Mastery and performance goal orientations can be further divided into approach and avoidance forms (Elliot, 1999; Pintrich, 2000b). For instance, an individual may focus on attempting to demonstrate competence (performance-approach) or avoid appearing incompetent (performance-avoidance). In the current paper, we employed a trichotomous model of achievement goal orientations, consisting of mastery, performance-approach, and performance-avoidance goal orientations. We use this trichotomous model instead of the 2 × 2 model because the mastery-avoidance goal construct is still not widely accepted and items assessing this goal may not be frequently endorsed or well understood by respondents (Ciani & Sheldon, 2010; Maehr & Zusho, 2009).

Mastery goal orientations are generally positively related to engagement and achievement, although the relations tend to be small for achievement (Anderman & Wolters, 2006; Hulleman, Schrager, Bodman, & Harackiewicz, 2010; Linnenbrink-Garcia & Patall, 2016). Performance-avoidance goals are consistently negatively related to engagement and achievement. The results are mixed for performance-approach goal orientations to engagement and achievement (Anderman & Wolters, 2006; Linnenbrink-Garcia & Patall, 2016; Maehr & Zusho, 2009); however, normative performance-approach goals (focus on performing better than peers) are consistently positively associated with achievement (Hulleman et al., 2010). Of note, the issue of whether it is beneficial to endorse performance goals alone or with mastery is central to resolving the debate about whether performance-approach goals are beneficial in academic settings (Wormington & Linnenbrink-Garcia, 2017), highlighting the importance of studying goal profiles and their relation to key outcomes.

Integrated theoretical approach

Drawing from these two theoretical perspectives, we aimed to identify integrative motivational profiles consisting of competence beliefs (representing expectancies from Expectancy-Value Theory), task value, and three types of achievement goal orientations (mastery, performance-approach, performance-avoidance). Competence beliefs align with the “Can I do this?” element of motivation identified by Wigfield et al. (2006), while task value and achievement goal orientations represent the “Why do I want to do this?” component. Although both task value and achievement goals overlap in addressing the “why” question, they are conceptually distinct. Task value captures students’ emotional response and assessment of the relative importance of a domain, while achievement goals assess the aim or focus of students' engagement (Wigfield & Cambria, 2010). Thus, students may be motivated by both developing competence (mastery goal) and an overall value for schooling, suggesting that both types of motivation may explain key academic outcomes. As noted above, perceived competence, achievement goals, and task value each are associated with different patterns of academic engagement and achievement. However, it is less certain how they cohere and function in synergy for different students, providing a clear need for a person-oriented approach.

Motivational Profiles: A Person-Oriented Approach

Prior research on the positive relation between motivation and educational outcomes is almost exclusively based on variable-oriented analyses such as multiple regression analysis or Analysis of Variance (ANOVA). This family of analyses, based within a general linear model framework, identifies isolated associations between independent motivational beliefs (e.g., perceived competence, achievement goals, task value) and academic outcomes (Bergman & Trost, 2006; Magnusson & Allen, 1983). However, variable-oriented statistical procedures have limitations in accounting for how multiple types of motivation simultaneously combine to predict outcomes. First, variable-oriented analyses isolate the unique variance explained, providing information about how each predictor relates to an outcome above and beyond other predictors but not about how a constellation of variables function together within an individual (Bergman & Trost, 2006). Second, given the focus on unique variance, highly correlated constructs compete to predict outcomes. Including highly correlated predictor variables can alter findings and may even raise concerns about multicollinearity and statistical suppression (Lewis-Beck, Bryman, & Liao, 2004; Horst, 1941). Third, interaction terms must be included to account for differences in the relation of one variable (e.g., performance-approach goals) to an outcome based on another variable (e.g., mastery goals). However, interaction terms may require very large samples for sufficient power, are sometimes difficult to interpret (Aiken & West, 1991), and may lead to claims about interaction patterns that do not accurately describe patterns of variables within the data (Bergman & Magnusson, 1997; Hair, Anderson, Black, & Tatham, 1998), such as rarely endorsed combinations of students' motivational beliefs (e.g., very high value but very low expectancy, see Trautwein et al., 2012).

In contrast, a person-oriented approach allows for the investigation of how predictors combine at the level of the individual to identify common patterns of predictors (e.g., profiles) and examine their relation to outcomes (Bergman, Magnusson, & El-Khouri, 2003). Thus, person-oriented analyses can be used to examine how multiple types of motivation combine and function together to predict outcomes. Considering motivational constructs in synergy is important, as various types of motivation may be endorsed simultaneously and dynamically influence each other (e.g., Pintrich, 2000a; Snyder & Linnenbrink-Garcia, 2013). Person-oriented analyses can also be useful practically, as modeling combinations of motivation may more closely reflect the interrelations among types of motivation as they exist within individuals and may allow researchers to identify common combinations that represent motivational typologies.

In the majority of prior person-oriented motivational research, profiles were created based on a single theoretical perspective such as Achievement Goal Theory (see Wormington & Linnenbrink-Garcia, 2017 for a review). However, several studies integrate across motivational theories to create profiles based on multiple forms of motivation or alongside indicators such as affect and self-regulation (Bråten & Olaussen, 2005; Conley, 2012; Dina & Efklides, 2009; Lau & Roeser, 2008; Nelson, Shell, Husman, Fishman, & Soh, 2015; Shell & Husman, 2008; Shell & Soh, 2013; Seifert & O'Keefe, 2001; Turner, Thorpe, & Meyer, 1998). Although the specific profiles and constructs included in profiles varies across studies, there is growing evidence of at least four profiles that consistently emerge from this prior work.

Most studies identify a "highly motivated" profile, characterized by strong endorsement of multiple goal orientations, value, and perceived competence. At the other extreme, studies report an "apathetic or amotivated" profile defined by low levels of multiple types of motivation. Several studies also identify a profile with strong mastery goal endorsement alongside high task value or intrinsic motivation and high competence. We consider this to reflect a pattern of "intrinsic and confident" motivation. The "intrinsic" label reflects the focus of mastery goals on elements internal to the self, given its emphasis on development and improvement for the sake of learning (Ames, 1992). It also reflects the emphasis of task value on more internal elements as reflected by seeing the task/domain as enjoyable, meaningful, and potentially useful for future identity-related goals (Wigfield & Cambria, 2010). Some studies also reveal a "performance-focused" or "learned helpless" profile, with lower levels of intrinsic motivation or mastery goal orientations and stronger endorsement of performance goal orientations or avoidance goal orientations; however, it is worth noting that a synthesis of person-oriented achievement goal literature indicated that such profiles were rare (Wormington & Linnenbrink-Garcia, 2017). Generally, both the highly motivated and intrinsically-based profiles are associated with heightened self-reported self-regulation, knowledge building, persistence, and achievement.

This prior work provides initial evidence for our current work, suggesting that the most beneficial motivation for schooling likely consists of systems of beliefs, rather than single types of motivation (Pintrich, 2003), a possibility that cannot be easily analyzed using a variable-oriented approach. However, many of these prior studies created profiles including motivation alongside other constructs such as affect and self-regulation (Dina & Efklides, 2009; Lau & Roeser, 2008; Nelson et al., 2015; Shell & Husman, 2008; Shell & Soh, 2013; Turner et al., 1998), and thus cannot be considered motivational profiles per se in that they do not provide information about the combination of motivational beliefs that students may hold. Several others focus solely on motivation in creating profiles, but either do not include achievement goals (Seifert & O'Keefe, 2001) or do not include the performance aspects of achievement goals (Bråten & Olaussen, 2005). We are aware of only one study conducted by Conley (2012) that used constructs from both Achievement Goal Theory and Expectancy-Value Theory without also including cognitive and/or emotion variables. We extend Conley's study by examining whether the observed profiles can be identified in multiple samples and evaluating whether profiles that used constructs from both Achievement Goal Theory and Expectancy-Value Theory provide a more accurate and predictive picture of student motivation than those created solely with achievement goals.

Potential Developmental Differences in Motivational Profiles

Although there is virtually no person-oriented research that considers developmental differences in profile membership using an integrated theoretical approach as we propose here, prior research conducted within Achievement Goal Theory provides some insight into potential age-related differences in integrated motivational profiles. Creating goal profiles separately for both ninth graders and eleventh and twelfth graders, Tuominen-Soini, Salmela-Aro, and Niemivirta (2011) identified similar profiles across age groups, although the age gap was relatively small compared to the current study. A recent meta-analysis found some variation in achievement goal profiles by grade level, with a high all goals profile most frequently observed in elementary samples and profiles with low goals or high performance-approach goals less frequently observed in elementary samples (Wormington & Linnenbrink-Garcia, 2017). Although not focused on goal profiles, Bong (2009) found that forms of achievement goals became more differentiated across levels of schooling, suggesting that more differentiated motivational profiles may be more likely to emerge in older samples.

Another important developmental difference to consider with respect to motivation is whether motivation is studied generally for schooling or more specifically to a particular domain, which may change as students begin to study more differentiated topics (e.g., different teacher for different subjects) at the secondary and post-secondary levels. Comparing middle and high school students, Bong (2001) found that middle school students' motivation was more highly correlated across subjects and with a domain general factor than that of high school students, providing evidence that motivation becomes more differentiated over time. Similarly, Hornstra, van der Veen, and Peetsma (2016) found that while elementary students can differentiate across domains in their self-reported motivation, there are higher cross-domain relations across constructs, particularly achievement goals, among elementary students compared to prior research on secondary students.

Current Study

We conducted two studies to examine integrative profiles consisting of five motivational constructs from Expectancy-Value Theory and Achievement Goal Theory: perceived competence, task value, mastery goals, performance-approach goals, and performance-avoidance goals. Our first aim in conducting this research was to identify profiles in two very different samples and contexts that varied by breadth and scope of achievement context (i.e., domain-specificity): (1) fifth grade (last year of elementary school) focused on the full range of schoolwork and (2) college focused on science. Systematically varying the scope and breadth of the achievement context increases the generalizability of the findings (Ben-Eliyahu & Bernacki, 2015). If we are able to identify similar profiles in these two distinct samples, which vary in age by almost ten years and differ broadly in context (local public elementary school versus elite university) and domain-specificity (general schooling versus science), it can provide greater confidence in the generalizability of integrative profiles across samples and contexts.

We hypothesized that several profiles would emerge, including both a highly-motivated profile and an amotivated or low motivation profile. We also expected several other profiles to emerge with varying levels of intrinsically-based motivation (mastery, task value) and performance goals (approach and/or avoidance); however, we did not make predictions about specific profiles given variability in prior research and the exploratory nature of profile analyses. We expected that there might be some differences in profile prevalence and type between the samples such that a truly amotivated profile might be less likely to emerge among elementary students.

Our second research question examined how profiles related to critical academic outcomes, including engagement, achievement, course-taking behavior, and career intentions. We hypothesized that profiles characterized by high levels of perceived competence and intrinsically-based motivation, with or without accompanying performance goal orientations, would be associated with the highest achievement and engagement in comparison to low/amotivated profiles. Given prior research suggesting varying levels of achievement, engagement, and other academic outcomes across different goal profiles based on school level (Wormington & Linnenbrink-Garcia, 2017), this is critical for assessing profile generalizability.

Finally, as part of a set of ancillary analyses, our third research question evaluated whether profiles that used constructs from *both* Achievement Goal Theory and Expectancy-Value Theory (a) more accurately predicted profile membership (e.g., greater probability of belonging to one particular profile) and (b) explained more variance in engagement and achievement than those created with achievement goals constructs alone. These ancillary analyses were conducted to evaluate our hypothesis that profiles created from multiple motivational theories would more accurately represent student motivation in the classroom.

Given developmental differences in domain specificity of motivation noted earlier (e.g., Bong, 2001, 2009; Hornstra et al., 2016) as well as the structure of the contexts studied (e.g., elementary students in Study 1 were taught all academic subjects by a single teacher, college students in Study 2 took a variety of courses from different professors, often in different departments), we measured domain-general motivation for elementary students and domain-specific motivation among college students (e.g., science).

Study 1

In Study 1, we sought to identify motivational profiles in a sample of upper elementary school students and to examine how profile membership related to engagement and academic achievement in reading and mathematics.

Method

Participants—One hundred and sixty fifth-grade students from one elementary school in the southeastern United States participated in the study during the fall semester of their fifth-grade year. Data were collected from two cohorts ($n_{cohort1} = 84$, $n_{cohort2} = 76$) across two academic years. The sample included both female ($n = 80$; 50%) and male ($n = 80$; 50%) students who were racially and ethnically diverse (30.0% Caucasian, 34.4% African

American, 15.6% Latino/a, 3.8% Asian, 5.0% mixed ethnicity, 8.1% other, 3.1% declined to answer). The sample could be considered lower to middle class; of the 140 students with available data, 48.0% (n = 72) qualified for free lunch, 12.0% (n = 18) qualified for reduced-fee lunch, and 33.3% (n = 50) did not qualify for free or reduced-fee lunch.

Procedures—During the fall semester (i.e., November), students completed online questionnaires regarding their general beliefs and attitudes related to schoolwork, their teacher, and their parents. The surveys were administered in the school's computer lab and read aloud by trained research assistants. Overall, 91.2% and 85.7% of eligible students participated from two cohorts, respectively. The study's procedures were approved by the Institutional Review Board at the first author's former (IRB No. 2871) and current university (IRB No. 14-795).

Measures—All survey items were measured using a 5-point Likert scale, ranging from 1 (*not at all true*) to 5 (*very true*). All items appear in the Appendix.

Motivational variables: Five indicators of motivation were used to create motivational profiles: mastery-approach goal orientations, performance-approach goal orientations, performance-avoidance goal orientations, perceived competence, and task value. A confirmatory factor analysis conducted using Mplus Version 7 (Muthén & Muthén, 1998–2015) on all five motivational variables initially indicated unacceptable fit, χ^2 (340) = 704.86, $p < .001$; CFI= .78; TLI = .76; RMSEA = .08 [95% CI = .07 – .09]; SRMR = .09. In general, acceptable fit is indicated by root mean square error of approximation (RMSEA) values at or below .06, comparative fit index (CFI) values greater than .90, and standardized root mean square residual (SRMR) values less than .08 (Hu & Bentler, 1999). Modification indices indicated an issue with one of the utility value items ("The things I learn in school help me in my daily life outside of school"), which was dropped, and suggested allowing several task value items to correlate with one another. After making these adjustments, the model fit the data acceptably, χ^2 (307) = 460.77, $p < .001$; CFI= .91; TLI = .90; RMSEA = .05 [95% CI = .05-.07]; SRMR = .06.[2]

Achievement goal orientations: Mastery-approach, performance-approach, and performance-avoidance goals were assessed using items from the Patterns of Adaptive Learning Survey (PALS, Midgley et al., 2000). The mastery-approach scale measured a student's focus on developing competence (n = 5; α = .75; e.g., "It's important to me that I learn a lot of new concepts this year"). The performance-approach scale assessed a focus on demonstrating competence to others (n = 5; α = .83; e.g., "One of my goals is to show others that I'm good at my class work"). The performance-avoidance scale measured a focus on avoiding demonstrating incompetence (n = 4; α = .75; e.g., "One of my goals in class is to avoid looking like I have trouble doing the work").

[2]Given conceptual overlap and theoretical considerations, we also tested two alternative models: one loading mastery-approach goal orientations and task value onto a single factor (Model 1b) and another separating task value into its three individual components (Model 1c). In both cases, the model fit was worse than the original proposed model [Model 1b: c^2 (318) = 668.62, $p < .001$; CFI= .78; TLI = .76; RMSEA = .08 [95% CI = .07-.09]; SRMR = .08, Δc^2(11) = 207.85, $p < .001$; Model 1c: c^2 (311) = 491.09, $p < .001$; CFI= .88; TLI = .87; RMSEA = .06 [95% CI = .05-.07]; SRMR = .07, Δc^2(4) = 30.32, $p < .001$].

Perceived competence: Perceived competence was assessed using the PALS (Midgley et al., 2000) measure of academic self-efficacy. Students responded to five items about their perceived competence to complete their schoolwork and learn (α = .87; e.g., "I'm certain I can figure out how to do the most difficult class work").

Task value: Nine items were used to measure task value for school work. These items were partially based on the Motivated Strategies for Learning Questionnaire (MSLQ; Pintrich, Smith, Garcia, & McKeachie, 1993) and also represented an earlier version of the scales employed by Conley (2012). The measure assessed students' enjoyment of school (e.g., "I like what I am in learning in school"), attainment value (e.g., "Being good at school is an important part of who I am"), and utility value (e.g., "I think the things I learn in school are useful"). After dropping one utility value item (see description of confirmatory factor analysis above), the combined scale displayed good internal reliability (α = .79).

Outcome variables: Two self-report indicators of engagement were assessed along with student achievement data from school records.

Engagement: The *behavioral engagement* scale assessed students' persistence when doing coursework (Linnenbrink, 2005[3] ; 4 items; α = .73; e.g., "Even when I don't want to work on my class work, I force myself to do the work"). The *cognitive engagement* scale, consisted of eight items assessing planning, monitoring, and evaluating. It was developed based on scales from the MSLQ (Pintrich et al., 1993) and Fredricks, Blumenfeld, Friedel, and Paris (2005) (α = .81; e.g., "When I become confused about something I'm learning in school, I go back and try to figure it out"). Confirmatory factor analysis indicated that the underlying factor structure for the two types of engagement (behavioral, cognitive) fit the data well (χ^2 (53) = 81.13, p = .007 CFI= .96; TLI = .95; SRMR = .04).

Achievement: Student achievement data were collected from state records. To broadly capture students' academic achievement, we operationalized achievement as mathematics and reading growth scores on statewide standardized tests. Growth scores are standardized values that capture the improvement in students' standardized score from the prior two years to the current academic school year. These growth scores represent the difference between a student's actual score for the current year and the student's average of the two prior assessments, with a correction for regression to the mean. Positive growth values represent increases in achievement, while negative growth values represent decreases in achievement. The internal consistency reliabilities for the relevant mathematics ($\alpha_{\text{third grade}}$ = .91, $\alpha_{\text{fourth grade}}$ = .92, $\alpha_{\text{fifth grade}}$ = .91) and reading ($\alpha_{\text{third grade}}$ = .88, $\alpha_{\text{fourth grade}}$ = .93, $\alpha_{\text{fifth grade}}$ = .91) assessments used to calculate the growth scores for mathematics and reading were high.[4]

[3]All items were adapted to focus on schoolwork (e.g., "math work" was replaced with "school work").
[4]The reliability information reported is from the 2006 assessment for mathematics and 2008 assessment for reading (North Carolina Department of Public Instruction, 2008, 2009); these versions of the assessment are the same as those used for the data reported here (collected from 2008 – 2011, T. Howard, personal communication, September 20, 2017). The state reports, available online, also provide strong evidence of content and criterion validity.

Statistical analysis strategy—The first step in our analysis was to identify underlying motivational profiles using latent profile analysis (LPA; Collins & Lanza, 2010; Muthén & Muthén, 1998–2015). Based in a structural equation modeling framework, LPA is a means to identify the ideal number of distinct combinations of variables within a given sample. Because models with different profile solutions are not nested within one another, identifying the most appropriate profile solution is guided by comparing fit indices appropriate for non-nested models (i.e., AIC, BIC, adjusted entropy values), the size of each resulting profile (Collins & Lanza, 2010), and theoretical expectations (Sterba & Bauer, 2010). As a general rule, lower comparative values of AIC, BIC, and adjusted BIC, and higher values of entropy indicate improved model fit. Raw scores were used as the basis for identifying profiles (Bergman et al., 2003). Missing data were imputed using a multiple imputation procedure, in which we generated and aggregated across ten separate data sets (see Royston, 2005). Before conducting LPA, we tested for outliers using Grubb's test (Grubbs, 1969). Two individuals were identified as outliers and deleted from the dataset, having reported significantly different responses from the rest of the sample for mastery-approach goal orientations, perceived competence, and task value during the fall assessment Grubbs' tests were conducted again on the reduced sample for each of the motivational variables; no additional outliers were identified. Thus, the final sample used for the remaining analyses consisted of 158 students. All LPAs were conducted using Mplus Version 7 (Muthén & Muthén, 1998–2015). Descriptive statistics and bivariate correlations for the sample are presented in Table 1.

To examine profile differences in academic correlates (i.e., behavioral engagement, cognitive engagement, mathematics growth achievement, reading growth achievement), we employed the modified three-step BCH method proposed by Bakk and Vermunt (2014). The modified BCH method, which we conducted using the BCH procedure in MPlus, involves estimating the latent profile model in Step 1, assigning cases to profiles based on posterior probabilities, and predicting meaningful outcomes using assigned class as the sole indicator variable. Analyses were conducted manually to allow for the inclusion of covariates (gender and free/reduced-fee lunch) in Step 2 of the process. We examined equality tests of means across classes to determine which profiles significantly differed from one another with respect to each academic correlate. The overall effect size for each outcome was calculated by dividing the average difference between profiles by the standard deviation of the outcome variable.

The BCH method was considered most appropriate for our current analyses for several reasons. First, the BCH method is preferable to the naïve three-step approach, which uses the most likely profile membership as a predictor variable, because it reflects the degree of inaccuracy in class assignment within a latent profile model (i.e., cases have a likelihood of belonging to a given latent profile, rather than being assigned to a single profile; Asparouhov & Muthén, 2015). Second, a BCH approach allowed us to examine how profile membership related to several dependent variables simultaneously in a single model. Third, the BCH method was determined to be most appropriate for our current sample following results from Vermunt's three-step approach (2010; DU3Step procedure in MPlus) indicating that profile membership changed by more than 20% from Step 1 to Step 3 (Asparouhov & Muthén, 2015). Finally, the manual BCH approach allowed us to control for covariates in the model.

Altogether, the BCH method is advantageous as it better enabled us to compare profiles across the two studies and to examine how the profiles related to multiple variables without profile membership changing.

Results

Final profile solution—Fit indices indicated that a four-profile solution best fit the data (see Table 2). Based on the changes in the AIC, BIC, and adjusted BIC, both a four and five profile solution were reasonable to consider. We selected a four-profile solution because the BIC substantially increased between the four- and five-profile solutions, the AIC and adjusted BIC were only slightly lower for the five-profile solution in comparison to the four-profile solution, and the five-profile solution yielded one class with only three participants.

Raw score values for motivational profiles weighted by estimated class probabilities are reported in Figure 1, with standardized scores available in Table 3. Following the general guidelines presented by Wormington & Linnenbrink-Garcia, 2017, we labeled the four profiles based on the absolute (raw score) level of motivation, but also took into account the relative level of motivation both within each profile and in comparison to other profiles in the sample (z score). The four profiles, described in further detail below, were labeled as (1) *Moderate-High All,* (2) *Intrinsic and Confident,* (3) *Average All,* and (4) *Very High All.* A multivariate analysis of variance (MANOVA) with follow-up univariate ANOVAs and Tukey HSD post-hoc tests indicated that the profiles differed from one another with respect to all of the motivational variables (Wilk's $\lambda = 39.91$, $p < .001$, $\eta^2 = .56$). However, several profiles did not differ from one another with respect to individual motivational indicators. In particular, the *Moderate-High All* and *Intrinsic and Confident* profiles were characterized by equally high levels of mastery-approach goal orientations, task value, and perceived competence. The *Moderate-High All* and *Intrinsic and Confident* profiles also did not differ on mastery-approach goals from the *Very High All* profile. The final profile solution accounted for 36–70% of the variance in each motivational variable.

Moderate-High All: The *Moderate-High All* profile is characterized by strong endorsement of the range of motivational variables measured in this study. Mean ratings for all motivational variables were above the sample average, with values above 4 on the 5-point Likert scale for all constructs except performance-approach goals, which were just below 4 (3.91). The *Moderate-High All* profile was the most common profile identified, representing 63 students when examining students' most likely classified profile (39.87%).

Intrinsic and Confident: This profile is characterized by equally high levels of mastery-approach goal orientations, task value, and perceived competence. Unlike the *Moderate-High All* profile, however, performance-approach and performance-avoidance goal orientations for this profile were lower than any other profile (i.e., ratings less than 2.7 on a 5-point scale). This profile was the second least common profile in the sample ($n = 29$, 18.35%).

Average All: The *Average All* profile contains ratings around the midpoint (3.0) on a 5-point Likert-type scale for all motivational indicators (mastery-approach goals were somewhat higher, but were the lowest levels of mastery endorsed within the sample). It is important to note that for this sample, the *Average All* profile represented the lowest endorsement of motivation in the sample and could be considered a relatively amotivated profile. Students best classified into this profile reported the lowest levels of mastery goals, perceived competence, and task value, and the second lowest performance-approach and performance-avoidance goals. One-third of the students in the sample were best classified into the *Average All* profile (54 students, 34.18%).

Very High All: The *Very High All* profile suggests a pattern of motivation that can be considered highly motivated by any means, even more so than the *Moderate-High All* profile. This profile consisted of very strong endorsement of all motivational variables, with mean ratings approaching ceiling levels on the 5-point Likert scale. Aside from mastery-approach goals, levels of all the motivational variables were significantly higher than those endorsed in any other profile. This profile was the smallest identified profile in the sample (n = 12, 7.59%).

Profile membership and academic outcomes—We examined whether profiles differed in academic engagement and achievement outcomes. This involved examining equality tests of means across classes in Step 3 of the BCH analyses to identify which profiles differed significantly from one another for each academic outcome. Results from these analyses, including overall effect size, mean values on each outcome, and significant differences between profiles are displayed in Table 3. The *Moderate-High All*, *Intrinsic and Confident*, and *Very High All* profiles were associated with higher behavioral and cognitive engagement than the *Average All* profile. Profiles also differed overall in terms of achievement. Again, the *Very High All* profile was associated with greater mathematics growth achievement than the *Average All* profile; the *Moderate-High All* and *Intrinsic and Confident* profiles did not differ in mathematics achievement growth from the other profiles. There were no significant differences in reading growth achievement based on the profiles.

Ancillary analyses: Goal profiles—An open empirical question is whether there is added value to creating profiles based on multiple theories. Thus, we also conducted LPA with only the variables from Achievement Goal Theory (mastery, performance-approach, performance-avoidance goals) and evaluated the profile solution in comparison to that obtained when constructs from both Achievement Goal Theory and Expectancy-Value Theory were included. The LPA analyses for profiles based on achievement goals alone suggested that a three-profile solution best fit the data (see additional text and Table S1 in supplemental materials for a justification of this profile solution).

We labeled the first profile as *High All* (n = 65; 41.13%), as students best classified in this profile strongly endorsed all three types of achievement goals (see Table S2 for z-scores and Figure S1 for raw scores). We labeled the second profile *Mastery High-Performance Low* (n = 19, 12.02%); students best classified in this profile strongly endorsed mastery goals and did not endorse performance-approach or performance-avoidance goals. The third profile was labeled as *Mastery High-Moderate Performance* (n = 74; 46.84%) given the high levels of mastery and more moderate levels of performance-approach and performance-avoidance goal endorsement. Notably, mastery goals did not significantly differ across the second two profiles.

Compared to the integrative profiles created with achievement goals, task value, and perceived competence, the *High All* profile aligns with the *Moderate-High All* profile from the integrative profiles (see Table S3 for the overlap between class solutions for the goals only versus integrative LPAs). The *Mastery High-Performance Low* profile also aligns with the *Intrinsic and Confident* profile from the integrative analyses, though it is smaller and also included a fair number of cases from the *Average All* profile (see Table S3). The final profile, *Mastery High-Moderate Performance*, appears to be a mix of the *Moderate-High All*, *Intrinsic and Confident*, and *Average All* profiles from the integrative analyses, with the majority of cases drawn from the *Average All* profile (see Table S3). We know from our integrative findings that these are distinct profiles with different relations to outcomes, highlighting the added benefit of being able to differentiate student membership in these two profiles.

In addition to considering whether unique classes emerged for the integrative profiles, we also evaluated the added benefit of using integrative profiles by comparing the classification probabilities for the most likely latent class membership between the two solutions. When only achievement goals were used to create profiles, the average probability for most likely latent class membership was .893 compared to .958 for the integrative profiles. LPA also provides information about the likelihood of individuals being classified into one of the other classes. For the goals profiles, the average probability was .054 compared to .014 for the integrative profiles. Together, these analyses suggest that including achievement goals, task value, and perceived competence together in the profiles (integrative analyses) results in a profile solution that is more accurate (i.e., the probability estimates of class membership are higher and the probability of being classified into a different profile are lower) suggesting that these profiles may better capture motivational profiles as they exist in the classroom. Adding to these claims, the amount of variance in the profiling variables that was explained by profile membership was higher for the integrative profiles compared to the goals only profiles, this was especially true for mastery goals (70% in the integrative profiles and 29% in the goal profiles, see Table 3 and Table S2).

Additionally, we considered which profile solution was a stronger predictor of outcomes. Following the same analysis procedure used for the integrative profile solutions, goal profile membership significantly predicted behavioral engagement, cognitive engagement, and growth in mathematics achievement (see Table S2). However, the overall effect sizes were smaller for the goals profiles compared to the integrative profiles for both behavioral engagement (goals = 0.47; integrative = 0.56) and cognitive engagement (goals = 0.43; integrative = 0.80). For growth in mathematics achievement, the effect sizes were somewhat larger for the goals profiles (goals = 0.43; integrative = 0.30).

Discussion

Our findings suggest that there are multiple ways in which motivational beliefs combine and relate to engagement. We identified three motivational patterns (*Moderate-High All; Intrinsic and Confident; Very High All*) that were associated with higher levels of student-reported engagement in this elementary context compared to one relatively common motivational profile (*Average All*). We also found differences in growth in mathematics achievement based on profile membership; the *Very High* profile was associated with more growth in mathematics achievement scores during fifth grade compared to achievement for the past two years than was the *Average All* profile, which was associated with a slight decline in achievement on average. Unlike mathematics achievement, profiles did not differ in reading achievement. It is somewhat surprising that we did not observe differences in reading growth, given that the profiles reflected domain-general motivation in school. Perhaps if we had measured motivation in relation to reading and mathematics more specifically, we might have been able to more clearly predict academic growth in different academic subjects. Indeed, it is unclear the extent to which students weighted different subject areas when responding to questions about their motivation towards school in general. Additionally, the non-significant findings for reading achievement may also reflect differences in the development of reading from third to fifth grade. By fifth grade, students may experience less growth in reading skills, as the shift from “learning to read” to “reading to learn” occurs around third grade (Chall, 1983).

Overall, the *Moderate-High All, Very High All* and *Intrinsic and Confident* profiles are consistent with prior research that created profiles using similar constructs (e.g., Conley, 2012; Shell & Husman, 2008; Turner et al., 1998). The identification of an *Average All* profile aligns with prior person-oriented research within the achievement goal literature (see Wormington & Linnenbrink-Garcia, 2017 for a review); however, it is not consistent with prior research based on integrative motivational profiles, which found an amotivated but not an average profile. The failure to identify an amotivated profile in the current study may be because we labeled the profiles based on raw scores. Indeed, the *Average All* profile was characterized by the lowest levels of motivation relative to the sample, and based on *z*-scores alone could have been labeled as amotivated. Though this group of students can be considered amotivated relative to the sample, we believe *Average All* label is most appropriate for generalizability (e.g., raw scores allow the comparison of findings across samples), as these same students might not be considered amotivated in other samples where students might have lower levels of motivation.

It is also noteworthy that, at least in terms of raw values, there was no profile characterized by high levels of performance goals but average or low mastery goals, task value, and perceived competence. This stands in contrast to prior studies that found performance goal focused or extrinsically motivated profiles (e.g., Shell & Husman, 2008; Turner et al., 1998). However, our findings are consistent with a recent synthesis of the achievement goal literature (Wormington & Linnenbrink-Garcia, 2017), which did not identify any profiles with both high performance-approach and performance-avoidance goals. Again, these discrepancies are likely a result of our focus on raw scores rather than *z*-scores. An examination of the *z*-scores reveals that the *Average All* profile had relatively higher performance goals in relation to mastery goals, perceived competence, and task value at the sample level, although performance goals were not high relative to the *Moderate-High All* or *Very High All* profiles.

Finally, our ancillary analyses lend support to the claim that there is added value, both theoretically and empirically, in creating motivational profiles that include constructs from multiple theories. Motivational profiles created with constructs integrating across these theories explained more variance in the profile variables, provided stronger estimates of profile membership (based on probabilities of membership), and accounted for more variance in engagement. These ancillary analyses extend prior research (e.g., Conley, 2012), which did not explicitly examine the differences between LPA-created profiles based on Achievement Goal Theory alone versus Achievement Goal Theory plus Expectancy-Value Theory.

Study 2

Study 1 provided evidence that upper elementary students' motivation can be characterized by four distinct profiles, which are associated with varying patterns of engagement and achievement. Person-oriented research has been critiqued for generalizability beyond a single sample (e.g., Pastor et al., 2007). To address this concern, we examined the same three research questions from Study 1 among an older sample of college students in a more academically selective educational context and different academic domain (i.e., science). As noted earlier and based on prior research (Wormington & Linnenbrink-Garcia, 2017), we anticipated that there might be some differences in the profiles and their frequency between elementary and college samples. Specifically, if differences emerged, we hypothesized that we would identify an amotivated profile in this college sample, even though we were not able to identify one in the elementary sample, and that we would not identify two high all profiles given that a pattern of high all endorsement is more frequently observed in elementary relative to secondary samples (Wormington & Linnenbrink-Garcia, 2017).

Another important distinction between our two samples is that Study 1 focused on schooling more generally while Study 2 focused specifically on science. The shift to focus on a specific domain is both developmentally important (Bong, 2001; Hornstra et al. 2016) and practically important, given the growing body of research highlighting the importance of motivation for understanding undergraduates' engagement and persistence in science, technology, engineering, and math (STEM) disciplines (Cromley, Perez, & Kaplan, 2016). Specifically, prior research indicates that perceived value for science (e.g., interest and perceived relevance) is associated with both achievement and persistence in STEM fields (Crisp, Nora, & Taggart, 2009; Jones, Paretti, Hein, & Knott, 2010; Zusho, Pintrich, & Coppola, 2003). Further, mastery goal orientations predict achievement in college chemistry courses (Zusho et al., 2003) and college more generally (Hernandez, Schultz, Estrada, Woodcock, & Chance, 2013), while performance-avoidance goals are associated with a greater likelihood of leaving a STEM major (Hernandez et al., 2013). Consistent with Expectancy-Value theory tenets, competence beliefs are less important for predicting intentions, but more important in terms of predicting achievement in STEM (Estrada, Woodcock, Hernandez, & Schultz, 2011; Muis, Ranellucci, Franco, & Crippen, 2013; Perez, Cromley, & Kaplan, 2014; Wang & Degol, 2013). Overall, these findings provide support for the critical role that students' motivation plays in predicting STEM achievement and persistence (e.g., Cromley et al., 2016).

Method

Participants—Three hundred twenty-five college students enrolled in gateway chemistry courses during their first year in college at an elite university in the southeastern United States participated in the current study.[5] Participants were primarily female (69.0%), with the majority of students identifying as Asian (41.2%) or White (30.3%). The remainder of participants self-identified as African American (13.6%), Hispanic/Latino (9.0%), or mixed ethnicity (5.9%). Parental level of education and annual household income were collected as indicators of socioeconomic status. The educational status of both mothers and fathers was fairly high, with a median value of a master's degree for both mothers and father and a modal value of college degree for mothers and doctorate or professional degree for fathers. Annual household income for the sample ranged from 1 (below $25,000) to 8 (more than $250,000), with a median value of $75,000-$99,000 and a modal value of more than $250,000. Fewer than 28% of the total sample reported average household incomes below $75,000. Data were collected from two cohorts ($n_{cohort1} = 145$, $n_{cohort2} = 180$).

Procedure—Data for the current study are taken from a survey administered in the spring semester of students' second year in college. The study's procedures were approved by the Institutional Review Board at the first author's former institution (IRB No. A0166) and were deemed exempt by the first author's current institution (IRB No. x16-881e). Eligible students were contacted during the beginning of the spring term (in late January/early February) by email and offered $10 to complete an online survey. Students were made aware that participation was voluntary and would not impact their standing at the university. Of those students invited to complete the second-year survey, 42.8% and 53.3% participated for cohorts 1 and 2. We compared responses on the first-year survey for those students invited to complete the spring survey versus those who actually completed it. Survey completers did not differ from non-completers on the predictor (motivation, *t*s = .08 – .32, *p*s = .74 – .94) or outcome variables (academic engagement or career intentions, *t*s = .32 – .43, *p*s = .67 – .75).[6] However, the groups differed by gender [χ^2 (1) = 44.48, $p < .001$] and race/ethnicity [χ^2 (6) = 104.88, $p < .001$]; women, African American, Asian, and Latino/a students were more likely than chance to respond to the spring survey.

Measures—All survey items were measured using a 5-point Likert scale (1 = *strongly disagree*, 5 = *strongly agree*) except for career intentions, which used a 10-point scale.

Motivational variables: Profiles were formed using the same five motivational constructs assessed in Study 1, with scales altered to focus on science. Specifically, students were

[5]The sample for this study was drawn from the first two cohorts of a large, multi-year longitudinal project, which included a summer enrichment program aimed at supporting college students' science motivation (see Godin et al., 2015; Linnenbrink-Garcia et al., under review). Of the total sample from those first two cohorts ($n = 2{,}532$), the sample used in the current study only included students who did not participate in the summer enrichment program, were randomly selected to participate in follow-up surveys, and completed the spring survey during their second year in college (see procedure section). Of note, we sampled all the gateway chemistry courses where the majority of the students were freshman, thus this initial sampling procedure included students in a range of chemistery courses (from advanced chemistry courses [organic] to introductory courses designed for students who were not yet ready for general chemistry).

[6]Participants did not provide consent to access institutional data until the second survey. Thus, we could not compare completers to non-completers on first year STEM GPA. However, completers and non-completers did not differ in terms of self-reported SAT and ACT scores, a proxy for academic achievement, $t(314) = 1.41$, $p = .16$.

Author Manuscript
Author Manuscript
Author Manuscript

asked to focus on their thoughts and feelings related to science (i.e., "These questions ask you about your thoughts and feelings about science"). *Mastery-approach goals* (α = .76), *performance-approach goals* (α = .90), *performance-avoidance goals* (α = .81), and *perceived competence* (α = .87) were assessed using the same measures as Study 1, and all displayed adequate internal reliability. *Task value* was measured using 12 items modified from Conley (2012)[7] assessing students' interest value (n = 5; e.g., "I enjoy doing science), attainment value (n = 4; e.g., "Being good in science is an important part of who I am"), and utility value (n = 3; e.g., "Science will be useful for me later in life"). The overall task value measure demonstrated good internal reliability (α = .94).

A confirmatory factor analysis conducted on all five motivational variables indicated that the underlying factor structure fit the data acceptably, $\chi^2(421) = 1110.80$, $p < .001$; CFI= .92; TLI = .91; RMSEA = .06 (95% CI = .055-.065); SRMR = .06.[8]

Outcome variables: As in Study 1, self-reported engagement in science was assessed. In addition, we assessed intentions to pursue a research-related career in science. Data from institutional records were used to assess STEM achievement and STEM course completion.

Engagement: Students were asked to focus specifically on their engagement in their science courses when responding to these items (i.e., "Here are some additional questions about how you study and prepare for the science courses you are taking this semester. For each item, indicate the extent to which the statement reflects how you study in science"). The *behavioral engagement* scale was analogous to Study 1 (α = .77). *Cognitive engagement* was assessed with 10 items measuring metacognitive strategy use from the MSLQ (Pintrich et al., 1993; α = .77; e.g., "If course materials are difficult to understand, I change the way I read the material"). Confirmatory factor analysis provided evidence of acceptable model fit, $\chi^2(75) = 173.96$, $p < .001$; CFI = .93; TLI = .92; RMSEA = .06 (95% CI = .05 – .08), SRMR = .05.

Career intentions: Students' science career intentions were assessed using a single item from Schultz and colleagues (2011). Participants responded to the prompt, "To what extent do you intend to pursue a research-related career in science?" using a 10-point Likert-type scale (1 = *definitely will not*, 10 = *definitely will*).

STEM grade point average (GPA) and course taking: Student grades from the first two years of enrollment were obtained from the institutional research office. Grades were

[7]Items were modified to be specific to science (rather than math). Additionally, Conley (2012) included three items that used a different rating scale ["How much do you like doing math?," "How useful is learning math for what you want to do after you graduate and go to work?," "I feel that, to me, being good at solving problems which involve math or reasoning mathematically is (not at all important to very important)"]. To maintain a consistent rating scale, these items were eliminated. Based on our prior work using Conley's measure, we also dropped one attainment value item ("Thinking scientifically is an important part of who I am").

[8]We tested two alternative models: mastery-approach goals and task value as a single latent variable (Model 2b) and task value as three individual components (Model 2c). For Model 2b, the fit was significantly worse, $c^2(425) = 1169.37$, $p < .001$; CFI= 0.89; TLI = 0.89; RMSEA = .07 (95% CI = .07-.08); SRMR = .07; $\Delta c^2(4) = 58.58$, $p < .001$. Model 2c fit the data better than the composite model, $c^2(410) = 790.04$, $p < .001$; CFI = .95; TLI = .94; RMSEA = .05 (95% CI = .05-.06); SRMR = .05; $\Delta c^2(11) = 320.76$, $p < .001$. However, the fit with the composite model was still acceptable. Given acceptable fit with the composite task value scale, we retained the composite measure for Study 2 so that (1) we could create profiles using the same variables in Study 1 and (2) profiles were not overly "weighted" towards task value (i.e., if we used three sub-scales to assess the task value components then task value would have a greater influence over the resulting profiles than achievement goals and perceived competence).

reported on a standard 4.0 scale (A = 4.0, A- = 3.7, etc.). We computed an average of students' GPA in all STEM courses for the first year (to be used a control variable) and for the fourth semester in college (corresponding to the spring survey). Additionally, we computed the total number of STEM courses completed for the first year (to be used as a control variable; ranged from 0 to 8) and fourth semester of college (ranged from 0 to 5). For both STEM variables, STEM courses included courses in the natural sciences (e.g., biology, chemistry, neuroscience), technology (e.g., computer science), engineering (e.g., electrical engineering), mathematics (e.g., mathematics, statistics); courses in social sciences (e.g., psychology, economics) were not included in these calculations.

Statistical analysis strategy—We followed an identical procedure as Study 1 to identify motivational profiles and examine their relation to academic outcomes. Before conducting LPA, we tested for outliers using Grubb's test (Grubbs, 1969); no univariate outliers were identified on any of the motivational variables (i.e., achievement goals, task value, perceived competence). We once again employed Bakk and Vermunt's (2014) BCH method to examine differences in academic correlates between motivational profiles. Analyses predicting behavioral engagement, cognitive engagement, and STEM GPA only included students enrolled in a science course when they took the survey (n = 293), as these outcomes were only appropriate for students currently enrolled in a science class. Analyses predicting science career intentions and number of STEM courses completed included all students. Gender, family income, first-year STEM GPA, and the first-year version of each outcome in all analyses were included as controls. Descriptive statistics and bivariate correlations are provided in Table 1.

Results

Integrative profile solution—Consistent with Study 1, fit indices indicated that a four-profile solution best fit the data (see Table 2). The AIC, BIC, and adjusted BIC all decreased from the three- to four-profile solution. While AIC and adjusted BIC values also decreased from a four- to five-profile solution, a five-profile solution yielded a profile with no cases in it. Accordingly, the four-profile solution was deemed most appropriate. Raw score values for motivational profiles weighted by estimated class probabilities are presented in Figure 2, and standardized scores are displayed in Table 4. The four profiles were labeled as (1) *Moderate-High All,* (2) *Intrinsic and Confident,* (3) *Average All,* and (4) *Moderate Intrinsic and Confident.* A multivariate analysis of variance (MANOVA) with follow-up univariate ANOVAs and Tukey HSD post-hoc tests indicated that the profiles differed on motivational variables overall (Wilk's $\lambda = 59.99$, $p < .001$, $\eta^2 = .48$) and individually (see Table 4). The final profile solution accounted for 31–59% of the variance in each motivational variable.

Moderate-High All: Similar to the elementary sample, the *Moderate-High All* profile was characterized by strong endorsement of all types of motivational constructs, with values just above or below 4 on a 5-point scale, and could be considered highly motivated by any means. The levels of mastery-approach goals, task value, and perceived competence were significantly lower for this profile than those in the *Intrinsic and Confident* profile, but this profile had the highest levels of performance-approach and performance-avoidance goals in the sample. The *Moderate-High All* profile was the most common profile identified, representing 125 students (38.46%). It is similar to the *Moderate-High All* profile from Study 1.

Intrinsic and Confident: This profile was characterized by mean levels of mastery-approach goal orientations, perceived competence, and task value well above 4.0. These levels were significantly higher than all other profiles. In contrast to the *Moderate-High All* profile, this profile was marked by low endorsement of performance-approach or performance-avoidance goal orientations, with among the lowest levels of performance goals in the sample. This profile was second least common profile, with 53 students (16.31%). It is similar to the *Intrinsic and Confident* profile identified in Study 1.

Average All: The third profile was labeled as *Average All* motivation. This profile was characterized by levels of motivation around the midpoint of each scale, suggesting a relatively indifferent stance with respect to all five indicators of motivation. This profile had the lowest levels of mastery-approach goals, perceived competence, and task value, which were significantly lower than those in the other profiles. The levels of performance-approach and performance-avoidance goals were among the lowest in the sample. The *Average All* profile was the least common profile identified, representing 11.69% of the sample ($n = 38$). Compared to Study 1, the *Average All* profile identified in Study 2 had lower raw levels of motivation (between 2 and 3 rather than 3 and 4 in Study 1). However, in both samples, the *Average All* profile represented the lowest overall levels of motivation, suggesting that this *Average All* profile was characterized by relative amotivation.

Moderate Intrinsic and Confident: The fourth profile we identified was unique to the college sample. The overall pattern of motivation was similar to that observed in the *Intrinsic and Confident* profile, but with lower overall motivation across measures. Specifically, this profile was characterized by moderate to moderate-high levels of mastery-approach goals, perceived competence, and task value (around 3.8) and very low performance-approach and performance-avoidance goals (around 2.0). The *Moderate Intrinsic and Confident* profile was the second most common profile identified in the sample, consisting of 109 students (33.54%).

Profile membership and academic outcomes—For all analyses, we controlled for student gender, family income, and first-year indicators of the dependent variable. First-year STEM grade point average was also included as a control for STEM GPA, STEM course-taking, and career intentions. The analyses for behavioral engagement, cognitive engagement, semester 4 GPA were only conducted for participants who were enrolled in a science course when they responded to the spring survey (n = 293; 90.2% of the full sample) because the survey items asked students to think about the science course(s) in which they were currently enrolled. As in Study 1, we determined whether profiles differed from one another on outcome variables by examining equality tests of means across classes in Step 3 of the BCH analysis process. Mean-level endorsement of outcomes, effect sizes, and significant differences among profiles based on equality tests are presented in Table 4.

For both behavioral and cognitive engagement, the *Intrinsic and Confident* profile had the highest overall engagement, which was significantly higher than all the other profiles except the *Moderate-High All* profile. Moreover, the *Moderate-High All* and *Moderate Intrinsic and Confident* profiles were associated with statistically significantly higher levels of engagement than the *Average All* profile, though they did not differ from each other. The pattern was somewhat different for career intentions. The highest career intentions were observed for the *Intrinsic and Confident* profile, which was significantly higher than the other three profiles. The next highest levels of intentions to pursue a research-related science career were observed for the *Moderate-High All* and *Moderate Intrinsic and Confident* profiles, which were both significantly higher than the *Average* All profile but did not significantly differ from each other. The *Average All* profile had the lowest career intentions.

For STEM GPA and STEM course completion, findings revealed that fourth semester STEM courses varied based on profile membership, with significantly fewer STEM courses associated with the *Average All* profile relative to the other three profiles, which did not differ from each other. There were no significant differences in STEM GPA by profile membership.

Ancillary analyses: Goal profiles—As in Study 1, we conducted LPA with achievement goals only and compared them to our integrative profiles (see Table S4 for *z*-scores and Figure S2 for raw scores). The LPA suggested that a six-profile solution best fit the data for the achievement goals only model (see additional text and Table S1 in supplemental materials for a justification of this profile solution).

We labeled the first profile *Very High All* (n = 11; 3.38%), as this profile was marked by endorsement of all three types of achievement goals at almost ceiling levels. A second larger profile, which we labeled *Moderate-High All* (n = 96, 29.54%), was also characterized by high overall levels of achievement goals around 4 on a 5-point scale. The next three profiles were all characterized by high mastery goals accompanied by average (*Mastery High-Performance Moderate; n* = 142; 43.69%), low (*Mastery High-Performance Low; n* = 45; 13.85%), or very low performance goals (*Mastery High-Performance Very Low; n* = 13; 4.00%). The final profile was labeled as *Mastery Moderate-Performance Low* (n = 18; 5.54%), as this profile was distinguished by endorsement of low performance goals and average mastery goals. When comparing profiles, the difference in profile size is striking; in particular, three profiles characterized fewer than 10% of the total sample while the *Mastery High-Performance Moderate* profile comprised more than 40% of the sample. Notably, mastery goals did not significantly differ across four of the six profiles identified.

We also examined overlap in profile membership between the achievement goal profiles and integrative profiles (see Table S5). Of note, almost all of the cases from the *Very High All* and *Moderate-High All* goal profiles were categorized in the *Moderate-High All* integrative profile. Similarly, nearly all of the cases for the *Mastery Moderate-Performance Low* goal profile were categorized as the *Average All* integrative profile. Membership for the three goal profiles characterized by high mastery goals were more mixed, and were primarily split between the *Intrinsic and Confident* and *Moderate Intrinsic and Confident* integrative profiles.

We also compared the classification probabilities for the most likely latent class membership between the goals only and integrative profile solutions. The average probability for most likely latent class membership for both profile solutions was almost identical, with .919 for integrative profiles and .918 for goal profiles. The likelihood of being classified into one of the other classes was also comparable, with .020 for integrative profiles and .032 for goal profiles. Although the goal profile solution contained two more profiles than the integrative profile solution, there was virtually no difference in classification probabilities. However, the amount of variance in the profiling variables that was explained by profile membership was slightly higher for the goals only profiles compared to the integrative profiles as show in Table 4 and S4; this is likely due to the larger number of goal profiles identified compared to integrative profiles. Notably, the goals only profiles were far less effective in explaining variance in mastery goals (35% for goal profiles versus 59% for integrative profiles), but more effective in explaining performance-approach (79% for goal profiles versus 57% for integrative profiles) and performance-avoidance goals (83% for goal profiles versus 53% for integrative profiles).

Finally, we considered which profile solution was a stronger predictor of outcomes (Table S4). Overall effect sizes between the two profile solutions were similar for behavioral engagement (goals = 0.73; integrative = 0.67) and cognitive engagement (goals = 0.69; integrative = 0.68). However, the effect sizes were larger for the integrative profiles compared to the goals only profiles with respect to career intentions (goals = 0.69; integrative = 0.81) and number of STEM courses completed (goals = 0.71; integrative = 1.02). And, goal profiles were not a statistically significant predictor of STEM courses. Moreover, with few exceptions, the goal profiles characterized by high goal endorsement (*Very High All* and *Moderate-High All*) and high mastery goal endorsement (*Mastery High-Performance Moderate, Mastery High-Performance Low, Mastery High-Performance Very Low*) did not generally differ in terms of outcomes. Because overall effect sizes were smaller for goal profiles and the additional goal profiles that were not identified in the integrative profiles generally did not differ from one another on outcomes, our findings suggest that considering perceived competence and task value alongside achievement goals when forming motivational profiles is useful.

Discussion

In this sample of college students, we identified four distinct integrative motivational profiles, which were largely similar to those observed in Study 1 (see General Discussion for a more elaborated comparison); ancillary analyses again highlighted the benefit of creating integrative profiles that combine constructs from two motivation theories. As in Study 1, the highest levels of engagement (as well as career intentions and course taking) were observed among the profiles characterized by strong endorsement of mastery goals and high levels of perceived competence and task value; these outcomes did not differ among profiles with accompanying high performance-approach and performance-avoidance goals (i.e., *Moderate-High All*) or low performance-approach and performance-avoidance goals (i.e., *Intrinsic and Confident*), except for career intentions where there was an advantage to having lower performance goals. Also consistent with findings from Study 1, membership in the *Average All* profile was associated with the lowest levels of engagement, career intentions, and course taking. Similar to Study 1, no profile characterized by low motivation emerged, perhaps due to the labeling of profiles based on raw scores or due to our specific sample (students attending an elite university). It may be that students truly amotivated for science would not be participating in science courses in college, let alone a top-ranked university. Studies targeting a different student population or educational context may identify the amotivated profile.

We identified one unique profile in Study 2: a moderate version of the *Intrinsic and Confident* profile, characterized by moderate-high levels of mastery goals, task value, and perceived competence but very low levels of performance goals. This pattern and level of motivation is consistent with the overall decline in motivation typically observed across schooling using variable-oriented approaches (e.g., Gottfried, Fleming, & Gottfried, 2001; Wigfield et al., 2009), but may also be due to differences in how task value was measured, context, and/or domain-specificity between the two samples. Overall, our results suggest that there are two primary patterns of profiles, with varying levels, among college students in this sample. One pattern involves similar endorsement of all levels of motivation, as reflected by the *Moderate-High All* and *Average All* profiles. The second pattern involves relatively higher mastery goals, task value, and perceived competence and lower performance goals, as reflected by the *Intrinsic and Confident* and *Moderate Intrinsic and Confident* profiles.

Finally, it important to note that there was some bias in responding to the primary surveys used in Study 2 in terms of gender and race/ethnicity. Women, African American, Asian, and Latino/a students were more likely than chance to respond to the second-year spring survey. These response rates might be due to a sense of social responsibility and/or the opportunity to earn $10 for participating in the survey. Nonetheless, there were no meaningful differences between students who did and did not respond to the survey in terms of first year motivation, engagement, and prior achievement, suggesting that response biases were unlikely to impact the overall pattern of profiles identified.

Ancillary Analyses Comparing Profile Membership for Studies 1 and 2

One primary aim of this research was to compare the profiles found in two very different samples and contexts. Because we identified three of the same four profiles in both studies, we compared the size of these three profiles (*Moderate-High All; Intrinsic and Confident; Average All*) across studies as an ancillary analysis. Chi-square analyses indicated that the pattern of profile membership differed between the elementary and college samples for the three common profiles overall [χ^2 (2) = 22.94, $p < .001$]. For these analyses, we used most probabilistic profile membership to assign students to classes (see Table 5), which is a reasonable approach for these ancillary analyses given that entropy was high for both samples. Given the cross-sectional nature of these analyses, demographic and contextual differences between the two samples, and the caution that classification only represents most likely classification as opposed to definitive “membership”, we urge readers to interpret findings within an exploratory lens.

Overall, the proportion of students in the *Moderate-High All* profile and the *Intrinsic and Confident* profile was similar in both samples. The *Moderate-High All* profile was the most common profile across samples, with more than one-third of the students from both studies best classified in this profile. By contrast, the *Intrinsic and Confident* profile was the second least common profile across studies, with slightly less than 20% of the students in both samples best classified into this profile. The proportion of students best classified into the *Average All* profile differed between the elementary and college samples. More than twice as many elementary students (34%) were best classified into the *Average All* profile than the college sample (12%).

General Discussion

Motivation profiles identified across our studies were remarkably similar. Three of the four profiles identified (*Moderate-High All, Intrinsic and Confident, Average All*) consistently emerged, with two profiles unique to each sample (elementary domain-general: *Very High All*; college science: *Moderate Intrinsic and Confident*). As noted in Study 1, our profiles were largely consistent with prior research. Evidence within a single theoretical perspective (e.g., Wormington & Linnenbrink-Garcia, 2017) or integrating across motivational theories (e.g., Conley, 2012) suggests that it is beneficial for engagement and achievement for students to either strongly endorse all types of motivation simultaneously (aligned with the *Moderate-High All* and *Very High All* profiles) or to focus solely on intrinsic types of motivation (aligned with the *Intrinsic and Confident* profile). In both samples, these two types of profiles were consistently associated with the most self-reported engagement. Together, our findings support the argument that there may be more than one combination of beliefs that supports students' success in school (e.g., Pintrich, 2000a) and that these combinations are likely to emerge across different learning contexts.

One key contribution of the current work is the integration of Achievement Goal Theory and Expectancy-Value Theory, as the majority of person-oriented motivation studies are based in single theoretical framework. Our findings suggest that there is value added by more fully capturing additional facets of students' achievement motivation. Specifically, our ancillary findings highlight the importance of considering students' competency beliefs and task value alongside achievement goal orientations, as these integrated profiles were generally superior in terms of the probability of accurate classification into profiles as well as the amount of variance explained in both the profile variables and the majority of the outcomes.

The combination of perceived competence, task value, and achievement goals may be especially powerful, as they capture key elements of four of the six major theories of motivation identified by Linnenbrink-Garcia and Patall (2016). Specifically, the inclusion of perceived competence (measured using the academic self-efficacy measure from PALS) represents an important component of Social Cognitive Theory and the inclusion of task value overlaps substantially with individual interest. Thus, our integrative profiles capture important elements from Expectancy-Value Theory, Achievement Goal Theory, Interest Theory, and Social Cognitive Theory without introducing unnecessary construct overlap.

Differences in Profile Membership across Studies

We also explored differences in profile membership cross-sectionally between two distinct samples. This is, to our knowledge, the first study to compare profile membership across very different groups of students (age and demographics) in such very different learning contexts (public v. elite private school, domain-general v. science; but see Vansteenkiste, Sierens, Soenens, Luyckx, & Lens, 2009 for a comparison of secondary and post-secondary students).

Our profile solutions are generally consistent with hypotheses and prior research on age-related differences in students' motivation. Students in the elementary sample were more likely to strongly endorse multiple, even opposing, types of motivation. Although a similar proportion of students in the elementary sample (40%) and college sample (39%) were best classified into the *Moderate-High All* profile, we identified a second high all profile (*Very High All*), with even more extreme (high) values than that observed for the *Moderate-High All* profile for the elementary sample. As a result, almost half (48%) of the students in the elementary sample were best classified in a high all profile (either *Moderate-High All* or *Very High All*) compared to 39% of the college sample. This pattern of findings suggests that younger students may be more likely to endorse high levels of motivation overall, even if those motivational beliefs stand in opposition to one another (e.g., performance-avoidance goals and perceived competence), consistent with prior research (Wormington & Linnenbrink-Garcia, 2017).

Surprisingly, more students in the elementary sample were best classified into the *Average All* profile compared to the college sample. However, this difference may be accounted for by the existence of a second large "average" profile for college students (e.g., *Moderate Intrinsic and Confident* profile). Although the pattern of higher mastery goals, task value, and perceived competence relative to performance goal endorsement was consistently associated with more desirable outcomes than the *Average All* profile in the college sample, it helps to explain how motivation might be lower overall for college students even though fewer college students were in the *Average All* profile. If the two "average" profiles are combined for college students, almost half (45%) of the students in the college sample can be best classified into a profile with more moderate levels of motivation compared to 34% for the elementary sample. It could also be a result of self-selection into an elite university for the college sample.

Another important distinction between the elementary and college samples is the mean levels of motivation observed for the *Average All* profile. The elementary sample *Average All* profile was characterized by higher motivation (between 3 and 4 on a 5-point scale) relative to the college sample *Average All* profile (values between 2 and 3). Yet, we still consider these profiles to be similar; for both groups the *z*-scores suggest that, relative to sample means, the *Average All* profiles represent students who endorse the lowest levels of motivation. The difference, then, is that the overall "low" levels are higher for elementary students given their overall higher levels of motivation. This difference illustrates an important point in generalizing across samples: although it may be possible to identify analogous patterns of motivation (e.g., profiles) across studies, there may be subtle differences at the sample level in the overall levels of motivation and relative endorsement between profiles (i.e., standardized scores).

Our cross-sectional comparison also provides new insights into patterns of motivational decline observed from variable-oriented research whereby more intrinsic types of motivation and perceived competence are lower when comparing elementary school to college while more extrinsic or performance-oriented types of motivation are higher in older samples (e.g., Gottfried et al., 2001; Jacobs, Lanza, Osgood, Eccles, & Wigfield, 2002; Otis, Grouzet, & Pelletier, 2005). Our cross-sectional results highlight that this decline does not occur for all students. Indeed, the proportion of students classified into the *Intrinsic and Confident* profile —characterized by high levels of mastery goals, perceived competence, and task value but low levels of performance goals—were similar across our elementary and college samples as were the proportion of students classified into the *Moderate-High All* profile. Therefore, a meaningful proportion of students may be able to maintain high levels of competence and intrinsic types of motivation in very different educational contexts, which is also consistent with other person-oriented research employing growth mixture modeling to identify latent classes of change in motivation (Archambault, Eccles, & Vida, 2010; Musu-Gillette, Wigfield, Harring, & Eccles; 2015).

Together with prior research, our findings provide insight into commonalities and differences in motivation across distinct samples and learning contexts beyond those already observed in variable-oriented studies. Three of the four profiles were observed in both samples, suggesting there may be combinations of motivation that describe most students. Moreover, we observed two unique patterns of motivation, which may have arisen as a result of developmental factors, educational context, domain-specificity, or other sample characteristics.

Implications for Practice and Theory

The profiles associated with the greatest engagement and achievement were characterized by high levels of mastery goals, task value, and perceived competence. As such, our findings suggest that supporting all three types of motivation in the classroom may yield the most beneficial patterns of engagement, achievement, and persistence; this conclusion aligns with findings from decades of variable-oriented research (e.g., Linnenbrink-Garcia, Patall, & Pekrun, 2016; Wigfield & Cambria, 2010). The two consistently engaged and high achieving profiles (i.e., *Moderate-High All* and *Intrinsic and Confident*) characterized students with different levels of performance-approach and performance-avoidance goals. This result suggests that, as long as mastery goals, task value, and perceived competence are also high, a focus on demonstrating competence may not necessarily be problematic. However, there does seem to be some benefit for lower performance goals in the college sample in terms of intentions to pursue science careers. Moreover, there seems to be little added benefit to creating contexts that also emphasize demonstrating competence (performance goal structures), as students appeared equally well off if they did not endorse performance goals. Emphasizing performance goals could also backfire. For students with average levels of mastery goals, task value, and perceived competence, an increased emphasis on performance goals might move them into an average all profile (which was associated with lower engagement, persistence, and achievement). Future research should directly investigate how specific classroom contexts support various motivational profiles.

Our results also have important implications for theory. On the whole, adding perceived competence and task value to profiles provided greater explanatory power (confidence in profile membership and in predicting outcomes), indicating that task valuation and competence beliefs should be considered alongside mastery and performance goal orientations. This highlights the importance of moving beyond theoretical silos to consider how multiple types of motivation derived from multiple theories combine to shape educational outcomes (Linnenbrink-Garcia & Wormington, 2017).

Our results also help inform a central debate within Achievement Goal Theory over whether performance-approach goals are uniformly related to adaptive or maladaptive outcomes (Harackiewicz, Barron, Pintrich, Elliot, & Thrash, 2002; Midgley et al., 2001; Senko, Hulleman, & Harackiewicz, 2011). First, performance-approach and performance-avoidance goals co-varied together in all of the profiles across both samples. This contributes to ongoing discussions about the high correlation among these two goal orientations and the implications for practice (see Law, Elliot, & Murayama, 2012; Linnenbrink-Garcia et al., 2012; Murayama, Elliot, & Yamagata, 2011). Second, as noted above, there appears to be little added academic benefit to endorsing performance-approach goals alongside mastery goals. With performance goals, it is essential to consider what other types of motivation are endorsed at the same time in order to understand how these goals relate to academic outcomes, further highlighting the utility of creating motivational profiles using a person-oriented theoretical and analytical approach. Although the beneficial pattern observed for the *Moderate-High All* profile could be used to argue for a multiple goal perspective, our finding that the *Intrinsic and Confident* profile was associated with equally high or higher academic outcomes favors the mastery goal perspective, which suggests that strongly endorsing performance-approach goals is not necessary for supporting engagement and persistence. Of note, we did find a *Very High All* profile in the elementary sample that was the most beneficial for achievement; thus, there may be circumstances where it is beneficial for all forms of motivation to be very high.

Limitations and Future Directions

The sample and context differences between our two studies limit our ability to make claims about which specific factors (development, demographics, educational context, domain-specificity) contributed to observed differences. For instance, in addition to age differences, the proportion of African American and Latino/a students was much larger in the elementary sample, while the proportion of Asian students was much larger in the college sample, suggesting that observed differences may be due to racial/ethnic make-up of the sample rather development or context. There were also differences in domain-specificity of measures, which could account for some of the differences observed across studies. Thus, it is imperative that future research consider the unique contributions of individual, contextual, and developmental influences on profile prevalence and the relation of profiles to academic outcomes. Future research should also replicate the current findings in more general populations. However, these distinct samples help to strengthen our argument that there may be several common motivational profiles (e.g., *Moderate-High All, Average All, Intrinsic and Confident*) that emerge across very different groups of individuals, academic subjects, and learning contexts

Further, we did not include types of motivation beyond value, perceived competence, task value, and achievement goals. An important additional variable to consider would be cost perceptions, an often-neglected component in Eccles' (1983) modern Expectancy-Value Theory and an important element to Conley's (2012) prior work on integrative profiles. There may be distinct types of cost, which may play out differently in forming motivational profiles (e.g., Flake, Barron, Hulleman, McCoach & Welsh, 2015; Perez et al., 2014). Although including additional motivational constructs may be illuminating, we urge researchers to systematically consider which constructs should be included to avoid a "kitchen sink" approach to creating profiles; parsimony is still critical for informing theory. Indeed, future research might consider using matched datasets to systematically examine which of the five constructs included in our studies are needed in the profiles. Relatedly, future research may also consider whether there is a higher-order motivational variable that better captures the aspects of motivation measured by task value, perceived competence, and mastery goals, given that these three forms of motivation covaried within profiles and were highly correlated. In doing so, researchers should also carefully consider the theoretical implications of such higher-order motivational factors.

Additionally, our reliance on self-reported engagement may be problematic for several reasons. First, there is considerable work questioning the reliance on self-report measures to assess metacognitive strategy use, suggesting that self-reported strategy use is not aligned with actual behavior especially when longer-term recall of general study behavior is used, as was the case in the current study (Bråten & Samuelstuen, 2007; Samuelstuen & Bråten, 2007; Schellings & Van Hout-Wolters, 2011; Veenman, 2011). Thus, our self-report engagement measures may not accurately reflect students' actual engagement in the classroom. Second, mono-method bias, whereby shared variance has more to do with similarities in measurement than with the underlying constructs being assessed (Winne & Perry, 2000), may also partially account for our findings. Nonetheless, it is encouraging that in addition to finding differences in profile membership based on self-report measures, we also found differences in variables taken from institutional data (Study 1 mathematics achievement, Study 2 STEM course completion). Future studies should examine how motivational profiles relate to engagement assessed in others ways to address these limitations. Third, we used a single-item indicator to assess career intentions; single-item indicators are typically discouraged given the inability to measure internal consistency adequately. Thus, future research should include multiple-item indicators for this variable.

Finally, our analysis focused on profiles during a single time point. Past research examining shifts in motivational profiles based on intrinsic and extrinsic motivation (Corpus & Wormington, 2014; Hayenga & Corpus, 2010) or goal orientations (Pulkka & Niemivirta, 2013; Schwinger & Wild, 2012; Tuominen-Soini, Salmela-Aro, & Niemivirta, 2011, 2012) typically finds that about half of the students shift profiles, regardless of the timespan studied, suggesting that profiles are unlikely to be highly stable over time. Thus, it will be important for future research to examine changes in profile membership. In doing so, research on both contextual and individual predictors of motivational profile shifts would be especially useful for explaining why students remain in highly-engaged and achieving profiles or shift into profiles associated with lower engagement and achievement. By doing so, researchers may be able to provide educators with clearer suggestions regarding how to effectively support student motivation, engagement, and learning. Equally important, researchers may be able to more clearly tailor these recommendations and student supports to address students' current motivational orientations.

Conclusion

Findings from this research highlight the utility of a person-oriented approach for studying motivation and the added theoretical benefit of cross-theory integration. Our findings help to clarify the potential role of performance goals, suggesting that the benefits or detriments associated with this controversial type of goal orientation likely vary as a function of other types of motivation (e.g., mastery goals, task value, perceived competence) that are also present. Moreover, we provide evidence that there may be several common types of motivational profiles that emerge across very different ages and contexts, but that there may also be unique profiles observed in any one context. These results help to highlight the complexity in understanding patterns of motivation in the classroom – and are an important first step in answering Pintrich's (2000a, 2003) call to consider multiple motivational pathways to achievement.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

References

Aiken LS, West SG. Multiple regression: Testing and interpreting interactions. Newbury Park: Sage; 1991.

Ames C. Classrooms: Goals, structures, and student motivation. Journal of Educational Psychology. 1992; 84:261–271. DOI: 10.1037//0022-0663.84.3.261

Anderman EM, Wolters CA. Goals, values, and affect: Influences on student motivation. In: Alexander PA, Winne PH, editorsHandbook of educational psychology. Mahwah, NJ US: Lawrence Erlbaum Associates Publishers; 2006. 369–389.

Archambault I, Eccles JS, Vida MN. Ability self-concepts and subjective value in literacy: Joint trajectories from grades 1 through 12. Journal of Educational Psychology. 2010; 102:804–816. DOI: 10.1037/a0021075

Asparouhov T, Muthén BO. Auxiliary variables in mixture modeling: Using the BCH method in Mplus to estimate a distal outcome model and an arbitrary second model. Version 2. 2015. Retrieved from http://www.statmodel.com/examples/webnotes/webnote21.pdf

Bakk Z, Vermunt JK. Robustness of stepwise latent class modeling with continuous distal outcomes. Structural Equation Modeling: A Multidisciplinary Journal. 2014; 23:20–31. DOI: 10.1080/10705511.2014.955104

Bandura A. Toward a psychology of human agency. Perspectives on Psychological Science. 2006; 1:164–180. DOI: 10.1111/j.1745-6916.2006.00011.x [PubMed: 26151469]

Ben-Eliyahu A, Bernacki ML. Addressing complexities in self-regulated learning: A focus on and contextual factors, contingencies, and dynamic relations. Metacognition & Learning. 2015; 10:1–13.

Bergman LR, Magnusson D. A person-oriented approach in research on developmental psychopathology. Development and Psychopathology. 1997; 9:291–319. DOI: 10.1017/S095457949700206X [PubMed: 9201446]

Bergman LR, Magnusson D, El Khouri B. Studying individual development in an interindividual context: A person-centered approach. Mahwah, NJ: Lawrence Erlbaum Associates; 2003.

Bergman LR, Trost K. The person-oriented versus the variable-oriented approach: Are they complementary, opposites, or exploring different worlds? Merrill-Palmer Quarterly. 2006; 52:601–632. DOI: 10.1353/mpq.2006.0023

Bong M. Between- and within-domain relations of academic motivation among middle and high school students: Self-efficacy, task-value, and achievement goals. Journal of Educational Psychology. 2001; 93:23–34. DOI: 10.1037/0022-0663.93.1.23

Bong M. Age-related differences in achievement goal differentiation. Journal of Educational Psychology. 2009; 101:879–896. DOI: 10.1037/a0015945

Bråten I, Olaussen BS. Profiling individual differences in student motivation: A longitudinal cluster-analytic study in different academic contexts. Contemporary Educational Psychology. 2005; 30:359–396. DOI: 10.1016/j.cedpsych.2005.01.003

Bråten I, Samuelstuen MS. Measuring strategic processing: Comparing task-specific self-reports to traces. Metacognition and Learning. 2007; 2:1–20. DOI: 10.1007/s11409-007-9004-y

Chall J. Stages of Reading Development. New York: McGraw Hill; 1983.

Ciani KD, Sheldon KM. Evaluating the mastery-avoidance goal construct: A study of elite college baseball players. Psychology of Sport and Exercise. 2010; 11:127–132. DOI: 10.1016/j.psychsport.2009.04.005

Collins LM, Lanza ST. Latent class and latent transition analysis: With applications in the social, behavioral, and health sciences. Hoboken, NJ: John Wiley & Sons; 2010.

Conley AM. Patterns of motivation beliefs: Combining achievement goal and expectancy-value perspectives. Journal of Educational Psychology. 2012; 104:32–47. DOI: 10.1037/a0026042

Corpus JH, Wormington SV. Profiles of intrinsic and extrinsic motivations in elementary school: A longitudinal analysis. Journal of Experimental Education. 2014; 82:480–501. DOI: 10.1080/00220973.2013.876225

Crisp G, Nora A, Taggart A. Student characteristics, pre-college, college, and environmental factors as predictors of majoring in and earning a STEM degree: An analysis of students attending a Hispanic serving institution. American Educational Research Journal. 2009; 46:924–942. DOI: 10.3102/0002831209349460

Cromley JG, Perez T, Kaplan A. Undergraduate STEM achievement and retention: Cognitive, motivational, and institutional factors and solutions. Policy Implications of the Brain and Behavioral Sciences. 2016; 3:4–11. DOI: 10.1177/2372732215622648

Dina F, Efklides A. Student profiles of achievement goals, goal instructions and external feedback: Their effect on mathematical task performance and affect. European Journal of Education and Psychology. 2009; 2:235–262.

Dweck CS, Elliot ES. Achievement motivation. In: Hetherington EM, editorSocialization, personality, and social development. New York: Wiley; 1983. 643–691.

Dweck C, Leggett E. A social-cognitive approach to motivation and personality. Psychological Review. 1988; 95:256–273. DOI: 10.1037//0033-295x.95.2.256

Eccles JS. Expectancies, values, and academic behaviors. In: Spence JT, editorAchievement and achievement motives. San Francisco: Freeman; 1983. 75–146.

Elliot AJ. Approach and avoidance motivation and achievement goals. Educational Psychologist. 1999; 34:169–189. DOI: 10.1207/s15326985ep3403_3

Estrada M, Woodcock A, Hernandez PR, Schultz P. Toward a model of social influence that explains minority student integration into the scientific community. Journal of Educational Psychology. 2011; 103:206–222. DOI: 10.1037/a0020743 [PubMed: 21552374]

Flake JK, Barron KE, Hulleman C, McCoach BD, Welsh ME. Measuring cost: The forgotten component of expectancy-value theory. Contemporary Educational Psychology. 2015; 41:232–244. DOI: 10.1016/j.cedpsych.2015.03.002

Fredricks JA, Blumenfeld P, Friedel J, Paris A. School engagement. In: Moore KA, Lippman LH, editorsWhat do children need to flourish: Conceptualizing and measuring indicators of positive development. New York, NY US: Springer; 2005. 305–321.

Godin EA, Wormington SV, Perez T, Barger MM, Snyder KE, Richman LS, Schwartz-Bloom R, Linnenbrink-Garcia L. A pharmacology-based enrichment program for undergraduates promotes interest in science. CBE Life Sciences Education. 2015; 14:1–12. DOI: 10.1187/cbe.15-02-0043

Gottfried AE, Fleming JS, Gottfried AW. Continuity of academic intrinsic motivation from childhood through late adolescence: A longitudinal study. Journal of Educational Psychology. 2001; 93:3–13. DOI: 10.1037//0022-0663.93.1.3

Grubbs F. Procedures for detecting outlying observations in samples. Technometrics. 1969; 11:1–21. DOI: 10.1080/00401706.1969.10490657

Hair JF, Anderson RE, Black WC, Tatham RL. Multivariate data analysis. 5. Upper Saddle River, NJ: Prentice Hall; 1998.

Harackiewicz JM, Barron KE, Pintrich PR, Elliot AJ, Thrash TM. Revision of achievement goal theory: Necessary and illuminating. Journal of Educational Psychology. 2002; 94:638–645. DOI: 10.1037/0022-0663.94.3.638

Hayenga AO, Corpus JH. Profiles of intrinsic and extrinsic motivations: A person-centered approach to motivation and achievement in middle school. Motivation and Emotion. 2010; 34:371–383. DOI: 10.1007/s11031-010-9181-x

Hernandez PR, Schultz PW, Estrada M, Woodcock A, Chance RC. Sustaining optimal motivation: A longitudinal analysis of interventions to broaden participation of underrepresented students in STEM. Journal of Educational Psychology. 2013; 105:89–107. DOI: 10.1037/a0029691

Hornstra L, van der Veen I, Peetsma T. Domain-specificity of motivation: A longitudinal study in upper primary school. Learning and Individual Differences. 2016; 51:167–178. DOI: 10.1016/j.lindif.2016.08.012

Horst P. Social Science Research Council Bulletin. Vol. 48. New York, NY: Social Science Research Council; 1941. The prediction of personal adjustment.

Hu LT, Bentler PM. Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. Structural Equation Modeling: A Multidisciplinary Journal. 1999; 6:1–55. DOI: 10.1080/10705519909540118

Hulleman CS, Schrager SM, Bodman SM, Harackiewicz JM. A meta-analytic review of achievement goal measures: Different labels for the same constructs or different constructs with similar labels? Psychological Bulletin. 2010; 136:422–449. DOI: 10.1037/a0018947 [PubMed: 20438145]

Jacobs JE, Lanza S, Osgood W, Eccles JS, Wigfield A. Changes in children's self-competence and values: Gender and domain differences across grades one through twelve. Child Development. 2002; 73:509–527. DOI: 10.1111/1467-8624.00421 [PubMed: 11949906]

Jones BD, Paretti MC, Hein SF, Knott TW. An analysis of motivation constructs with first-year engineering students: Relationships among expectancies, values, achievement, and career plans. Journal of Engineering Education. 2010; 99:319–336. DOI: 10.1002/j.2168-9830.2010.tb01066.x

Krapp A. Structural and dynamic aspects of interest development: Theoretical considerations from an ontogenetic perspective. Learning and Instruction. 2002; 12:383–409. DOI: 10.1016/S0959-4752(01)00011-1

Lau S, Roeser RW. Cognitive abilities and motivational processes in science achievement and engagement: A person-centered analysis. Learning and Individual Differences. 2008; 18:497–504. DOI: 10.1016/j.lindif.2007.11.002

Law W, Elliot AJ, Murayama K. Perceived competence moderates the relation between performance-approach and performance-avoidance goals. Journal of Educational Psychology. 2012; 104:806–819. DOI: 10.1037/a0027179

Lewis-Beck MS, Bryman A, Liao TF, editorsThe Sage encyclopedia of social science research methods. 3. Thousand Oaks, CA: Sage Publications Inc; 2004.

Linnenbrink EA. The dilemma of performance-approach goals: The use of multiple goal contexts to promote students' motivation and learning. Journal of Educational Psychology. 2005; 97:197–213. DOI: 10.1037/0022-0663.97.2.197

Linnenbrink-Garcia L, Middleton MJ, Ciani KD, Easter MA, O'Keefe PA, Zusho A. The strength of the relation between performance-approach and performance-avoidance goal orientations: Theoretical, methodological, and instructional implications. Educational Psychologist. 2012; 47:281–301. DOI: 10.1080/00461520.2012.722515

Linnenbrink-Garcia L, Patall EA. Motivation. In: Anderman E, Corno L, editorsHandbook of educational psychology. 3. New York: Taylor & Francis; 2016. 91–103.

Linnenbrink-Garcia L, Patall EA, Pekrun R. Adaptive motivation and emotion in education: Research and principles for instructional design. Policy Insights from the Behavioral and Brain Sciences. 2016; 3:228–236. DOI: 10.1177/2372732216644450

Linnenbrink-Garcia L, Perez T, Barger MM, Wormington SV, Godin E, Snyder KE, Richman LS, Schwartz-Bloom R. Repairing the leaky pipeline: A motivationally supportive intervention to enhance persistence in undergraduate science pathways. (under review).

Linnenbrink-Garcia L, Wormington SV. Key challenges and potential solutions for studying the complexity of motivation in schooling: An integrative, dynamic person-oriented perspective. British Journal of Educational Psychology Monograph Series. 2017; 12:89–108.

Maehr ML, Zusho A. Achievement goal theory: The past, present, and future. In: Wentzel KR, Wigfield A, editorsHandbook of motivation at school. New York, NY US: Routledge/Taylor & Francis Group; 2009. 77–104.

Magnusson D, Allen V. An interactional perspective for human development. In: Magnusson D, Allen V, editorsHuman development: An interactional perspective. New York: Academic Press; 1983. 3–31.

Midgley C, Kaplan A, Middleton M. Performance-approach goals: Good for what, for whom, under what circumstances, and at what cost? Journal of Educational Psychology. 2001; 93:77–86. DOI: 10.1037/0022-0663.93.1.77

Midgley C, Maehr ML, Hruda LZ, Anderman E, Anderman L, Freeman KE. , et al. Manual for the Patterns of Adaptive Learning Scales (PALS). Ann Arbor, MI: University of Michigan; 2000.

Muis KR, Ranellucci J, Franco GM, Crippen KJ. The interactive effects of personal achievement goals and performance feedback in an undergraduate science class. Journal of Experimental Education. 2013; 81:556–578. DOI: 10.1080/00220973.2012.738257

Murayama K, Elliot AJ, Yamagata S. Separation of performance-approach and performance-avoidance achievement goals: A broader analysis. Journal of Educational Psychology. 2011; 103:238–256. DOI: 10.1037/a0021948

Musu-Gillette LE, Wigfield A, Harring JR, Eccles JS. Trajectories of change in students' self-concepts of ability and values in math and college major choice. Educational Research and Evaluation. 2015; 21:343–370. DOI: 10.1080/13803611.2015.1057161

Muthén LK, Muthén BO. Mplus User's Guide, Seventh Edition. Los Angeles, CA: Muthén & Muthén; 1998–2015.

Nagengast B, Marsh HW, Scalas LF, Xu MK, Hau KT, Trautwein U. Who took the "×" out of expectancy-value theory? A psychological mystery, a substantive-methodological synergy, and a cross-national generalization. Psychological Science. 2011; 22:1058–1066. DOI: 10.1177/0956797611415540 [PubMed: 21750248]

Nelson KG, Shell DF, Husman J, Fishman EJ, Soh LK. Motivational and self-regulated learning profiles of students taking a foundational engineering course. Journal of Engineering Education. 2015; 104:74–100. DOI: 10.1002/jee.20066

North Carolina Department of Public Instruction. The North Carolina mathematics tests, Edition 3: Technical report. 2008. Retrieved from http://www.ncpublicschools.org/docs/accountability/reports/mathtechmanualdrafted2.pdf

North Carolina Department of Public Instruction. The North Carolina reading comprehension tests: Technical report. 2009. Retrieved from http://www.ncpublicschools.org/docs/accountability/testing/reports/eogreadingtechman3.pdf

Otis N, Grouzet FME, Pelletier LG. Latent motivational change in an academic setting: A 3-year longitudinal study. Journal of Educational Psychology. 2005; 97:170–183. DOI: 10.1037/0022-0663.97.2.170

Pastor DA, Barron KE, Miller BJ, Davis SL. A latent profile analysis of college students' achievement goal orientation. Contemporary Educational Psychology. 2007; 32:8–47. DOI: 10.1016/j.cedpsych.2006.10.003

Perez T, Cromley J, Kaplan A. The role of identity development, values, and costs in college STEM retention. Journal of Educational Psychology. 2014; 106:315–329. DOI: 10.1037/a0034027

Pintrich PR. Multiple goals, multiple pathways: The role of goal orientation in learning and achievement. Journal of Educational Psychology. 2000a; 92:544–555. DOI: 10.1037//0022-0663.92.3.544

Pintrich PR. The role of goal orientation in self-regulated learning. In: Boekaerts M, Pintrich PR, Zeidner M, editorsHandbook of self-regulation: Theory, research and applications. San Diego, CA: Academic Press; 2000b. 451–502.

Pintrich PR. A motivational science perspective on the role of student motivation in learning and teaching contexts. Journal of Educational Psychology. 2003; 95:667–686. DOI: 10.1037/0022-0663.95.4.667

Pintrich PR, Smith D, Garcia T, McKeachie W. Predictive validity and reliability of the Motivated Strategies for Learning Questionnaire (MSLQ). Educational and Psychological Measurement. 1993; 53:801–813. DOI: 10.1177/0013164493053003024

Pulkka AT, Niemivirta M. Adult students' achievement goal orientations and evaluations of the learning environment: A person-centered longitudinal analysis. Educational Research and Evaluation. 2013; 19:297–322. DOI: 10.1080/13803611.2013.767741

Royston P. Multiple imputation of missing values: Update of ice. Stata Journal. 2005; 5:527–536.

Ryan RM, Deci EL. Self-determination theory and facilitation of intrinsic motivation, social development, and well-being. American Psychologist. 2000; 55:68–78. DOI: 10.1037/0003-066X.55.1.68 [PubMed: 11392867]

Samuelstuen MS, Bråten I. Examining the validity of self-reports on scales measuring students' strategic processing. The British Journal of Educational Psychology. 2007; 77:351–378. DOI: 10.1348/000709906X106147 [PubMed: 17504552]

Schultz PW, Hernandez PR, Woodcock A, Estrada M, Chance RC, Aguilar M, Serpe RT. Patching the pipeline reducing educational disparities in the sciences through minority training programs. Educational Evaluation and Policy Analysis. 2011; 33:95–114. DOI: 10.3102/0162373710392371

Schunk DH, Pajares F. Competence perceptions and academic functioning. In: Elliot AJ, Dweck CS, editorsHandbook of competence and motivation. New York: Guilford Press; 2005. 85–104.

Schellings G, Hout-Woltersv B. Measuring strategy use with self-report instruments: Theoretical and empirical considerations. Metacognition and Learning. 2011; 6:83–90. DOI: 10.1007/s11409-011-9081-9

Schiefele U. Situational and individual interest. In: Wentzel KR, Wigfield A, editorsHandbook of motivation at school. New York: Routledge; 2009. 197–222.

Schwinger M, Wild E. Prevalence, stability, and functionality of achievement goal profiles in mathematics from third to seventh grade. Contemporary Educational Psychology. 2012; 37:1–13. DOI: 10.1016/j.cedpsych.2011.08.001

Seifert TL, O'Keefe BA. The relationship of work avoidance and learning goals to perceived competence, externality, and meaning. British Journal of Educational Psychology. 2001; 71:81–92. DOI: 10.1348/000709901158406 [PubMed: 11307710]

Senko C, Hulleman CS, Harackiewicz JM. Achievement goal theory at the crossroads: Old controversies, current challenges, and new directions. Educational Psychologist. 2011; 46:26–47. DOI: 10.1080/00461520.2011.538646

Shell DF, Husman J. Control, motivation, affect, and strategic self-regulation in the college classroom: A multidimensional phenomenon. Journal of Educational Psychology. 2008; 100:443–459. DOI: 10.1037/0022-0663.100.2.443

Shell DF, Soh L. Profiles of motivated self-regulation in college computer science courses: Differences in major versus required non-major courses. Journal of Science Education and Technology. 2013; 22:899–913. DOI: 10.1007/s10956-013-9437-9

Snyder KE, Linnenbrink-Garcia L. A developmental, person-centered approach to exploring multiple motivational pathways in gifted underachievement. Educational Psychologist. 2013; 48:209–228. DOI: 10.1080/00461520.2013.835597

Sterba SK, Bauer DJ. Matching method with theory in person-oriented developmental psychopathology research. Development and Psychopathology. 2010; 22:239–254. DOI: 10.1017/S0954579410000015 [PubMed: 20423538]

Trautwein U, Marsh HW, Nagengast B, Lüdtke O, Nagy G, Jonkmann K. Probing for the multiplicative term in modern expectancy–value theory: A latent interaction modeling study. Journal of Educational Psychology. 2012; 104:763–777. DOI: 10.1037/a0027470

Tuominen-Soini H, Salmela-Aro K, Niemivirta M. Stability and change in achievement goal orientations: A person-centered approach. Contemporary Educational Psychology. 2011; 36:82–100. DOI: 10.1016/j.cedpsych.2010.08.002

Tuominen-Soini H, Salmela-Aro K, Niemivirta M. Achievement goal orientations and academic well-being across the transition to upper secondary education. Learning and Individual Differences. 2012; 22:290–305. DOI: 10.1016/j.lindif.2012.01.002

Turner JC, Thorpe PK, Meyer DK. Students' reports of motivation and negative affect: A theoretical and empirical analysis. Journal of Educational Psychology. 1998; 90:758–771. DOI: 10.1037//0022-0663.90.4.758

Vansteenkiste M, Sierens E, Soenens B, Luyckx K, Lens W. Motivational profiles from a self-determination perspective: The quality of motivation matters. Journal of Educational Psychology. 2009; 101:671–688. DOI: 10.1037/a0015083

Veenman MVJ. Alternative assessment of strategy use with self-report instruments: A discussion. Metacognition and Learning. 2011; 6:205–211. DOI: 10.1007/s11409-011-9080-x

Vermunt JK. Latent class modeling with covariates: Two improved three-step approaches. Political Analysis. 2010; 18:450–469. DOI: 10.1093/pan/mpq025

Wang MT, Degol J. Motivational pathways to STEM career choices: Using expectancy-value perspective to understand individual and gender differences in STEM fields. Developmental Review. 2013; 33:304–340. DOI: 10.1016/j.dr.2013.08.001

Wigfield A, Cambria J. Students' achievement values, goal orientations, and interest: Definitions, development, and relations to achievement outcomes. Developmental Review. 2010; 30:1–35. DOI: 10.1016/j.dr.2009.12.001

Wigfield A, Eccles JS. Expectancy–value theory of achievement motivation. Contemporary Educational Psychology. 2000; 25:68–81. DOI: 10.1006/ceps.1999.1015 [PubMed: 10620382]

Wigfield A, Eccles JS, Fredricks J, SimpkinsRoeser R, Schiefele U. Development of achievement motivation and engagement. In: Lerner R, Lamb M, Garcia Coll C, editorsHandbook of child psychology and developmental science. 7. Vol. 3. New York: Wiley; 2015. 657–700.

Wigfield A, Eccles JS, Schiefele U, Roeser RW, Davis-Kean P. Development of achievement motivation. In: Eisenberg N, Damon W, Lerner RM, editorsHandbook of child psychology: Vol. 3, Social, emotional, and personality development. 6. Hoboken, NJ, US: John Wiley & Sons Inc; 2006. 933–1002.

Wigfield A, Tonks S, Klauda SL. Expectancy-value theory. In: Wentzel KR, Wigfield A, editorsHandbook of motivation in school. New York: Taylor Francis; 2009. 55–76.

Winne PH, Perry NE. Measuring self-regulated learning. In: Boekaerts M, Pintrich PR, Zeidner M, editorsHandbook of self-regulation. San Diego, CA: Academic Press; 2000. 531–566.

Wormington SV, Linnenbrink-Garcia L. A new look at multiple goal pursuit: The promise of a person-centered approach. Educational Psychology Review. 2017; 29:407–445. DOI: 10.1007/s10648-016-9358-2

Zusho A, Pintrich PR, Coppola B. Skill and will: The role of motivation and cognition in the learning of college chemistry. International Journal of Science Education. 2003; 25:1081–1094. DOI: 10.1080/0950069032000052207

Appendix A. Survey Items for Elementary and College Samples

Elementary Sample

Achievement Goal Orientations (Midgley et al., 2000)

Mastery-Approach Goals

1. It's important to me that I learn a lot of new concepts this year.

2. One of my goals in class is to learn as much as I can.
3. It's important to me that I improve my skills this year.
4. One of my goals is to master a lot of new skills this year.
5. It's important to me that I thoroughly understand my class work.

Performance-Approach Goals

1. One of my goals is to look smart in comparison to the other students in my class.
2. It's important to me that other students in my class think I am good at my classwork.
3. One of my goals is to show others that class work is easy for me.
4. It's important to me that I look smart compared to others in my class.
5. One of my goals is to show others that I'm good at my class work.

Performance-Avoidance Goals

1 One of my goals in class is to avoid looking like I have trouble doing the work.

2 It's important that I don't look stupid in class.

3 It's important to me that my teacher doesn't think that I know less than others in class.

3 One of my goals is to keep others from thinking I'm not smart in class.

Task Value (developed based on Pintrich et al., 1993 and Conley, 2012)

1. What I am learning in school is exciting to me.
2. Being good at school is an important part of who I am.
3. I like what I am learning in school.
4. It is important to me to do well in school.
5. For me, doing well in school is very important.
6. I enjoy what I am learning in school.
7. The things I learn in school are practical for me to know. (dropped)
8. I think the things I learn in school are useful.
9. The things I learn in school help me in my daily life outside of school.

Perceived Competence (Midgley et al., 2000)

1. I'm certain I can figure out how to do the most difficult class work.
2. Even if the work is hard, I can learn it.
3. I can do even the hardest work in this class if I try.

4. I'm certain I can master the skills taught in class this year.
5. I can do almost all the work in class if I don't give up.

Behavioral Engagement (Linnenbrink, 2005)

1. Even if I don't see the importance of a particular assignment, I still complete it.
2. Even when I don't want to work on my class work, I force myself to do the work.
3. I force myself to finish my class work even when there are other things I'd rather be doing.
4. Even when my schoolwork is dull and uninteresting, I keep working until I finish.

Cognitive Engagement (developed based on Pintrich et al., 1993 and Fredricks et al., 2005)

1. When I do school work, I check over my work for mistakes.
2. If I don't understand what I read, I go back and read it over again.
3. Before I start my schoolwork, I look through the materials to see how I should organize my work.
4. When I do schoolwork, I ask myself questions to help me understand what to do.
5. When I become confused about something I'm learning in school, I go back and try to figure it out.
6. When I make a mistake, I try to figure out where I went wrong.
7. When I do my schoolwork, I try to figure out which things I don't really understand.
8. I ask myself questions to make sure I understand the material I've been studying or reading.

College Sample

Achievement Goal Orientations (Midgley et al., 2000)

Mastery-Approach Goals

1. It's important to me that I learn a lot of new concepts in science.
2. One of my goals in science is to learn as much as I can.
3. It's important to me that I improve my skills in science this year.
4. One of my goals is to master a lot of new skills in science this year.
5. It's important to me that I thoroughly understand coursework in science.

Performance-Approach Goals

1. One of my goals is to look smart in comparison to the other students in science.

2. It's important to me that other students think I am good at science.
3. One of my goals is to show others that science is easy for me.
4. It's important to me that I look smart compared to others in science.
5. One of my goals is to show others that I'm good at science.

Performance-Avoidance Goals

1. One of my goals in science is to avoid looking like I have trouble doing the work.
2. It's important to me that my professors don't think that I know less than others in science.
3. One of my goals is to keep others from thinking I'm not smart in science.
4. It's important to me that I don't look stupid in science.

Task Value (adapted from Conley, 2012)

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.
6. It is important for me to be a person who reasons scientifically.
7. Being someone who is good at science is important to me.
8. It is important for me to be someone who is good at solving problems that involve science.
9. Being good in science is an important part of who I am.
10. Science concepts are valuable because they will help me in the future.
11. Science will be useful for me later in life.
12. Being good in science will be important for my future (like when I get a job or go to graduate school).

Perceived Competence (Midgley et al., 2000)

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

Behavioral Engagement (Linnenbrink, 2005)

1. Even when my coursework is dull and uninteresting, I keep working until I finish.
2. Even when I don't want to do my class readings and assignments, I force myself to do the work.
3. Even if I don't see the importance of a particular class reading or assignment, I still complete it.
4. I force myself to finish my coursework even when there are other things I'd rather be doing.

Cognitive Engagement (Pintrich et al., 1993)

1. When reading for my courses, I make up questions to help focus my reading.
2. When I become confused about something I'm reading for class, I go back and try to figure it out.
3. If course materials are difficult to understand, I change the way I read the material.
4. Before I study new course material thoroughly, I often skim it to see how it is organized.
5. I ask myself questions to make sure I understand the material I have been studying.
6. I try to change the way I study in order to fit the course requirements and instructor's teaching style.
7. I try to think through a topic and decide what I am supposed to learn from it rather than just reading it over when studying.
8. When studying for my courses I try to determine which concepts I don't understand well.
9. When I study for this class, I set goals for myself in order to direct my activities in each study period.
10. If I get confused taking notes in class, I make sure I sort it out afterwards.

Career Intentions (Schultz et al., 2011)

1. To what extent do you intend to pursue a research-related career in science?" (1 = *definitely will not*, 10 = *definitely will*).

Educational Impact and Implications

Three common patterns of motivation (*Moderate-High All, Intrinsic and Confident,* and *Average All*) were identified across a sample of elementary students (focused on schooling generally) and college students (focused on science specifically), with one unique pattern identified in each sample (*Very High All* – elementary only; *Moderate Intrinsic and Confident* – college only). Across studies, profiles characterized by a focus on learning and understanding, value for coursework, and high confidence in one's abilities to do course work were associated with higher levels of engagement, mathematics achievement (elementary only), STEM course completion (college only), and intentions to pursue a science career (college only), generally regardless of whether a strong focus on looking smart and avoiding appearing incompetent was also included in the profile. In contrast, profiles characterized by more moderate levels of motivation had the lowest levels of academic engagement, achievement, and persistence. Results highlight the importance of creating educational contexts that support goals to develop and learn, and support students' valuing of school (or a specific domain) and their confidence in their abilities to learn.

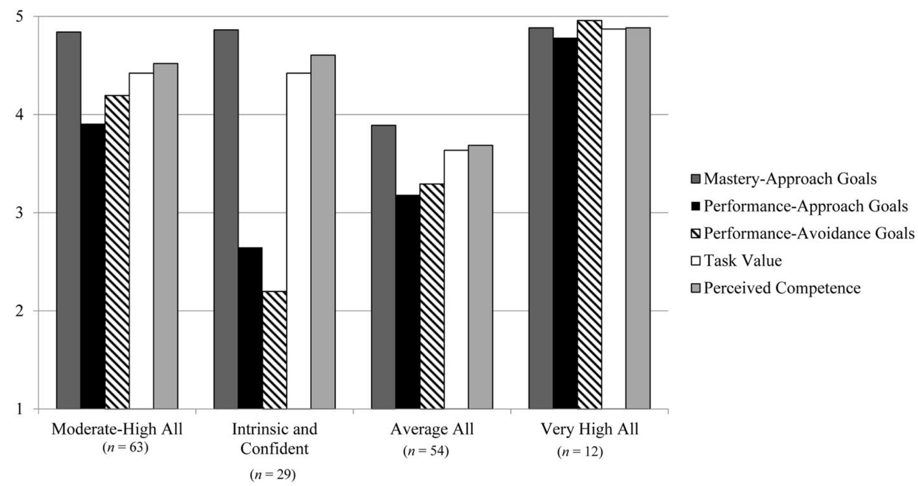

Figure 1.

Raw values of integrative motivational profiles in elementary sample.

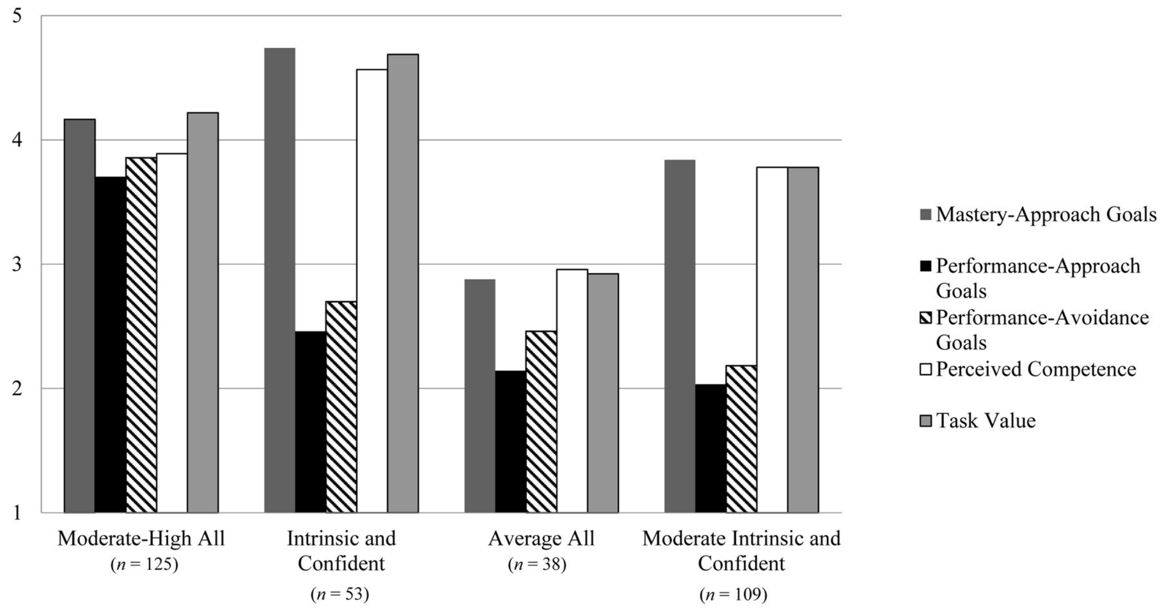

Figure 2.

Raw values of integrative motivational profiles in college sample.

Table 1

Bivariate Correlations and Descriptive Statistics for all Study Variables in Studies 1 and 2

	1	2	3	4	5	6	7	8	9	10	11	Study 2: Mean (SD)
1. Mastery-approach goals	--	.22**	.20**	.53**	.82**	.47**	.49**	.07	--	.46**	.34**	4.07 (0.64)
2. Performance-approach goals	.16*	--	.80**	.15**	.31**	.02	.21**	.03	--	.18**	.25**	2.82 (0.93)
3. Performance-avoidance goals	.18*	.64**	--	.07	.26**	.05	.14*	-.02	--	.14*	.15*	3.05 (0.89)
4. Perceived competence	.60**	.16*	.11	--	.55*	.25**	.46**	.05	--	.30**	.23**	3.86 (0.77)
5. Task value	.68**	.20*	.17*	.56**	--	.38**	.51**	.19**	--	.53**	.38**	4.06 (0.64)
6. Behavioral engagement	.48**	-.03	-.08	.50**	.41**	--	.47**	.14*	--	.22**	.18**	3.85 (0.74)
7. Cognitive engagement	.59**	.15	.07	.54**	.52**	.54**	--	.14*	--	.31**	.20**	3.55 (0.56)
8. Math/science achievement	.18*	-.05	-.09	.19*	.24**	.25**	.15	--	--	.02	.15**	3.33 (0.71)
9. Reading achievement (Study 1)	.08	.14	.12	.05	.09	.14	.07	.14	--	--	--	--
10. Career intentions (Study 2)	--	--	--	--	--	--	--	--	--	--	.25**	5.19 (3.08)
11. STEM courses (Study 2)	--	--	--	--	--	--	--	--	--	--	--	2.30 (1.21)
Study 1: Mean (SD)	4.57 (0.47)	3.51 (0.99)	3.58 (1.06)	4.28 (0.62)	4.19 (0.58)	4.44 (0.58)	3.90 (0.64)	0.16 (0.45)	0.08 (0.51)	--	--	

Note: Values below diagonal correspond to Study 1; values above diagonal correspond to Study 2.

* = $p < .05$;

** $p < .01$.

Math/science achievement represents math growth achievement for Study 1 and STEM GPA for Study 2. Unless otherwise noted, all items measured on a 5-point Likert-type scale. Math/research achievement are standardized scores. Career intentions measured on a 10-point Likert-type scale; STEM GPA measured on a 4-point scale.

Table 2

Fit indices for integrative profile solutions

Number of profiles	AIC	BIC	Adjusted BIC	Entropy	Class Sizes
Elementary Sample					
2	1466.950	1531.400	1464.920	.860	103, 56
3	1397.340	1495.545	1394.247	.883	30, 74, 55
4	**1341.257**	**1473.220**	**1337.101**	**.909**	**29, 64, 54, 12**
5	1331.397	1497.118	1326.178	.925	51, 28, 12, 3, 65
College Sample					
2	3267.299	3389.256	3287.749	.857	90, 235
3	3144.448	3308.327	3171.927	.840	40, 208, 77
4	**3076.017**	**3281.818**	**3110.526**	**.853**	**38, 53, 125, 109**
5	3016.759	3306.406	3065.327	.892	109, 0, 51, 111, 54

Note: AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion. Bolded rows indicate select profile solution.

Table 3

Profile and Outcome Variables for Motivational Profiles in Elementary School Sample (Study 1)

	Moderate-High All	**Intrinsic and Confident**	**Average All**	**Very High All**	***F* (p-value)**	**Effect Size**
Mastery-Approach	0.53_a	0.62_a	-1.16_b	0.66_a	119.22 ($p < .001$)	0.70
Performance-Approach	0.70_b	-0.85_d	-0.31_c	1.29_a	28.85 ($p < .001$)	0.36
Performance-Avoidance	0.62_b	-1.30_d	-0.27_c	1.30_a	75.15 ($p < .001$)	0.59
Perceived Competence	0.49_b	0.53_b	-0.95_c	1.18_a	50.55 ($p < .001$)	0.50
Task Value	0.60_b	0.41_b	-0.95_c	0.98_a	53.99 ($p < .001$)	0.51
Behavioral Engagement	4.60_a (0.06)	4.64_a (0.05)	4.06_b (0.10)	4.70_a (0.07)		0.56
Cognitive Engagement	4.20_a (0.09)	4.14_a (0.08)	3.29_b (0.08)	4.30_a (0.07)		0.80
Math Growth Achievement	0.08_{ab} (0.07)	0.10_{ab} (0.09)	-0.11_b (0.07)	0.15_a (0.07)		0.30
Read Growth Achievement	0.15 (0.09)	0.11 (0.10)	0.13 (0.10)	0.20 (0.07)		0.09

Note: Motivational variables presented as standardized *Z* scores. Values in parentheses represent standard error values. Values with different subscripts in same row represent significantly different values based on Tukey HSD tests for motivational variables and equality tests of means for outcome variables. Effect size represents η^2 for motivational variables and the mean difference between groups divided by the standard deviation of the outcome for outcome variables. Bakk and Vermunt's (2014) modified BCH method was employed to examine the relation between the profiles and outcomes, controlling for student gender and reduced-fee lunch status.

Table 4

Profile and Outcome Variables for Motivational Profiles in College Sample (Study 2)

	Moderate-High All	Intrinsic and Confident	Average All	Moderate Intrinsic & Confident	*F* (*p*-value)	Effect Size
Mastery-Approach	0.14_{b}	1.04_{a}	-1.86_{c}	-0.05_{b}	153.48 ($p < .001$)	0.59
Performance-Approach	0.95_{a}	-0.39_{b}	-0.73_{c}	-0.63_{c}	143.52 ($p < .001$)	0.57
Performance-Avoidance	0.91_{a}	-0.40_{b}	-0.66_{b}	-0.64_{b}	118.40 ($p < .001$)	0.53
Perceived Competence	0.04_{b}	0.92_{a}	-1.16_{c}	-0.10_{b}	48.68 ($p < .001$)	0.31
Task Value	0.25_{b}	0.98_{a}	-1.79_{d}	-0.13_{c}	145.27 ($p < .001$)	0.58
Behavioral Engagement	3.92_{ab} (0.04)	4.12_{a} (0.07)	3.16_{c} (0.16)	3.84_{b} (0.07)		0.67
Cognitive Engagement	3.60_{ab} (0.04)	3.77_{a} (0.06)	3.04_{c} (0.07)	3.52_{b} (0.03)		0.68
Career Intentions	5.32_{b} (0.29)	7.09_{a} (0.26)	2.45_{c} (0.20)	4.84_{b} (0.23)		0.81
Semester 4 STEM GPA	3.34 (0.05)	3.33 (0.06)	3.07 (0.16)	3.20 (0.05)		0.13
Semester 4 STEM Courses	2.60_{a} (0.10)	2.54_{a} (0.12)	1.20_{b} (0.09)	2.42_{a} (0.10)		1.02

Note: Motivational variables presented as standardized *Z* scores. Values in parentheses represent standard error values. Values with different subscripts in same row represent significantly different values based on Tukey HSD tests for motivational variables and equality tests of means for outcome variables. Effect size represents η^2 for motivational variables and the mean difference between groups divided by the standard deviation of the outcome for outcome variables. A MANOVA was conducted to examine differences in the motivational variables included in the profiles (n = 325). Bakk and Vermunt's (2014) modified BCH method was employed to examine the relation between the profiles and outcomes. For all outcome analyses, we controlled for student gender, family income, and the first-year version of each outcome. We also controlled for first year STEM GPA for analyses predicting career intentions, STEM GPA, and STEM courses. Analyses predicting behavioral engagement, cognitive engagement, and STEM GPA only included students enrolled in a science course when they took the survey.

Author Manuscript
Author Manuscript
Author Manuscript

Table 5

Motivational Profile Membership Among Elementary and College-Aged Students

	Moderate-High All	Intrinsic and Confident	Average All	Very High All	Moderate Intrinsic and Confident
Elementary (*n* = 158)	39.9% (*n* = 63)	18.4% (*n* = 29)	34.2% (*n* = 54)	7.6% (*n* = 12)	-- --
College (*n* = 325)	38.5% (*n* = 125)	16.3% (*n* = 53)	11.7% (*n* = 38)	-- --	33.5% (*n* = 109)