# *Profiles of Motivated Self-Regulation in College Computer Science Courses: Differences in Major versus Required Non-Major Courses*

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# Profiles of Motivated Self-Regulation in College Computer Science Courses: Differences in Major versus Required Non-Major Courses

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**Abstract** The goal of the present study was to utilize a profiling approach to understand differences in motivation and strategic self-regulation among post-secondary STEM students in major versus required non-major computer science courses. Participants were 233 students from required introductory computer science courses (194 men; 35 women; 4 unknown) at a large Midwestern state university. Cluster analysis identified five profiles: (1) a strategic profile of a highly motivated by-any-means good strategy user; (2) a knowledge-building profile of an intrinsically motivated autonomous, mastery-oriented student; (3) a surface learning profile of a utility motivated minimally engaged student; (4) an apathetic profile of an amotivational disengaged student; and (5) a learned helpless profile of a motivated but unable to effectively self-regulate student. Among CS majors and students in courses in their major field, the strategic and knowledge-building profiles were the most prevalent. Among non-CS majors and students in required non-major courses, the learned helpless, surface learning, and apathetic profiles were the most prevalent. Students in the strategic and knowledge-building profiles had significantly higher retention of computational thinking knowledge than students in other profiles. Students in the apathetic and surface learning profiles saw little instrumentality of the course for their future academic and career objectives. Findings show that students in STEM fields taking required computer science courses exhibit the same constellation of motivated strategic self-regulation profiles found in other post-secondary and K-12 settings.

**Keywords** Student self-regulation · Student motivation · Discipline-based education · Computational thinking · Approaches to learning · Learning profiles

## Introduction

The need for more post-secondary students to major and graduate in STEM fields is widely recognized as in the National Academies report "Rising above the gathering storm: Energizing and employing America for a brighter economic future" (Committee 2007). Considerable funding is provided for enhancing instruction in STEM fields (Kuenzi et al. 2006). A relatively low percentage of students major in STEM fields, and despite attracting students with generally better academic preparation and aptitude, students in STEM fields experience higher attrition than those in other post-secondary majors (Kuenzi et al. 2006). Students' strategic self-regulation has been identified as playing a critical role in their success in STEM learning (Donovan and Bransford 2005). However, how students' motivation and self-regulation in college STEM courses affects their achievement and attrition is still not well understood.

Recently, there has been a growing interest in conceptualizing the complex links among motivation, affect, and the cognitions that underlie strategic and self-regulated behavior (e.g., Bandura 1997; Boekaerts and Cascallar 2006; Eccles and Wigfield 2002; Goetz et al. 2006; Linnenbrink 2007; Pekrun et al. 2007; Pekrun and

D. F. Shell (✉)
Department of Educational Psychology, 114 TEAC, University of Nebraska-Lincoln, Lincoln, NE 68588-0345, USA
e-mail: dshell2@unl.edu

L.-K. Soh
Department of Computer Science and Engineering, 122E AVH, University of Nebraska-Lincoln, Lincoln, NE 68588-0115, USA

Linnenbrink-Garcia 2012; Pintrich 2000, 2003; Shell and Husman 2008; Zimmerman 2008). However, examinations of this complexity have typically focused on the individual motivational constructs and strategic self-regulatory behaviors with the examination of the relative contributions of each separate variable and the many interaction, mediator, and moderator effects among them (e.g., Eccles an Wigfield 2002; Pekrun et al. 2007; Zimmerman 2008).

An alternative perspective is to focus on the joint or combined influence of multiple motivators on multiple aspects of strategic self-regulation. This approach follows Snow's (1992) observation that "Human beings are not lists of independent variables; they are coordinated wholes" (p. 10) and reflects Pintrich's (2003) call for integrative and synthetic research that examines how motivational constructs relate to each other and serve possibly similar motivating functions. From this perspective, if one considers a student as "motivated," one must account for multiple aspects of motivation including the student's current goals, expectancies, affect, and so on. Similarly, the identification of a student as being strategic or self-regulated, as in Pressley et al.'s (1987) good strategy user, includes a constellation of behaviors and cognitions, not simply effort or use of a specific strategy. In this approach, motivation and strategic self-regulation are viewed as profiles that portray coordinated patterns of motivational influences and strategic self-regulatory action. Profile analysis focuses on the pattern of influence across all variables rather than on attempting to partition variance among the constituent constructs.

Research into profiles has accelerated in recent years as researchers have seen the benefits of the profile framework (Chen 2012; Conley 2012; Daniels et al. 2008; Guthrie et al. 2009; Hayenga and Corpus 2010; Schwinger et al. 2012; Shell and Husman 2008; Tuominen-Soini et al. 2011; Vansteenkiste et al. 2009). These recent studies have not followed a systematic theoretical and empirical course. Despite this, a pattern of stable, replicable profiles has been emerging.

In the study assessing the widest range of motivational, affective, and strategic self-regulatory constructs to date, Shell and Husman (2008) identified 5 profiles of college students' motivated self-regulation. Using canonical correlation, they found one bipolar dimension contrasting profiles of a highly motivated by-any-means good strategy user (Pressley et al. 1987) with an amotivational (Reeve et al. 2004) or apathetic student; a second bipolar dimension contrasting profiles of an intrinsically motivated knowledge-building (Scardamalia and Bereiter 2003, 2006), autonomous (Reeve et al. 2004), mastery-oriented (Pintrich 2003) student with a utility motivated surface learning student; and a third unipolar dimension with a profile of a learned helpless student (Dweck 1999).

Other recent studies have typically replicated these profiles, but because they have assessed fewer motivational and strategic self-regulatory variables, they often have found only a subset of the five Shell and Husman profiles. All studies have replicated the motivated by-any-means good strategy user and mastery-oriented knowledge-building profiles in some form. Studies also typically find an apathetic or amotivated profile and a profile resembling the surface learner (see Chen 2012; Daniels et al. 2008; Hayenga and Corpus 2010; Tuominen-Soini et al. 2011; Vansteenkiste et al. 2009). Studies finding four profiles all have used a clustering or latent profiles framework derived from either goal theory (Daniels et al. 2008; Tuominen-Soini et al. 2011) using mastery and performance goals or self-determination theory (Hayenga and Corpus 2010; Vansteenkiste et al. 2009) using autonomous—controlled or intrinsic—extrinsic motivation. These frameworks do not allow a solution with more than four profiles, however, because that is the maximum number of combinations.

Schwinger et al. (2012) using a broader array of constructs found a five profile solution similar to Shell and Husman. Importantly, like Shell and Husman, they included self-regulatory strategies in the profile determination. Other recent studies, while examining impacts on strategic self-regulation, have profiled only using motivational constructs. This may explain why Conley (2012) using a broad array of goal and expectancy-value constructs, but not self-regulatory constructs found seven profiles. It is impossible to know if the somewhat minor distinctions between profiles actually have meaningful behavioral, strategy, and self-regulatory consequences.

Findings from these recent efforts mirror those found previously by researchers working in the tradition of student approaches to learning (SAL) theory (e.g., Ainley 1993; Biggs 1976; Entwistle and Mc Cune 2004; Tait and Entwistle 1996; Vermunt and Vermetten 2004). As reviewed by Entwistle and Mc Cune (2004), multiple studies identified three profiles: (a) a reproducing or surface approach linking rote or surface level strategies to motives based on fear of failure and extrinsic motivation, (b) a meaning making or deep approach linking deep processing meaning making strategies to intrinsic motivation and interest, and (c) an achieving or strategic approach linking effective management strategies to achievement motivation. Tait and Entwistle (1996) identified a fourth apathetic profile characterized by lack of interest and motivation, and Vermunt and Vermetten (2004) identified a fifth profile linking lack of regulation to an ambivalent motivation consisting of uncertainty about goals and capability. The close correspondence to the Shell and Husman (2008) profiles lends further credence to their five profile framework.

Shell et al. (2010; also Entwistle and Mc Cune 2004) note that profiles are dynamic. A student's profile may shift across different courses and subject matter domains as well as in response to contextual factors within a course. Hayenga and Corpus (2010) and Tuominen-Soini et al. (2011) found that students' profile adoption was relatively stable across an academic school year, but in both studies, approximately 40 % of students shifted profiles. Linnenbrink-Garcia (2011) found that profiles were affected by classroom interventions designed to establish mastery or performance goal structures. These prior studies suggest that classroom factors influence profile adoption. However, the impact of contextual and classroom factors is not well understood, especially at the post-secondary level.

## The Present Study

The goal of the present study was to utilize the profiling approach to better understand motivation and strategic self-regulation in post-secondary STEM courses, specifically differences in profiles for students in courses in their major field versus students in required but non-major courses. The courses examined were part of a suite of introductory computer science (CS-1) courses designed to improve learning of computational thinking and better incorporate computational thinking principles into the disciplines (Soh et al. 2009). Courses include one for CS majors, one for combined business/computer science honors program majors, one for engineering majors with content tailored for engineering, and one for a mix of CS, engineering, and general science majors. These courses are all required within the students' major field of study (e.g., engineering, physics, computer science, etc.). But little is known about how students' motivation and strategic self-regulation may differ in a course that is integral to their major, like computer science majors in a CS course versus a course that is supplemental to their major field of study, like engineering majors in a CS course. We wanted to know whether students in these two different scenarios adopt similar or different profiles of motivated strategic self-regulation.

The goal of profiling is to examine the joint or combined influences of variables. Profiling, therefore, requires methods that, as Ainley (1993) notes, "preserve the integrity of the combinations" (p. 396). Early research by SAL theorists (e.g., Biggs 1976; Entwistle and Mc Cune 2004; Tait and Entwistle 1996; Vermunt and Vermetten 2004) drew on qualitative phenomenographic interviews from which surveys were developed. Factor analysis was then used to identify profile dimensions based on survey responses reflecting various approaches to learning, studying, and motivation. Shell and Husman (2008) utilized canonical correlation to identify profiles from dimensions relating motivation to strategic self-regulation. Most recent profiling studies (Chen 2012; Conley 2012; Daniels et al. 2008; Hayenga and Corpus 2010; Schwinger et al. 2012; Tuominen-Soini et al. 2011; Vansteenkiste et al. 2009) have adopted a *person-centered* approach using cluster analysis to determine whether coherent groups of students who share common motivational and strategic self-regulatory characteristics can be identified.

Each of these methods has particular strengths and weaknesses. The goal of factor analysis is to place each variable within a single dimension. This is effective in identifying unique profiles, but biases results toward one-to-one relationships. Although factor analysis allows for the possibility of variables contributing to multiple dimensions, it is designed to reduce these secondary contributions. Both canonical correlation and cluster analysis have an advantage in allowing for one-to-many relationships. Variables can contribute in different ways within different profile dimensions. Canonical correlation has the additional advantage of being the only profiling method that considers the relationship between variable sets, like motivation and self-regulation, in determining dimensions rather than just the shared covariance among all variables; however, this requires rather large sample sizes (see Thompson 1984).

Recent profiling research (Chen 2012; Conley 2012; Daniels et al. 2008; Hayenga and Corpus 2010; Schwinger et al. 2012; Shell and Husman 2008; Tuominen-Soini et al. 2011; Vansteenkiste et al. 2009) suggests that motivational and strategic self-regulatory variables have one-to-many relationships. Because of this, we chose cluster analysis over factor analysis for identifying profiles. We also chose cluster analysis over canonical correlation because we lacked suitable sample size.

All of the methods used for profile analysis are interpretive. Regardless of the extent to which statistical indicators are available to suggest the number of profiles present, the ultimate decision relies on theoretical coherence. The patterns of variables within a profile must be explainable in the context of the theories and prior research on the constituent constructs. We also considered it important to include both motivation and strategic self-regulation within the profile determination. The prior studies that have included both motivation and self-regulation constructs in the profile determination (Biggs 1976; Entwistle and Mc Cune 2004; Schwinger et al. 2012; Shell and Husman 2008; Tait and Entwistle 1996; Vermunt and Vermetten 2004) have generally identified a five profile solution corresponding to the Shell and Husman (2008) profiles. Because this five profile solution appears to have the best theoretical and empirical coherence, we have chosen to anchor our examination of profiles in the five profile framework.

Motivation and Affect Variables

Motivational variables in this study were drawn from goal orientation (Dweck and Leggett 1988; Elliot et al. 2011; Senko et al. 2011), future time perspective (FTP) (Husman and Lens 1999), and emotion/affect (Linnenbrink 2007; Pekrun et al. 2007; Pekrun and Linnenbrink-Garcia 2012).

Our goal orientation measures were based on the framework proposed by Shell et al. (2010). Elliot et al. (2011) recently argued that achievement goals are goals about specific tasks and assignments anchored in the context of doing or evaluating the task. Shell et al. follow another tradition in goal theory that has focused on goals students set for courses (see discussion in Elliot et al. 2011; Senko et al. 2011). Drawing on Dweck's formulations (e.g., Dweck and Leggett 1988) and based on extensions of this work (Schraw et al. 1995; Shell and Husman 2008), the Shell et al. framework examines goals in three dimensions (learning, performance, and task) with each dimension having an approach and avoid component.

Learning approach goals are goals directed at learning new knowledge or gaining competence consistent with most past formulations of learning or mastery goals (Dweck and Leggett 1988; Senko et al. 2011). Within the achievement goal literature, learning avoid goals have been difficult to clarify (see Elliot et al. 2011; Senko et al. 2011). The most recent formulation by Elliot et al. (2011) focusses on avoiding doing worse than prior work. Although the Elliot et al. formulation may be appropriate for individual assignments or tests, Shell et al. (2010) proposed that the most logical contrast to the desire to learn or master course material was a deliberate goal to avoid learning anything. Think about the old saying *you can lead a horse to water, but you can't make it drink*. This reflects the Shell et al.'s notion of learning avoidance. A student might complete all assignments and do enough to get a score on a test or a grade in a class, but not put forth the additional effort to fully learn the material. A student who does not care about a class might not care to learn anything from the class and therefore might set a goal to avoid really learning the material in a meaningful way. Bereiter and Scardamalia (1989) have observed that students often approach school as a series of tasks to complete rather than as an opportunity to learn. Shell et al. (2010) argue that when assessing goal orientation for a class as a general tendency, learning avoidance reflects this active desire to not learn material or take anything away from the course.

Performance goals were assessed consistent with prior formulations (Senko et al. 2011). Performance approach goals reflect a desire to obtain favorable judgments of one's abilities by others or perform better than others in the class. Performance avoid goals reflect the desire to avoid negative judgments of one's ability or do worse relative to others in the class. Approach and avoid performance goals have been found to motivate very different behaviors. Approach seems to be positive for increasing effort and working memory allocation; avoid seems to be detrimental; decreasing effort and allocation (Senko et al. 2011).

Task or work avoid goals reflect a desire to get through the class with as little time and effort as possible (Ames 1992; Shell and Husman 2008; Wolters 2003). Recent research (Grant and Dweck 2003) has identified outcome or task goals that appear to be the approach counterpart to work avoid. Performance goal orientation is about normative performance, doing better or worse in relation to others or gaining positive or avoiding negative evaluations of competence by others. Students, however, also appear to set general, non-normative, goals such as goals to get a good grade. These goals reflect wanting to perform a task well. They differ from learning goals in that there is no learning outcome specified. Students can have a goal to "do my work to the best of my ability" without any expectation that they will learn anything. They simply want to get the job done well as opposed to quick and easy in a work avoid goal. These kinds of task approach goals probably typify most goals that we pursue in work and other real world settings.

Future time perspective (FTP) is a motivational construct that links utility value—perceived relevance and usefulness for the specific task—with a perception of time in which goals and achievements exist (Husman and Lens 1999; Husman and Shell 2008; Shell and Husman 2008). Connectedness is the cognitive aspect of FTP that refers to the ability to make connections between present activities and some future goal (Husman and Shell 2008). Individuals who have a stronger or longer FTP are more able to see the connection between their present activity and future goals. Shell and Husman (2001) found that connectedness is a predictor of student achievement in post- secondary classrooms.

Perceived instrumentality (PI) is defined as a person's perception of how useful a present task is for a future goal (Husman et al. 2004; Husman and Hilpert 2007). Past literature indicates that an individual's perception of instrumentality positively affects learning in the classroom. Students with a long FTP can more easily see the connection between their current class activities for the more distant future (instrumentality) and thus have an increased instrumentality and subsequent motivation for their present learning in school (Husman and Lens 1999).

Affect/emotion involves students' general feelings and reactions to the class (Pekrun et al. 2007; Pekrun and Linnenbrink-Garcia 2012). Positive emotions have been shown to increase students' engagement in academic work and support more adaptive self-regulation (Pekrun and Linnenbrink-Garcia 2012; Shell and Husman 2008).

Negative emotions have been found to decrease motivation and lead to maladaptive self-regulation (Shell and Husman 2008).

Strategic Self-Regulated Learning Variables

Strategic self-regulated learning variables were drawn from Shell and Husman (2008). They assessed four aspects of student strategic self-regulation in classes. The first aspect is general metacognitive self-regulation. Students who are self-regulating engage in active planning, monitoring, and evaluation of their learning and apply general learning strategies to accomplish these (e.g., Boekaerts and Cascallar 2006; Weinstein and Mayer 1986). They are what Pressley et al. (1987) called good strategy users.

The second aspect comes from the knowledge-building approach to learning proposed by Bereiter, Scardamalia, and their colleagues (Scardamalia and Bereiter 2003, 2006). Central to the knowledge-building approach is the idea that meaningful learning involves the production of knowledge rather than the reproduction of knowledge. This knowledge building is accomplished by an in-depth study of a topic that goes beyond simple factual or recall learning. Learning is tied to personally meaningful goals and includes examination and connection of new knowledge to existing knowledge and coursework in other classes.

The third aspect is student engagement with the class as reflected in active participation and effort. Engagement is assessed with student reported study time and effort for the class (Shell and Husman 2001, 2008). Engagement also considers the extent of student active course involvement by examining question asking (Scardamalia and Bereiter 1992; Shell and Husman 2008). Students who are more engaged tend to have more positive experiences in the class (Pekrun and Linnenbrink-Garcia 2012) and higher achievement.

The final aspect of self-regulation was drawn from research examining more dysfunctional self-regulatory strategies (e.g., Dweck and Leggett 1988; Shell et al. 2005; Vermunt and Vermetten 2004; Wolters 2003; Zimmerman and Martinez-Pons 1988). Lack of regulation (Shell and Husman 2008; Shell et al. 2005) assesses students' confusion and difficulty in effectively studying and self-regulating along with need for support from others. It has been shown to be negatively associated with grades (Shell et al. 2005) and a key component of learned helplessness in classes (Shell and Husman 2008).

## Research Questions and Hypotheses

Our central research question was whether profiles corresponding to the five profile model of Shell and Husman (2008) could be identified among college students taking introductory CS-1 computer science courses. We specifically hypothesized that:

1. Students in the strategic and knowledge-building profiles will retain more core course content than students in the other profiles.
2. Students in courses that are part of their major field of study will be more likely to be in the strategic or knowledge-building profiles, whereas students in required but non-major courses will be more likely to be in the apathetic or surface learning profiles.
3. Learned helplessness will be more prevalent among students in required non-major courses.
4. Men and women students will not differ in profile distribution.

## Methods

### Participants

Participants were 233 students from required introductory computer science courses (194 men; 35 women; 4 unknown) at a large Midwestern state university. One hundred nineteen were freshmen, 63 were sophomores, 32 were juniors, 8 were seniors, and 11 were other/unknown. One course was for computer science majors, one course was for engineering students who were not computer science majors, one course contained a mixture of computer science and non-computer science majors, and one course was in an interdisciplinary business—computer science honors program.

### Instruments

#### *Strategic Self-Regulation Instruments*

Strategic self-regulation was assessed with the Student Perceptions of Classroom Knowledge Building (SPOCK, Shell and Husman 2008; Shell et al. 2005). The instrument asks students about strategic self-regulatory behavior within a specific course. Students were asked to respond only for the class from which they were recruited. All questions were answered on a five-point Likert scale from 1 (*almost never*) to 5 (*almost always*). The SPOCK measures four aspects of students' perceptions of their own strategic self-regulation.

*Self-regulated strategy use* (9 items) assesses the extent of student planning, goal setting, monitoring, and evaluation of studying and learning (e.g., In this class, I try to determine the best approach for studying each assignment; In this class, I try to monitor my progress when I study; In this class, I make plans for how I will study). These items assess strategic behaviors and study strategies typically associated with models of strategic self-regulation (e.g., Pintrich 2004; Weinstein and Mayer 1986) and what Pressley et al. (1987) have termed the good strategy user.

*Knowledge building* (10 items) assesses the extent of student exploration and interconnection of knowledge from the class based on the knowledge building and intentional learning models of Scardamalia and Bereiter (2003, 2006). Questions in this scale focus on going beyond the given material and on tying the information being learned to other courses and existing knowledge (e.g., Whenever I learn something new in this class, I try to tie it to other facts and ideas that I already know; In this class, I tried to examine what I was learning in depth; In this class, I focused on those topics that were personally meaningful to me).

Two scales assess the extent of question asking in class (see Scardamalia and Bereiter 1992; Shell and Husman 2008; Shell et al. 2005). *High-level question asking* (5 items) assesses the extent to which students ask questions that extend or expand on the basic information being provided in the class (e.g., In this class, I ask questions about things I am curious about.; In this class, I ask questions to help me know more about the topics we are covering in class.;). *Low-level question asking* (4 items) assesses the extent to which students ask questions to obtain or clarify basic course information (e.g., In this class, I ask questions so that I can be sure I know the right answers for tests; In this class, I ask questions to be clear about what the instructor wants me to learn).

*Lack of regulation* (10 items) assesses students' lack of understanding of how to study and need for assistance and guidance in studying (e.g., In this class, I couldn't figure out how I should study the material.; In this class, I had difficulty determining how I should be studying the material.; In this class, I relied on someone else to tell me what to do.). This scale assessed behaviors similar to those in the lack of regulation orientation identified by Vermunt and Vermetten (2004).

Scale scores were computed as the mean score of the scale items. Coefficient alpha reliability estimates for the self-regulated strategy, knowledge building, high-level question asking, low-level question asking, and lack of regulation scales were, respectively, .90, .90, .89, .87, and .87.

Study measures were drawn from Shell and Husman (2001, 2008). *Study time* was assessed by asking participants to indicate the average number of hours per week they spent studying on a 1–7 scale representing 5 h units from 1 (*<5 h per week*) to 7 (*over 30 h per week*). *Perceived study effort* was assessed by asking participants to indicate their perception of the effort they put forth studying relative to most students on a 5-point Likert scale as follows: 1 (*I put forth much less effort studying*), 2 (*I put forth somewhat less effort studying*), 3 (*I put forth about the same effort studying*), 4 (*I put forth somewhat more effort studying*), and 5 (*I put forth much more effort studying*).

### *Motivation and Affect Measures*

*Class Goal Orientation* Students' classroom goal orientation was measured with an instrument adapted from that used by Shell and Husman (2008) based on Dweck's (e.g., Dweck and Leggett 1988) formulation and Schraw et al. (1995). The Shell and Husman (2008) instrument was extended based on the goal framework described in Shell et al. (2010). The instrument assesses approach and avoid goals for the course in three dimensions: (a) learning or mastery for personal growth and development (b) normative performance relative to other students or ego protection, and (c) task effort. *Learning approach goals* (5 items) assess goals for developing long-term, deep understanding of class information and skills (e.g., Learning new knowledge or skills in the class just for the sake of learning them; Really understanding the course material.). *Learning avoid goals* (4 items) assess deliberate avoidance of long-term learning or retention of class information (e.g., Getting a grade whether I remember anything beyond that or not; Getting this course done even though I don't care about the content).

*Performance approach goals* (5 items) assess normative performance relative to other students and favorable assessments of ability by others for ego protection (e.g., Doing better than the other students in the class on tests and assignments; Impressing the instructor with your performance.). *Performance avoid goals* (3 items) assess avoiding negative performance evaluations and unfavorable assessments of ability by others (e.g., Keeping others from thinking you are dumb; Avoiding looking like you do not understand the class material).

*Task approach goals* (4 items; also called outcome goals, see Grant and Dweck 2003) assess efforts to accomplish high achievement and do well on class assignments and activities without reference to normative comparisons (e.g., Getting a good grade in the class. Getting high grades on tests and other graded assignments.). *Task or work avoid goals* (3 items; see Ames 1992; Wolters 2003) assess deliberate intention to put forth minimal effort in the course (e.g., Getting a passing grade with as little studying as possible; Getting through the course with the least amount of time and effort).

Students rated goals on a 5-point Likert scale from 1 (*very unimportant*) to 5 (*very important*). Scores were computed as the mean score of the items in each scale. Coefficient alpha reliability estimates for the learning approach, learning avoid, performance approach, performance avoid, task approach, task/work avoid scales were, respectively, .89, .88, .78, .87, .91, and .82.

*Future Time Perspective* Future time perspective was measured by two instruments. The first was an adaptation of the Future Time Perspective Scale connectedness subscale from Husman and Shell (2008; also, Shell and Husman 2001, 2008). Eleven of the original 16 items were used and the question stem changed to assess connectedness between the present and the student's future career (e.g., One should be taking steps today to help realize future career goals.; What will happen in the future in my career is an important consideration in deciding what action to take now). Participants are asked to indicate their agreement with each question using a 5-point Likert scale from 1 (*strongly disagree*) to 5 (*strongly agree*). The connectedness score was computed as the mean of the items in the scale, with negatively worded items reverse scored. Coefficient alpha reliability estimate for the connectedness scale was .89.

The second was the Perceptions of Instrumentality Scale (Husman and Hilpert 2007). This scale measures student perceptions of the instrumental relationship between their specific course work and attaining STEM academic and career goals. The scale measures both endogenous instrumentality (4 items; e.g., I will use the information I learn in this CS1 class in the future.; What I learn in this CS1 will be important for my future occupational success) and exogenous instrumentality (4 items; e.g., The grade I get in this CS1 class will not be important for my future academic success (reverse scored); The grade I get in this CS1 class will affect my future). Participants are asked to indicate their agreement with each question using a 5-point Likert scale from 1 (*strongly disagree*) to 5 (*strongly agree*). Endogenous and exogenous scale scores are computed as the mean of the items in each scale, with negatively worded items reverse scored. Coefficient alpha reliability estimates for the endogenous and exogenous scales were, respectively, .94 and .62.

*Course Affect* Affect was measured by a modified version of the Positive and Negative Affect Scale (PANAS; Watson et al. 1988). The modified PANAS contains 20 items which asked students to rate the frequency with which they experience 10 positive and 10 negative emotions in their class on a 5-point scale from 1 (*a few times or none*) to 5 (*most of the time, 80–100 % of the time*). Positive emotions are interested, excited, attentive, capable, active, enthusiastic, proud, alert, inspired, and determined. Negative emotions are irritable, scared, ashamed, nervous, distressed, upset, guilty, hostile, frustrated, and afraid. Scale scores were computed as the mean of the items in each scale. Coefficient alpha reliability estimates for the positive and negative affect scales were, respectively, .91 and .91.

*Computational Thinking Knowledge* Students' computational thinking was measured with a knowledge test developed by CSCE faculty. The computational knowledge test contained a blend of conceptual and problem-solving application questions for the core computational thinking content common to all CS-1 classes. The test was refined across three semesters from an initial set of 26 items based on psychometric evaluations of the test. The final 13-item version from has strong psychometric properties. The Chronbach's Alpha reliability estimate is .78 and items range in difficulty from 50 to 67 percent passing indicating neither too easy nor too difficult items with good discrimination. Sample items are provided in the Appendix.

*Procedures* Participants completed the questionnaires using a Web-based survey program [Survey Monkey] during proctored course laboratory periods during the final week of classes in the semester.

## Results

Cluster analysis was conducted with SPSS V.18 and 19 using the two-step cluster procedure (Chiu et al. 2001; Zhang et al. 1996). This method has two steps: (1) do a pre-clustering to derive a set of small sub-clusters and (2) cluster the resulting sub-clusters into clusters. The pre-cluster step uses a sequential clustering approach. Data records are scanned one by one, and based on the distance criterion, the current case is either merged with a previously formed cluster or used to start a new cluster. The pre-cluster procedure constructs a modified cluster feature (CF) tree with the CF tree containing levels of nodes with each node containing a number of records. The cluster step takes these pre-cluster sub-clusters as input and then groups them into the desired number of clusters using an agglomerative hierarchical clustering method. We used log-likelihood as the measure for cluster distance and the bayesian information criterion (BIC) as the cluster criterion. All variables were standardized prior to clustering.

In relation to our central research question, the cluster analysis found an acceptable five cluster solution corresponding to the Shell and Husman (2008) five profiles. To determine whether a better solution could be identified, we tested six, four, and three cluster solutions. None of these provided a meaningfully better solution based on two-step cluster fit results. Also, none of these solutions provided a better theoretically interpretable result. The six cluster solution produced an additional cluster that was not theoretically interpretable. The four and three cluster solutions collapsed clusters and resulted in loss of theoretically and practically important nuances differentiating clusters in the five cluster solution.

The results of the cluster analysis are shown in Table 1. A multivariate analysis of variance (MANOVA) was conducted to test whether motivation and strategic self-regulation variables significantly differed across the five profile clusters. The clusters were significantly different, Wilks' Lambda = .051, $F(64, 836.13) = 14.90$, $p < .0001$, partial $\text{Eta}^2 = .525$. Each individual variable also was significantly different across the clusters. Although all variables contribute to distinguishing the clusters, the most important variables for determining clusters were in order, SPOCK knowledge building, learning avoid goal orientation, SPOCK self-regulated strategy use, FTP endogenous instrumentality, positive affect, SPOCK lack of regulation, negative affect, learning approach goal orientation, study time, SPOCK high-level question asking, and task/work avoidance goal orientation.

The *strategic profile cluster* corresponded closely to traditional views of a strategic, self-regulated student (e.g., Pressley et al. 1987; Weinstein and Mayer 1986). Students had high levels of self-regulated strategy use, knowledge building, and engagement and low levels of lack of regulation. This strategic self-regulation was motivated by high learning approach and task approach goals, high levels of both endogenous and exogenous instrumentality, high FTP connectedness, and high positive affect coupled with low negative affect. Students in the *learned helpless profile cluster* had similar reports of high self-regulated strategy use and high engagement along with moderate levels of knowledge building. But learned helpless students reported high levels of lack of regulation, suggesting that their efforts toward being strategically self-regulated and engaged were not being successful. It is likely that strategic profile students' question asking was strategic in order to further understanding, whereas learned helpless students' question asking was to get support from others or help in overcoming difficulties. Students in these two profiles were similar in many aspects of their motivation and affect. However, students in the learned helpless profile reported much higher learning avoid goals, performance goals (both approach and avoid), and higher task/work avoid goals. Learned helpless students also reported much lower endogenous instrumentality suggesting less connection of the class to personally meaningful future goals. The

**Table 1** Variable means for profile clusters

| Variables | Profile cluster | | | | |
|---|---|---|---|---|---|
| | Strategic ($n$ = 52) | Knowledge building ($n$ = 60) | Apathetic ($n$ = 14) | Surface learning ($n$ = 63) | Learned helpless $n$ = 44) |
| *Strategic self-regulatory* | | | | | |
| Self-regulated strategy use | 3.86 | 2.86 | 1.48 | 2.86 | 3.47 |
| Knowledge building | 3.79 | 3.25 | 1.52 | 2.60 | 3.12 |
| High-level question asking | 3.55 | 2.48 | 1.30 | 2.49 | 2.98 |
| Low-level question asking | 3.45 | 2.34 | 1.23 | 2.63 | 3.10 |
| Lack of regulation | 2.40 | 2.41 | 2.12 | 3.46 | 3.40 |
| Study time | 3.54 | 1.97 | 2.14 | 2.24 | 4.43 |
| Perceived study effort | 3.71 | 2.47 | 2.00 | 2.63 | 3.75 |
| *Motivation and affect* | | | | | |
| Goal orientation | | | | | |
| Learning approach | 4.59 | 4.30 | 3.09 | 3.42 | 4.05 |
| Learning avoidance | 1.70 | 2.18 | 2.97 | 3.72 | 3.22 |
| Performance approach | 2.68 | 3.06 | 2.26 | 2.87 | 3.27 |
| Performance avoidance | 2.05 | 2.83 | 2.31 | 3.40 | 3.35 |
| Task/work approach | 4.12 | 4.21 | 3.39 | 3.90 | 4.24 |
| Task/work avoidance | 1.62 | 2.61 | 2.64 | 3.17 | 2.65 |
| FTP instrumentality | | | | | |
| Endogenous | 4.41 | 4.20 | 2.41 | 2.41 | 3.55 |
| Exogenous | 3.81 | 3.76 | 2.96 | 3.24 | 3.68 |
| FTP connectedness | 4.52 | 4.14 | 3.83 | 3.96 | 4.38 |
| Affect | | | | | |
| Positive | 3.69 | 3.14 | 1.81 | 2.37 | 2.87 |
| Negative | 1.61 | 1.66 | 2.59 | 2.80 | 2.78 |

combination of high performance goals and failure as expressed in the high lack of regulation scores and achievement (Table 2) is consistent with Dweck and Leggett's (1988) description of the precursors to learned helplessness. This likely contributes to the high levels of negative affect in the class these students report experiencing.

Motivationally, students in the strategic profile and *knowledge-building profile cluster* were almost identical. Both had high learning approach and low learning avoid goals, high task approach and low task/work avoid goals, and low to moderate levels of performance approach and avoid goals. Both had high endogenous and exogenous instrumentality and connectedness and both had high positive and low negative affect. Despite this similarity in motivation, their strategic self-regulatory behaviors were very different. Only the apathetic profile students had lower levels of metacognitive self-regulated strategy use and engagement (question asking and study time and effort) than knowledge-building students. Knowledge-building students, however, reported high levels of knowledge-building strategies, second only to the strategic profile cluster. As shown in Table 2, however, this lack of active engagement in question asking, studying, and self-regulation did not appear to hinder the achievement of knowledge-building students.

These two profiles highlight how similar motivation can lead to very different self-regulatory outcomes. This reinforces the need to consider both a broad range of motivational constructs and the assessment of strategic self-regulation in constructing profiles. Other motivators, such as self-efficacy (Bandura 1997) or causal attribution (Weiner 2004) that were not assessed in this study may also play a significant role in motivating the differences in strategic self-regulation in these two profiles (see Shell and Husman 2008).

The *surface learning profile cluster* and *apathetic profile cluster* shared many motivational and affect characteristics. They had the lowest levels of all profiles for learning approach and task approach goals, endogenous and exogenous instrumentality, connectedness, and positive affect. They had high levels of learning avoid goals, task/work avoid goals, and negative affect. Students in both these profiles saw little value in the course, had little personal investment, and no desire to learn course content. They had a negative affective experience, and they primarily just wanted the course to be over and to do the minimum they had to. But like students in the knowledge-building and strategic profiles, there were differences in strategic self-regulation. The apathetic students essentially had no engagement in the class. They did no self-regulation, no use of metacognitive or knowledge-building strategies, no question asking, and minimal study time and effort. They reported the lowest levels of lack of regulation suggesting that they were unmotivated rather than experiencing difficulty because of trying diligently and failing. The surface learning students, on the other hand, were somewhat engaged and self-regulating. They were in the middle of all profiles in engagement measures of question asking and study time and effort and in use of metacognitive self-regulation strategies. All of these were equal to or higher than knowledge-building students. But they had low levels of knowledge building indicating little attempt at deep personally meaningful learning. They also reported the highest level of lack of regulation suggesting that their attempts at self-regulating and engaging may not have been very successful. What appears to motivate their higher level of strategic self-regulation and engagement relative to the apathetic students was somewhat higher exogenous instrumentality, performance goals, and task approach goals. The surface learners saw just enough utility in the class to engage. They also cared about avoiding negative evaluations of their ability, as demonstrated by the highest performance avoid goals of any profile. They may not have cared about learning the course content, but they did appear to care about achieving.

**Hypothesis 1** To test hypothesis 1, one-way ANOVA with Tukey's post hoc tests was done for profile cluster differences on the computational thinking knowledge test. Computational thinking knowledge test scores were significantly different across profiles, $F(4, 209) = 21.60$, $p < .0001$. As shown in Table 2, students in the knowledge-building and strategic self-regulatory profile clusters scored significantly higher than students in the other profile clusters. Also, students in the apathetic and surface learning profile clusters scored lower than those in the learned helpless profile cluster. These findings suggest that in

**Table 2** Computational thinking knowledge test scores by profile cluster

| | Profile cluster | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Strategic | | Knowledge building | | Apathetic | | Surface learning | | Learned helpless | |
| | *M* | *SD* | *M* | *SD* | *M* | *SD* | *M* | *SD* | *M* | *SD* |
| Total | $9.23_a$ | 2.83 | $9.50_a$ | 2.68 | $5.00_b$ | 2.86 | $5.35_b$ | 2.80 | $7.07_c$ | 3.33 |

Means with different subscripts are different at $p < .05$ using Tukey's post hoc tests academically rigorous courses, the achievement differences between students in the knowledge-building and strategic self-regulatory profiles and students in the other profiles become more salient. The results also suggest that learned helplessness in this context means something different than in K-12 settings. Students in the learned helpless profile have dysfunctional characteristics, but they also retain more motivation toward learning and continue attempts toward more productive strategies than the students in the surface learning or apathetic profiles. This allows them to achieve at a somewhat higher level.

**Hypothesis 2** and **3** In relation to hypothesis 2, students in courses that were part of their major field of study were more likely to be in the strategic or knowledge-building profiles and students in required but non-major courses were be more likely to be in the apathetic or surface learning profiles. As shown in Table 3, 71 % of students in CSCE155 for computer science majors were in the strategic or knowledge-building profiles versus 19 % in the surface learning or apathetic profiles. Similarly, 70 % of the students in the RAIKE183H course for the combined business and computer science majors were in the strategic or knowledge-building profiles versus only 3 % in the surface learning or apathetic profiles. Conversely, in the CSCE150E course which is a required but non-major course for engineering students, 52 % of the students were in the apathetic or surface learning profiles and only 23 % were in the strategic or knowledge-building profiles. Interestingly, in the CSCE150A course which contains a mixture of CS, engineering, and science (physics, chemistry, etc.) majors, the profile distribution reflected a hybrid pattern with 58 % in the strategic or knowledge-building profiles, but 32 % in the apathetic or surface learning profiles. Looking specifically at the differences between students reporting majoring or minoring or planning on majoring or minoring in computer science (Table 3), 77 % of students already majoring/minoring, and 63 % of students considering majoring or minoring were in the strategic or knowledge-building profiles compared to only 28 % of those not considering a computer science major or minor.

An interesting difference was apparent between computer science majors in CSCE155 and the combined business/computer science students in RAIK183H. Although both courses were about equal in the percentage of students in the strategic and knowledge-building profiles combined, the CSCE155 course had a much higher percentage (51 %) in the knowledge-building profile than the RAIKE183H course (23 %). This difference suggests that although this course is central to their chosen field, students in the interdisciplinary combined program did not approach it with the same level of personal investment as computer science majors approached their course.

In relation to hypothesis 3, learned helplessness was not necessarily higher among students in required non-major courses (Table 3). The CSCE150E course for engineers did have more students in the learned helpless profile than either the CSCE155 course for computer science majors or the CSCE150A course with a mixture of majors and non-majors. However, an almost equal percentage of students in the RAIKE183H course were in the learned helpless profile.

**Hypothesis 4** In relation to hypothesis 4, there were some differences between men and women in profile distribution (Table 4). Men were more likely to be in the knowledge-building profile, whereas women were more likely to be in the surface learning profile. The small percentage of women in the sample, however, precludes drawing any strong conclusions about gender differences in profiles.

## Discussion and Conclusions

It is meaningful to ask whether students in the STEM (science, technology, engineering, and math) fields adopt profiles of motivated strategic self-regulation similar to students in other K-12 and post-secondary courses. Most of the recent research into profiles has examined K-12 settings (Chen 2012; Conley 2012; Guthrie et al. 2009; Hayenga and Corpus 2010; Schwinger et al. 2012; Tuominen-Soini et al. 2011; Vansteenkiste et al. 2009). Fewer recent studies have examined post-secondary students (Chen 2012; Daniels et al. 2008; Schwinger et al. 2012; Shell and Husman 2008), although SAL researchers looked primarily at college students (Entwistle and Mc Cune 2004). Although profiles have generally been consistent across both K-12 and post-secondary settings, especially in studies examining both populations (Schwinger et al. 2012; Vansteenkiste et al. 2009), studies at the post-secondary level have not specifically focused on students in science or technical fields.

We found that students in STEM fields taking required computer science courses exhibited the same constellation of motivated strategic self-regulation profiles found in other post-secondary and K-12 settings. Students in these courses did not exhibit any new patterns of motivation or self-regulation that might indicate unique post-secondary STEM related profiles. Specifically, finding provided further evidence that students in college STEM courses adopt one of the five profiles identified by Shell and Husman (2008) and others (Entwistle and Mc Cune 2004; Schwinger et al. 2012).

**Table 3** Cross tabulation of profile cluster by characteristics of course and major

| Variables | Profile cluster | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Strategic | | Knowledge building | | Apathetic | | Surface learning | | Learned helpless | |
| | *n* | % | *n* | % | *n* | % | *n* | % | *n* | % |
| *Course* | | | | | | | | | | |
| CSCE 155 [CSCE major] | 11 | 20 | 28 | 51 | 2 | 4 | 8 | 15 | 6 | 11 |
| CSCE 150E [engineering] | 10 | 11 | 11 | 12 | 10 | 11 | 39 | 41 | 24 | 26 |
| CSCE 150A [mixed] | 17 | 32 | 14 | 26 | 2 | 4 | 15 | 28 | 6 | 11 |
| RAIKE183H [Bus./CSCE] | 14 | 47 | 7 | 23 | 0 | 0 | 1 | 3 | 8 | 27 |
| *Computer science major/minor* | | | | | | | | | | |
| Considering | 12 | 30 | 13 | 33 | 0 | 0 | 7 | 18 | 8 | 20 |
| Not considering | 16 | 13 | 18 | 15 | 11 | 9 | 51 | 41 | 28 | 23 |
| Already major/minor | 23 | 34 | 29 | 43 | 2 | 3 | 5 | 8 | 8 | 12 |

Zero (0) cells preclude statistical tests

**Table 4** Cross tabulation of profile cluster by gender

| Variables | Profile cluster | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Strategic | | Knowledge building | | Apathetic | | Surface learning | | Learned helpless | |
| | *n* | % | *n* | % | *n* | % | *n* | % | *n* | % |
| Men | 41 | 21 | 56 | 29 | 13 | 7 | 49 | 25 | 35 | 18 |
| Women | 9 | 26 | 3 | 9 | 0 | 0 | 14 | 40 | 9 | 26 |

Zero (0) cells preclude statistical tests

Results demonstrated how profile adoption can affect academic achievement. Unlike class grades, the computational thinking knowledge test examined long-term retention of the knowledge and skills that formed the core curriculum for the courses. Students adopting the strategic and knowledge-building profiles learned significantly more of this computational thinking knowledge. Students adopting the apathetic and surface learning profiles retained very little of this knowledge. Students adopting the learned helpless profile had decreased learning relative to those in the strategic and knowledge-building profiles, but did retain significantly more knowledge than those in the apathetic and surface learning profiles. It is clear that the strategic self-regulatory profile adopted makes a substantial difference in long-term retention of course content. While a student may be able to "get a grade" with a less effective approach, long-term retention of information and subsequent development of an expert knowledge base appears to require adoption of the strategic or knowledge-building profiles.

The strategic and knowledge-building profiles are characterized by high levels of learning approach goals. These goals to develop deep understanding and build one's knowledge have been singled out by Shell et al. (2010) as the most critical for effective learning. Students lacking strong commitment to these learning goals or having high levels of learning avoid goals are unlikely to engage in the strategic self-regulatory behaviors needed to build understanding of course content. This commitment to learning approach goals is supported by high task approach goals of doing one's best and putting forth one's best effort. Learning approach goals are also supported by high levels of both endogenous and exogenous instrumentality. Students in the strategic and knowledge-building profiles see both personal and utilitarian connections between the course and their future. They also are highly connected to their future career goals. For these students, the course is a positive affective/emotional experience.

The apathetic and surface learning profiles are almost mirror images of the strategic and knowledge-building profiles. In the Shell and Husman (2008) study using canonical correlation, the strategic and apathetic and knowledge-building and surface learning profiles actually were opposed ends of bidirectional canonical dimensions. The apathetic and surface learning profiles are characterized by high levels of learning avoid goals and low levels of endogenous and exogenous instrumentality and FTP connectedness. Students in these profiles see little connection between the course and their future and have little or no desire to develop personally meaningful understanding of the course material or build any long-term expertise in the area. For these students, the course is a negative affective/emotional experience.

These key distinctions suggest avenues for intervention. Students adopting the surface learning and apathetic profiles do not see either personal or utilitarian value in the class. This suggests that the first step in impacting these students' profile choice is building greater understanding of the instrumentality of the course for their future personal, academic, and career objectives. Puruhito et al. (2011) found that instrumentality could be enhanced for engineering students in a required calculus course using videos of students who had taken the course previously describing how important understanding calculus was for their subsequent coursework. Seeing higher instrumentality should help students in the apathetic and surface learning profiles adopt more learning approach goals and lessen tendencies toward learning avoid goals as they see more usefulness in retaining class material beyond the course. These changes could help shift students toward the strategic and knowledge-building profiles.

There was clear differentiation of profile adoption for STEM students who were in a course that was part of their major field of study and students who were in required but non-major courses. About 70 % of students in the CSCE 155 course for CS majors and RAIKE183H course for a combined business-CS program were in the strategic and knowledge-building profiles, whereas about 50 % of engineering students in their required CSCE150E course were in the apathetic or surface learning profiles. Almost 80 % of those already majoring or minoring in CS and 63 % of those considering majoring or minoring in CS were in the strategic or knowledge-building profiles compared to 50 % of those not considering a CS major or minor who were in the apathetic and surface learning profiles. These differences likely relate to the low levels of instrumentality and learning approach goals and resultant lack of knowledge-building strategies among non-majors and students in required non-major courses. Because of zero or low cell frequencies, we were not able to statistically test the observed differences between courses in the student's major and required but non-major courses. The observed pattern of differences suggests meaningful distinctions in profile adoption between major and required non-major courses, but further research is needed to substantiate how prevalent these are and under what circumstances differences occur.

Students in STEM fields typically are required to take foundational courses such as mathematics and computer science that are integral to their chosen major but are not themselves specifically courses in their major. Success in and mastery of the content of these courses is necessary for success in their major. STEM students in required non-major courses, like the students in the CSCE150E course for engineers, apparently do not see connection between these foundational courses and their academic major and subsequent career goals or the need to build long-term understanding of the material in these courses. This suggests need for interventions to increase these students' awareness of how these courses relate to their majors and long-term goals. The results are interesting because the CSCE150E course for the engineers had been tailored to focus on engineering programing language (MATLAB) and use engineering applications for problems and lab exercises (Soh et al. 2009). Even with this, the majority of students in this course adopted surface learning or apathetic profiles. This suggests that students may not see relevance, even if faculty thinks it has been built into the course. Interventions may need to focus on making instrumental connections very overt and reinforcing these connections throughout the course.

Contrary to expectations, learned helplessness was not necessarily higher in the CSCE150E required non-major course than in a course for majors (RAIKE183H). This suggests that learned helplessness may be a more emergent property within courses depending on how students are succeeding and evaluating their success. That would be consistent with Dweck and Leggett's (1988) initial formulations of learned helplessness. They noted that students pursuing performance goals, which are characteristic of the learned helpless profile, performed well until they experienced failure. At that point, they began to adopt what are now considered performance avoid goals to protect their ability perceptions and to engage in negative self-regulatory strategies like those measured in the lack of regulation SPOCK scale. These students still seem to be attempting to pursue positive strategic self-regulation and remain motivated to learn but appear to be having difficulties in the class that are pushing them into negative motivational and strategic self-regulatory directions.

Difficulties with strategic self-regulation may be especially prevalent in STEM courses because these tend to be academically demanding and difficult (Donovan and Bransford 2005; Kuenzi et al. 2006). Even previously successful students may experience difficulties with course content and demands leading to learned helplessness (Kuenzi et al. 2006). But unlike students adopting apathetic and surface learning profiles, students in the learned helpless profile retain positive motivation. Addressing their needs will require interventions focused on helping them with strategies for successful studying and strategic self-regulation. Because these students remain motivated, helping them acquire better studying and strategic self-regulation skills may help alleviate some of the higher attrition experienced in STEM fields (Kuenzi et al. 2006) by helping them find success.

The findings contribute to the growing body of evidence that student motivation and strategic self-regulation occur within a consistent, definable set of profiles. The research identifying profiles has emerged from diverse methodologies including factor analysis (Biggs 1976; Entwistle and Mc Cune 2004; Tait and Entwistle 1996; Vermunt and Vermetten 2004), canonical correlation (Shell and Husman 2008), and cluster analysis (this study, also. Chen 2012; Conley 2012; Daniels et al. 2008; Hayenga and Corpus 2010; Schwinger et al. 2012; Tuominen-Soini et al. 2011; Vansteenkiste et al. 2009) as well as qualitative phenomenographic approaches (see Entwistle and Mc Cune 2004). This convergence of findings from multiple methodologies supports the Shell et al. (2010) contention that the vast array of potential motivational influences students may experience (Eccles and Wigfield 2002; Pintrich 2003) and multitude of possible strategic and self-regulatory behaviors that students might utilize (Boekaerts and Cascallar 2006; Pintrich 2004; Weinstein and Mayer 1986) can be understood within a manageable set of profiles depicting specific patterns of motivation and associated strategic self-regulation. These profiles can be used to focus interventions to enhance students' motivation and learning in post-secondary STEM courses. Intervention may be especially critical in required, foundational courses where students may be unmotivated and prone to pursuing apathetic or surface learning profiles. Providing ways to support student adoption of the strategic and knowledge-building profiles in courses, especially their foundational required courses, could help increase the number of students who choose to major in STEM fields and reduce the attrition of those already choosing STEM majors.

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## Appendix

Sample Computational Thinking Knowledge Test Items

1. Which of the following is not a benefit of using functions in computational problem solving?
   a. A function is a black box that encapsulates a particular sequence of actions that accomplishes a specific task such that we do not necessarily need to know what those actions are in order to use it—it allows for modularity in problem solving.
   b. A function can be used simply by knowing what it needs as inputs and what it generates as outputs.
   c. A function is a mathematical function.
   d. Functions can be used to break the solution to a problem down into subproblems.
   e. A function can be reused in different solutions.

2. Why are algorithms necessary in computational problem solving?
   I. The concept of algorithm can be used to define the notion of decidability—whether an outcome can be achieved by following a set of steps.
   II. An algorithm is a blue-print for the actual implementation of a solution, enabling the conversion of a conceptual solution to a program.
   III. Expressing solutions in algorithms allow us to solve problems without having to deal with programming details that might be specific to a particular programming language.
   IV. Algorithms are needed for programs to compile.

   a. I only
   b. I, II, and III
   c. III and IV
   d. I, II, III, and IV

3. After two passes of bubble sort, what should the following list be? 3, 9, 8, 6, 4, 1, 10
   a. 3, 8, 6, 4, 1, 9, 10
   b. 3, 6, 4, 1, 8, 9, 10
   c. 3, 8, 9, 6, 4, 1, 10
   d. 3, 1, 8, 6, 4, 9, 10
   e. 3, 1, 4, 6, 8, 9, 10

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