Student approaches to learning in a foundational engineering course: a motivational and self-regulated learning profiles perspective

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Abstract

Background Technical, non-engineering, required courses taken at the onset of an engineering degree provide students a foundation for future engineering coursework. Engineering students performing poorly in these foundational courses typically find limited success in engineering, even in courses tailored toward engineering. A profiling approach can help explain why these courses are problematic for engineering students. The profiling approach examines the coordinated interaction among numerous motivation, self-regulation, and engagement constructs.

Purpose (Hypothesis) The purpose of this work was to determine what motivated, self-regulated learning profiles engineering students adopt within foundational courses. It was hypothesized that engineering students would adopt profiles associated with maladaptive motivational beliefs and self-regulated learning behaviors. The effects of profile adoption on learning and differences associated with major/minor and gender were analyzed.

Design/Method Five hundred and thirty eight students, 332 engineering majors, were surveyed on numerous motivation, self-regulated learning, and engagement variables. Data were analyzed from a 'learner-centered' profiling approach using cluster analysis.

Results A five-profile solution consistent with prior studies was identified. Approximately 83% of engineering students enrolled in an engineering-tailored required introductory computer science course adopted maladaptive profiles. These students learned less than those that adopted adaptive profiles. Profile adoption differed by pursuit of a major/minor in computer science in addition to the engineering major.

Conclusions Findings shed light on the motivational and self-regulatory profiles engineering students adopt in foundational courses and the effect of profile adoption on learning. Findings can provide guidance to enhance motivation and self-regulated learning in the classroom.

Keywords profiling method; foundational courses; student approaches to learning

Introduction

Many factors influence engineering students' success. Recent research has focused on several aspects of undergraduate students' motivation for persevering (e.g., Hutchison et al., 2006; Jones et al., 2010). The goal of this study is to consider how engineering students' approaches to learning in foundational course fosters or impedes their success using a quantitative multivariate perspective. Our examination of the beliefs students have about themselves and the course, and how these beliefs motivate their strategic self-regulation could create a comprehensive picture of engineering students' successes and struggles in classroom learning. Findings could help faculty and researchers see how students' many motivational beliefs and self-regulatory behaviors work together to influence achievement, which could aid educators as they aid learners toward academic success. The context of our research is a foundational course required of most engineering students: introductory computer science.

The Problem with Foundational Courses

Most engineering programs require students to take 'foundational' technology, science, and mathematics courses at the onset of the student's enrollment in his or her undergraduate studies, often as early as their first semester. These courses are foundational in that they provide necessary scaffolding towards following technical coursework within the students' major field. The content covered in these foundational courses is critical to subsequent understanding of engineering. Each university or college approaches instruction in these foundational courses differently. Some programs teach these courses within the engineering program itself, whereas others work with science, mathematics, and computer science departments to specifically tailor their courses towards engineering (Sheppard et al., 2009).

The first year is the time when students are more likely to drop out of engineering– with close to 35% leaving introductory courses (Gainen, 1995), courses that are foundational. Budny, Bjedov, and LeBold (1998) use the term 'high risk' to describe these foundational courses in technical and scientific disciplines because they may inadvertently eliminate those first- and second-year engineering students who perform poorly in them. These courses also have been referred to as gatekeeper courses (Gainen, 1995) or barrier courses (Suresh, 2006) because poor performance can act as a barrier to continued pursuit of engineering. First-year grade point average (GPA) is a strong indicator of persistence beyond the first year of engineering coursework (see French, Immekus, & Oakes, 2005; Veenstra, Dey & Herrin, 2009) and of degree completion (Adelman, 1999). Low grades in foundational barrier courses can contribute to lower GPA, inducing student movement to other degree programs; whereas successful completion of foundational courses has been found to promote successful completion of an engineering program (Budny et al., 1998).

Due in large part to national concern over the number of engineering students and their retention (National Research Council, 2007), administrators and faculty have raised questions regarding how to best support first- and second- year engineering students' persistence and success in these courses. Research has begun to identify how instructors and programs can support success in courses and degree completion. Froyd and Ohland (2005) found that when engineering programs take an integrated approach, linking engineering with other required, non-major courses, retention in engineering increases. Sathianathan and colleagues (1999) provided further evidence in support of the need to contextualize courses by demonstrating that students who are given engineering applied problems and projects in calculus performed better than other students. Miller and colleagues (2013; 2014) found that adding exercises in creative thinking skills to the curriculum improved achievement and learning in introductory computer science courses, including a foundational computer science course for engineering students. In addition to pedagogical approaches, engineering educators have begun using motivational theories to advance understanding of what motivates engineering students to persist and achieve in the field and what curricular interventions would be the most beneficial in remediating the ongoing problems with engineering student attrition (e.g., Jones et al., 2010) and content understanding (e.g., Stump et al., 2011).

This study examined the motivational and self-regulatory implications of a foundational introductory computer science (CS1-level) course at a large Mid-Western state university as part of a National Science Foundation funded initiative called “Renaissance Computing” (Soh et al., 2009). A suite of parallel introductory CS1 courses was created with each course tailored for students from different engineering, science, business, and computer science majors. For the engineering course, students were taught programming using Matlab, and the content in the course was tailored towards engineering applications. To understand the many ways that motivation and self-regulation might be influenced by these tailored foundational introductory computer science courses, we used a profiling approach to examine students’ motivation and self-regulation.

The Profiling Approach

In the last few decades significant strides have been taken to understand the numerous constructs that characterize students’ motivation, self-regulated learning, and engagement and to explore their implications for learning within various fields (e.g., Bandura, 1997; Boekaerts & Cascallar, 2006; Eccles & Wigfield, 2002; Pekrun & Linnenbrink-Garcia, 2012; Zimmerman & Schunk, 2011). Educational research in engineering (Hilpert et al., 2012), computer science (Shell et al., 2013), science (Pugh et al., 2010), middle and high school (Wigfield, Byrnes, & Eccles, 2006), and post-secondary education (Acee & Weinstein, 2010) has consistently demonstrated relationships between motivational constructs and students’ approach to learning within and outside of the classroom.

Consideration of multiple aspects of students’ motivation and their approach to learning is especially important for engineering education research. Engineering, like all disciplines, is one that requires students to engage in self-regulated learning inside (e.g., note-taking, question asking) and outside of the classroom (e.g., studying), and requires students to persist, even in the face of failure. In these self-directed learning situations, students’ motivational beliefs and self-regulated learning skills influence their achievement and retention in the field (Jones et al., 2010). Engineering educators and researchers need to better understand how to enhance engineering students’ motivation and self-regulated learning (Streveler et al., 2008).

Theorists have discussed the complex and reciprocal relationships between motivation constructs and self-regulated learning (Shell et al., 2010). Prior work in these fields typically has examined individual motivation and self-regulation constructs, often examining them in isolation or at most, considering the ways in which individual variables interact (e.g., McInerney & Van Etten, 2004). Recently, however, researchers have begun to shift their interests towards examining the complex reciprocity among motivational and self-regulated learning variables (e.g., Schunk & Zimmerman, 2013; Shell & Husman, 2008; Shell & Soh, 2013). Understanding the complex and reciprocal relationships between motivation and self-regulated learning requires an integrated multivariate approach. These approaches have been referred to as profiling. The profiling approach is being taken by an expanding number of researchers (Conley, 2012; Guthrie, Coddington, & Wigfield, 2009; Shell & Soh, 2013). In the profiling approach, profiles of motivation and strategic self-regulation portray coordinated patterns of motivational influences and strategic self-regulatory actions. Using profiling, researchers can consider interactions among a multitude of separate, well-established psychological constructs, leveraging over thirty years of psychological research on the individual constructs while considering the specific engineering educational context.

Theoretical framework

Motivational research has established that students' engagement, effort, persistence, and approaches to learning are influenced by a multitude of beliefs, needs, and perceptions (Schunk, Pintrich, & Meece, 2008). Examples of key constructs that influence learning and engagement are goals, self-efficacy, expectancies, and affect/emotion. Similarly, strategic or self-regulated learning involves a constellation of behaviors and cognitions with successful students employing many different strategic approaches throughout their learning experiences (Husman & Corno, 2010), like Pressley and colleagues' (1987) Good Strategy User.

Profiles, as depicted in Figure 1, identify coherent constellations of motivations, cognitions, and self-regulatory behaviors that inform a learner-centered approach to learning and instruction. Because profiling examines combinations of constructs, it requires methods that, as Ainley (1993) noted, "preserve the integrity of the combinations" (p. 396). These methods include factor analysis (Entwistle & McCune, 2004), canonical correlation (Shell & Husman, 2008), and cluster analysis (Conley, 2012; Shell & Soh, 2013).

Research into profiling has accelerated in recent years as researchers have seen the benefits of the profiling framework (Chen, 2012; Conley, 2012; Daniels et al., 2008; Guthrie et al., 2009; Schwinger, Steinmayr, & Spinath, 2011). A group of replicable profiles appears to be emerging. Shell and Husman (2008), using canonical correlation, identified five profiles of college students' motivated self-regulation. These were a) a strategic profile fitting previous descriptions of high motivated, strategic, self-regulated students (Boekaerts & Cascallar, 2006); b) a knowledge building profile fitting previous descriptions of an intrinsically motivated, knowledge building (Scardamalia & Bereiter, 2006), autonomous (Reeve, Deci, & Ryan, 2004), or mastery oriented (Pintrich, 2003) student; c) an apathetic profile fitting previous descriptions of an amotivational (Reeve et al., 2004) or apathetic (Tait & Entwistle, 1996) student; d) a surface learning profile fitting previous descriptions of an extrinsically motivated rote or surface learning student (Entwistle & McCune, 2004); and e) a learned helpless profile fitting previous descriptions of a learned helpless student (Dweck, 1999). Shell and Soh (2013) recently replicated these five profiles with college students in computer science courses using cluster analysis. Prior research in the student approaches to learning (SAL) tradition has also identified similar five profile solutions using factor analysis (e.g., Entwistle & McCune, 2004; Tait & Entwistle, 1996; Vermunt & Vermetten, 2004).

Shell et al. (2010) and Entwistle and McCune (2004), argue that within specific classes at any point in time, students adopt one or the other of the profiles as a function of the subject matter and classroom context. In a typical college classroom with a diverse student body, there may be some students who are adopting each of the five profiles (Shell & Soh, 2013). Although, students may typically adopt a preferred profile, profile adoption likely remains dynamic. Students may shift profiles in different courses and subject matter domains as well as in response to contextual factors and personal reactions 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 with about one-third of the students changing profile. Linnenbrink-Garcia (2011) found that profiles were affected by classroom interventions designed to establish different types of goal orientations. These studies examined students in K-12 settings. The extent to which student profile adoption changes in college classrooms is unknown. Shell and Soh (2013) found that profile adoption differed for college students who were majoring or not majoring in the course subject matter and that the distribution of profiles was different across different courses. All these findings suggest that although students tend to adopt stable profiles within a course, profile adoption is potentially malleable by the classroom environment and by how students' view their classroom.

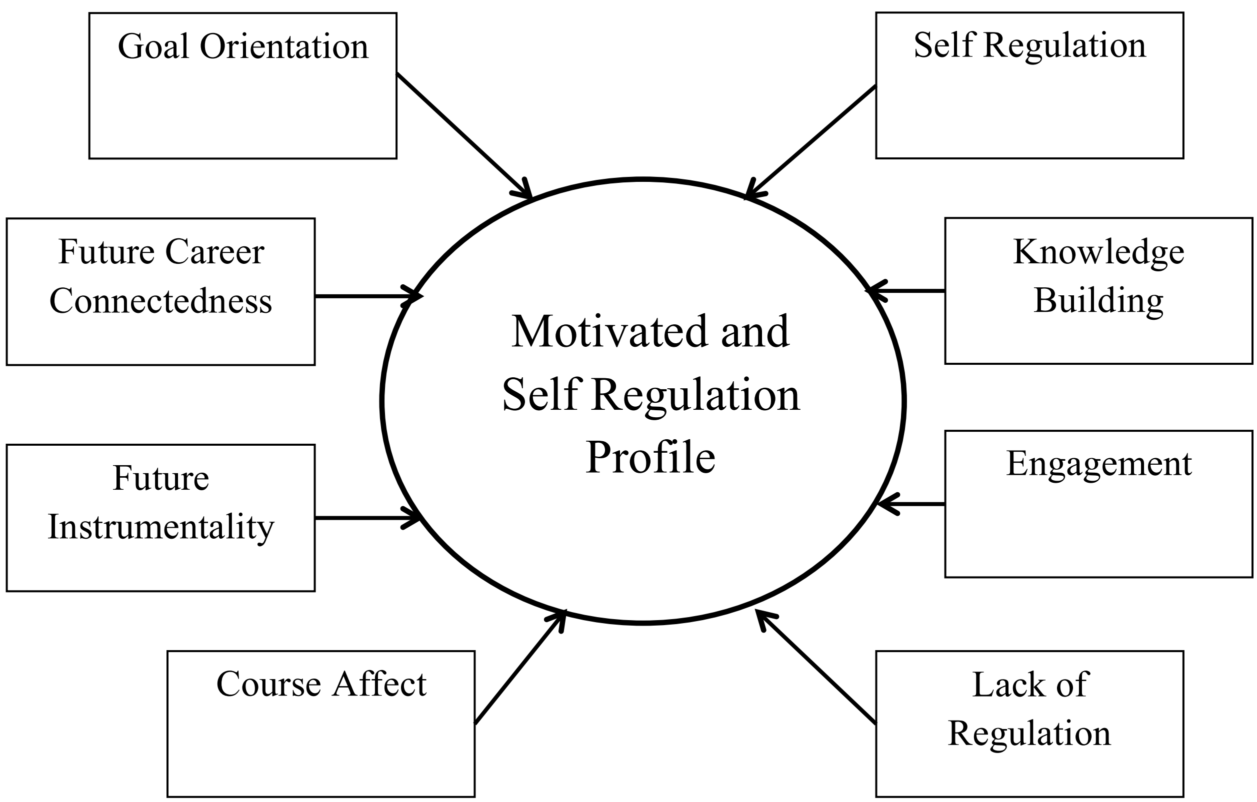

Figure 1. Learner-centered approach to assessing the constellation of behaviors and cognitions inherent in a learner.

Motivational and Self-regulated Learning Profiling Variables

Motivation variables

The motivational variables of focus in this study were goal orientation (Dweck & Leggett, 1988; Elliot, Murayama, & Pekrun, 2011), future time perspective (FTP) (Husman & Lens, 1999), and emotion/affect (Linnenbrink, 2007; Pekrun et al., 2007; Pekrun & Linnenbrink-Garcia, 2012).

Goal Orientation. Goal orientation measures were based on a framework that follows a tradition in goal theory focused on the goals students set for courses (see discussions in Senko, Hulleman, & Harackiewicz, 2011; Shell et al., 2010). Goals are examined in three dimensions (learning, performance, and task), with each dimension having an approach as well as an 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 & Leggett, 1988; Senko et al., 2011). Learning avoid goals reflect an active desire to not learn material or take anything away from the course (Shell & Soh, 2013). A student who does not care about a course might set a goal to just complete course assignments without retaining any of the course content. 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. Task or work approach goals reflect wanting to perform a task well or achieve to a high level (Grant & Dweck, 2003). Task or work avoid goals reflect a desire to get through the class with as little time and effort as possible (Ames, 1992; Wolters, 2003).

Future Time Perspective. Future Time Perspective (FTP) is a set of psychological constructs that together explain some of the differences we see in students' tendency to plan for the future, delay gratification, and make responsible life choices (Zimbardo & Boyd, 2009). Two components of FTP were examined in this study. *Connectedness* refers to the general ability to make connections between present activities and some future goal. It is one of the most predictive components in engineering education contexts (Hilpert et al., 2012). *Perceived Instrumentality* (PI) is defined as a person's perception of how useful a specific present task is for achieving future goal. Students with a long FTP can more easily see the connection between their current course activities and their distant future and thus have an increased perceived instrumentality for their present learning in school (Husman & Lens, 1999).

Emotion/Affect. Emotion/affect involves students' general feelings and reactions to the class. Positive emotions have been shown to increase students' engagement in academic work and support more adaptive self-regulation (Pekrun & Linnenbrink-Garcia, 2012). Negative emotions have been found to decrease motivation and lead to maladaptive self-regulation (Shell & Soh, 2013).

Self-regulated learning variables

Four aspects of students' strategic self-regulation were the focus of this study. 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. These students have been called good strategy users (Pressley et al., 1987). The second aspect comes from the knowledge building approach to learning proposed by 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. Knowledge building is characterized by going *above and beyond* surface-level learning (e.g., memorization) by connecting new information to existing knowledge, integrating new knowledge across topics, and pursuing deep understanding of course material. The third aspect is student engagement with the class as reflected in active participation and effort, including active course involvement such as question asking (Scardamalia & Bereiter, 1992) and studying (Shell & Husman, 2008; Shell & Soh, 2013). The final aspect of self-regulation was drawn from research examining more dysfunctional self-regulatory strategies (e.g., Vermunt & Vermetten, 2004; Wolters, 2003). Lack of regulation examines students' confusion and difficulty in effectively studying and self-regulating along with need for excessive support from others.

Research Aims

The purpose of this work was to determine what motivational and self-regulated learning profiles engineering students adopt within foundational courses. To identify profiles, we took the *person centered* approach that has been utilized in most recent profiling studies (Chen, 2012; Conley, 2012; Daniels et al., 2008; Schwinger et al., 2011; Shell & Soh, 2013; Tuominen-Soini et al., 2011). The person centered approach focuses on determining if groups of students can be identified who share common motivational and strategic self-regulatory characteristics. We used cluster analysis, an analytic method that groups people by patterns of variables, to identify profiles. We included both motivation and strategic self-regulation within the cluster analysis for profile determination. The prior studies that have included both motivation and self-regulation constructs in the profile determination (Entwistle & McCune, 2004; Linnenbrink-Garcia, 2011; Schwinger et al., 2012; Shell & Husman, 2008; Shell & Soh, 2013; Tait & Entwistle, 1996; Vermunt & 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 coherence and empirical support, we hypothesized that a similar five profile solution would be found in the cluster analysis.

Based on recent findings by Shell and Soh (2013), who examined student profiles across multiple computer science courses during one semester, we hypothesized that engineering students taking the foundational introductory computer science course in this study would be more likely to adopt maladaptive profiles like the apathetic and learned helpless profiles identified by Shell and Husman (2008). Consistent with prior research (Shell & Soh, 2013), we hypothesized that the profile adopted by students would have significant impact on their learning. Students who adopt the strategic and knowledge building profiles should have higher retention of course content. Also, based on findings by Shell and Soh, (2013), we hypothesized that engineering students who were considering a major or minor in computer science along with their engineering major would be more likely to adopt the adaptive strategic and knowledge building profiles.

Method

Participants

Students volunteered as part of a larger evaluation of an NSF-sponsored effort to revise the undergraduate computer science curriculum at a large Mid-Western state university (Soh et al., 2009). Instead of a single introductory computer science course (CS1 level), a *suite* of parallel introductory CS1 level courses was developed. Core content was the same for all courses; but, courses were tailored for students from different majors with different programming languages and lab exercises consistent with the students' major field. CS1-Computer Science was for computer science majors who could be enrolled in computer science either through the College of Arts and Sciences or the College of Engineering. CS1-Honors was for combined business/computer science honors program majors. CS1-Mixed was comprised of half computer science majors who preferred the language (C++) used and half business and general science majors. CS1-Engineering, which was the primary focus of this study, was for non-computer science engineering majors (mechanical engineering, civil engineering, electrical engineering, etc.). The CS1-Computer Science and CS1-Honors courses are part of major field for students majoring in computer science or the combined business/computer science honors program. The CS1-Mixed course is part of the major field for computer science students and a foundational course that may or may not be required for students majoring in business or science disciplines. The CS1-Engineering course is a required foundational course for the non-computer science engineering majors. Students can receive credit for only one of the courses.

The CS1-Engineering course consisted of regular lectures (3 hours per week), with five homework programming assignments and thirteen weekly 1.5 hour inquiry-based, problem-driven laboratory assignments focused on engineering applications. The primary programming language was Matlab, a versatile language popularly used in engineering disciplines for various applications involving analysis of numerics. Matlab was chosen based on consultation with engineering faculty. The topics covered included (a) typical introductory computer science CS1 level topics such as repetition, selection, functions, character manipulations, arrays, I/O, file I/O, search, sorting, recursion, debugging, and problem solving and (b) more Matlab-facilitated topics such as vectors matrices, 2-D plotting, and cell structures. Lectures of the course illustrate these topics with examples in engineering applications. See Soh et al. (2009) for more information on the tailoring of the courses.

Participants were 538 students from this suite of introductory computer science courses across four semesters (439 men, 93 women, 6 unknown; 262 freshmen, 143 sophomores, 86 juniors, 32 seniors, 15 other/unknown). This participant sample was used for cluster analysis to determine the composition of student profiles. From this sample, there were 332 students in the CS1-Engineering course (279 men, 50 women, 3 unknown; 118 freshmen (first-year), 109 sophomores (second-year), 70 juniors (third-year), 20 seniors (fourth year), 6 other/unknown). This sample subset was used for subsequent analyses focused on engineering majors.

Race-ethnicity information was not collected directly due to IRB concerns about indirect identification because of low numbers of certain ethnicities. The CS1 courses, because they are required, reflect general demographics of the colleges and majors involved. The approximate demographic breakdowns for the semesters studied based on University enrollment records were (a) engineering majors: 92% White, 2% African American, 3% Asian, 3% Hispanic, 4% foreign; (b) computer science majors: 87% White, 2% African American, 6% Asian, 5% Hispanic, 7% foreign; (c) combined business-computer science honors program: 89% White, 0% African American, 9% Asian, 2% Hispanic, 0% foreign; and (d) general business and other science majors: 77% White, 2% African American, 2% Asian, 3% Hispanic, 17% foreign.

Student participation was voluntary but retention was generally high. Student participation in a pre-survey given the first week of the course in the spring 2010, fall 2010, and fall 2011 semesters was almost 100% in all courses. The pre- to post-survey retention for these three semesters was: CS1-Engineering - 79%; CS1-Honors - 98%; CS1-Computer Science - 60%; and CS1-Mixed - 70%. Although no pre-survey data were available for fall 2009, participation and retention were consistent with other semesters. There were no differences in demographic make-up (gender or year in school) between those who completed the post survey and those who did not.

Data Sources

Motivation and Affect Measures

Class Goal Orientation. Students' class goal orientation was measured using the instrument in Shell and Soh (2013). The instrument is an extension of the Shell and Husman (2008) instrument based on the goal framework described in Shell et al. (2010).

Learning approach goal orientation (5 items) assesses goals for developing long-term, deep understanding of course content 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 goal orientation* (4 items) assesses deliberate avoidance of long-term learning or retention of course content (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 goal orientation (6 items) assesses 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 goal orientation* (3 items) assesses avoiding negative performance evaluations and unfavorable assessments of ability by others (e.g., "Keeping others from thinking you are dumb; Avoiding looking like you don't understand the class material").

Task approach goal orientation (4 items; also called outcome goals, see Grant & Dweck, 2003) assesses 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 avoid goal orientation* (3 items; also called work avoidance goals, see Ames, 1992; Wolters, 2003) assesses 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 as follows: 1 (*very unimportant*), 2 (*unimportant*), 3 (*neither important nor unimportant*), 4 (*important*), 5 (*very important*). Scores were computed as the mean score of the items in each scale. Cronbach's alpha reliability estimates for the learning approach, learning avoid, performance approach, performance avoid, task approach, and task avoid scales were respectively .87, .86, .79, .85, .90, and .81. Additional instrument validation information is available in Shell and Husman (2008) and Shell and Soh (2013).

Future Time Perspective. Future time perspective was measured by two instruments.

Career Connectedness (11 items) assesses connections between a student's present and their future career goals (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"). The instrument was an adaptation of the Future Time Perspective Scale connectedness subscale from Husman and Shell (2008). Additional instrument validation information is available in Shell and Husman (2001) and Shell and Soh (2013). Item wording was changed from asking about the general future to specifically asking about future in the context of careers. Students indicated their agreement with each question using a 5-point Likert scale as follows: 1 (*strongly disagree*), 2 (*disagree*), 3 (*neutral*), 4 (*agree*), 5 (*strongly agree*). The career connectedness score was computed as the mean of the items in the scale, with negative items reverse scored. Cronbach's alpha reliability estimate for the scale was .88.

Perceptions of Instrumentality (PI) measures student perceptions of the instrumental relationship between their specific course work and attaining STEM academic and career goals. Additional validation information is available in Husman and Lens (1999), Husman et al. (2007) and Shell and Soh (2013).

Endogenous PI (4 items) assesses the instrumentality for learning the course material (e.g., "I will use the information I learn in this CS1 class in the future; What I learn in this CS1 class will be important for my future occupational success"). *Exogenous PI* (4 items) assesses the instrumentality for course grades and achievement (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"). Students indicated their agreement with each question using a 5-point Likert scale as follows: 1 (*strongly disagree*), 2 (*disagree*), 3 (*neutral*), 4 (*agree*), 5 (*strongly agree*). Endogenous and exogenous PI scale scores were computed as the mean of the items in each scale, with negative items reverse scored. Cronbach's alpha reliability estimates for the endogenous and exogenous PI scales were .93 and .64 respectively.

Course affect. Affect was measured by a modified version of the Positive and Negative Affect Scale (PANAS) (as used in Shell & Husman, 2008; Shell & Soh, 2013). Instrument validation information is available in Watson, Clark and Tellegen (1988). *Positive affect* (10 items) assesses the frequency of experiencing positive emotions and feelings in the course (e.g., excited, proud). *Negative affect* (10 items) assesses the frequency of experiencing negative emotions and feelings in the course (e.g., frustrated, afraid, distressed).

Students rated the frequency of experiencing each emotion/feeling on a 5 point scale as follows: 1 (*a few times or not at all*), 2 *occasionally, 25% of the time*), 3 (*quite often, 50% of the time*), 4 (*very often, 75% of the time*), 5 (*most of the time, 80%-100% of the time*). Positive and negative scale scores were computed as the mean of the items in each scale. Cronbach's alpha reliability estimates for the positive and negative affect scales were .91 and .90 respectively.

Strategic Self-Regulation Instruments

Strategic self-regulation was assessed with the *Student Perceptions of Classroom Knowledge Building* (SPOCK). Additional validation information is available in Shell et al. (2005), Shell and Husman (2008), and Shell and Soh (2013). The instrument asks students about strategic self-regulatory behavior within a specific course. The SPOCK measures four aspects of students' perceptions of their own strategic self-regulation.

Self-regulated strategy use (8 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"). These items assess strategic behaviors and study strategies typically associated with models of strategic self-regulation (e.g., Pintrich, 2004; Weinstein & Mayer, 1986) and what Pressley et al. (1987) have termed the "good strategy user."

Knowledge building (9 items) assesses the extent of student exploration and interconnection of 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 focused on those topics that were personally meaningful to me"). Questions in this scale are based on the knowledge building and intentional learning models of Scardamalia and Bereiter (2003; 2006) and focus on going beyond the given material and on tying the information being learned to other courses and existing knowledge.

Engagement was assessed by two scales measuring the extent of question asking in class (see Scardamalia & Bereiter, 1992). *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 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).

Students were asked to respond only for the course from which they were recruited and not for other courses or school in general. Students rated their frequency of the behaviors on a five-point Likert scale as follows: 1 (*almost never)*, 2 (*seldom*), 3 (*sometimes*), 4 (*often*), 5 (*almost always*). Scale scores were computed as the mean score of the scale items. Cronbach's alpha reliability estimates for the self-regulated strategy use, knowledge building, high-level question asking, low-level question asking, and lack of regulation scales were respectively .89, .90, .90, .85, and .85.

Engagement was further assessed using two scales measuring student self-reported studying (Shell & Husman, 2001; Shell & Husman, 2008; Shell & Soh, 2013). *Study time* (1 item) was assessed by asking students to indicate the average number of hours per week they spent studying for their computer science course on a 1 to 7 scale representing two hour units from 1 (*less than 2 hours per week)* to 7 (*over 12 hours per week*). In the United States, the phrase "studying for class" typically means activities done outside of the actual class time. Although unlikely, some students may have included in-class time in their response.

Perceived study effort (1 item) was assessed by asking students to indicate their perception of the effort they put forth studying for their computer science course 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*), 5 (*I put forth much more effort studying*).

Knowledge Test

The suite of introductory computer science (CS1) courses from which participants were recruited include the same basic core of computer science topics. To create a common measure of retention of these core topics that could be used across all of the courses, a Web based 13-item test of computational thinking and computer science knowledge containing a blend of conceptual and problem-solving questions was developed by computer science and engineering faculty. The test addresses common core content including selection, looping, arrays, functions, algorithms, search, and sorting. The test was refined across the fall 2009, spring 2010, and fall 2010 semesters from an initial set of 26 items. The original 26 items were reduced to 18 on the basis of item redundancy because of concerns by the Computer Science and Engineering faculty about the time needed to administer the test. The 18item version was examined using item discrimination (percent passing) and item-total (point bi-serial) correlations. Four items with poor discrimination in fall 2009 and spring 2010 were eliminated. A fifth item was eliminated due to low item-total correlation of less than .30 along with relatively poor discrimination. The final 13-item version had reasonably strong psychometric properties. In fall 2010 and fall 2011, the Cronbach's alpha reliability estimates were .78 with point bi-serial correlations of .36-.58 (2010) and .30-.62 (2011) with two exceptions below .26. The two items with poor point bi-serial correlations, however, are among the most difficult and cover important course topics not covered by other items. The knowledge test was separate from the regular course examinations and did not count toward course grades.

Procedures

Participants completed the questionnaire battery using the Survey Monkey Web-based survey program. Data were collected during four semesters (fall 2009, spring 2010, fall 2010, and fall 2011). Participants completed surveys and the knowledge test during proctored course laboratory periods in the final week of the semester or outside of the course (fall 2009 only). Missing data was handled with list-wise deletion. Missing data varied by analysis and ranged from two to three percent (8 or 9 participants) for all analyses except for knowledge test scores with had 17 (5%) participants missing.

Results

Profile Determination

Cluster analysis was conducted with SPSS V.20, using the two-step cluster procedure (Chiu et al., 2001; Zhang, Ramakrishnon, & Livny, 1996). This cluster procedure has two steps: 1) a pre-clustering to derive a set of small sub-clusters and 2) clustering of the resulting sub-clusters into final clusters. The pre-clustering step uses a sequential clustering approach. Data records are scanned one-by-one and the current case is either merged with a previously formed cluster or used to start a new cluster based on the distance criterion. The pre-clustering 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 clustering step takes these sub-clusters and input and groups them into the desired number of clusters using an agglomerative hierarchical clustering method. Log-likelihood was specified as the measure for cluster distance for pre-clustering and the Bayesian Information Criterion (BIC) was specified as the clustering criterion for the clustering step. All variables were standardized prior to clustering and 10% noise handling was used to eliminate the effect of extreme outliers.

Cluster analysis is interpretive. Regardless of the extent to which statistical indicators are available to suggest the number of clusters present, the ultimate decision relies on theoretical coherence. The patterns of variables within a cluster must be explainable in the context of the theories and prior research on the constituent constructs. As we had hypothesized, a five-cluster solution was identified corresponding to the five profiles identified by Shell and Husman (2008; also Shell & Soh, 2013). To determine if a better solution could be identified, three, four, and six cluster solutions were tested. Goodness-of-fit indicators for the three, four, five, and six cluster solutions respectively were .150, .138, .130, and .129 for sums of squares within group (SSE), which measures cohesions within clusters with lower scores indicating better fit; .042,

.060, .067, and .070 for sums of squares between groups (SSB), which measures separation with higher scores indicating better fit; and .192, .202, .199, and .173 for average silhouette, which measures how tightly clusters group with higher scores indicating better fit. Few differences between the indices for the four, five, and six cluster solutions were found. The best overall balance among all indices was achieved with the five cluster solution that had the second best fit indicator scores for all measures. Although the six cluster solution had the best SSE and SSB indicator scores, it had the worst silhouette indicator score. As discussed in the introduction, the five cluster solution also has the best theoretical anchoring and prior research support; thus, it was preferred on theoretical grounds absent any strong statistical evidence for a better solution.

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 = .059, $F(72, 1996.01) = 29.29$, $p < .0001$, partial $\text{Eta}^2 = .508$. Also, in univariate follow-up tests, each individual variable was significantly different across the clusters (all $p < .0001$). Although all variables contribute to distinguishing the clusters, the most important variables for determining clusters were in order, learning avoid goal orientation, positive affect, learning approach goal orientation, SPOCK knowledge building, SPOCK self-regulated strategy use, endogenous PI, SPOCK high-level question asking, SPOCK lack of regulation, and task avoid goal orientation.

Profile clusters are shown in Table 1 and the conceptual distinctions between the clusters are described in Table 2. As discussed in Shell and Husman (2008), Shell et al. (2010), and Shell and Soh (2013), profiles are distinguished by, at times, subtle differences. The S*trategic Profile* cluster corresponds closely to traditional views of a strategic, self-regulated student (e.g., Pressley et al., 1987; Weinstein & Mayer, 1986). These students had high levels of both self-regulated strategy use and knowledge building strategies along with active engagement as indicated by high levels of question asking, study time, and perceived study effort. Students in the L*earned Helpless Profile* cluster had similar characteristics with high levels of self-regulated strategy use and study time and moderate levels of knowledge building strategies, question asking, and perceived study effort. Students adopting the Learned Helpless Profile, however, reported high lack of regulation, suggesting that they were distinguished from student in the Strategic Profile largely by not being successful in their self-regulation strategy use, knowledge building, and engagement efforts.

Students in these two profiles were similar in many aspects of their motivation and affect. Both were high or moderate in learning, performance, and task approach goal orientation; career connectedness; endogenous and exogenous PI; and positive affect suggesting that their positive motivation was similar. Students who adopted the Learned Helpless Profile, however, contrasted dramatically with those who adopted the Strategic Profile in learning, performance, and task avoid goal orientation, with students in the Learned Helpless Profile reporting high levels of these, whereas, students in the Strategic Profile reported low levels. A similar contrast was apparent for negative affect. These contrasts suggest that the positive motivation of students who adopted the Learned Helpless Profile was being offset by high levels of negative motivation similar to how their positive attempts at strategic self-regulation were being undermined by high lack of regulation. The combination of high performance goal orientation and failure, as expressed in the high lack of regulation scores, is consistent with Dweck and Leggett's (1988) description of the precursors to learned helplessness.

Table 1
Variable Means for Profile Clusters

Variables	Profile Cluster Strategic (n= 104)	Knowledge Building (n= 63)	Apathetic (n=121)	Surface Learning (n= 102)	Learned Helpless (n= 139)
Strategic Self-Regulatory					
Self-regulated strategy use	3.80	2.56	2.37	3.08	3.44
Knowledge building	3.72	3.20	2.13	3.03	3.04
High-level question asking	3.59	2.06	2.06	2.85	2.97
Low-level question asking	3.50	1.97	2.25	2.93	3.07
Lack of regulation	2.37	2.15	3.28	2.90	3.28
Study time	3.93	1.89	2.30	3.17	3.44
Perceived study effort	3.83	2.10	2.55	3.20	3.35
Motivational Beliefs					
Goal orientation					
Learning approach	4.66	4.41	3.23	3.55	4.16
Learning avoid	1.83	1.92	3.68	2.81	3.31
Performance approach	3.09	2.86	2.91	2.65	3.74
Performance avoid	2.48	2.80	3.13	2.46	3.70
Task approach	4.44	4.26	3.86	3.56	4.53
Task avoid	1.80	2.51	3.29	2.57	2.99
FTP Instrumentality					
Endogenous PI	4.36	4.32	2.29	3.33	3.54
Exogenous PI	3.92	3.90	3.16	3.25	3.75
FTP Connectedness	4.49	4.13	3.94	3.99	4.34
Affect					
Positive	3.77	3.13	2.03	2.73	3.04
Negative	1.68	1.49	2.76	2.13	2.51

Table 2
Conceptual Distinctions Among Clusters

Variables	Profile Cluster: Strategic	Knowledge Building	Apathetic	Surface Learning	Learned Helpless
Strategic Self-Regulatory					
Self-regulated strategy use	High	Low	Low	Moderate	High
Knowledge building	High	High	Low	Moderate	Moderate
High-level question asking	High	Low	Low	Moderate	Moderate
Low-level question asking	High	Low	Low	Moderate	Moderate
Lack of regulation	Low	Low	High	Moderate	High
Study time	High	Low	Low	Moderate	High
Perceived study effort	High	Low	Low	Moderate	Moderate
Motivational Beliefs					
Goal orientation					
Learning approach	High	High	Low	Low	Moderate
Learning avoid	Low	Low	High	Moderate	High
Performance approach	Moderate	Moderate	Moderate	Low	High
Performance avoid	Low	Low	Moderate	Low	High
Task approach	High	High	Moderate	Low	High
Task avoid	Low	Moderate	High	Moderate	High
FTP Instrumentality					
Endogenous PI	High	High	Low	Moderate	Moderate
Exogenous PI	High	High	Low	Low	High
FTP Connectedness	High	Moderate	Moderate	Moderate	High
Affect					
Positive	High	Moderate	Low	Low	Moderate
Negative	Low	Low	High	Moderate	High

Note: Descriptors reflect relative levels of a variable (row) across profiles (columns). They do not indicate absolute levels of variables or the level of a variable compared with other variables.

Motivationally, students in the *Strategic Profile* and *Knowledge Building Profile* clusters were highly similar motivationally. Both had high learning approach and low learning avoid goal orientation, moderate performance approach and low performance avoid goal orientation, and high task approach goal orientation. Both had high endogenous PI and exogenous PI and low negative affect. But, they differed slightly as students who adopted the Knowledge Building Profile had only moderate rather than high levels of career connectedness and positive affect and moderate rather than low levels of task avoid goal orientation. Interestingly, despite their motivational similarities, these two groups of students' strategic self-regulatory behaviors were very different. Students adopting the Knowledge Building Profile reported high levels of knowledge building strategies but low levels of all other self-regulatory and engagement measures.

Students in the *Surface Learning* and *Apathetic Profile* clusters shared many motivational and affective characteristics. They had the lowest levels of all profiles for learning approach and task approach goal orientation, both endogenous and exogenous PI, career connectedness, and positive affect. Students in both of these profiles saw little value in the course, had little personal investment or desire to learn course content, and experienced negative emotions. They primarily just wanted the course to be over and to do the minimum amount of work possible. Despite these similarities, students in the Apathetic Profile had higher levels of learning avoid, performance avoid, and task avoid goal orientation and negative affect, suggesting not just a lack of positive motivation but heightened negative emotions and motivation for the course.

Students in the Apathetic and Surface Learning Profiles differed in their strategic self-regulation. Students in the Apathetic Profile essentially reported no active strategic self-regulation or engagement in the course. They reported the lowest levels of self-regulated strategy use, knowledge building strategies and engagement. They did, however, report the highest level of lack of regulation. These students apparently are not motivated enough to try and do not feel that they were successful if they did try. So, rather than continuing to try and fail in their strategic and self-regulatory efforts, like the students in the Learned Helpless Profile, the students in the Apathetic Profile do not even try. The students in the Surface Learning Profile, on the other hand, were somewhat engaged and self-regulating. They were in the middle of all profiles in engagement measures of question asking, study time, and perceived study effort and in self-regulated strategy use. Relative to students in the Strategic and Knowledge Building Profiles, however, they reported less knowledge building, suggesting that they did not engage in as much deep personally meaningful learning.

What appears to motivate this higher level of strategic self-regulation and engagement relative to the students in the Apathetic Profile was higher endogenous PI. Although low relative to students in the Strategic or Knowledge Building Profiles, students in the Surface Learning Profile were more likely to see learning the material in the course as at least somewhat instrumental to their future academic and career goals. This relationship apparently was enough for them to at least minimally engage. This relationship was also reflected in lower task avoid goal orientation than students in the Apathetic Profile. Although the surface learning students do not seem to care about demonstrating performance as reflected in the lowest performance approach and avoid goal orientation of all profiles; or doing well in general as reflected by the lowest task approach goal orientation of all profiles, perhaps the students in the Surface Learning Profile to perceive enough instrumentality in the course to try to at least get an average grade.

Profiles of Engineering Students

Differences between students in CS1-Enginnering and in other CS1 courses. As hypothesized, students in the foundational CS1-Engineering course were more likely to adopt the Apathetic or Learned Helpless Profiles, with about 61% adopting these (Table 3). Compared to the primarily computer science majors in the other introductory computer science courses (CS1-Honors, CS1-Computer Science, CS1-Mixed), engineering majors in the foundational CS1-Engineering course adopted the more maladaptive Surface Learning, Apathetic, and Learned Helpless Profiles at higher rates (83% vs 45%). The differences were most striking for adoption of the Apathetic Profile with 32% of students in CS1-Engineering adopting this profile versus only 7% of students in the other three courses. The inverse pattern occurred for the more adaptive profiles, as the Strategic or Knowledge Building Profiles were adopted by 56% of students in the other three CS1 courses; whereas, they were only adopted by 17% of the students in CS1-Engineering.

Table 3

Comparison of Profile Distribution between Students in the CS1-Engineering Course and Students in the CS1-Computer Science, CS1-Honors, and CS1-Mixed Courses

	Profile Cluster									
	Strategic		Knowledge Building		Apathetic		Surface Learning		Learned Helpless	
	n	%	n	%	n	%	n	%	n	%
CS1-Engineering	38	12	17	5	106	32	72	22	94	29
Other CS1 Courses	66	33	46	23	15	7	30	15	45	22

$\chi^2(4) = 99.94$, $p < .0001$.

Effect of profile adoption on learning. To examine how the adoption of different profiles affected engineering students' learning in CS1-Engineering, a one-way ANOVA was conducted. Knowledge test scores were significantly different across profiles, $F(4, 310) = 6.78$, $p < .0001$. Because variances were unequal, Dunnett T3 pair-wise post-hoc comparisons were conducted. Students in the Strategic ($M = 6.82$, $SD = 2.47$) and Knowledge Building ($M = 8.24$, $SD = 2.82$) Profile clusters did not significantly differ from each other and students in the Apathetic ($M = 5.02$, $SD = 2.60$), Surface Learning ($M = 5.38$, $SD = 3.29$), and Learned Helpless ($M = 5.79$, $SD = 2.69$) Profile clusters did not significantly differ from each other. Students in the Knowledge Building Profile cluster scored significantly higher than the Apathetic (Cohen's $d = 1.15$), Surface Learning (Cohen's $d = 1.03$), and Learned Helpless (Cohen's $d = .88$) Profile clusters. Students in the Strategic Profile cluster scored significantly higher than students in the Apathetic Profile cluster (Cohen's $d = .65$), but not students in the Surface Learning (Cohen's $d = .52$) or Learned Helpless (Cohen's $d = .37$) Profile clusters. Engineering students adopting the Knowledge Building Profile scored around one standard deviation higher on the knowledge test than students adopting the Apathetic, Surface Learning, or Learned Helpless Profiles. Engineering students adopting the Strategic Profile scored around one-half standard deviation higher on the knowledge test than students adopting the Apathetic, Surface Learning, or Learned Helpless Profiles. These large effect sizes suggest non-trivial differences even though only the difference between the Strategic and the Apathetic Profile was statistically significant.

Association of profiles with computer science major. Intent to major or minor in computer science was assessed in the fall 2010 and fall 2011 semesters. Among engineering students in the CS1-Engineering course, profile choice was significantly associated with their expressed intentions to major or minor in computer science in addition to their engineering major (Table 4). The low number of engineering students indicating consideration of or already majoring or minoring in computer science (13 students out of 165) and presence of many cells with expected values less than five makes the statistical tests problematic. Despite these limitations, the differences in the patterns of profile adoption are striking. A far greater percent of engineering students considering computer science as part of their academic program were adopting the Knowledge Building and Strategic Profiles than those not considering a computer science major or minor (61% vs. 17 %). Almost one-third of engineering students not intending to major or minor in computer science were in the Apathetic Profile; whereas, no students who were considering or already majoring or minoring in computer science adopted an Apathetic Profile. The large percentage of engineering students adopting the Apathetic Profile suggests that there is a notable difference between how students approach courses in their chosen field versus foundational required or elective courses outside their area of interest and, appears to be true even when the course is directly applicable to the students' major as the computer science courses here are for engineers.

Table 4

Cross Tabulation of Profile Cluster by Consideration of Computer Science Major/Minor

	Profile Cluster									
Computer Science Major or Minor	Strategic		Knowledge Building		Apathetic		Surface Learning		Learned Helpless	
	n	%	n	%	n	%	n	%	n	%
Considering or Already	6	46	2	15	0	0.0	3	23	2	15
Not Considering	18	12	7	5	49	32.2	30	20	48	32

$\chi^2(4) = 17.54$, $p = .002$. Note: Expected values less than five in four cells makes χ^2 values unreliable.

Gender differences in profiles. Table 5 shows the different distribution of profile cluster membership for men and women in the CS1-Engineering course. Men and women engineering majors did not significantly differ in profile composition. The relatively few women among the engineering majors, however, preclude drawing any strong conclusions about gender differences.

Table 5

Cross Tabulation of Profile Cluster by Gender

	Profile Cluster									
	Strategic		Knowledge Building		Apathetic		Surface Learning		Learned Helpless	
	n	%	n	%	n	%	n	%	n	%
Men	30	11	13	5	90	33	63	23	79	29
Women	8	16	3	6	15	31	8	16	15	31

$\chi^2(4) = 2.14$, $p = .711$.

Discussion

Faculty who teach foundational courses already know that students exhibit attitudes, beliefs, and behaviors in these courses that are counterproductive to their motivation and learning. The purpose of this study was to better understand how students approach foundational courses by identifying profiles of students who share common motivational and self-regulatory characteristics within the unique context of a suite of foundational computer science courses designed for both computer science majors and non-computer science majors, including engineering students. The five profiles identified here replicate and extend findings from prior studies of post-secondary students in non-engineering (Chen, 2012; Daniels et al., 2008; Schwinger et al., 2011; Shell & Husman, 2008) and engineering/technical fields (Entwistle & McCune, 2004; Shell & Soh, 2013). They also replicate profiles found in K-12 settings (Chen, 2012; Hayenga & Corpus, 2010; Tuominen-Soini et al., 2011; Vansteenkiste et al., 2009). Identification of these profiles in multiple studies across diverse grade levels and content areas supports the argument by Shell et al. (2010) that these five profiles capture the general motivated strategic self-regulatory approaches typical of most students in formal educational settings.

Are these the only five possible profiles that students can adopt when approaching their coursework? Perhaps not, as evidenced by the findings of more profiles of motivation by Conley (2012); but her additional profiles have not been replicated in other studies. The profiling literature, however, is still in its infancy. The generality of these profiles needs to be examined across more post-secondary courses and content areas. Also, a broader array of engineering courses needs to be studied, especially those at more advanced levels, as well as other foundational courses commonly taken by engineering students.

The identified profiles shed light on the motivational and self-regulatory approaches engineering students adopt in foundational courses and the effect of profile adoption on learning. Unfortunately, but not unexpectedly, approximately 83% of engineering students taking the CS1-Engineering course in this study adopted one of the maladaptive profiles of Apathetic, Surface Learning, or Learned Helplessness. Students who adopted these maladaptive profiles learned less content than students adopting the Strategic or Knowledge Building profiles. Adoption of these maladaptive profiles by engineering students in foundational required courses may be contributing to reduced first year GPA and ultimately leading to higher rates of dropping out of engineering (Burtner, 2004; French, Immekus, & Oakes, 2005; Veenstra, Dey, & Herrin, 2009).

These data provide additional detail concerning the struggles with motivation and self-regulation that engineering students may face when they take required foundational courses outside of their major. The findings do not provide any evidence that engineering students themselves are inherently maladaptive learners. Shell et al. (2010; also Entwistle & McCune, 2004; Shell & Husman, 2008) note that profiles are dynamic, responsive to context. A student's profile may shift across different courses and subject matter domains as well as in response to contextual factors within a course. Rather, the findings indicate that participating in a foundational non-major course may create a particular context, producing a *perfect storm* of conditions that impact how engineering students approach coursework *in that course.* In another course, they may act entirely differently.

Findings provide further evidence that students' goals (goal orientation) and beliefs about the course (perceptions of instrumentality) may be key pivot points, that together influence students' approaches regarding how or if they self-regulate their learning in these courses

(Simons et al., 2004; Tabachnick, Miller, & Relyea, 2008). The tendency of engineering students to see foundational courses as less instrumental than courses within their major field has also been consistently reported (Husman & Corno, 2010; Puruhito et al., 2011).

In addition to the Strategic and Knowledge Building profiles, the results indicated that high perceived instrumentality also was linked to the maladaptive Learned Helpless Profile. Students in the Learned Helpless Profile have contradictory beliefs and self-regulatory behaviors. They have high learning approach, but also high learning avoid goal orientation. They report high self-regulation, knowledge building, and engagement, but also high lack of regulation. Their high perceived instrumentality for the courses does not appear to be enough to overcome the lack of success and negative emotions leading to their contradictory motivation and self-regulation. Apparently, the perception that a course is useful can only produce positive motivation and self-regulated learning when students feel that they are in control of their learning and are confident that their self-regulatory efforts and engagement are leading to success. Knowing that a course is important for one's future may increase feelings of helplessness if students do not feel it is within their control to succeed in that course.

Consistent with the impetus for pursuing a profiling approach, the results of this study indicate that student engagement in any given course cannot be understood through the lens of just one motivational construct. Students' beliefs, perceptions, skills, and strategic approaches interact and affect each other. Although it is clear that goal orientations and perceived instrumentality do play an important role in orienting a students' approach to learning, they do not motivate success on their own.

Implications

The findings provide further evidence for the validity of the profiling approach as a framework for educators. Profiling can help educators better understand the motivations and behaviors they see students exhibit; an understanding that can provide guidance for instructional and curricular strategies to encourage optimal motivation and self-regulation in particular courses. Once profiles are identified, efforts can be made to change them. As shown by Hulleman and Harackiewicz (2009), beliefs about a course can be manipulated and this manipulation can lead to adaptive motivational and self-regulatory approaches to learning. Although at this time neither researchers or educators have a reliable method for classifying students' classroom beliefs, nor do the authors of this paper expect that one will be developed soon, we argue that the replication of these profiles across many studies (Chen, 2012; Entwistle & McCune, 2004; Daniels et al., 2008; Schwinger et al., 2011; Shell & Husman, 2008; Shell & Soh, 2013) demonstrates a common set of approaches or postures students take when engaging in learning in traditional post-secondary education settings. Educators can consider how their instructional practice may cue one of the less adaptive profiles, or how it could support an adaptive profile. Instructors may also be on the lookout for signs of the cluster of beliefs which could be supporting, or indicating trouble for students in their course. There is evidence that suggests changes to instruction can change students' profiles. For example, in a study of elementary school students, Linnenbrink-Garcia, (2011) found that profiles similar to those identified here were influenced by both a classroom intervention and students' perceptions of the classroom environment.

There is evidence to suggest that even small changes to homework assignments can influence students' motivational beliefs. Research has demonstrated that if students are asked to write about their own ideas of utility or importance for the task at hand, they are more likely to persist in that task in the future (Hulleman & Harackiewicz, 2009). In that study, the researchers asked their study participants (high school science students) to provide written explanations for why certain tasks that they were completing were useful to them. After completing these mini interventions, students exhibited increased persistence and achievement in science.

Prior research has demonstrated that instructional cues can influence both perceptions of instrumentality and goal orientation (Vansteenkiste et al., 2004). Puruhito et al. (2011) found that instrumentality could be enhanced in engineering students through an intervention in their calculus courses. In this study, calculus students (who were majoring in engineering) were shown videos of students who had taken the course previously (approximately 2-3 years earlier). In these videos, the older engineering students described how important understanding calculus was for their subsequent coursework. The current calculus engineering students' instrumentality increased after watching these videos. This last example especially provides an effective approach that professors can utilize when teaching foundational courses.

Heyman et al. (2002) showed that engineering students have fixed mindsets about their intelligence – meaning that they are more likely to have performance goals versus mastery goals (learning goals). However, fixed mindsets can be overcome through interventions. Blackwell et al. (2007) showed the malleability of mindsets through an intervention with middle school students. Specifically, they provided materials and exposed students to content where the key message was that learning is the process of creating connections in the brain, something that is within the students' control. Through this process, the students learned that they have control for their own learning – it is not something that they are born with (Blackwell, 2007). This work has not been extended to engineering at present, however, mindset is not a domain-specific phenomenon. Foundational courses could be tailored to include mini-interventions to teach students that their intelligence is not fixed. If these courses can be tailored to encourage students to adopt more adaptive goal orientations (learning approach), there is a greater likelihood that students will shift towards more adaptive motivational profiles and enhance their performance and overall learning in foundational courses. All of these findings suggest that despite the general stability present in the profiles, they could be influenced by the classroom environment, students' perception of the course, and how it is taught.

However, the purpose behind a profiling approach is to consider the constellation of behaviors and cognitions that result in certain patterns related to, in this case, academic achievement in engineering foundational courses. The Puruhito et al. (2011) intervention may be effective at enhancing student persistence in foundational courses, however, a consideration for interventions that enhance additional variables or even the entire constellation of variables within the profiling matrix should be considered when attempting to support students' overall motivation and self-regulation. That is, interventions designed to promote the adoption of adaptive profiles, as opposed to a single motivational or self-regulative construct, is encouraged.

Limitations

Profiling is not an inferential statistical technique; it is a descriptive methodology that is highly interpretive. There were only minor statistical differences among the four, five, and six profile solutions. Any of these could have been legitimately justified on purely statistical grounds. As discussed, differences in profiles are sometimes subtle. Interpretation of profile solutions relies as much on theoretical grounds as it does on the available statistics. We can argue, as have other researchers (Entwistle & McCune, 2004; Shell et al., 2010), that these profiles will be found within all courses; however, there is no way yet to validly infer any particular distribution of profiles in a course. We can suggest that the results here are typical of how engineering students may approach required foundational courses; but, we would not expect to find the same distributions of profiles in other foundational required courses. We would, however, expect that engineering students are more likely to adopt maladaptive profiles within these courses than they would in courses within their major. The types of profiles engineering (and other students) are adopting can only be determined by additional research. This future research needs to consider differences in students' individual profiles as they enroll in different courses in their engineering program of study and include samples with more extensive minority and female populations. Consideration of differences will shed light on how students perceive their courses, their perceived capability to learn the content, and how they self-regulate their own learning.

This study examined only students at a single university as part of a specific funded exploratory project. Use of a single university has implications for generalization. The suite of introductory computer science courses examined is similar in content to introductory computer science CS1-level courses at most colleges and universities, but not all of these courses are tailored for different student populations or taught using the same pedagogy. We cannot say whether similar introductory computer science courses at other schools would show the same profile distributions.

There also may have been effects of different instructors within the courses studied. The different courses in the study were all taught by rotating computer science faculty. With the exception of the CS1-Honors course that was taught by one faculty member, all of the other courses were taught by different faculty in different semesters, with all faculty teaching each course at some point. Additionally, although aspects of the courses were tailored, all of them had the same basic content and instructional format of lecture and lab. The common curriculum and rotating faculty would suggest that there were not large instructor or pedagogical differences that could account for the study findings. We note that different instructors or pedagogy would likely affect the distribution of profiles within a specific offering of any one of the courses studied. In fact, we would expect that they would. They should not, however, affect the identification of the profiles themselves.

Finally, although findings replicated Shell and Soh (2013), their study used the same fall 2010 students as this study. Overall, 233 of the 538 students in the total sample and 94 of the 332 engineering students in CS1-Engineering overlapped. Although this study examined three additional semesters of data, the findings cannot be considered independent from those of Shell and Soh.

Conclusions

The present findings provide an important first step toward using a profiling approach in engineering education. Many of the students participating in a foundational computer science course tailored for engineering exhibited maladaptive motivational self-regulation profiles – that is, profiles that indicated limited perceptions of utility for learning the course content, dysfunctional goals to avoid learning the course material, as well as a lack of effective self-regulated learning strategies. Few engineering students in our study adopted adaptive profiles in which students are motivated to do well and apply effective metacognitive, self-regulatory, and knowledge building strategies toward the content they are learning in the course. Those engineering students who adopted adaptive profiles were, more often than not, intending to pursue a major or minor in the subject of the course (computer science) in addition to their degree in engineering which suggests that they value learning the content in the course more than their fellow engineering majors. Even though engineering students in these courses primarily adopted maladaptive profiles, previous research has shown that steps can be taken by educators to encourage engineering students to shift to more adaptive profiles (e.g., Linnenbrink-Garcia, 2011). Overall, the findings indicate that a profiling approach may be a good first step for engineering educators as they begin to better tailor their courses and especially their foundational courses. Additionally, the profiling approach informs educators who wish to create interventions that encourage more motivated and self-regulated learning in the classroom.

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