frontiers | Frontiers in Education

TYPE Original Research
PUBLISHED 23 October 2024
DOI 10.3389/feduc.2024.1181616

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RECEIVED 07 March 2023
ACCEPTED 04 October 2024
PUBLISHED 23 October 2024

CITATION
Laitinen S, Christopoulos A, Laitinen P and Nieminen V (2024) Relationships between self-efficacy and learning approaches as perceived by computer science students. *Front. Educ.* 9:1181616.
doi: 10.3389/feduc.2024.1181616

Relationships between self-efficacy and learning approaches as perceived by computer science students

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Optimizing learning outcomes in university students necessitates an understanding of the processes that drive high-quality learning outcomes. This study investigates the motivational factors and learning methodologies perceived by computer science students during an introductory course. A cross-sectional study was conducted with 171 computer science students asked to complete a psychometric instrument ("Study Skills Inventory for Students") during the first year of their university studies. Two major theoretical frameworks in educational psychology, namely students' self-efficacy and learning approaches were tested relative to a factor structure obtained from learning situations. The findings supported self-efficacy and three learning approaches among computer science students. Models for deep, surface, and strategic learning approaches suggest that students with higher self-efficacy tend to adopt a deeper approach to learning. Conversely, students with lower self-efficacy were more inclined toward surface learning methods. Furthermore, a link was identified between strategic learning approaches and students' experiences within their learning environments. The results substantiate earlier research and align with learning approach theories. The findings indicated that, in higher education settings, focus should be directed toward understanding the motivational factors influencing students and their learning approaches for educational outcomes.

KEYWORDS

motivation, learning approaches, computer science students, higher education, behavior

1 Introduction

1.1 The role of motivation in learning

A substantial body of literature suggests that motivation is pivotal for shaping the learning and study habits of higher education students, largely due to the intimate connection between students' perceptions of their learning capabilities and the learning approaches they choose to adopt (Entwistle et al., 2001). Factors of motivation, including self-efficacy, significantly influence the selection of learning approaches within given contexts (see Asikainen and Gijbels, 2017, for a review). However, it is noteworthy to mention that the correlation between motivational elements and learning approaches may not consistently manifest across all individuals (Lonka et al., 2004).

Despite the demonstrated categorization of motivation characteristics in higher education in three primary learning approaches (Lonka et al., 2004), there is still limited research (e.g., Gorson and O'Rourke, 2020; Steinhorst et al., 2020) regarding the association between self-efficacy and learning approaches among computer science students. Similarly, studies on learning approaches are also notably lacking, even though comprehending the learning tactics employed by higher education students early in their undergraduate experiences could provide valuable insights into tailoring effective educational resources and enhancing their learning processes (Brown et al., 2015; Diseth, 2001). This scarcity of research is also evident in studies examining the relationship between motivational factors and learning approaches among computer science students (Figueiredo and García-Peñalvo, 2020; Umapathy et al., 2020). Consequently, the current study is designed to explore the structure of self-efficacy and learning approaches and the relationship between these dimensions adopted by first-year computer science students.

1.2 Motivation and self-efficacy

Motivation energizes, directs, and sustains students' individual learning activities (Ford, 1992; Reeve, 2012). It is intimately linked to the behavioral, social, cognitive, and affective aspects that manifest in diverse learning approaches (Dweck and Leggett, 1988). Therefore, motivation serves as a critical component in helping students adapt to increasing task demands and manage their individual education within an environment of interpersonally regulated learning (Vauras et al., 2019).

Murphy and Alexander (2000) proposed that self-efficacy is a motivational construct capable of elucidating students' learning approaches in situations requiring both task processing and subsequent performance (Bandura, 1982). Self-efficacy is conceived of as the personal judgment of one's capability to organize and accomplish a course of action that will achieve a particular task goal (Bandura, 1977, 2006). "Self-efficacy" is also called "self-efficacy beliefs" (Bandura, 2006), a term that denotes students' perceptions of their capabilities to execute and master academic achievements.

As per Bandura's theory (2006), individuals' beliefs about their abilities in learning situations are related to their learning behaviors and approaches. This explains how self-efficacy beliefs profoundly influence the following: (a) goal setting, (b) the choice of approach, (c) the amount of effort and persistence invested in a task situation, (d) the continuity and persistence of the action, and (e) how an individual applies knowledge and skills in a task situation (Bandura and Locke, 2003). For example, one who considers one's self-efficacy "high" is likelier to master and persist with at task, whereas one who rates one's self-efficacy "low" may abandon the task more readily, potentially leading to failure (Bandura, 1989).

Recent studies have explored the relationship between self-efficacy and learning approaches among university students (e.g., Phan, 2011; Trigwell et al., 2013). Findings from these studies suggest that the higher university students' self-efficacy beliefs regarding their learning tasks, the more capable they perceive themselves in achieving goals. These students tend to embrace a deep learning approach and attain higher academic accomplishments compared to their counterparts with low self-efficacy beliefs. Consequently, the construct of self-efficacy aligns seamlessly with self-determination theory (Deci and Ryan, 1985) and underscores the importance of cultivating a sense of competence and control in task situations.

Furthermore, research has shown that self-efficacy is crucial for academic performance (Linnenbrink and Pintrich, 2002). For instance, a high sense of self-efficacy is associated with better academic outcomes, such as the ability to focus on deeper meanings and to combine new information with what was previously known, which is essential for scientific thinking (Parpala et al., 2022). Additionally, Cordova et al. (2014) discovered that having self-efficacy in learning about a specific subject helps with conceptual change. It does this by boosting confidence in one's ability to understand and modify one's thoughts, much like an expert in development. Therefore, self-efficacy can be seen as "expected constructions" because it relates to a student's confidence in performing a task (Pintrich, 2003). Van Dinther et al. (2011) reviewed this and concluded that self-efficacy is not only key to academic performance but also plays a significant role in students' achievements and learning processes.

In this study, we recognize the significant role that a student's level of self-efficacy and perceived ability to achieve in study tasks play in the adoption of a learning approach (Brown et al., 2015). We aim to investigate how self-efficacy is applied (Bandura, 2006; Chen et al., 2001) to the motivation of computer science students in relation to their learning approaches.

1.3 Behavioral approaches and learning strategies

Studies indicate that students with varying levels of motivation may adopt different behavioral approaches, such as a deep, surface, or strategic, for their learning tasks (Asikainen and Gijbels, 2017). Existing research has established that students' goal orientation (Geitz et al., 2016) and self-regulation, as interpreted through self-determination theory (Kyndt et al., 2011), are closely related to their behavioral approaches in learning situations. Specifically, it has been reported that university students with high levels of self-efficacy align a deep learning approach; those with lower self-efficacy levels tend toward a surface approach to learning (Trigwell et al., 2013). Moreover, studies by Phan (2011) and Prat-Sala and Redford (2010) suggested that distinct associations emerge between self-efficacy and the learning approaches.

For instance, Milienos et al. (2021) identified four different learning profiles encompassing self-efficacy, cognitive, emotional, and resilience aspects among first-year higher education students. They illustrated that students possessing emotionally stable and adaptive learner profiles had the highest level of Grade Point Average (GPAs), whereas students with emotionally dysregulated and at-risk profiles hade the lowest GPAs. Students characterized by emotionally dysregulated and highly adaptive learner profile underscored the significance of learning factors upon entering higher education. Conversely, the emotionally stable at-risk learner profile group lacked self-efficacy, employed inadequate learning processing strategies, and demonstrated a minimal resilience.

Regarding learning situations, Karagiannopoulou et al. (2018) proposed that defense styles and preferences for various courses function as precursors to learning approaches. They found that these approaches mediate the effects of defenses and preferences on achievement, even though these impacts vary among students (Karagiannopoulou et al., 2018). In light of these findings, we hypothesis that students' self-efficacy will cultivate positive emotions about their learning situations, thereby fortifying their task-oriented learning approach. Moreover, Biggs (1993) emphasized that prior knowledge plays a crucial role in the preference for learning approaches, since choosing deep approaches is the exclusive privilege of students with much knowledge. Without such knowledge, an overview of the topic to master and the steps necessary for mastery, one might do no better than follow a surface learning approach. Simultaneously, previous knowledge might be the prime antecedent of self-efficacy. Therefore, any relationship between self-efficacy and preferred learning approaches suggests the confounding of previous knowledge. One would prefer to study the relationship between previous knowledge, self-efficacy, and learning approaches.

1.4 Understanding learning approaches

The term *learning approach* refers to individual students' variations in intention when confronted with learning situations and the corresponding strategies they utilize to realize those intentions (Entwistle et al., 2001; Marton and Säljö, 1976, 1997). This concept originates from Marton and Säljö (1976, 1997) seminal research on "approaches to learning", in which they explored the divergent ways students approach learning and studying. Their findings suggest that students' intentions before studying determine their learning strategies and, consequently, their understanding of the material. Furthermore, they discerned that students tend to adopt either a deep, surface, or strategic approach to learning and studying.

Recent studies confirm the prevalence of these three learning approaches among various disciplines, including medicine (Negash et al., 2022), biology (Dedos and Fouskakis, 2021), and chemistry (Brown et al., 2015). Each approach (deep, surface, or strategic) contains distinct elements (subscales) concerning students' intentions and processes during learning situations (Entwistle et al., 2001). Beyond the established positive relationship between self-efficacy and the deep learning approach (Trigwell et al., 2013), there also appear to be conceptual and empirical intercorrelations between the three learning approaches.

A systematic review by Asikainen and Gijbels (2017) emphasizes that higher education students employ a wide array of learning strategies neatly encompassed within the three broad learning approaches. Each approach exhibits a unique pattern of student engagement and study methodology. For example, Dedos and Fouskakis (2021) found positive correlations between deep and strategic approaches among biology students. However, the surface approach negatively correlated with both deep and strategic approaches (Dedos and Fouskakis, 2021).

According to Entwistle et al. (2001), a deep approach to learning is characterized by a student's intention to understand, actively relate ideas to previous knowledge and experiences, and use evidence to reflect on learning content. Students adopting a deep approach often prefer teaching methods that stimulate and challenge their understanding. This process aligns closely with the intention to seek meaning and interest in ideas, overlapping with concepts such as intrinsic motivation (Ryan and Deci, 2000). Conversely, a surface approach to learning and studying usually involves minimal effort by students, which is often limited to memorizing information to meet task requirements (Marton and Säljö, 1997). This phenomenon tends to result in a lack of purpose and understanding (Entwistle et al., 2001). Students with a strategic approach will pay meticulous attention to details, such as the structure of course content, with the goal of doing well and achieving personal goals. These students effectively identify and utilize elements of the learning environment that support their study approaches. Within the strategic approach is a clear link between the approach and the motive, as achievement motivation strongly correlates with organized studying, effective time management, and efficient monitoring (Entwistle et al., 2001).

These findings suggest a strong relationship between university students' motivational behaviors and learning approaches and their learning and studying situations (Asikainen and Gijbels, 2017; Lonka et al., 2004). Moreover, students are believed to enter learning situations with experiences that influence their motivation and further their learning behaviors to achieve their learning outcomes (e.g., see Ward, 2011). Learning approaches are partially influenced by motivation (i.e., self-efficacy), but may be modified by student-oriented processes, such as feedback on selected learning approaches (Entwistle et al., 2003). Thus, the extent to which motivational differences (i.e., self-efficacy) relate to the learning approaches adopted by computer science students should be studied.

1.5 Objectives and significance of this study

Given the aforementioned findings, it is a necessary to explore the manifestation of motivational factors and learning approaches within the academic literature (e.g., Asikainen and Gijbels, 2017). However, such studies remain scarce among computer science students. For instance, Adamopoulos (2020) emphasized the need for an in-depth investigation of student motivations for learning programming—a field that remains largely unexplored. Additionally, the recent shift toward more independent and online learning, particularly for programming instruction, calls for research into its impact on students' learning behaviors. In a similar vein, Wolz et al. (2022) advocated for research to ascertain whether fostering self-efficacy and subject identification, particularly in programming courses, could enhance students' beliefs about effort. Hence, the intrinsic nature of learning in computer science (e.g., students must consider variables, their roles, their problem-solving processes, and the processes of the computers that they are attempting to model and control) differs from other disciplines. One cannot merely assume that findings from other disciplines are suitable for describing learning in computer science (Morrison, 2015). This distinct nature raises the question of whether computer science students' learning approaches, influenced by their unique curriculum and the complexity of the subject matter, differ fundamentally from those in other STEM fields. Consequently, problem-focused coping strategies and emotional intelligence are intrapersonal variables that assist computer science students' ways of behaving in stressful situations and peer dynamics compared to other majors (Bélanger et al., 2007). In addition, the specific curriculum of the selected course, alongside other courses that students take during their first year, may significantly influence their choice of learning approach. This influence extends to the consideration of students' past educational experiences and their flexibility in adapting their learning approaches to meet the demands of each course.

Taken together, these sources indicate a gap in the literature concerning motivational factors and learning approaches among computer science students. To address this research gap, the current study examines the motivational factor of self-efficacy and the three learning approaches (deep, strategic, and surface) concerning the learning and studying habits of first-year computer science students. More specifically, the first objective of this study is whether the data support the hypothesis of self-efficacy and three dimensions of learning approaches, and whether these dimensions can adequately describe each of the computer science student's perceived behavior in learning situations. In particular, based on theoretical assumptions and research findings (e.g., Asikainen and Gijbels, 2017; Entwistle et al., 2001; Lonka et al., 2004), it seems important to examine the structure of the factor model, for instance, to distinguish between the deep and surface learning approaches as well as motivation in learning situations (*H1*). The exploration of whether these patterns of relationships will be consistent or vary compared to students in other STEM majors is a crucial aspect of this research. Previously, for instance, Parpala et al. (2010) have investigated university students' perceived learning approaches, and found evidence for variations between disciplines. According to that, the surface approach was overrepresented in the faculty of Science.

The second objective focuses on investigating the relationship between students' self-rated self-efficacy and their propensity to adopt deep, surface, and strategic approaches in learning situations. The reasonable assumption is that higher level of self-efficacy corresponds to greater adoption of the deep learning approach (as illustrated in the conceptual model, Figure 1) (see also Phan, 2011; Trigwell et al., 2013). Instead, lower level of self-efficacy may lead to a surface approach, such as isolated content memorization rather than application, which is expected to be the least beneficial for computer science students in learning situations (*H2*). Finally, we explored the potential relationships between previous knowledge and self-efficacy and, furthermore, between learning approaches and task performance. According to previous research (Parpala et al., 2022), high level of self-efficacy is associated with good academic performance, such as analysing and understanding information in a larger picture with underlying meanings and integrating new knowledge with previous knowledge, whereas surface approach entails unreflective studying rather than memorization and repetition of knowledge (Lindblom-Ylänne et al., 2019). We expected previous knowledge of algorithms and programming to positively relate to self-efficacy (e.g., Biggs, 1993), and learning approaches to task performance (*H3*). However, such hypotheses have not yet received adequate attention in the academic literature. Additionally, the strategic approach (Entwistle et al., 2001), which students may perceive primarily as an organizational tool, could be differentially associated with deep and surface approaches. Accordingly, this study aims to expand on previous research by examining the relationships between self-efficacy and deep, surface, and strategic approaches among first-year computer science students.

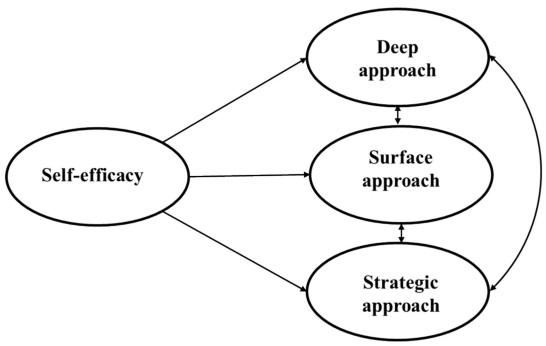

FIGURE 1
Conceptual model illustrating relationships between students' perceived self-efficacy and learning approaches.

2 Materials and methods

2.1 Context and participants

The participants in this study were Computer Science students in the first year of a Computer Science training program at a public university in Finland. The data were collected as part of a course named "Basic Course on Algorithms and Programming." The instructional methodology comprises lectures, mandatory tutorials, demonstrations, and assignments, with a cumulative examination. The course was delivered in Finnish indicating that participants, regardless of their national origin, had sufficient proficiency in the language. This aspect, however, adds a unique dimension to our study, as language proficiency and cultural integration could influence academic engagement and perceptions in such educational settings.

The curriculum is designed to introduce students to the foundational principles and practical applications of programming with a focus on developing algorithmic thinking. The course aims to equip students with the ability to create functional applications by employing basic programming constructs such as sequencing, selection, and repetition. The course content covers a comprehensive array of topics including effective use of an editor and compiler, adherence to good programming practices, understanding of variables, references, arrays, basic control structures, input/output operations, algorithmic problem-solving techniques, modularity, and methods. Initial and final conditions, as well as the concept of recursion, are also introduced. Although the course delves into the utilization of objects, it specifically excludes the creation of custom classes representing object-oriented programming. To ensure a robust understanding of these concepts, students are required to engage in continuous, independent practical exercises.

All participants were provided with preliminary information about the study and were asked to complete a questionnaire on a voluntary basis. Written informed consent was obtained from all participating students. The questionnaire was sent out once. The ethical guidelines for scientific research from the University's Ethics Committee and the Academy of Finland were followed.

2.2 Data collection tool

The data collection survey contained two types of questionnaire items. The Approaches and Study Skills Inventory for Students (ASSIST) survey was adopted to determine the approach and study skills of computer science students. The ASSIST survey is based on previous studies (e.g., Entwistle and Ramsden, 1983; Marton and Säljö, 1997; Pask, 1976; Vermunt and Vermetten, 2004) and was developed to provide a wider understanding of learning and studying strategies. The ASSIST part of the survey consisted of 50 items. Students were asked to indicate their agreement with each item using a five-point Likert scale (1 = "Disagree"; 5 = "Agree"). The tool provides good overall coverage of different ways of studying and measures

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students' learning approaches from three perspectives. These perspectives, namely, the deep approach, the surface approach, and the strategic approach, reflected students' perceptions of their learning approaches (Entwistle and Ramsden,1983) and their preferences for adopting different approaches to learning (e.g., Lonka et al., 2004). In addition to the ASSIST questionnaire, eight items were added to the present study to measure self-efficacy as a motivational dimension (see Parpala et al., 2010; Parpala and Lindblom-Ylänne, 2012). Thus, a total of 58 items measured the four factors: self-efficacy, deep approach, surface approach, and strategic approach. This position corroborates the measurement of these factors in previous studies. The self-efficacy items and the sub-measures for the ASSIST factors in the questionnaire and the descriptive statistics for the data collected are presented in Table 1. Specifically, self-efficacy as a measure of motivation has eight items, such as "I am confident that I can perform effectively on many different tasks" (Chen et al., 2001). The deep learning approach (Entwistle et al., 2001) included four sub-measures: *seeking meaning* (covered by four items), for example, "I usually set out to understand for myself the meaning of what we have to learn"; *relating ideas* (four items), for example, "I try to relate ideas I come across to those in other topics or other courses whenever possible"; *use of evidence* (four items), for example, "I look at the evidence carefully and try to reach my own conclusion about what I'm studying"; and *interest in ideas* (four items), for example, "Regularly, I find myself thinking about ideas from lectures when I'm doing other things." The surface learning approach included four sub-measures: *lack of purpose* (four items), for example, "Often I find myself wondering whether the work I am doing here is really worthwhile"; *unrelated memorising* (four items), for example, "Much of what I'm studying makes little sense: it is like unrelated bits and pieces"; *syllabus boundness* (four items), for example, "I tend to read very little beyond what is actually required to pass"; and *fear of failure* (three items), for example, "I often worry about whether I will ever be able to cope with the work properly." The strategic learning approach contained five sub-measures: *time management* (four items), for example, "I organize my study time carefully to make the best use of it"; *achieving* (four items), for example, "I feel that I'm getting on well, and this helps me put more effort into the work"; *organized studying* (three items), for example, "I usually plan out my week's work in advance, either on paper or in my head"; *alertness to assessment demands* (four items), for example, "When working on an assignment, I'm keeping in mind how best to impress the marker"; *monitoring effectiveness* (four items), for example, "I go over the work I've done carefully to check the

TABLE 1 Descriptive statistics for self-efficacy items and learning approach subscales ($N = 171$).

Factors and items	Min	Max	M(SD)	Skewness	Kurtosis
Self-efficacy					
Self1. I will be able to achieve most of the goals that I set for myself.	1.00	5.00	3.84(0.81)	−0.84	1.22
Self2. When facing difficult tasks, I am certain I will accomplish them.	1.00	5.00	3.30(0.97)	−0.25	−0.49
Self3 In general, I think that I can obtain outcomes that are important to me.	1.00	5.00	4.18(0.79)	−0.85	0.88
Self4. I believe I can succeed at most any endeavor to which I set my mind.	1.00	5.00	3.63(1.03)	−0.39	−0.46
Self5. I will be able to successfully overcome many challenges.	2.00	5.00	3.65(0.78)	−0.13	−0.35
Self6. I am confident that I can perform effectively on many different tasks.	1.00	5.00	3.74(0.89)	−0.33	−0.34
Self7. Compared to other people, I can do most tasks very well.	1.00	5.00	3.47(0.86)	−0.14	0.14
Self8. Even when things are tough, I can perform quite well.	1.00	5.00	3.58(0.97)	−0.58	−0.12
Deep approach					
Deep1. Seeking meaning (4 items)	1.50	5.00	3.75(0.68)	−0.68	0.77
Deep2. Relating ideas (4 items)	1.25	5.00	3.45(0.83)	−0.34	−0.30
Deep3. Use of evidence (4 items)	1.25	5.00	3.32(0.69)	−0.17	−0.07
Deep4. Interest in ideas (4 items)	1.50	5.00	3.75(0.76)	−0.31	−0.37
Surface approach					
Surf1. Lack of purpose (4 items)	1.00	4.50	2.75(0.82)	0.11	−0.54
Surf2. Unrelated memorizing (4 items)	1.00	4.75	2.63(0.81)	0.21	−0.42
Surf3. Syllabus boundness (4 items)	1.25	5.00	3.21(0.81)	0.07	−0.58
Surf4. Fear of failure (3 items)	1.00	5.00	3.05(1.08)	−0.02	−0.97
Strategic approach					
Str1. Time management (4 items)	1.00	5.00	2.95(0.98)	−0.03	−0.96
Str2. Achieving (4 items)	1.50	5.00	3.31(0.82)	0.03	−0.90
Str3. Organized studying (3 items)	1.33	5.00	3.25(0.90)	−0.28	−0.52
Str4. Alertness to assessment demands (4 items)	1.00	5.00	3.28(0.85)	−0.37	−0.04
Str5. Monitoring effectiveness (4 items)	1.50	5.00	3.84(0.68)	−0.70	0.37

reasoning and that it makes sense." Cronbach's alphas for self-efficacy, deep approach, surface approach, and strategic approach were 0.90, 0.84, 0.73, and 0.78, respectively.

The expected three-factor structure (corresponding to deep, surface, and strategic learning approaches) emerged from an analysis at the subscale level (as in Karagiannopoulou and Milienos, 2015). Although ASSIST has been used in a wide range of studies, only a few have used a structural equation model (SEM) approach to explore relationships between achievement and learning approaches (e.g., Diseth et al., 2006; Karagiannopoulou and Milienos, 2015; Karagiannopoulou et al., 2018), with even fewer relationships between motivation and learning approaches (e.g., see Asikainen and Gijbels, 2017).

Second, students' baseline skills in course content on algorithms and programming, used to indicate previous knowledge, were obtained from self-ratings (on a scale of 1 = beginner to 4 = experienced; M = 1.42, SD = 0.66). Third, students' task performance was measured using a course performance test, with a maximum of 90 points (M = 73.01, SD = 10.92).

2.3 Data analysis

Before the main analysis, preliminary analyses concerning structural validity were first conducted for the main study variables using Confirmatory Factor Analysis (CFA). To understand the interrelations among the variables in this study, bivariate correlations were conducted. Second, the interrelations between the deep, surface, and strategic approaches were examined with a latent SEM. Third, the model was specified and tested (see, Figure 2), in which task performance was regressed on the learning approaches and, in turn, the learning approaches on task performance.

All of the models were fitted to the covariance matrix using the maximum likelihood robust method with Mplus 8.4 (Muthén and Muthén, 1998–2017). The fit of the models was evaluated using the chi-square method; the comparative fit index (CFI) ≥ 0.90; the Tucker-Lewis Index (TLI) ≥ 0.90 (Tucker and Lewis, 1973), indicating the extent to which the model fits compared with the independence model the root mean square error of approximation (RMSEA) < 0.08, as an index of discrepancy per the degree of freedom; and the standardized root mean square residual (SRMR) < 0.08, as an index is the average of the standardised residuals between the observed and the predicted covariance matrix (Hu and Bentler, 1995).

3 Results

3.1 Descriptive statistics

Of the total sample (N = 171), 51% were males, 48% were females, and 1% did not disclose their gender. The mean age of the participants was 22.7 years (SD = 4.2).

Table 1 shows the means, standard deviations, skewness, and kurtosis for the items and subscales that represent the students' perceived self-efficacy and the learning approaches adopted during the course. The estimates of skewness and kurtosis were within reasonable limits. That is, the statistics were well below 2.0 for skewness and 7.0 for kurtosis (Curran et al., 1996).

The correlation results are presented in Table 2, and they support convergent and discriminant validity. The correlations within self-efficacy, within the learning approaches, and between self-efficacy and the learning approaches all agreed with our expectations (see Table 2). Our findings reveal intriguing patterns of association. Specifically, self-efficacy is linked with both deep and strategic approaches in a similar manner. However, these relationships diverge from the connection between self-efficacy and the surface approach. These variances in associations imply a complex mesh of intrinsic and extrinsic motivational factors in the learning process. Thus, educational pursuits do not just encompass singular motivations, but rather a dynamic interaction between self-driven incentives (such as self-efficacy and a deeper understanding) and strategic, possibly externally influenced approaches. Interestingly, both previous knowledge and task performance were positively associated with self-efficacy, the deep approach, and the strategic approach, whereas they were negatively associated with the surface approach.

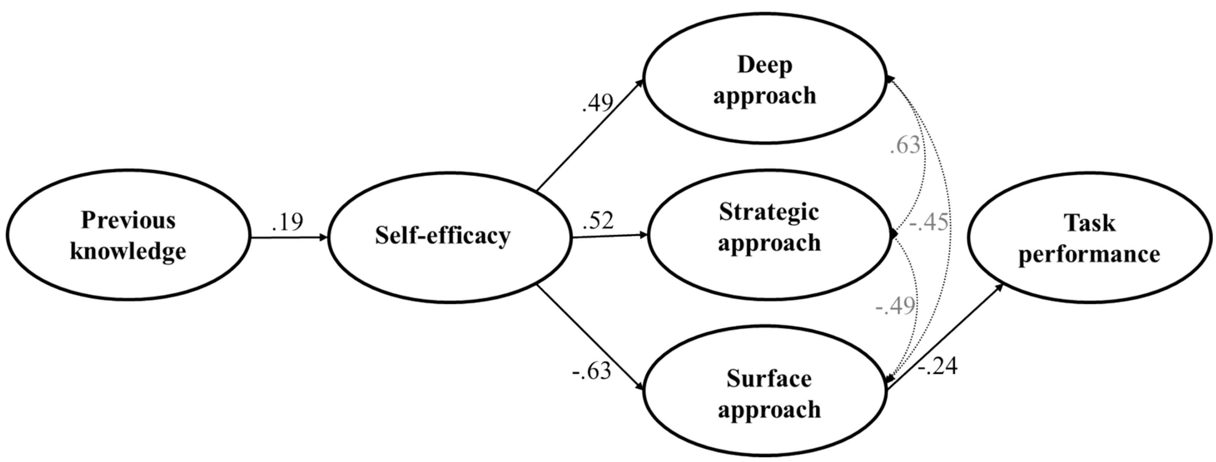

FIGURE 2
Results of students' previous knowledge, self-efficacy, learning approaches, and task performance (N = 171). For clarity, the factor loadings of latent variables are omitted. Only significant (p < 0.05) relationships (β) are reported. The fit statistics for model: [χ^2(225) = 495.17], CFI = 0.90, TLI = 0.90, RMSEA = 0.08, SRMR = 0.08.

TABLE 2 The score coefficient matrix of self-efficacy items and learning approach subscales, previous knowledge, task performance, and factor correlation matrix (N = 171).

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
1. Self1	-																						
2. Self2	0.57**	–																					
3. Self3	0.63**	0.58**	–																				
4. Self4	0.57**	0.65**	0.60**	–																			
5. Self5	0.51**	0.59**	0.48**	0.64**	–																		
6. Self6	0.52**	0.53**	0.51**	0.56**	0.61**	–																	
7. Self7	0.49**	0.50**	.,41**	.,44**	0.51**	0.50**	–																
8. Self8	0.54**	0.52**	0.54**	.,51**	.,47**	0.51**	0.55**	–															
9. Deep1	0.29**	0.21**	0.31**	0.07	0.23**	0.17*	0.15	0.28**	–														
10. Deep2	0.25**	0.34**	0.30**	0.21**	0.35**	0.26**	0.21**	0.29**	0.61**	–													
11. Deep3	0.34**	0.34**	0.28**	0.19*	0.34**	0.20*	0.27**	0.23**	0.58**	0.62**	–												
12. Deep4	0.31**	0.37**	0.36**	0.26**	0.26**	0.30**	0.22**	0.30**	0.46**	0.68**	0.47**	–											
13. Surf1	−0.21**	−0.22**	−0.09	−0.18*	−0.16*	−0.17*	−0.14	−0.21**	−0.25**	−0.34**	−0.22**	−0.38**	–										
14. Surf2	−0.22**	−0.29**	−0.29**	−0.32**	−0.33**	−0.25**	−0.26**	−0.33**	−0.22**	−0.28**	−0.13	−0.27**	0.38**	–									
15. Surf3	−0.17*	−0.32**	−0.21**	−0.17*	−0.26**	−0.20**	−0.16*	−0.28**	−0.19*	−0.29**	−0.17*	−0.29**	0.29**	0.36**	–								
16. Surf4	−0.23**	−0.37**	−0.30**	−0.38**	−0.31**	−0.34**	−0.27**	−0.38**	−0.05	−0.03	−0.03	−0.08	0.21**	0.40**	0.24**								
17. Str1	0.27**	0.12	0.20*	0.19*	0.24**	0.24**	0.18*	0.28**	0.30**	0.29**	0.24**	0.21**	−0.21**	−0.11	−0.23**	−0.18*	–						
18. Str2	0.43**	0.35**	0.37**	0.36**	0.36**	0.33**	0.35**	0.45**	0.43**	0.49**	0.37**	0.46**	−0.42**	−0.25**	−0.34**	−0.22**	0.67**	–					
19. Str3	0.21**	0.13	0.16*	0.24**	0.22**	0.18*	0.16*	0.11	0.19*	0.28**	0.26**	0.23**	−0.17*	−0.18*	−0.23**	−0.08	0.59**	0.51**	–				
20. Str4	0.12	0.07	0.10	0.12	0.18*	0.09	0.09	0.09	0.39**	0.35**	0.35**	0.24**	−0.17*	−0.05	−0.04	−0.01	0.32**	0.33**	0.29**	–			
21. Str5	0.34**	0.15	0.28**	0.17*	0.34**	0.20**	0.24**	0.26**	0.61**	0.42**	0.52**	0.25**	−0.17*	−0.13	−0.10	−0.11	0.34**	0.36**	0.32**	0.42**	–		
22. Previous knowledge	0.01	0.14	0.06	0.12	0.19*	0.20*	0.14	0.25**	0.03	0.06	0.08	0.10	-,02	−0.19*	−0.16*	−0.18*	0.10	0.08	0.04	0.14	0.05	–	
23. Task performance	0.09	0.11	0.03	0.05	0.11	0.04	0.15	0.19*	0.17*	0.05	0.05	0.09	−0.23**	−0.14	−0.29**	−0.11	0.00	0.23**	−0.08	0.11	0.07	0.25**	–

Factor correlation matrix	Self-efficacy	Deep approach	Surface approach	Strategic approach
Self-efficacy				
Deep approach	0.46**	–		
Surface approach	−0.60**	−0.47**	–	
Strategic approach	0.50**	0.63**	−0.50**	–

*Correlation is significant at the 0.05 level (2-tailed). **Correlation is significant at the 0.01 level (2-tailed).

3.2 Students' self-efficacy and learning approaches

To examine whether students' perceptions of their self-efficacy were associated with their learning approaches, CFA was conducted. Based on the literature review, the analyses of the learning approaches were performed (see Figure 1). To identify how self-efficacy was associated with differences in the outcome factors, we explored the effects of self-efficacy on the deep, surface and strategic approaches. In the first step, we ran the measurement model and tested the structural validity of the self-efficacy and learning approach variables. In the second step, by including the latent structural equation model, we tested the theoretically based model in which the relationships between self-efficacy and the learning approaches were estimated.

3.2.1 Factor pattern and factor structure of the variables

The indices of overall fit suggest that the measurement model with four correlated factors (self-efficacy, a deep approach, a surface approach, and a strategic approach) indicated a good fit [χ^2 (183, $N = 171$) = 382.63, CFI = 0.90, TLI = 0.91, RMSEA = 0.08, SRMR = 0.07]. All estimated factor loadings were statistically significant. Most standardised loadings were above 0.60, two were between 0.44 and 0.50, namely, those for the strategic approach. Interestingly, self-efficacy was significantly positively related to the deep approach ($r = 0.46$) and to the strategic approach ($r = 0.50$). In addition, the correlation between the deep approach and the strategic approach was relatively high ($r = 0.63$). This may reflect the reciprocal bidirectional influences of the deep and strategic approaches. Importantly, the correlation between the surface approach and all other factors, such self-efficacy ($r = -$ 0.60), the deep approach ($r = -0.47$), and the strategic approach ($r = -0.50$), was negative.

3.2.2 Relationships between variables

By including the latent structural equation model, we tested the theoretically based model in which the relationships were estimated between self-efficacy and the three learning approaches. The results of the analyses are presented in Figure 3, as are the goodness-of-fit indices of the model (see Figure 3). In the model, we identified the relationships between self-efficacy, the deep approach, the surface approach, and the strategic approach. According to the goodness-of-fit indices, the model fits the data well, as Figure 3 demonstrates. The results of the regression coefficient indicated that self-efficacy and the deep approach had positive associations ($\beta = 0.46$). Students who reported positive beliefs, self-confidence, and good expectations regarding their studying and learning tended to use the deep approach, which included seeking meaning, finding interest, and relating to the ideas learned in their studies. The relationship between the students' perceived self-efficacy and their use of the strategic approach also achieved statistical significance ($\beta = 0.50$). Besides students' reported self-efficacy, they perceived that they managed their time and assessment demands well while achieving and monitoring their effectiveness in their studies. In turn, this increased and was indirectly related to their use of the deep approach.

Figure 3 also reveals that students' perceived self-efficacy was strongly associated with their surface approach. However, unlike the deep approach, the regression coefficient between self-efficacy and the surface approach was negative ($\beta = -0.60$). This indicates that the lower the level at which students perceived their self-efficacy in relation to studying and learning, the more they perceived their own lack of purpose or engagement with the syllabus and their fear of failure. Simultaneously, the use of unrelated memorisation indicated a surface approach to studying and learning.

3.2.3 Role of knowledge in self-efficacy and learning approaches in task performance

Finally, the model was specified and tested (see, Figure 2), wherein relationships were estimated between previous knowledge as a covariate and self-efficacy, as well as between the three learning approaches and task performance as an outcome variable. The results of the analysis, along with the goodness-of-fit indices, are presented in Figure 2 (see Figure 2). According to these indices, the model reached an acceptable fit. The regression coefficients revealed a significant positive relationship between previous knowledge and self-efficacy ($\beta = 0.19$), as expected. Thus, the higher the students' perceived level of previous knowledge regarding the course content, the more capable and confident they felt in performing effectively on various tasks. Conversely, the lower the students' perceived level of previous knowledge, the lower their self-efficacy. This was associated with a higher-level surface approach characterized by lack of purpose or engagement with the syllabus and a fear of failure, which, in turn, related to a lower level of task performance in the course. Additionally, the results also indicated a relationship between learning approaches and task performance, as anticipated. Specifically, a pronounced negative relationship was found between the surface approach and task performance ($\beta = 0.24$).

4 Discussion

Although prior research has thoroughly examined the effects of motivation and learning approaches on higher education students across a range of fields (e.g., Brown et al., 2015; Dedos and Fouskakis, 2021; Negash et al., 2022), such exploration within the field of computer science education remains remarkably limited.

The current study possesses three significant strengths. First, it evaluated the structure of first-year computer science students' perceived self-efficacy and learning approaches and, second, it identified the factors that influence their approach to learning situations. Third, the relationships were explore between previous knowledge and self-efficacy and, furthermore between learning approaches and task performance. These relationships were analysed using structural equation modeling to discern the differences between two principal learning approaches: deep and surface.

The findings indicate that computer science students follow distinct learning behaviors that reflect, as hypothesized, their perceived self-efficacy and their learning approaches in specific learning situations. These results align with earlier discoveries that motivation-related behavior and learning approaches vary significantly among students during the teaching-learning experience (e.g., Asikainen and Gijbels, 2017; Entwistle et al., 2001; Lonka et al., 2004). Moreover, according to students' ratings, the previous knowledge related significantly to their self-efficacy and, their surface approach played a crucial role in their task performance. Therefore,

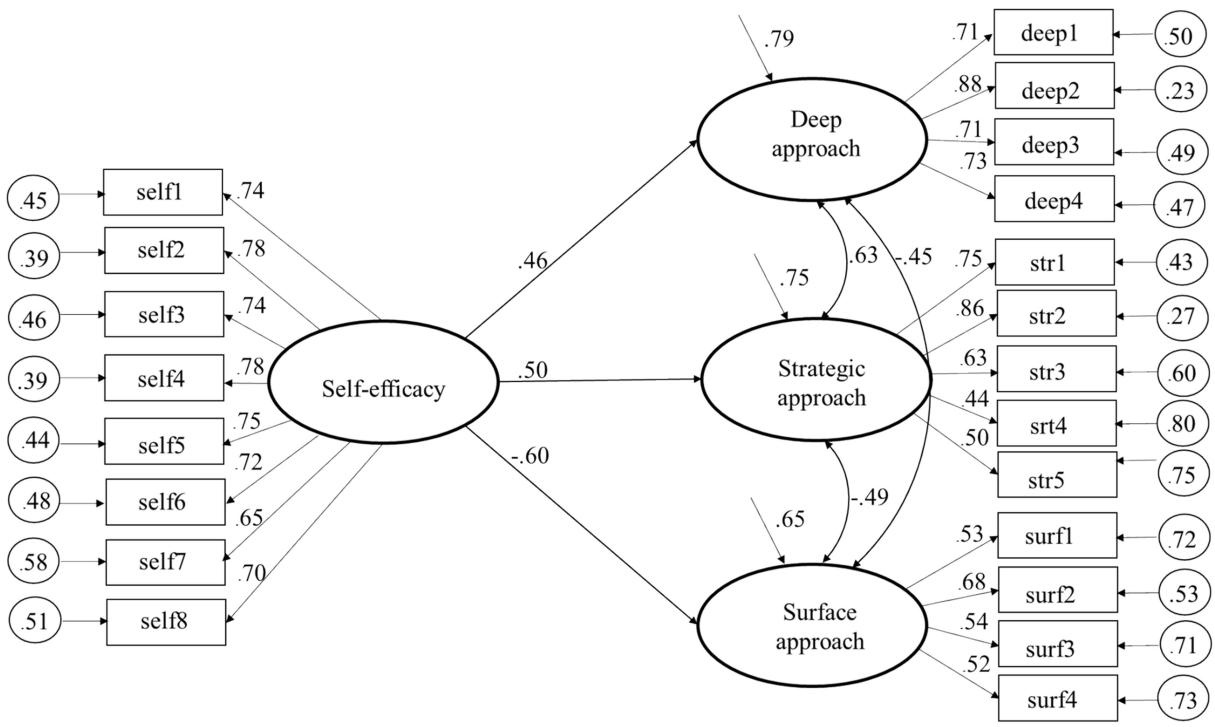

FIGURE 3
Students' perceived self-efficacy and learning approaches. Standardised regression coefficients (N = 171). All relationships displayed are significant at $p < 0.05$ (two-tailed). The fit statistics for model: [χ^2(183) = 382.63], CFI = 0.91, TLI = 0.90, RMSEA = 0.08, SRMR = 0.07.

the findings substantiate both theoretically and empirically the significance of considering students' perceived motivation and learning approaches when evaluating their learning behaviors.

4.1 Motivational factor and patterns of learning approaches (*H1*)

The first objective of the current study was to investigate whether the motivational factor as self-efficacy and learning approaches in learning situations of Entwistle et al. (2001) could also be found in the data of computer science students. Considering that motivation and learning approaches among computer science students have not attracted much research, one significant result of this study was that both the students' perceived self-efficacy and three learning approaches were found. Self-efficacy and the three original factors—deep, surface, and strategic approaches—appeared as separate dimension of students' learning behavior.

Self-efficacy and learning approaches, such as ASSIST, are commonly defined as estimations of how much students perceive themselves as capable of behaving the varied tasks associated with learning and studying. As such, it is theoretically justifiable to include the deep, surface, and strategic approaches, defined as estimations of the ability to cope with learning demands, as aspects of ASSIST. Indeed, while studying the correlations between the self-efficacy and the learning approaches, the surface approach was the one factor that correlated negatively with both self-efficacy and other learning approaches, which substantiates the findings of Phan (2011) and Prat-Sala and Redford (2010).

4.2 Role of self-efficacy in the deep, surface, and strategic approaches to learning (*H2*)

According to our hypothesis (*H2*), computer science students displaying a high level of self-efficacy and a deep learning approach reported an intrinsic desire to explore the subject area, confidence in their abilities, their acceptance of challenges, and the capability to consider alternatives in learning situations. This aligns with the findings of Geitz et al. (2016), who demonstrated a relationship between the self-evaluation of one's ability and competence resulting from experience as well as the adoption of the deep learning approach among first-year university students. Similar to Lonka et al. (2004), the current study's findings are relevant to motivation theories, highlighting the significance of students' motivation in their adaptation to learning situations in higher education. Hence, the constructs of self-efficacy in learning activities coincide with self-determination theory (Deci and Ryan, 1985), underscoring the importance of students' need for a sense of competence and control in task situations.

The findings also resonate with those of Prat-Sala and Redford (2010), who discovered that higher education students employed the deep approach the more they engaged with the strategic approach. Entwistle et al. (2001) proposed that students adopting the strategic approach possess the "determination to do well." At an initial glance, these results might suggest that students who adopt a deep approach also tend to be aware of assessment demands and focus on receiving feedback. However, the strategic approach is also linked to achievement motivation, efficiency monitoring, organized studying, and time management. As such, the strong positive link between the deep and strategic approaches may not solely reflect these students' desire to perform well but might mirror their approach to monitoring their learning progress and receiving feedback on their skills, abilities, and performance. From an educational perspective, these behaviors correspond to behavioral (on-task behavior), cognitive (planning), emotional (enjoyment), and social (environment) engagement during a learning activity (Vauras et al., 2019). This insight can broaden the understanding of the role of pedagogical practices generally and computer science students' experiences concerning their teaching–learning environment specifically. A recent study examined higher education students' profiles considering learning approaches and emotional variables; it confirmed a deeply organized profile as a distinct group among students (Karagiannopoulou et al., 2022). Students in the deeply organized profile group score highly on deep and strategic approaches, along with high scores on positive emotions, a combination that supports adaptive academic success (Postareff et al., 2017). Furthermore, students studying softer disciplines score higher on the deep approach to learning than those studying harder disciplines (e.g., Brown et al., 2015; Entwistle and Ramsden, 1983; Lonka and Lindblom-Ylänne, 1996; for a categorization of disciplines, see Biglan, 1973). Parpala et al. (2010) investigated university students' perceived learning approaches across disciplines. Based on cluster analysis, they found evidence for variations between disciplines. For instance, the most common clusters of students in the faculties of behavioral and social sciences were applying the deep approach to learning. The surface approach was overrepresented in the faculties of science and pharmacy.

In addition, our hypothesis found support in the structural equation model results, demonstrating that students reporting lower self-efficacy, indicative of less motivation, were more inclined to adopt the surface approach to studying, which was concurrently negatively associated with the strategic approach. This corroborates other evidence (e.g., Parpala et al., 2010) suggesting that when students utilize a surface approach, the positive impact of a strategic approach to learning situations diminished, now—noticeable with the deep approach. Furthermore, the results of our latent structural equation model revealed that students reporting low levels of belief in their ability to comprehend and learn the skills necessary for their learning activities often resorted to memorization and the bare minimum to pass upcoming assessments. Students favoring a surface approach to learning situations preferred teaching methods that simply conveyed information and steered their learning toward assessment requirements. Such surface-approach learners might also define strict syllabus boundaries, compartmentalising their knowledge and lacking a holistic perspective and purpose in their learning. This could doubly impact students with low self-efficacy, inducing them to adopt ineffective learning approaches in response to their low confidence in their abilities, leading to poorer performance, eroding their self-belief, and exacerbating their fear of failure (e.g., Prat-Sala and Redford, 2010). Additionally, Karagiannopoulou et al. (2018) detected adaptive and maladaptive defense styles among higher education students, with the latter associated with learning activities leading to task completion with minimal personal engagement.

These findings are consistent with research indicating that the strategic approach positively correlates with the deep approach and negatively with the surface approach (e.g., Entwistle et al., 2001). Moreover, empirical evidence suggests that the strategic approach, when combined with the deep approach, is more beneficial than when paired with the surface approach for success in various domains (Entwistle and Ramsden, 1983; Lonka and Lindblom-Ylänne, 1996). Thus, the deep and surface approaches are conceptually distinct (Entwistle et al., 2001). By eliminating any irrelevant variance between the deep and surface approaches, we can derive a more effective relationship that could have theoretical and practical significance (Lonka and Lindblom-Ylänne, 1996). Our findings support and expand recent evidence indicating that high levels of students' self-efficacy are related to the adoption of the deep approach, while low self-efficacy levels are related to the surface approach. Furthermore, this suggests that students' self-reported levels of motivation can possess concurrent validity. Our findings uphold the relationship between motivational factors and learning approaches, which is consistent with the theoretical premise that learning approaches are driven by motivation (Bandura, 1982).

4.3 Role of previous knowledge in self-efficacy and learning approaches in task performance (*H3*)

The third objective was to explore how computer science students' previous knowledge relates to their self-efficacy and, furthermore, their learning approaches to task performance. Students with a higher level of previous knowledge tended to exhibit higher self-efficacy, while those with a lower level of previous knowledge demonstrated significantly lower self-efficacy levels. This finding aligns with our hypothesis and expands upon previous research, suggesting a strong relationship between previous knowledge and computer science students' self-efficacy. Importantly, training that enhances computer science students' perceived levels of previous knowledge within their programs also holds the potential to improve their ability to engage more deeply in learning situations.

As hypothesized, learning approaches also related to task performance. Although a significant negative relationship was found only between the surface approach and course performance, this underscores the importance of coping strategies (Vauras et al., 2019) in computer science students' approaches to learning situations, particularly problem-focused coping strategies that address the issue at hand. In addition to these functional and cognitive aspects, students' adaptive abilities, such as the regulation and the utilization of emotion in problem-solving, are associate with their academic performance (Bélanger et al., 2007). This result also suggests that computer science students' self-ratings in studying and learning possess concurrent and predictive validity. Therefore, it is noteworthy that study requirements (which necessitate increasing self-direction as studies progress) and personality factors underscore the importance for higher education institutions to provide support services from the onset of the first year (Bargmann et al., 2022). For example, counseling interviews could be conducted with students at the end of each academic year to assess their motivation, learning strategies, study success, and wellbeing. Furthermore, students' vulnerabilities may trigger negative developmental cycles that progressively lead to increased task avoidance (Salonen et al., 1998) and deviate them from their learning paths, thereby complicating their ability to graduate from higher education (Salmela-Aro and Read, 2017).

5 Limitations and future directions

A recent study with psychology students delineated the developmental changes in students' perceived motivation levels

10.3389/feduc.2024.1181616

and learning approaches (Prat-Sala and Redford, 2010). Additional evidence detailing similar longitudinal impacts on varying factors, including academic performance among computer science students, would be a valuable addition. Nevertheless, this study contributes to the theoretical discussion surrounding the relationship between perceptions and approaches by utilizing a detailed statistical model and a well-developed instrument to measure teaching and learning experiences (e.g., Karagiannopoulou and Milienos, 2015). The study also reinforces findings about the positive relationship between motivation perception and the deep and strategic approaches, along with the negative relationship of the surface approach to learning (e.g., Phan, 2011; Prat-Sala and Redford, 2010). Accordingly, even considering the potential self-rating limitations in the study, the significant correlations between motivation and learning approaches strengthened the measures' validity and reliability. For example, students' perceptions of self-efficacy could be influenced by their current wellbeing or a recent grade, which may not accurately reflect their typical learning approaches, but also indicates the sensitivity of self-ratings.

Second, the empirical findings of the current research require cautious interpretation because of the small sample size and its specific demographic and geographic context. Although the model of self-efficacy and learning approaches is compatible with some of the existing research (Asikainen and Gijbels, 2017; see also Phan, 2011; Prat-Sala and Redford, 2010; Trigwell et al., 2013), further study is necessary to examine whether these factors relate to academic performance with a larger, more diverse sample and through a longitudinal study design involving computer science students from various backgrounds.

Third, earlier research has emphasized the importance of reciprocal feedback to support and foster students' developmental processes and their progress toward learning goals (Boud and Molloy, 2013; Wigfield et al., 2012), as well as the impact of curriculum design (Malecka et al., 2022). Furthermore, considering the course's delivery language (in Finnish), investigating the role of language proficiency and cultural integration in educational engagement and success represents a crucial avenue for future research. Adopting a person-oriented approach could provide an individual perspective on how computer science students address and reflect on their own needs and challenges. This approach would involve exploring their change processes, feelings of efficacy, and beliefs. Each factor contributes substantially to their professional development. This growth may be manifested as improved cognition, the adoption of new practices, or enhancements of existing methodologies. Research in this area is supported by studies such as Lonka et al. (2004) and Parpala et al. (2010).

Fourth, a set of limitations revolves around the role that teachers play in supporting students' learning, which was not the focus of this study. The impact of teacher-student interactions and the pedagogical strategies employed, especially in the context of the Finnish education system, could further elucidate the dynamics of learning engagement and performance. Past studies have found that diverse teaching methods and environments (e.g., "flipped learning," Sointu et al., 2019; "problem-based learning," Lehtinen et al., 2019; "student-focused vs. teacher-focused," Trigwell et al., 1999) affect students' behaviors in learning situations, and thus critical evaluations of the context in which the study was conducted is needed (e.g., Postareff et al., 2018).

6 Conclusion

The results underscore that it is both educationally and practically pertinent to understand the diverse motivational learning approaches that first-year computer science students utilize. While securing a place and initiating studies are generally considered positive phases for all students, some students report relatively maladaptive motivational and learning approaches (e.g., Lonka et al., 2004). Analysing both adaptive and maladaptive motivational tendencies and learning approaches can support students in comprehending the roles these factors play at the onset of their professional development. From a theoretical standpoint, our results enhance factor-based studies on motivation and learning approaches by expanding our understanding of the relationships between these factors, specifically by including first-year computer science students. Furthermore, our results reveal that these factors have already begun to differentiate students, to some degree, during their inaugural year of study. A more comprehensive examination of cognitive mechanisms, such as academic achievement as indicated by grades (e.g., Diseth et al., 2006), or learning analytics (Lokkila et al., 2022), along with social mechanisms such as social belongingness (see "self-determination theory"; Deci and Ryan, 2000), is needed to expand our comprehension of the development of students' learning paths. Such data would be invaluable for developing empirically based interventions, guidance, and tutorial tools for fostering learning progress and informing teaching practice.

Data availability statement

The data analyzed in this study is subject to the following licenses/restrictions: requests to access these datasets should be directed to the corresponding author Satu Laitinen, satu.laitinen@utu.fi.

Ethics statement

Written informed consent was obtained from the individual(s) for the publication of data included in this article.

Author contributions

SL: Conceptualization, Visualization, Formal analysis, Investigation, Writing – review & editing, Writing – original draft. AC: Formal analysis, Investigation, Writing – review & editing, Writing – original draft. PL: Formal analysis, Investigation, Writing – review & editing, Writing – original draft. VN: Formal analysis, Investigation, Writing – review & editing, Writing – original draft.

Funding

The author(s) declare that financial support was received for the research, authorship, and/or publication of this article. The APC was funded by Faculty of Education, University of Turku, Finland.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

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