

# Exploring Engagement and Self-Efficacy in an Introductory Computer Science Course

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# Abstract

Introductory computer science courses often pose unique challenges for non-computer science majoring students, and understanding the factors that contribute to these struggles is crucial for enhancing students' learning experiences. This research delves into the engagement and self-efficacy of 14 international undergraduate students enrolled in an introductory computer science course tailored for non-CS majors. We use a combination of an initial online survey and the Experience Sampling Method (ESM) to gather data on students' experiences and perceptions throughout the course. The ESM interviews conducted during students' tutorials offer real-time insight into the fluctuations of their engagement and self-efficacy. Findings reveal a positive correlation between aspects of engagement and self-efficacy, indicating that students' higher levels of engagement coincide with stronger beliefs in their capabilities to succeed in the course. Moreover, we identified course topics with which students were disengaged and that corresponded to lower self-efficacy. By recognizing the challenges faced by non-CS majoring students and the impact of specific course topics and teaching styles on their engagement and self-efficacy, we provide advice for designing tailored interventions and instructional strategies.

# CCS Concepts: • Social and professional topics $\rightarrow$ Computing education.

*Keywords:* engagement, self-efficacy, experience sampling method, CS1, international students

ACM ISBN 979-8-4007-0390-4/23/10...\$15.00 https://doi.org/10.1145/3622780.3623649

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## **ACM Reference Format:**

Rory Kelly and Meghan Allen. 2023. Exploring Engagement and Self-Efficacy in an Introductory Computer Science Course. In *Proceed*ings of the 2023 ACM SIGPLAN International Symposium on SPLASH-E (SPLASH-E '23), October 25, 2023, Cascais, Portugal. ACM, New York, NY, USA, 9 pages. https://doi.org/10.1145/3622780.3623649

## 1 Introduction

Computer science courses are becoming increasingly relevant for non-computer science majors due to the ubiquity of technology and the growing demand for digital literacy in various fields. However, students tend to struggle in early computer science courses, translating into high failure rates and poor retention [13]. Computer science education is "well known to suffer from poor retention of students interested in computing and students not learning what instructors expect" [13, p. 319]. It has also been shown that a student's engagement and self-efficacy likely impact their success in introductory computer science courses [8]. Specifically, higher levels of self-efficacy have been linked to lower levels of frustration, higher levels of interest, and even higher grades [8]. Understanding how engagement and self-efficacy fluctuate in a course context is vital for educators and curriculum designers seeking to optimize the learning environment and support student success.

Engagement encompasses various dimensions including behaviors such as effort, persistence, and concentration, reactions such as interest, happiness, and anxiety, and psychological aspects such as a student's own investment toward learning [6]. Self-efficacy refers to students' beliefs in their ability to succeed in a specific domain [1]. It influences students' motivation, persistence, and performance. Exploring how engagement and self-efficacy fluctuate amongst noncomputer science majoring students is important as it provides a look into the unique challenges and experiences of these students.

In the sections that follow, we will first present the course context and purpose of the study, then review the relevant literature on engagement, self-efficacy, and their significance in educational settings. We will then present our research methodology, including details on the participants, data collection instruments, and analysis procedures. Finally, we will discuss the potential implications of the study's findings, along with suggestions for future research.

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#### 1.1 Course Context

This study took place in a first-year computer science course with 42 students at the University of British Columbia – a large, research-intensive university in Canada. The course is introductory and does not assume any prior programming experience. It is one of two first-year introductory programming courses at our university. This course is intended for students who do not plan to major in computer science and the other is a more traditional CS1 offering intended for students who will major in computer science. Both courses are based on the How to Design Programs curriculum [5] and focus on a systematic approach to program design. Our course provided an introduction to foundational software development principles using the Python programming language. Further context is available in an experience report describing the design and evaluation of this course [4].

The particular course offering that we studied was taught in an eight-week 2023 summer term in a program for international students. The pace of the course was faster than our usual 13-week semester, however, the curriculum was consistent with our 13-week offerings; summer students completed the same modules, assignments, exams, and project.

### 1.2 Purpose of the Study

While some prior research has examined engagement and self-efficacy in computer science education [8–10, 13, 15], there is limited knowledge regarding their fluctuations and causes of disengagement among non-computer science majoring students and international students. By focusing on this student population, we aim to uncover a unique view into their engagement and self-efficacy patterns, as well as factors that contribute to their disengagement from learning.

This study makes contributions to computer science education as it can inform the design of tailored interventions, instructional strategies, and support mechanisms that enhance engagement and self-efficacy among students. By addressing the research gaps in understanding how engagement and self-efficacy fluctuate in this specific context, we can develop effective approaches to engage and support these students in their learning journey. The following two research questions guided the study:

- How do international, non-CS major students' engagement and self efficacy fluctuate in an introductory computer science course?
- What causes these students to disengage from their learning?

## 2 Related Work

We will explore the three main components of our study: the Experience Sampling Method, self-efficacy, and student engagement.

#### 2.1 Experience Sampling Method

The Experience Sampling Method (ESM) is a research method that enables learning about participants' lives in context by measuring their feelings, thoughts, actions, and/or activities as they go about their daily lives [19]. By capturing data in the moment and with repeated measures, ESM allows researchers to investigate, describe, and better understand how people and contexts shape these experiences [19]. ESM often involves the use of electronic devices or interviews to prompt participants to report on their current thoughts, feelings, or activities. It allows researchers to capture momentary experiences, recording individuals' subjective experiences and context-dependent behaviors. ESM has been used extensively in psychology and social sciences, demonstrating its value in studying emotions, well-being, and daily activities [3].

In educational studies, ESM has proven to be a valuable tool for investigating various aspects of learning experiences. For instance, Zirkel, Garcia, and Murphy [19] highlight the potential of Experience-Sampling Research Methods in the field of education research. Their study explores ESM in educational contexts and discusses the benefits and challenges associated with its use. The authors emphasize that ESM allows for the collection of real-time data on students' experiences and behaviors, providing valuable information about their engagement, motivation, and self-regulation. By using ESM, researchers can gain a nuanced understanding of students' experiences in educational settings, allowing for targeted interventions and instructional improvements. By collecting momentary data on students' experiences and activities, researchers gain valuable information on the factors influencing their learning processes. In educational contexts, Xie et al. [18] showed the effectiveness of event-based ESM, meaning that sampling is done after specific events such as study sessions. Research has shown that event-based ESM is an effective way of assessing an individual's critical thinking skills and problem solving ability [7].

Within the field of computer science education, ESM has been used to gain insight into students' experiences and engagement in computer science courses. For example, Lishinski and Rosenberg [9] used ESM to examine students' momentary motivation, interest, and self-efficacy in programming tasks; their results suggest that students' experiences play a significant role in their longer-term interest and learning outcomes in computer science. By collecting real-time data, researchers have been able to investigate the factors that influence students' engagement and self-efficacy in computer science learning environments quite effectively, which will be further explored in Sections 2.2 and 2.3.

Common themes emerge from past research involving the Experience Sampling Method in educational contexts. Studies often focus on understanding students' affective experiences, including their emotions, motivation, and engagement, and how these experiences relate to learning outcomes. Researchers also explore the contextual factors, instructional strategies, and interventions that impact students' engagement and learning experiences. At its core, the topics of engagement and self-efficacy frequently emerge as significant when ESM is conducted [8, 16].

Despite the value of the Experience Sampling Method in educational research, knowledge gaps still exist, particularly in the context of computer science education. Limited research has focused on using ESM to understand engagement and self-efficacy in computer science courses and even less research has been done to explore the reasons behind non-CS majors' struggles in introductory computer science courses. Furthermore, we believe that there is a need for more studies that use in-person interviewing for ESM as opposed to electronic device surveying. We conject that students are more willing to share the details of their experiences when they feel like they are simply speaking to one of their peers, rather than responding to a device. These gaps highlight the importance of further investigations to enhance our understanding of how the Experience Sampling Method can be effectively used in computer science education research.

#### 2.2 Self-efficacy

Self-efficacy, a concept introduced by Bandura [1], refers to an individual's belief in their own ability to successfully accomplish specific tasks or goals. Bandura defines self-efficacy as "people's beliefs about their capabilities to produce designated levels of performance that exercise influence over events that affect their lives" [2, p. 2]. It is a key component of motivation and plays a crucial role in determining the level of effort individuals put forth, their persistence in the face of challenges, and their ultimate performance outcomes.

Self-efficacy has been widely studied in educational research, as it influences students' academic achievement and ability to effectively engage in learning activities. Research by Pajares and Schunk [12] emphasizes the significant role of self-efficacy in shaping students' motivation, effort, and academic performance. They argue that when students possess high beliefs of self-efficacy, they are more likely to set challenging goals, exert effort, persist in the face of difficulties, and achieve positive learning outcomes. Meera and Jumana argue that a "strong sense of self-efficacy enhances human accomplishment and personal well-being in many ways. It is considered as an accurate predictor of performance; furthermore, self-efficacy is an important cognitive skill which ensures success in life" [11, p. 29]. Various educational interventions have been designed to enhance self-efficacy, such as providing mastery experiences, offering feedback and encouragement to cultivate self-beliefs of achievement, and promoting interest and engagement in materials [11].

In the realm of computer science education, the impact of self-efficacy on students' learning experiences and performance has been explored [8–10]. Higher beliefs of selfefficacy in computer science have been found to lead to greater engagement, higher levels of persistence, and ultimately better learning outcomes [8]. Self-efficacy is one of the underlying factors for success in computer science; as Mahatanankoon writes, "[students] must believe that their effort will lead to a specific set of programming outcomes" [10, p. 2]. Understanding the role of self-efficacy in computer science education can inform the design of effective instructional strategies and interventions to support students' selfconfidence and success in the discipline.

Common themes emerge from research involving selfefficacy in educational contexts. Studies consistently highlight the positive relationship between beliefs of self-efficacy and students' academic performance, engagement, and motivation [8–10]. Furthermore, the importance of providing students with authentic learning experiences, mastery opportunities, and supportive environments that foster their beliefs of self-efficacy is emphasized [1, 12]. Cultivating self-beliefs of achievement and promoting self-efficacy-enhancing instructional practices are identified as key strategies to promote success in educational settings [8, 9, 11].

Despite the extensive research on self-efficacy in education, several knowledge gaps remain. One knowledge gap is the need for further exploration of the specific factors that contribute to the development and enhancement of selfefficacy in the context of computer science education. Additionally, research is warranted to examine how instructional strategies, learning environments, and curriculum design can effectively foster self-efficacy among computer science students. Most importantly, there is a significant gap in research involving the self-efficacy of non-computer science majors in introductory computer science courses, which our research aims to address.

#### 2.3 Engagement

For the purposes of our research, we define engagement to be the extent to which individuals are invested, involved, and motivated in a particular activity or learning process. However, the definition of engagement can be much more complex. Fredricks, Blumenfeld, and Paris [6] describe engagement as encompassing cognitive, emotional, and behavioral dimensions. They offer various definitions for each dimension such as "involvement in learning and academic tasks including behaviors such as effort, persistence, concentration, attention, asking questions, and contributing to class discussion" [6, p. 62] for behavioral engagement, "students' affective reactions in the classroom, including interest, boredom, happiness, sadness, and anxiety" [6, p. 63] for emotional engagement, and "student's psychological investment in and effort directed toward learning, understanding, mastering the knowledge, skills or crafts that the academic work is intended to promote" [6, p. 64] for cognitive engagement.

Engagement has been extensively studied in educational research, highlighting its significance in predicting students' academic achievement and overall learning outcomes. A meta-analysis by Wang and Eccles [17] examined the impact of student engagement on academic success across various educational contexts. They found a positive relationship between engagement and academic performance, demonstrating that engaged students are more likely to exhibit higher levels of achievement and persistence in their learning endeavors. Moreover, engagement has been linked to other positive educational outcomes, such as higher levels of motivation, self-regulation, and overall well-being.

In the field of computer science education, understanding and promoting student engagement is crucial for fostering successful learning experiences. Engaged students in computer science demonstrate active involvement in hands-on programming tasks, collaboration with peers, and a deeper interest and curiosity towards the subject matter [8, 9, 15]. However, as a field, computer science has lower engagement measures than other STEM subjects [15].

Common themes emerge from research on engagement, suggesting key factors that contribute to students' engagement in educational contexts. These themes include the importance of providing meaningful and authentic learning experiences, fostering positive teacher-student relationships, and creating a supportive and inclusive learning environment. Certain instructional strategies, such as active learning, collaborative activities, and problem-solving tasks, are commonly identified as effective approaches to promote student engagement. Engagement has been shown to play a role in student success and enjoyment in their courses [8, 9, 15, 17], and the study of a computer science student's engagement should offer critical insight into the effectiveness of a course.

Despite the extensive research on engagement, there are still knowledge gaps that need to be addressed. Further investigation is needed to understand the complex interplay of individual, contextual, and instructional factors that influence engagement in computer science education. Additionally, more research of the engagement of students in introductory computer science courses would help to further strengthen the existing literature.

## 3 Method

We chose the Experience Sampling Method to investigate the experiences of non-computer science majoring students in an introductory computer science course. By using ESM, we aimed to capture students' real-time engagement and perceived self-efficacy throughout the course duration.

## 3.1 Ethical Considerations

The study was approved by our institution's behavioural research ethics board.

The first author conducted the study and was not a member of the course staff. The second author was the course instructor; no data was shared with her until after final grades had been submitted.

## 3.2 Participants

Fourteen undergraduate students (33% of enrolled students) from an introductory computer science course comprised of international non-computer science majoring students participated in this study.

The participants were those students who consented to join the study from the students enrolled in the course. It is important to note that the students had varying levels of prior exposure to computer science, with some having little to no prior experience, while others had limited exposure through previous coursework or self-study. This difference in background knowledge was explored through an introductory survey that was conducted at the beginning of the study. We did not collect data on participants' gender, ethnicity, or country of birth.

## 3.3 Data Collection

Data for this study was collected through a combination of an initial online survey conducted at the start of the term and the Experience Sampling Method (ESM) throughout the course. The online survey gathered general information about the participants, including their prior experience with computer science concepts. We used event-based experience sampling, with the students' tutorials serving as the events of interest. Tutorials were chosen as they provided a consistent weekly snapshot of the students' active engagement with the course materials.

The ESM data collection involved conducting brief two to five minute interviews with the participants during six weekly tutorial sessions. The same set of questions were asked each week to maintain consistency and enable comparative analysis. The questions were designed to ensure that they did not push participants toward a particular response, and participants were told that their responses would be anonymized to maintain confidentiality. The interviews were specifically designed to gather information related to student engagement and self-efficacy. The course modules associated with each interview were as shown in Table 1. By focusing on engagement and self-efficacy in the ESM interviews, we sought a comprehensive understanding of the students' experiences.

By combining the start of term online survey and the ESM interviews, we aimed to gather both general information about the participants and a detailed understanding of their weekly experiences. The data collected will provide valuable information into the participants' engagement and self-efficacy fluctuations over time, specifically in moments when they actively engage with the course material.

#### 3.4 Interview Questions

We aimed to capture relevant aspects of students' experiences, perceptions, and reflections on their engagement and

Week	Topic	Scheduled Interview
Week One	Intro to Python and How to Design Functions	
Week Two	How to Design Data Types	Interview 1
Week Three	Designing Compound Data Types	Interview 2
Week Four	Designing Arbitrary-Sized Data Types	Interview 3
Week Five	One Task per Function	Interview 4
Week Six	How to Design a Program for Data Analysis	Interview 5
Week Seven	Visualization	Interview 6
Week Eight	Projects	

Table 1. Course Topic and Interview Schedule

self-efficacy. The following questions were included in the interviews:

Self-Efficacy Questions

- 1. I feel capable of doing well in the course.
- 2. I feel interested in the course materials.
- 3. I feel proud of my accomplishments thus far.

These self-efficacy questions were selected to assess students' beliefs in their capabilities and interest in the course materials. They were informed by prior research, such as Lishinski et al.'s study [8] which emphasized the importance of self-efficacy in predicting students' motivation and success in computer science education. By exploring students' thoughts and perceptions related to self-efficacy, we aimed to gain information on how students' beliefs influenced their learning experiences.

**Engagement Questions:** 

- 1. Have you been enjoying class?
- 2. Has the course been moving at a reasonable pace?
- 3. Have the course topics been interesting?
- 4. Has the course been too challenging? If so, what has been most difficult?
- 5. Do you feel that you have learned new skills?

The engagement questions in the ESM interviews were designed to capture students' experiences and perceptions since their last interview. These questions were chosen to provide a week-to-week view of how students were relating to the specific course content and their feelings of enjoyment, challenge, and skill development. The selection of these questions was informed by Schaffer's work [14], which describes the best ways to build engagement questionnaires.

During each interview we took notes detailing participants' responses to each question. Some responses were short, such as 'yes' or 'no', while others were longer.

## 3.5 Data Analysis

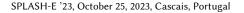
We chose to represent students' responses with numbers: 0 for responses equivalent or adjacent to 'no', 1 for responses equivalent or adjacent to 'yes', and 0.5 for responses in between. We recognize that this coarse representation does not capture all nuances in students' responses, but believe that it will be sufficient for initial exploration of our research questions. With this representation, we created plots to visualize the trends in the data, and found the Spearman's  $\rho$  correlation coefficient between the responses for each question. Participants were occasionally absent from tutorial and therefore missed the corresponding interview.

We also dove into students' more detailed responses, such as what they found to be the most difficult, and what they did/did not enjoy. We noted which topics were brought up the most when students shared lessons that they found to be interesting or difficult.

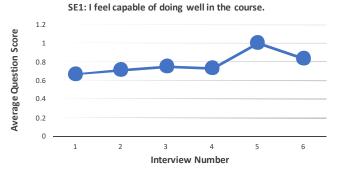
# 4 Results

The trend plots for each interview question are displayed in Figure 1. The shorthand 'SE1' is used to represent the first self-efficacy question as outlined in Section 3.4, 'SE2' is the second self-efficacy question, and so on. Similarly, 'E1' represents the first engagement question, and so on.

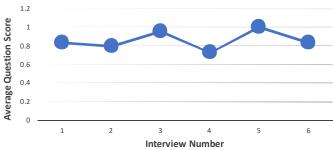
Through the plots, we see that engagement and self-efficacy started off lower at the beginning of the term, and generally followed a positive trend upwards as time went on. The students seem to have lost some of their self-efficacy by interviews 2, 4 and 6, and self-efficacy seems to have peaked by interview 5. Some example responses of students that seem to have lost some self-efficacy by these interviews are "I know how [the topics] work, but I am not interested" and "[The content] is not interesting and too hard for me". The feedback indicating positive self-efficacy during interview 5 was largely short 'yes' responses to the student feeling capable, interested, and proud that week. The students also seem to have experienced some disengagement by sessions 2, 4, and 6, finding the course more challenging and less interesting at these times. The students were the most engaged in interview 5, much like with self-efficacy. Some example responses of students that seem to be disengaged by these interviews are "I feel lost after module 5" and "Maybe I'm simply not interested in CS". The feedback indicating positive engagement during interview 5 was also largely short 'yes' responses to the student enjoying class, remaining interested, having learned new skills that week, and feeling



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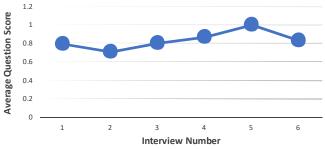


SE2: I feel interested in the course materials.





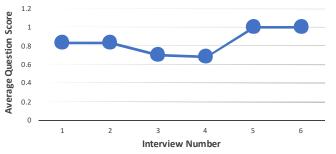
E1: Have you been enjoying class?



1.2 1.2 1.2 0.8 0.6 0.4 0.2 0 1 2 3 4 5 6 Interview Number

E2: Has the course been moving at a reasonable pace?

E3: Have the course topics been interesting?



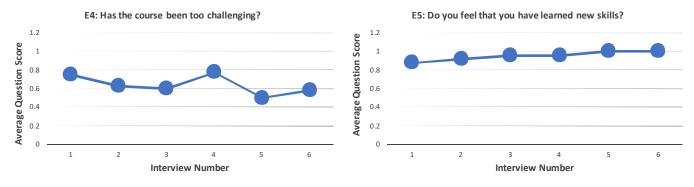


Figure 1. Trend plots for the interview questions.

Questions	SE1	SE2	SE3	E1	E2	E3	E4	E5
SE1		0.45	0.27	0.59	0.19	0.23	-0.13	0.20
SE2			0.10	0.69	0.09	0.52	-0.12	0.19
SE3				0.23	-0.04	-0.10	-0.23	0.38
E1					0.18	0.34	-0.13	0.31
E2						-0.05	-0.17	-0.01
E3							-0.08	0.13
E4								0.07
E5								

**Table 2.** Spearman's  $\rho$  correlation coefficients for all questions

that the course is moving at an appropriate pace and is not too difficult.

The plots show that student engagement and self-efficacy trends upwards as the course moves forward. However, topics that students find more difficult seem to correspond with lower engagement. By changing how the more difficult topics in the course are handled, and addressing what disengages students with what helps them to stay engaged, student engagement and self-efficacy could potentially be increased. As shown above, if students believe that they are able to do well in the course they are likely also enjoying themselves.

In order to compare how each question's responses were correlated with each other question, we calculated the Spearman's  $\rho$  correlation coefficient. We used all responses from all participants to calculate the correlation coefficients, which are summarized in Table 2.

By examining the Spearman's  $\rho$  correlation coefficients of each question, we can see that the aspects of engagement and self-efficacy that are at least moderately correlated are:

- Belief in the ability to do well in the course is correlated to students feeling interested in the course materials.
- Belief in the ability to do well in the course is correlated to students enjoying class.
- Feeling interested in the course materials is correlated to students enjoying class.
- Feeling proud of their accomplishments is correlated to students feeling that they have learned new skills.
- Enjoying class is correlated to students finding the course topics interesting.
- Enjoying class is correlated to students feeling that they have learned new skills.

From the interview responses, students found most of the course topics to be interesting, except for the modules focused on compound data types and arbitrary-sized data types. The students found modules 3, 5, and 6 (corresponding to interviews 2, 3, and 4) to be the most difficult topics in the course. This all makes sense, since the topics that students directly stated to have enjoyed the least were presented in the weeks of interviews 2 and 3, and the topic that the students found to be the most difficult was presented in the week of interview 4, which are all also weeks in which students had lower engagement scores.

Some students explained why they disengaged. One student outlined slow discussion forum response times during difficult course modules as a reason that they disengaged. Others described a fast course pacing and difficulty with large example programs as activities that caused them to disengage. Interviews also provided valuable insight into the strategies that effectively kept students interested in the course content. Receiving quick feedback on uncertainties, facilitated study groups, and easily accessible online lessons were key factors that sustained student involvement.

## 5 Discussion

This study was formed as an exploratory assessment of how international, non-CS majors' self-efficacy and engagement change through a term of an introductory computer science course. It has been shown in prior research that self-efficacy is an excellent indicator for student success in their courses, and it has also been demonstrated that the experience sampling method is a great way to assess the week-to-week engagement of students in their course materials. Therefore, if engagement can be shown to be linked to self-efficacy, then using ESM to identify what causes students to disengage from their course topics may also be able to show how we can promote student self-efficacy and, in turn, their success.

We cannot make any claims of causation from this data, however, key findings may be used to fuel future studies investigating the significance of our results. The correlations can be investigated further, the teaching strategies that promoted interest can be practised, the causes of disengagement can be addressed, and the questions that proved useful to our interviews can be repurposed.

#### 5.1 Key Findings

The primary contribution of this study is the tracking of week-to-week engagement and self-efficacy in an introductory computer science course. Students who reported higher levels of engagement with the course material often had a matching boost in their beliefs of self-efficacy. The study revealed that consistent, positive experiences throughout the semester, such as enjoying class and finding course topics interesting, were correlated with a stronger sense of some aspects of self-efficacy. This finding underscores the importance of fostering regular and positive engagement which may enhance students' confidence in their abilities to succeed in computer science.

The study also identified certain course topics that corresponded with student disengagement. Specifically, students reported disengagement when encountering challenging concepts that lacked clear structure and reinforcement. Understanding the topics that may trigger disengagement is essential for curriculum design and instructional strategies to effectively address student needs and minimize disengagement factors. The course topics that students found to be the most difficult involved subjects that they likely had limited exposure to before, such as designing and using data. Finding a topic too difficult was not always enough for a student to disengage, but combining this with also not offering ways for students to get immediate feedback when handling these topics fueled student disengagement.

The findings that quick feedback on uncertainties, facilitated study groups, and easily accessible online lessons sustain student engagement emphasize the importance of interactive and supportive elements in a course to maintain high levels of engagement and motivation among students. Certain topics are going to be difficult for some students but incorporating these elements into course design can help disengaging students to catch back up to the lesson plan and reengage.

# 5.2 Limitations and Recommendations for Future Research

As all research, the study was limited by a number of factors. The sample size of 14 undergraduate students and the constrained number of interviews per student represent considerable limitations to our results. To enhance future research, increasing the sample size and conducting more interviews could yield a richer and more comprehensive understanding of how engagement and self-efficacy fluctuate throughout an introductory computer science course. Further, our participants were all international students; expanding the participant pool may yield more generalizable results.

In addition, some interview responses were brief, limiting the depth of data analysis. To mitigate this concern, researchers may lay out clear ground rules for interview responses and encourage participants to provide more elaborate answers. This approach would yield more rich qualitative data suitable for a thematic analysis, contributing to a deeper understanding of student experiences.

Finally, the data was collected during a fast-paced summer course which could potentially be more intense and difficult for students. Future studies may look to apply these methods to a standard-length course offering in order to assess whether similar conclusions can be drawn.

By addressing these limitations and implementing the recommended strategies, future research can further enhance understanding of how engagement and self-efficacy impact student experiences and learning outcomes in the context of an introductory computer science course using ESM. These improvements in methodology and question design will contribute to a more comprehensive exploration of students' engagement and self-efficacy in computer science education.

# Acknowledgments

We are grateful to the students who participated in this study and the anonymous reviewers for their thoughtful feedback.

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Received 2023-07-27; accepted 2023-08-24