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Exploring student motivation and instructor reflections in a flipped project-based drone computing course

Dr. Mihwa Park, Texas Tech University

Dr. Mihwa Park is an Associate Professor of STEM education at Texas Tech University. Her research interests involve developing measurement instruments to assess students' understanding of scientific concepts and their emotions when learning science. She is also interested in teachers' emotions about teaching science and teacher identity.

Sungwon Shin, Texas Tech University

Sungwon Shin is an Associate Professor of Instructional Technology at Texas Tech University.

Dr. Sunho Lim, Texas Tech University

He is an Associate Professor in the Department of Computer Science, Texas Tech University. His primary research interests are in the areas of Cyber Aerial Computing, Mobile Data Privacy, and Wireless Networks and Mobile Computing. He is a senior member of the IEEE.

Sarah Meilani Fadillah, Texas Tech University

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Introduction

In 2025, the U.S. Bureau of Labor Statistics reported that computer science- and information science-related occupations are projected to be among the fastest growing over the next decade. For example, employment for computer and information research scientists is projected to grow by 20% through 2034, which exceeds the projected average growth rate across all occupations (3%) [1]. Computer hardware engineers are also projected to experience above-average growth [1]. With rapid developments in artificial intelligence, cybersecurity, and robotics, computer science, information science, and computer engineering remain among the most popular undergraduate majors.

However, prior studies have critiqued common instructional practices in computer science and information science programs for emphasizing isolated skills, overprioritizing conceptual or theoretical knowledge, and providing limited opportunities for authentic, collaborative learning environments that engage students [2, 3, 4]. These critiques have led to calls for more student-centered approaches, such as project-based learning (PBL) and flipped instruction, to support meaningful engagement and learning [3, 5]

The current project responds to this need by implementing a flipped project-based learning (FPBL) model grounded in authentic, hands-on activities using small-scale drones. This paper is connected to a companion study by the authors that focuses on curriculum and intervention design ("[NSF IUSE] Flipped Learning for Enhanced Project-Based Learning in Cyber-Aerial Computing: Privacy Protection and Security Enhancement"). Briefly, the project aims to design a new computer science course in which students operate drones to solve problems through coding, testing, and iterative refinement.

The course was developed in a blended format combining online flipped instruction with in-person, hands-on lab sessions. During the online flipped learning, students engaged with cyber-aerial computing lecture videos (AI voice recorded), online quizzes, and curated reading materials. During the face-to-face lab sessions, students worked in pairs to solve instructor-designed challenges using small drones. For example, students were required to program, implement, and test course projects, including (a) random waypoint mobility, (b) a user-drone paired game, and (c) racing with collision avoidance. This course differed from traditional computer science offerings at the university because it integrated blended learning with simultaneous engagement in programming and hands-on activities of physical hardware. The course was implemented in Fall 2025 with 20 undergraduate computer science and/or software engineering students. It was offered as an elective, and students voluntarily enrolled. All enrolled students completed the course without dropping or failing.

While the companion paper focuses on course design and learning assessments, the present paper examines students' intrapersonal factors—particularly self-regulated learning (SRL), which is widely recognized as central to academic performance and persistence. Zimmerman emphasizes that when learners recognize their strengths and limitations, monitor progress toward learning goals, and evaluate the effectiveness of their learning approaches, student retention and achievement improve [6]. Pintrich and De Groot's SRL model conceptualizes SRL as consisting of metacognitive strategies, motivational beliefs, and behavioral processes for planning and modifying academic performance [7]. Their model highlights two primary components: motivational orientations and learning strategies.

In this paper, we examine students' motivational orientations and learning strategies in the FPBL drone computing course. Because the course was elective and project-based, understanding student motivation and SRL strategies provides insight into the characteristics of students who voluntarily enrolled and how SRL may relate to learning engagement and success.

Methods

Data

Building on Pintrich and De Groot's SRL model [7], Pintrich and colleagues developed the Motivated Strategies for Learning Questionnaire (MSLQ) [8], which has been widely used to measure student SRL, particularly motivational orientation and learning strategies [9, 10]. Motivational orientations include value, expectancy, and affective components. The value component includes intrinsic goal orientation, extrinsic goal orientation, and task value. Expectancy includes control-of-learning beliefs and self-efficacy for learning and performance. The affective component is commonly operationalized as test anxiety.

Learning strategies include cognitive, metacognitive, and resource-management strategies. Cognitive and metacognitive strategies include rehearsal, elaboration, organization, critical thinking, and metacognitive self-regulation. Resource-management strategies include time and study environment management, effort regulation, peer learning, and help seeking. In this study, we adapted the MSLQ to better align with the course context. We administered the motivational orientation scale at the beginning of the semester to capture students' initial motivation and administered the learning strategies scale midway through the course to assess enacted strategies. The original motivational orientation section of the MSLQ includes three sub-constructs: (1) interest, (2) expectancy for success, and (3) test anxiety. Because our instrument was administered prior to the course's summative assessment, we excluded test anxiety items. We also reduced redundancy by removing overlapping items. The interest subscale included 14 items, and expectancy for success included 12 items.

The learning strategies scale included three subscales: cognitive and metacognitive control strategies and resource management. We administered 42 items: 26 items assessing cognitive and metacognitive strategies and 16 items assessing resource management strategies. The response format for both instruments was modified from a 7-point scale to a 5-point Likert scale.

In addition, the course instructor wrote weekly reflective journals and participated in semi-structured interviews in the middle and at the end of the semester. These qualitative data were analyzed with particular attention to the instructor's perceptions of student engagement.

Student Participants

A total of 20 students enrolled in the course, and 17 students agreed to participate in the study, three juniors and 14 seniors majoring in computer science and/or software engineering. The participant group included 12 males (66.67%) and five females (27.78%).

Findings and Discussion

Students' responses to the motivational orientation scale showed high levels of interest in the course. The average interest score was 57.2 (range: 44–68), where the maximum possible score was 70. Students' expectancy for success was also high, with an average score of 50.35 (range: 41–58) out of a maximum possible score of 60. Both the mean and minimum scores exceeded the midpoint of each scale, suggesting overall high levels of interest and confidence (Figure 1a).

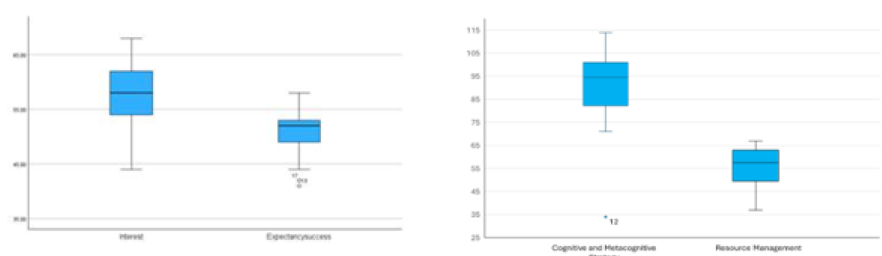

Figure 1a. Motivation

Figure 1b. Learning Strategy

Figure 1. Box-and-whisker plots for student motivational orientation(a) and learning strategy (b)

In terms of learning strategies, students' cognitive and metacognitive strategy scores averaged 90.25 (range: 34–114) out of a maximum possible score of 130. Resource management scores averaged 56.00 (range: 37–67) out of a maximum possible score of 80. Both averages exceeded the midpoints of the scales, indicating that participating students reported relatively strong learning strategy use overall. Although the minimum cognitive and metacognitive strategy score (34) fell substantially below the midpoint score (65), that was due to one student reporting an unusually low score (34), which was treated as an outlier. However, the box and whisker plot for the scale lies above the midpoint, indicating students' cognitive and metacognitive strategy scores were generally higher (Figure 1b).

Overall, students' responses to the modified MSLQ suggest that participating students demonstrated relatively high SRL, which may have contributed to their successful completion of the course. Notably, all students enrolled in the course—including those who did not participate in the study—completed all learning tasks and the course without failing.

Instructor Reflections on Student Engagement

The course instructor also observed unusually high student engagement. In his reflective journals, he described common engagement challenges in undergraduate computer science (CS) courses, including declining attendance and participation after midterm exams. However, in interviews he noted that when tasks are challenging and hands-on, students tend to participate actively: "I can tell that they are definitely CS students (laugh); when they face programming challenges, they want to get it work, so they try repeatedly." (Instructor interview)

Because the FPBL model-based CS course intentionally incorporated challenging hands-on activities, it may have contributed to this engagement. The instructor also noted that programming in combination with controlling physical hardware was relatively new for most students. Since students had no prior experience with embedded programming, the instructor considered the course challenging but engaging.

Across journals and interviews, the instructor described several indicators of high motivation and engagement of students. Below, we highlight three recurring themes.

Maintaining Sustained Focus. The instructor noted that students maintained sustained attention during in-person lab sessions, often remaining fully immersed in their tasks: "These labs, I don't see a single student going to restroom; it sounds funny, but it really is! They are very into it; they are immersed in it for sure."

He emphasized that students appeared to shift noticeably when lab activities began: "I can see them focused. When they started the hands-on activities, it seemed that they changed completely. I can see them keep on going without being distracted. It is a HUGE DIFFERENCE!"

He attributed this sustained focus to the integration of hardware and software components, which allowed students to see tangible outcomes from their programming: "Overall, I was very surprised because students were so focused and engaged. It almost felt like their eyes were sparkling with joy."

Demonstrating Learning Persistence

The instructor observed high attendance and persistence even after midterm exams—a time when attendance often decreases in other courses: "Students came to the lab on time even after the midterm exam. This doesn't happen often."

He also noted that some students stayed beyond scheduled lab time, which he interpreted as further evidence of motivation and persistence.

Going Beyond Minimum Expectations

The instructor was surprised that all students completed every project and that some engaged in additional work beyond course requirements. Students attended extra lab sessions outside scheduled times and completed bonus tasks that were not required: "They kept coming to the extra labs. They did the minimal requirements during the lab, but they really wanted to do more for the bonus tasks, so they came."

The instructor described this as highly commendable and expressed pride in students' dedication.

Conclusion

This work-in-progress study suggests that integrating both hardware and software elements in FPBL CS courses may enhance student motivation, engagement, and persistence. Students reported high interest and expectancy for success and demonstrated strong learning strategy use overall. Instructor reflections further support that students maintained sustained focus, persisted through challenging tasks, and frequently exceeded minimum requirements.

These findings suggest that hands-on, hardware-integrated, project-based tasks may foster engagement in computer science courses, especially when paired with flipped instructional supports. In addition, the elective nature of the course may attract highly motivated students, contributing to high levels of persistence and completion.

Future work will expand the set of learning tasks and seek to recruit larger cohorts to further examine engagement and learning outcomes. The course evaluation results were highly positive, with participating students rating the course 5 out of 5. The project aims to continue refining the FPBL curriculum and contribute implications for advancing CS course design.

Acknowledgement

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