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Unique Contributions of Individual Reflections and Teamwork on Engineering Students' Academic Performance and Achievement Goals*

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Prior literature in engineering education has focused on student-centered learning by utilizing active, constructive, and interactive instructional strategies. However, most research focused on evaluating the effectiveness of these instructional strategies by comparing them with traditional approaches, which typically placed students in passive roles. The goal of this paper is to investigate the relative effectiveness of constructive and interactive strategies and understand the unique contribution of each once introduced simultaneously in a large engineering class. Specifically, we used team-based learning and prompting students to reflect on their learning experiences. We hypothesized that these instructional strategies enhance students' academic performance and achievement goals. In this semester-long study, we collected data from 120 engineering students. The dataset included a total of 3430 student reflections in 26 lectures, teamwork behaviors, collected four times during the semester, pre and post-survey of students' achievement goals, students' prior academic success, and students' three exam scores as academic performance measures. To effectively collect the data, we used educational technology tools designed specifically for these instructional strategies. We used CourseMIRROR to collect students' reflections data, and CATME Smarter Teamwork to collect students' peer evaluation of teamwork behaviors. The results indicated that students' reflection specificity and teamwork behaviors improved over time in a semester. Further, teamwork behaviors were strong predictors of students' academic performance in the exams after controlling for prior success. We also found that while teamwork behavior had a better contribution predicting students' mastery and performance goals, the reflection specificity was a better predictor of students' avoidance goals. Lastly, while there was no significant difference from pre to post in performance-approach and performance-avoidance, there was a significant decline in students' mastery approach after being engaged in both instructional strategies.

Keywords: reflective thinking; teamwork behaviors; achievement goals; students' motivation; students' learning; students' performance

1. Introduction

Over the decades, education researchers have focused on integrating different instructional strategies in college classrooms to enhance student engagement and achievement. Literature supported that active involvement is essential for improving students' understanding of fundamental Science, Technology, Engineering, and Mathematics (STEM) concepts [1–4]. Beyond ensuring subject comprehension, most of these instructional strategies were introduced to (1) actively engage students in their learning process, (2) support students in becoming self-regulated learners, and (3) promote students' motivation.

In the same realm of actively engaging students in their learning processes, prior studies on engineering education have also emphasized on the use of different instructional strategies [1, 5, 6] such as project-based learning [7–9], reflective thinking [10–12], and collaborative teamwork [13, 14]. Also, to explore the relative effectiveness of different instructional strategies on student learning, Chi [15] hypothesized the Interactive-Constructive-Active-Passive (ICAP) framework. The ICAP framework proposes a testable hypothesis that suggests that interactive strategies (e.g., collaborating in team settings) could promote greater learning than constructive strategies (e.g., generating individual reflections) [16, 17].

Similarly, the literature also focused on introducing multiple instructional strategies to support students in becoming self-regulated learners. Self-regulated learning (SRL) strategies help students to acquire both the knowledge of engineering fundamentals and professional skills [18]. The premise of SRL theory suggests two kinds of skills: (1) personal competence which indicates students' ability to self-describe, self-reflect, become self-aware or regulate themselves); and (2) social competence which indicates students' ability to manage relationships and work effectively with peers, colleagues, and mentors [19, 20]. Prior studies on engineering education have used both personal competence (e.g., reflecting on

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your experiences), and social competence (e.g., being an effective team member) as approaches to enhance students' learning [18]. Prior studies described being an effective team member as an essential skill for all engineers [21, 22], and it is included as a required core competency in engineering education [23].

An extensive literature has explored the effectiveness of individual instructional strategies while comparing them with traditional approaches. In this paper, we focused on introducing two instructional strategies (i.e., reflective thinking and teamwork) simultaneously in an engineering class. Student-centered learning guided the idea of introducing two strategies. The premise suggests to engage students in their learning experiences, and to support them in becoming self- regulated learners. Besides these instructional strategies being commonly used in engineering classes, we selected them based on SRL theory, and the Interactive-Constructive-Active-Passive (ICAP) framework. In this paper, we explored the unique contributions of interactive activities (i.e., working on teamwork projects) and constructive activities (i.e., generating individual reflections) to promote students' academic performance. We used students' exam scores as the measure of their academic performance. We accounted for students' prior success while exploring the relative effectiveness of these strategies. Further, we also studied the relative effectiveness of these two instructional strategies on engineering students' achievement goals. More specifically, in this semester-long study, we addressed the following research questions:

RQ.1. What is the unique contribution of two instructional strategies (i.e., reflective thinking, and teamwork) to predict students' academic performance?
RQ.2. What is the unique contribution of two instructional strategies (i.e., reflective thinking, and teamwork) to predict students' achievement goal gains?
RQ.3. How do students' reflection specificity and teamwork behaviors change during a semester?
RQ.4. How do students' achievement goals change from the beginning of the semester to the end of the semester?

The next section introduces the literature review that guided the study, followed by the research methods, analysis, results, discussion, limitations, future directions, and conclusion.

2. Literature Review

This study is designed based on three principles. First, these two instructional strategies can improve students' SRL skills, such as their ability to reflect on their learning experiences and teamwork membership behaviors. Second, based on the ICAP framework, interactive activities can promote greater learning outcomes than constructive activities. Lastly, these instructional strategies can influence students' achievement goals, as explained by the achievement goal theory [24, 25]. To explore the literature, we first focused on studies that described the role of instructional strategies. Further, we reviewed the SRL theory and how various instructional strategies can help to promote self-regulation. Then, we focused on the ICAP framework and reviewed different instructional strategies used for both interactive and constructive activities. We also explored why it is essential to explore the ICAP hypothesis in a real classroom setting. Also, we explored the literature to establish the connection between SRL and achievement goals.

2.1 Reflective Thinking and Collaborative Teamwork

Literature defined reflective thinking as an active and persistent cognitive process of analyzing, and describing beliefs about knowledge [26]. Thus, reflection is a process that consists of judgment and reaction [27, 28]. Rodgers [29] distilled four criteria to describe John Dewey's characterization of reflection: (1) reflection as "meaning-making process" that helps the student to make connections between a prior and new experience, (2) reflection as "systematic and rigorous way of thinking," (3) reflection best happen in the community and with peers, and (4) reflection requires an attitude of valuing self and others beliefs. As reflection is a meaning-making process of thinking, students involved in the process of reflective thinking analyze the situation and make judgments about their learning by trying to assess what they know, and what more is needed. The reflection activities encourage students to monitor their prior knowledge and connect them to new knowledge. Literature showed that prompting students to reflect on their learning experiences can help them to identify their confusion and make connections among different concepts [30, 31].

Also, some studies suggested that reflection best happens in collaborative learning environments [32, 33]. Collaborative learning environments allow students to work in small teams for a common goal, listen to others' opinions, have discussions, and receive feedback [34]. Some benefits of collaborative learning environments include motivating students to engage, staying focused on the task, sharing their ideas, getting involved in the decision-making process [35], foster higher-order thinking of students [36], and learning the concepts better [9]. Furthermore, teamwork can facilitate students' self-regulation due to explicit peer feedback [37, 38], discussions to promote planning and evaluation of tasks [39], and encourage social interactions in classrooms [40, 41].

Prior studies have discussed the role of reflection and the role of teamwork in general. Also, these studies have studied the role of reflective thinking as an essential aspect of the collaborative learning environment [42]. However, the literature lacks evidence of discussing the relative contribution of these instructional strategies on students' performance once introduced simultaneously in a classroom environment. This study focuses on this literature gap by introducing two instructional strategies in an engineering classroom.

2.2 Self-Regulated Learning (SRL)

Literature defines SRL as a deliberate process that requires judgment and adaptation [20]. This process has three important components that are relevant to students' performance: (1) students' behavior of monitoring and controlling their effort [43], (2) students' ability to reflect on their learning experiences and prior knowledge [44], and (3) students' use of cognitive strategies to learn and understand the material [45]. Research on SRL processes indicated that students with better SRL skills, set better learning goals, use more effective learning strategies, create a productive learning environment, and monitor their progress in an efficient manner [46]. The premise of the SRL theory suggests that if introduced in classrooms, students can not show better performance and achievement through an ongoing experiential development but can also attain competency at both personal and social levels [18, 47]. Students acquire these competencies by sustaining beliefs about their abilities, and while working with their peers [48]. They understand the difficulty of learning tasks by seeing the viewpoints of their peers and regulate their effort to accomplish their set goals [49, p. 66].

Literature has suggested various instructional strategies for personal competence and social competence. For example, to promote personal competence, literature showed that reflective thinking [50, 51], problem-based learning [52], goal-setting and planning [53] were effective. Also, to promote social competence, the literature showed the use of project-based learning [54], group work [55, 56], and peer instruction [57] based instructional strategies. However, existing literature has focused on studying the effect of one kind of strategy at a time or its combined effect on students' learning [58, 59]. In this study, we focus on one of each kind of strategy to ensure including practices that promote both personal and social competence in students.

2.3 ICAP Framework

We also utilized the ICAP framework to choose the instructional strategies used in this study. The ICAP framework provides guidelines to understand the relative effectiveness of different types of activities on student learning. The framework describes four modes of learning activities and the resultant behaviors by the observable (overt) characteristics, and underlying cognitive processes [15]. The four modes are interactive, constructive, active, and passive [2]. In this framework, students in passive mode show no physical activity of processing or overt behaviors such as listening to a lecture or video without taking any notes [15]. Students in active mode physically do something by exploring or manipulating the instructional materials, such as doing a matching task. In the constructive mode, students are supported to generate explicit outputs in different activities, such as creating a concept map. The interactive mode involves social interaction with another person (e.g., peer, teacher, parent, computer system), who is involved in the co-construction process [15]. The term interactive is about engaging in not only the conversations but also getting connected by receiving or providing feedback, guidance, or scaffolding [15]. The ICAP hypothesis suggested that interactive activities most likely promote better learning outcomes than constructive activities, which in turn might be better than active activities, which are better than being passive [15]. Existing studies investigated these different modes of learning and provided some evidence on the benefit of interactive and constructive activities over active or passive activities [17].

However, there is good literature that showed this suggested hypothesis might not always be accurate, especially for the comparison of interactive versus constructive activities [16, 17, 60]. Prior studies suggested that there can be other factors such as conversation dynamics, prior experiences, students' willingness to collaborate, and other motivational factors that may contribute towards students' learning in small group settings [16, 61]. Besides, not many studies explored the role of interactive versus constructive activities on student success in classroom settings, e.g., [17]. Also, much fewer studies investigated the relative effectiveness of interactive versus constructive activities. The limited studies in this realm were either conducted in a lab setting or did not find differences between these two kinds of activities [16, 17]. In this study, we selected the two instructional strategies (one constructive and one interactive) to address the literature gap of investigating which strategy is relatively more effective in predicting students' performance and achievement goals.

2.4 Achievement Goals

Most goal orientation theorists connected achievement goal orientation with judgment and improvement in one's competence [62–64]. The achievement goal theory is also driven by students' motivation and competence-based aims [65]. Based on the evaluation of personal competence, two distinctive goal categories were identified as mastery and performance goals [63]. Mastery goals are about increasing ones' competence for their own sake. These goals rely on one's internal comparison of motivation, prior attainment, and performance [63, 66]. The performance goals are relative goals which are formed by using the perception of competence relative to the performance of others [62, 63]. Students make interpersonal and normative comparisons to define their performance goals. Both of these goals thus direct students' behavior towards the attainment of learning outcomes. Research on achievement goals showed that students' high perception of their competence could result in positive achievement outcomes [67, 68]. Researchers of achievement goal theory also introduced the approach-avoidance distinction to this theory [69]. In this distinction, performance-approach strived to outperform others, and the performance-avoidance was categorized by the variation where students strive to avoid being appearing as incompetent or exceeded by others [70, p. 77]. Similarly, in the mastery approach, students strive to learn and improve their skills [53, 71].

Research on achievement goals showed that changes in these goals have an impact on students' learning [72]. Also, students with strong performance and mastery goals frequently used learning strategies and improved their performance [73]. These use of strategies and improvements indicated students' proactive approach and adjustments in the process by self-regulating themselves [51, 74]. Literature also suggested an integration of achievement goal approach to the social cognitive model of self-regulation [75], and have shown the positive relationship between achievement goals and self-regulation strategies [71]. Similarly, Zimmerman & Schunk [77] have described students' goal orientation as both the key precursor as well as the natural co-existent of students' self-regulated learning (SRL) processes. Studies have studied the role of students' achievement goals or goal orientation on students' self-regulation [53, 76]. Research on SRL processes indicated that students with better SRL skills, set better learning goals, use more effective learning strategies, and can monitor their progress in an efficient manner [46]. In this study, we further elaborated on the relationship and changes in students' goals after being introduced to SRL based instructional strategies that promote both personal and social competence.

3. Research Methods

3.1 Participants

One-hundred and twenty first-year engineering students participated in this study. The data was collected in a required engineering course at a large mid-western university located in the United States. The main topics taught in the course include data visualization and analysis, ethics, engineering design, application of computer programming by using MATLAB, and development of mathematical models to solve engineering problems in a collaborative teamwork manner. The dataset included a total of 3430 student reflections in 26 lectures, team membership evaluations (that was collected four times during the semester), pre and post-survey of students' achievement goals, students' SAT, or converted ACT score and their exam scores in three exams. Table 1 shows the demographic information of the participants by race and gender.

3.2 Instruments

The data were collected using multiple instruments. The reflective thinking and teamwork behaviors data were collected using two applications: (1) CourseMIRROR- Mobile In-situ Reflections and Review with Optimized Rubrics [78–80] was used for students' reflection, and (2) CATME Smarter Teamwork [81–83] for peers' evaluation in collaborative teamwork.

Table 1. Demographic information of students by race and gender

	Male	**Female**	**Total**
Gender	**100**	**20**	**120**
Race			
Over-Represented Students	64	10	74
International Students	19	7	26
Under-Represented Students	17	3	20

With the CourseMIRROR application, students wrote the reflection on the concepts and problems discussed in the lecture from two perspectives: (1) Muddiest Points (MP) and (2) Points of Interest (POI). In addition to prompting students to reflect on the lecture, the application generated a summary of reflections for each class based on phrase-based natural language processing algorithms [84]. In this data collection set, students voluntarily participated in the reflection submission for 26 lectures. There was a total number of 3430 reflections, which indicates a ~55% completion rate. The collected reflections for both perspectives were in textual form. These textual reflections were converted into an equivalent quality score based on a rubric that we previously used in our past studies [11, 68]. Two human raters independently used the rubric to convert the reflections into the quality score for both MP and POI. There was a good agreement between the two coders, as κ (MP) = 0.617, and κ (POI) = 0.652 [85].

Teamwork was a mandatory component of this class and CATME (Comprehensive Assessment of Team Member Effectiveness) Smarter Teamwork [81–83, 86] was used to collect students' evaluations of their peers in the team project after each milestone of the project (four-time points). There were three or four students in each team, which means for each student, there have been two or three peer evaluations and one self-evaluation. Students were assigned to teams based on their weekly schedule of availability to meet with other team members outside of the class to complete specific assignments as a team. Students evaluated their team members in five dimensions: (1) Contribution to teamwork (C); (2) Interaction with teammates (I); (3) Keeping the team on track (K); (4) Expecting quality (E); and (5) Having relevant knowledge, skills, and abilities (H). Students rated their peers using 5-level behaviorally anchored rating scales, where one indicated poor, and five indicated excellent behavior.

In addition to students' reflection and teamwork behaviors data, students' achievement goals data was collected using Qualtrics survey system. We used the Achievement Goal Questionnaire-Revised (AGQ-R) survey [87] for students' achievement goals data. The survey was conducted twice, once at the beginning of the semester, and the second one at the end. We also collected students' SAT or ACT scores to control for their prior success. Furthermore, students took three exams during the semester. The maximum score for each exam was 120 points. These exams were graded by teaching assistants and instructors without any involvement from the research team. These exam scores were used as students' academic performance.

3.3 Procedure and Analysis

For this study, we used students' standardized test scores (SAT or ACT) as a measure of prior academic success. More students had reported SAT scores compared to ACT scores; therefore, the ACT scores were converted to SAT-equivalent scores by using a concordance table (College Board, 2018). In the rest of the paper, these scores will be referred to as "SAT scores."

To predict student exam scores, we transformed the teamwork behaviors, and reflection data according to the time when course exams occurred and converted each data item into three-time points of the data. Table 2 indicates the structure of the dataset.

Also, the achievement goals include the survey data for the mastery approach, performance approach, and performance-avoidance, where each of these categories had three items. For analysis, we used these categories as separate sets. We conducted these surveys twice in the semester with the same items. The first survey was administered at the beginning of the semester (pre-mastery approach, pre-performance approach, and pre-performance avoidance), and the second survey was administered at the end of the semester (post mastery approach, post-performance approach, and post-performance avoidance). We also calculated students' achievement goals gains for all mastery approach, performance approach, and

Table 2. Data transformation

Timepoint	Data Sets	Dependent Variable
1.	• The combined average of the first seven reflections quality scores (MP1 and POI1). • Teamwork behaviors set1 (C1, I1, K1, E1, H1) – Average of peer evaluation only • A measure of students' prior success (SAT scores)	Exam1
2.	• The combined average of the next eight reflections quality scores (MP2 and POI2). • Teamwork behaviors set2 (C2, I2, K2, E2, H2) – Average of peer evaluation only • A measure of students' prior success (SAT scores)	Exam2
3.	• The combined average of the next eleven reflections quality scores (MP3 and POI3). • The combined average of Teamwork behaviors set3 and set4 for each dimension (C34, I34, K34, E34, H34) – Average peer evaluation only • A measure of students' prior success (SAT scores)	Exam3

Table 3. Variances to predict exam scores – Determination of order of sets

Predictors	Exam 1		Exam 2		Exam 3	
	R^2	ΔR^2	R^2	ΔR^2	R^2	ΔR^2
Step 1						
Team-Behaviors	0.095		0.165		0.413	
Reflection-Spec	0.006		0.015		0.002	
P-Success	0.083		0.029		0.015	
Step 2						
Team-Behaviors &Reflection-Spec		0.014		0.014		0.005
Team-Behaviors & P-Success		0.066		0.038		0.000

ΔR^2 represents the changes in R^2.

performance-avoidance separately. For calculating mastery gains, we took the average of all items of pre mastery approach; we took the average of items of post mastery approach, and subtracted the pre mastery approach average from the post mastery approach average. The following equation describes this conversion:

Mastery approach gains = Average (Post mastery approach items) – Average (Pre mastery approach items).

Similarly, we calculated the performance approach gains and performance-avoidance gains for all students. To predict students' achievement goals gains, we took the average of the reflection data (~26 lectures) and calculated an overall MP value and overall POI value. Similarly, we took the average of teamwork behaviors (~4-time points) and calculated an overall C, K, I, E, H values.

We used different statistical methods to address each research question. To answer the research question 1, and 2, we used hierarchical multiple regression analysis to determine which strategy accounted for most variance, and simultaneous regression analysis to determine the unique contribution of each strategy. To answer research question 3, and 4, and determine the changes over time in a semester, we conducted multivariate repeated measures ANOVAs.

4. Results

At first, we checked for the statistical assumptions. We tested the linearity assumption using scatter plots. Multicollinearity in the data is checked for each regression, using multicollinearity diagnosis variable – Variance Inflation Factor (VIF), we found little or no multicollinearity between predictor variables. In this section, we present the results of each question.

4.1 RQ1: What is the Unique Contribution of Two Instructional Strategies (i.e., Reflective Thinking, and Teamwork) to Predict Students' Academic Performance?

We used stepwise hierarchical regression analysis to determine the relationship between students' academic performance and reflection specificity and teamwork behaviors while accounting for students' prior success. Additionally, we used simultaneous analysis to determine the unique contribution of students' reflection specificity (Reflection-Spec), teamwork behaviors (Team-Behaviors), and prior success (P-Success) to predict their academic performance in the course.

In this stepwise process, at first, to determine the order of the sets, we have considered the value of R^2 to determine the variable that accounts for the most variance in the model. In the second step, we considered the value of change in R^2 to determine that variable that adds the most variance and predictability in the model. Table 3 presents the steps to determine the order of the sets.

For all three exams, the teamwork behaviors data accounted for the most variance to predict the exam scores. The results of changes in R^2 indicated that for exam1 and exam2, the order of the good model was teamwork behaviors, prior success, and reflection specificity data. For exam3, the order of good model was teamwork behaviors, reflection specificity, and prior success. The results of the regression analysis to predict academic performance are presented in Table 4.

The results of the changes in R^2 indicate that teamwork behaviors account for 8.5% variance to predict exam1, 17.6% variance to predict exam2, and 36.3% variance to predict exam 3. The prior success additionally adds 8.7% for exam 1, 2.8% for exam2, and 0.2% for exam3. The reflection specificity data additionally accounts for 1.5% for exam1, 1.1% for exam 2, and 0.9% for exam3. Table 5 shows the significant predictions for each exam.

Table 4. Summary of hierarchical regression analysis relating teamwork behaviors, prior success, and reflection specificity to exam scores

	Exam 1		Exam 2		Exam 3	
	R^2	ΔR^2	R^2	ΔR^2	R^2	ΔR^2
Team-Behaviors	0.085	0.085	0.176	0.176	0.363	0.363
Team-Behaviors & P-Success	0.163	0.087	0.203	0.028		
Team-Behaviors, P-Success & Reflection-Spec	0.178	0.015	0.214	0.011		
Team-Behaviors & Reflection-Spec					0.373	0.009
Team-Behaviors, Reflection-Spec & P-Success					0.374	0.002

The results of stepwise regression indicate that students' SAT score, which is a measure of students' prior success, was a significant predictor to predict exam1. With every unit increase in prior success, the value of exam1 will rise to 0.017 units. We found that although teamwork behaviors appeared as the strongest predictor of exam2, no coefficient was significant to predict exam2 score. For exam3, Contribution to teamwork (C), and, and Having relevant knowledge, skills, and abilities (H) dimensions of teamwork behaviors data emerged as significant predictors with Having relevant knowledge, skills, and abilities (H) being the strongest positive predictor. With every unit increase in Contribution to teamwork (C) and Having relevant knowledge, skills, and abilities (H) dimension, the value of exam3 will rise to 12.472 and 14.606 units, respectively.

To determine the unique contribution of each of these sets to predict exam1, exam2, and exam3, we further conducted simultaneous regression analysis. Table 6 summarizes the results.

The results of simultaneous regression analysis indicate that teamwork behaviors have the unique contribution of 7.40%, 13.90%, and 35.10% to predict exam1, exam2, and exam3, respectively. Similarly, reflection specificity uniquely accounts for 2.60%, 1.10%, and –6.70% to predict exam1, exam2, and exam3, respectively. Prior success account for 7.10% variance to predict exam1, 2.40% to predict exam2, and 1.60% to predict exam3 scores. Overall, the results indicate that teamwork behaviors account for the most contribution to predict exam scores.

4.2 RQ2: What is the Unique Contribution of Two Instructional Strategies (i.e., Reflective Thinking, and Teamwork) to Predict Students' Achievement Goal Gains?

For this question, we used students' achievement goals gains (mastery gains, performance gains, and avoidance gains) as dependent variables. We used stepwise hierarchical regression analysis to determine the relationship between students' achievement goals gains and reflection specificity and teamwork behaviors while accounting for students' prior success. Additionally, we used simultaneous analysis to determine the unique contribution of students' overall reflection specificity (Avg-Reflection-Spec), overall teamwork behaviors

Table 5. Significant predictors – Stepwise hierarchical regression analysis summary for teamwork behaviors, prior success, and reflection specificity to predict exam scores

	Significant predictors	B	β	sr^2
Exam1	Prior-Success	0.017**	0.288**	0.277**
Exam2	*No coefficient is significant*			
Exam3	C	12.472*	0.598*	0.217*
	H	14.606**	0.655**	0.282**

* $p < 0.05$, ** $p < 0.01$; sr^2 indicates the % of variance uniquely explained by the predictor.

Table 6. Summary of simultaneous regression analysis for the unique contribution of teamwork behaviors, reflection specificity, and prior success to predict exam scores

	Exam 1 R^2	Exam 2 R^2	Exam 3 R^2
All sets	0.178	0.214	0.374
Team-Behaviors & Reflection-Spec	0.107	0.190	0.358
Team-Behaviors & P-Success	0.152	0.203	0.441
Reflection-Spec & P-Success	0.104	0.075	0.023

Table 7. Variances to predict exam scores – Determination of order of sets

	Mastery Gains		**Performance Gains**		**Avoidance Gains**	
Predictors	**R^2**	**ΔR^2**	**R^2**	**ΔR^2**	**R^2**	**ΔR^2**
Step 1						
Avg-Team-Behaviors	0.032		0.081		0.020	
Avg-Reflection-Spec	0.021		0.011		0.035	
P-Success	0.000		0.036		0.036	
Step 2						
Avg-Team-Behaviors & Avg-Reflection-Spec		0.026		0.056		
Avg-Team-Behaviors & P-Success		0.000		0.033		
P-Success & Avg-Team-Behaviors						0.016
P-Success & Avg-Reflection-Spec						0.054

ΔR^2 represents the changes in R^2.

(Avg-Team-Behaviors), and prior success (P-Success) to predict their achievement goals gains in the course. The set of overall reflection specificity comprises of two items: the average of MP values, and the average of all POI values. Similarly, overall teamwork behaviors set comprise five items: the average of four C values, the average of I values, the average of K values, the average of E values, and the average of H values.

In this stepwise process, at first, to determine the order of the sets, we have considered the value of R^2 to determine the variable that accounts for the most variance in the model. In the second step, we considered the value of change in R^2 to determine that variable that adds the most variance and predictability in the model. Table 7 shows the variances to determine the order of the sets.

In the first step, the teamwork behaviors data accounted for the most variance to predict both the approach category gains, i.e., mastery gains, and performance gains. For avoidance gains, prior success accounted for the most variance. The results of changes in R^2 indicated that for approach categories (mastery gains, and performance gains), the order of the good model was teamwork behaviors, reflection specificity, and prior success data. For avoidance category, the order of good model was a prior success, reflection specificity, and teamwork behaviors. The results of the regression analysis to predict achievement goals gains are presented in Table 8.

The results of the changes in R^2 indicate that teamwork behaviors account for 3.6% variance to predict mastery gains, 8.6% variance to predict performance gains, and 1.8% variance to predict avoidance gains. The prior success additionally adds 0.0% variance to predict mastery gains, 3.6% variance for performance gains, and 3.6% variance to predict for students' avoidance gains. The reflection specificity data additionally accounts for 3.2% to predict mastery gains, 2.0% to predict performance gains, and 5.4% for avoidance gains.

The results of stepwise hierarchical regression indicate that students' teamwork behaviors accounted for the most variance to predict approach categories. In contrast, reflection specificity accounted for the most variance to predict students' performance-avoidance. However, no coefficient was significant to predict achievement goal gains.

To determine the unique contribution of each of these sets to predict mastery gains, performance gains, and avoidance gains, we further conducted simultaneous regression analysis. Table 9 provided a summary of the results.

Table 8. Summary of hierarchical regression analysis relating teamwork behaviors, prior success, and reflection specificity to achievement goals gains

	Mastery Gains		**Performance Gains**		**Avoidance Gains**	
	R^2	**ΔR^2**	**R^2**	**ΔR^2**	**R^2**	**ΔR^2**
Avg-Team-Behaviors	0.036	0.036	0.086	0.086		
Avg-Team-Behaviors & Avg-Reflection-Spec	0.068	0.032	0.106	0.020		
Avg-Team-Behaviors, Avg-Reflection-Spec & P-Success	0.068	0.000	0.142	0.036		
P-Success					0.036	0.036
P-Success & Avg-Reflection-Spec					0.090	0.054
P-Success, Avg-Reflection-Spec & Avg-Team-Behaviors					0.108	0.018

Table 9. Summary of simultaneous regression analysis for the unique contribution of teamwork behaviors, reflection specificity, and prior success to predict students' achievement goals

	Mastery Gains R^2	Performance Gains R^2	Avoidance Gains R^2
All sets	0.068	0.142	0.108
Avg-Team-Behaviors & Avg-Reflection-Spec	0.057	0.092	0.056
Avg-Team-Behaviors & P-Success	0.036	0.120	0.051
Avg-Reflection-Spec & P-Success	0.024	0.057	0.090

The results of simultaneous regression analysis indicate that teamwork behaviors have the unique contribution of 4.40%, 8.50%, and 1.80% to predict mastery gains, performance gains, and avoidance gains, respectively. Similarly, reflection specificity uniquely accounts for 3.20%, 2.20%, and 5.70% to predict mastery gains, performance gains, and avoidance gains, respectively. Prior success account for 1.10% variance to predict mastery gains, 5.00% to predict performance gains, and 5.20% to predict avoidance gains. Overall, the results indicate that teamwork behaviors account for the most contribution predicting approach gains, while reflection specificity accounted for most contribution to predict students' avoidance behaviors. Teamwork was also a better predictor of students' performance behaviors than mastery behaviors.

4.3 RQ3: How do Students' Reflection Quality and Teamwork Behaviors change during a semester?

To answer the research question, we used repeated-measures ANOVA for each dimension of teamwork behaviors (Team-Behaviors) and both aspects of reflection specificity scores (Reflection-Spec). We conducted repeated measures by three-time points and on transformed data to observe changes in three-time points.

We used Mauchly's W test of sphericity. The epsilons (ε), which are estimates of the degree of sphericity in the population, are less than 1.0, indicating the sphericity assumption is violated. We thus used the Huynh-Feldt epsilons for adjusting the degrees of freedom. Table 10 indicates the results of repeated measures ANOVA.

Huynh-Feldt values indicate that for Contribution to teamwork (C) dimension of teamwork behaviors data with $F(1.802, 203.603) = 14.260$, $p = 0.000$ at least one of means is significantly different. We used Bonferroni test for pairwise comparison and found that Contribution to teamwork (C) dimension shows the positive significant mean difference from time point one to time point two, and from time point one to time point three, but changes from time point two to three are insignificant. Same results were obtained for dimensions of Interaction with teammates (I) dimension with $F(1.771, 200.077) = 23.089$, $p = 0.000$; for Keeping team on track (K) dimension with $F(1.692, 191.168) = 9.654$, $p = 0.000$, and for Expecting quality (E) dimension with $F(1.826, 206.295) = 8.675$, $p = 0.000$, where the significant positive difference was evident from time point one to two, and from time point one to three, but no significance was proven for time point two to three. In Having relevant knowledge, skills, and abilities (H) dimension with $F(1.754, 198.151) = 4.747$, $p = 0.013$, we only observed significant mean difference from time points one to three. Table 11 shows the mean difference of each CATME dimensions and aspects of reflection data.

Table 10. Results of Changes in Teamwork Behaviors and Reflection Specificity

	Mauchly's W	Huynh-Feldt ε	Effect Size (η^2)
Team-Behaviors			
C	0.874**	0.901	0.112
I	0.854**	0.885	0.170
K	0.802**	0.846	0.079
E	0.888**	0.913	0.071
H	0.843**	0.877	0.040
Reflection-Spec			
MP	0.991**	1.000	0.378
POI	0.966**	0.987	0.263

* $p < 0.05$, ** $p < 0.01$.

Table 11. Mean difference between time points of teamwork behaviors and reflection specificity

	Timepoint 1 to 2	Timepoint 1 to 3	Timepoint 2 to 3
Team-Behaviors			
C	0.230**	0.247**	0.017
I	0.255**	0.294**	0.040
K	0.169**	0.201**	0.032
E	0.179**	0.197**	0.018
H	0.081	0.162**	0.080
Reflection-Spec			
MP	0.486**	0.562**	0.076
POI	0.263**	0.289**	0.026

*$p < 0.05$, **$p < 0.01$.

Table 12. Multivariate repeated-measures ANOVA for achievement goals (changes from pre to post)

	Mauchly's W	Huynh-Feldt ε	Effect Size η^2
Mastery Approach	0.833	0.871	0.217
Performance Approach	0.755	0.815	0.006
Performance Avoidance	0.764	0.821	0.004

*$p < 0.05$, **$p < 0.01$.

Similarly, for reflection specificity score, Huynh-Feldt values indicated, MP with values $F(2, 186) = 56.477$, $p = 0.000$ indicated at least one of means is significantly different. We used Bonferroni test for pairwise comparison and found that MP shows the positive significant mean difference from time point one to time point two, and from time point one to time point three, but changes from time points two to three were positive but insignificant. POI with values $F(1.975,183.641) = 33.195$, $p = 0.000$ also indicated at least one mean is significantly different. Bonferroni test for pairwise comparison showed that POI has a positive significant mean difference from time point one to time point two and from time point one to time point three but changes from time point two to three although were positive but insignificant. Overall, the results indicate a significant positive change in students' teamwork behaviors and reflection specificity from the beginning of the semester to the end of the semester.

4.4 RQ4: How do Students' Achievement Goals Change from the Beginning of the Semester to the End of the Semester?

To answer the fourth research question, we used the multivariate repeated-measures ANOVA. The multivariate analysis was chosen due to of multi-item nature of the variable mastery approach, performance-approach, and performance-avoidance. Table 12 indicates the result of multivariate repeated-measures ANOVA.

Huynh-Feldt values indicate that in mastery approach $F(1.886, 175.392) = 26.368$, $p = 0.000$, there is a significant mean difference between pre and post mastery approach. The pairwise comparison based on time indicates a significant decline in the mastery approach from pre to post. Huynh-Feldt values indicate that for performance approach $F(1.630, 154.843) = 0.531$, $p = 0.553$ there is no significant mean difference between pre and post-performance approach. Huynh-Feldt values indicate that for performance avoidance $F(1.641, 155.934) = 0.420$, $p = 0.618$, there is non-significant mean difference between pre and post. Overall, the results indicate that contrary to our hypothesis, there is no significant positive difference in students' achievement goals after being introduced to reflective thinking and collaborative learning in class. Rather there is an observable adverse effect on students' mastery approach.

5. Discussion

In this semester-long study, we studied the role of two instructional strategies on students' academic performance and achievement goals. The two instructional strategies were reflective thinking and teamwork. Besides being the commonly used instructional strategies in engineering classes, we selected these two strategies to promote students' self-regulation (both personal competence and social competence). The reflective thinking was introduced to enhance personal competence (i.e., ability to self-describe, being self-aware, self-reflect, and monitor) aspect of self-regulation. Teamwork was utilized to enhance social competence (i.e., the ability to work with peers in team settings). Also, this study compared the relative effectiveness of interactive activities (teamwork) and constructive activities (reflective thinking) based on the classification from the ICAP framework.

We collected students' reflections for 26 lectures during an academic semester. The reflections were on two dimensions as muddiest points and points of interest. We converted these reflections into an equivalent score based on their specificity to the lecture on a scale of 0 to 4. Students were also assigned to specific teams at the beginning of the semester, and they periodically evaluated their peer team membership behaviors on five dimensions during the semester.

The data of these two instructional strategies were collected using specific technology tools as (1) CourseMIRROR (for recording students' reflections), and (2) CATME Smarter Teamwork (for organizing students in teams, and collecting their peer evaluations). In this study, by using these tools, we explored how engineering students' reflection specificity and their team membership behaviors changed over time in a semester and investigated the unique contribution of each strategy while predicting students' performance and achievement goal gains after accounting for students' prior success. Also, we investigated how students' achievement goals change as a result of these experiences, and to what degree these goals relate to students' academic performances.

Our first research question was about exploring the unique contribution of each instructional strategy over and above the other while predicting students' academic performance, after accounting for students' prior success. The results of both stepwise and simultaneous regressions indicated that teamwork is the strongest of the two strategies in predicting students' performance on the exams. Teamwork behaviors had a unique contribution of 7.40%, 13.90%, and 35.10% to predict exam1, exam2, and exam3, respectively. In literature, several studies on the ICAP hypothesis showed contrary or null results [16, 17, 60]. However, our study results confirmed the ICAP hypothesis [2, 15] in a classroom setting. These results provided some evidence that interactive activities could promote higher performance than constructive activities [2, 16]. These results are also novel, as no prior study has evaluated the effects of both strategies in a single engineering classroom environment. These results were interesting as we noticed a diminishing effect of students' prior success on their performance. The prior success uniquely accounted for 7.10% variance to predict exam1, which dropped to 2.40% to predict exam2 and further reduced to 1.60% to predict exam3.

In the second research question, we explored the unique contribution of each instructional strategy over and above the other while predicting students' achievement goal gains after accounting for students' prior success. The results of both simultaneous and hierarchical regression analysis revealed that teamwork behaviors were a better predictor of approach category of achievement goals (mastery and performance approach): 4.40% to predict mastery approach gains, 8.50% to predict performance approach gains, and 1.80% variance to predict avoidance gains. On the other hand, reflection specificity was a better predictor of students' avoidance gains, where it was uniquely accounted for a 5.70% variance. Overall, results show that teamwork behaviors help students towards their positive goal development of attaining success [71]. Also, similar to existing studies, results showed that reflections help students to develop achievement goals towards avoiding failures [68, 88]. It was also interesting to note that students' prior success accounted for a better variance for performance approach and avoidance, and had very low predictability for mastery approach. This observation indicates that students' prior success can have an effect on students' motivational patterns, where they attribute the failure to lack of their ability and withdraw their effort when faced with difficulties [88]. These results are novel because of studying the relative effects of two simultaneously introduced instructional strategies on students' achievement goals motivation.

Based on our third research question on students' team membership behaviors and reflection specificity change over time, the results revealed significant and positive differences between time points for dimensions of both reflections quality and team membership. Students showed significant improvement in both reflective thinking and teamwork behaviors during the semester. The results align with the findings from previous literature, which emphasize incorporating these strategies in a classroom environment for the development of students' skills [89–91]. For example, Ramdass & Zimmerman [90] evaluated the relationship between homework and reflective thinking strategies with other factors such as self-efficacy, perceived responsibility for learning, and time management. Their results showed a significant development over time with the repeated practice of the strategies to work on homework assignments. On peer evaluation, Brutus & Donia [91] described the impact of peer evaluations on students becoming effective team members. Their results showed that the effectiveness of students as team members improved over semesters in undergraduate business classes. In our study, we have simultaneously used both reflective thinking and teamwork behaviors, and our results have shown similar results that skills improve over time.

The last research question was related to the changes in students' achievement goals over time. The question addressed the difference in students' achievement goals once they are introduced to instructional strategies using educational learning technologies. We found that there was a significant decline in students' mastery-approach goals post usage of mobile technologies in class. On the other hand, there was no significant difference from pre to post in performance-approach and performance-avoidance goals. The results may indicate the potential negative implication of using mobile learning technologies on achievement goals. Students' did not change their performance goals after being introduced to instructional strategies using educational technologies; however, they showed a decline in mastery-approach goals. One reason for such no-change result of performance-related goals could be due to the sample of engineering students in this study, who might have already established performance-related goals and motivation [62].

Overall this study provided valuable information about the role of the instructional strategies on students' achievement goals and academic performances [92]. The study also suggested the use of educational technologies to incorporate instructional strategies in the classroom. These findings indicate that mobile technologies could be effective tools for improving students' academic performances. Our results are evidence of positive outcomes, which include: (1) Increased skill development of reflective thinking (personal competence) and teamwork behaviors (social competence) in students. (2) A significant relationship between students' academic performance and team working, where interactive activities promoted greater learning than constructive activities. (3) Teamwork behaviors accounted for most variance while predicting mastery and performance approach, while reflection specificity accounted for the most variance to predict students' avoidance gains. (4) The effect of students' prior success diminishes over time in a semester while predicting students' academic performance. Although these results indicate positive outcomes of the instructional strategies, the effect of these strategies was not evident on changes in students' performance goals. Also, the adverse effect was observed on the students' mastery-approach goals.

6. Limitations and Future Directions

The present study has certain limitations. First, this study is limited by a relatively small sample size (i.e., 120 students) from one classroom. On the other hand, this study was designed where student data (i.e., daily reflections, teamwork behaviors, exam scores, and surveys) were continuously collected for an entire academic semester instead of one-time data collection. Further, this study was exploratory and can be considered as a preliminary study with engineering students. More confirmatory studies can be designed with larger sample sizes in multiple courses.

Moreover, as this study was exploratory, we converted our data based on exam time-points and limited our statistical methods to regression techniques and ANOVA. However, besides this limitation being the venue of future studies, we believe that our results are confirmed with two techniques of regression analysis and thus provides the credibility of reporting. Although we have used AGQ-R Survey [87] for students' achievement goals, the present study has not evaluated the effect of other motivational factors and their interactions with students' academic performance. Also, in the present study, the quality of students' team membership relied on their peer evaluation, and we did not collect any process data of actual student observations while working on team tasks/assignments. This limitation of process data is countered with multiple time-points of data collection, where students evaluated their team members after each milestone. Also, each team member was evaluated by more than one peer.

As this study was based on students' self-reports of achievement goals, and reflections about lectures, the data may have an inflation effect or inaccuracies due to the self-report effect. The other sources, such as instructor reports/evaluations about students' achievement goals or interviews with students about muddiest points and points of interest, could be other future sources. However, prior literature also indicates that students' self-reports are valid indicators of their abilities, e.g., [93, 94]. Currently, teamwork behaviors area significant predictor of students' performance, but these results might be inflated due to the variation in the requirement of two strategies. The CATME teamwork behaviors was a mandatory component of the course with 15% weight in course grade, while participation in the CourseMIRROR reflection was voluntary. We countered this limitation by designing 26 data collection times for reflections, but in future studies, we can also study the effect of these two technologies without a biased element.

With the results of this study, we see the direction of future studies with time series analysis of the data without converting it into three time-points. We further would design exploratory research to investigate other motivational scales, such as self-efficacy. Furthermore, the study can be designed to investigate the interaction effect of students' motivational factors on their academic performance. Also, replication studies can be designed with a larger sample size and more classes.

7. Conclusion

In this study, we conceptualized teamwork and reflective thinking as key SRL skills, which could contribute to students' academic performance and achievement goals. In this semester-long study, we introduced these skills and answered four research questions. We identified the unique contributions of these two strategies to predict students' performance and achievement goal gains. We also explored how students become a more effective team member and generate more specific reflections over time. In addition, we observed the changes in students' achievement goals from the beginning of the semester to the end of the semester. By using two educational technologies, we implemented our instructional strategies in a real engineering classroom throughout an academic semester.

Our results showed that students' teamwork behaviors (*interactive*) were the better predictor of their academic performances over and above their reflections (*constructive*). Furthermore, we found a significant and positive improvement regarding students becoming better at being a more effective team member. Also, students constructed more specific reflections as the semester progress. Although students' reflections became more specific over time, the reflection specificity scores did not appear as much of a significant factor to predict students' academic performances beyond the teamwork scores.

Additionally, we studied how students' achievement goals change because of these learning experiences. Our results showed that there was a significant decrease in students' mastery-approach goals over the semester. However, we found no change regarding both the performance-approach and performance-avoidance goals. Finally, we explored how these instructional strategies relate to students' achievement goals. The results showed that teamwork behaviors were a better predictor of students' approach categories, while reflection specificity accounted for the most variance to predict avoidance gains.

The findings of this study are particularly interesting and unique due to the reason for being the first study to evaluate the role of reflections and teamwork behaviors introduced by using educational technologies to predict students' academic performances. The novelty of the research design extends prior research by lending support to the use of educational technologies to effectively integrate instructional strategies in a large class. Further, as existing studies showed limited evidence of the ICAP hypothesis on interactive vs. constructive activities, this study adds a piece of evidence in support of the hypothesis. Also, while these strategies and use of mobile technologies have not changed students' performance goals, they have shown a significant decline in students' evaluation of their mastery-approach goals. This relationship could become the venue for future studies in this direction.

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