ROLE OF DIFFERENT INSTRUCTIONAL STRATEGIES ON ENGINEERING STUDENTS' ACADEMIC PERFORMANCE AND MOTIVATIONAL CONSTRUCTS

by

Saira Anwar

A Dissertation

Submitted to the Faculty of Purdue University

In Partial Fulfillment of the Requirements for the degree of

Doctor of Philosophy

School of Engineering Education

West Lafayette, Indiana

August 2020

THE PURDUE UNIVERSITY GRADUATE SCHOOL
STATEMENT OF COMMITTEE APPROVAL

Dr. Muhsin Menekşe, Chair
School of Engineering Education

Dr. Michael Loui
School of Engineering Education

Dr. Ruth Streveler
School of Engineering Education

Dr. Şenay Purzer
School of Engineering Education

Approved by:
Dr. Donna Riley

To my sister (Dr. Ayesha Anwar) and my parents (Anwar Islam Ehsan, and Najam Anwar), whom I miss each day. Without you all, I witnessed a journey where I was short of praying hands. I felt empty, breathless, and tired but your memories gave me the strength to continue,

To Fatima and Omar, for supporting me even when I am wrong, helping me when I am not strong, taking care of me without a frown, pulling me up when I am down, and making me laugh always. This journey was not possible without both of you,

And

To my grandparents, whose stories and memories I cherish!

ACKNOWLEDGMENTS

I would like first to acknowledge and thank my advisor Dr. Muhsin Menekşe and his wife, Aylin Çeltik. Dr. Muhsin, you have helped me in all possible ways. I was fortunate to have you as my advisor and could not ask for a better mentor. I admire your patience and willingness to guide me at all times. In this academic journey, you encouraged me, put effort into advancing my research work, and supported me in my career path. In my personal life, you helped me in dealing with all issues, understood me, and made me smile. I am and will always be appreciative of what you did, and I wish I could be the same light of hope in my advisees' life in the future. Thank you for being there, thank you for being supportive, thank you for being so caring, and thank you for being you. Aylin, I found a good friend in you, and thank you for all those times when your presence made me happy.

I want to thank my amazing committee members: Dr. Michael Loui, Dr. Ruth Streveler, and Dr. Senay Purzer. Dr. Loui, I am immensely grateful for your feedback on my research design, methods, and of course, writing. Dr. Streveler, you are in my committee since my first month of this journey. I appreciate you for always being there, listening to me, and giving me the best possible advice. Your comments during my readiness helped me to write the paper you suggested, and during my preliminary exams enabled me to write my dissertation in this way. I am immensely grateful and will always be seeking your guidance. Dr. Purzer, you helped me a lot in understanding the motivational constructs. Your comments and advice are always instrumental. I thank you all for being so kind, helpful, and supportive.

The ENE faculty, who always helped me. I would like to express my gratitude to Dr. Matthew Ohland, Dr. Brent Jesiek, Dr. Tamara Moore, Dr. Alice Pawley, Dr. Alejandra Magana, Dr. Selcen Guzey, Dr. Morgan Hynes, and Dr. Joyce Main. Thank you so much.

My ENE journey was impossible without Loretta McKinniss and Carol Brock. Loretta, you are a darling. I will miss your hugs, friendly conversations, and smile. Carol, you are a beautiful soul. I will always remember your sweet gestures.

My very dear and close friends Imran, Swetha, Zahra, Anuradha, and Zainab. Each one of you has an exceptional place in my heart. Imran, your confidence in me, and friendly advice made this all possible. You helped me see a new perspective on life. Swetha, I found a little sister in you. Your caring nature, pure soul, and humanity made me your biggest fan. I learned a lot from you.

Thank you for all little and big kind gestures. You made me smile in my toughest hours; you gave me hope, and love, which I can never repay. Zahra, we were colleagues, turned friends, and are now a family. From my even planning to come to Purdue, to my degree completion, you have been instrumental. Be it your house or my place, be it your milestones or mine, I always enjoyed the food and good laugh. Anuradha, in these years, you had been the best roommate. You were a compassionate listener who always supported, motivated, appreciated, and guided me. I will not deny, I enjoyed both the compliments and your involuntary scary screams. Zainab, we grew together, cried, fought, and laughed together. Thank you for all your prayers and continuous support.

I would also like to acknowledge my friends, mentees, and coauthors at my lab group. Ahmed, you were a student, and now my academic brother and a great friend. Because of your excellent attention to detail, I was able to polish my work immensely. I enjoy our debates and conversations. Zeynep and Kadir, thank you for being so understanding.

I owe a great deal and grateful to the friendship of Hoda, Hossein, and Hadi; Matilde, Yuri, and Amelia; Asefeh, Abbas, and Ryan. You people were my go-to people on this journey. Whenever I felt down or needed any help, be it academic or otherwise, I always called you, and you always helped. I appreciate it, and I am deeply grateful. Hadi, Amelia, and Ryan will always be my sweethearts.

I am incredibly grateful to my cohort for their immense support. I learned so much from all of you. Claudio and Julianna Pen-apple will always remain our secret joke, and reason for a laugh. Taylor, Jessica, Kayla, Brianna, Amanda, and Rohit, you made this journey easier to navigate. Genisson, Aziz, Moses, Jacki, and Tikyna, you are not my cohort, but you always helped me, so thank you.

I owe a lot to my uncles, aunts, and cousins. I especially want to thank Taya Abu, Tayi Jan, All Chachus, and Chachis, Khalas, Khalos, Mamus, and Mamis for all love and support.

I acknowledge the support of CourseMIRROR (www.CourseMIRROR.com) and CATME Smarter Teamwork (www.CATME.org) research teams. These two software were instrumental in collecting the data used in this dissertation. I also would like to acknowledge that the first study and the second study of this dissertation are re-produced and are copyrighted by Springer Nature Switzerland AG, and Tempus Publication, respectively. The permission to reproduce is attached in Appendix C.

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ABSTRACT

The use of student-centered instructional strategies is a common practice in engineering classes. Instructors often use such strategies to promote greater learning outcomes and student engagement. However, prior research studies also acknowledge students' resistance and lack of motivation towards such innovative strategies. In both cases, the existing literature compares these strategies with the traditional approach of lecture-based teaching. However, there is limited literature on exploring the relative effectiveness of different student-centered instructional strategies in engineering classrooms. Understanding which instructional strategies have a more profound effect on students' performance and motivation is fundamental in course design. Such comparisons would allow instructors to design and plan their courses with better learning activities, which could lead to better student engagement and learning. In this three-paper dissertation, I explored the relative effectiveness of two instructional strategies 1) reflective thinking, and 2) teamwork participation by primarily using quantitative methods. Self-regulated learning theory and the Interactive-Constructive-Active-Passive (ICAP) framework guided the selection of these two strategies. I collected students' reflection data using CourseMIRROR technology. In addition, for teamwork participation, CATME smarter teamwork was used.

The first study investigated the relationship of an instructional strategy and a motivational construct through the following research questions: 1) Do students with high academic self-efficacy generate high-quality reflections? 2) To what degree do students' self-efficacy beliefs and reflection quality scores predict their learning outcomes? Bivariate Pearson product-moment correlation and multiple linear regression were used to analyze the relationships. The results show that the correlation between self-efficacy scores and the total number of reflections was significant. Also, 62% of the variance of students' learning outcomes score could be accounted for by the linear combination of self-efficacy score, muddiest point quality, and a number of reflections.

Based on the first study, in the second study, I focused on studying the relative effectiveness of two instructional strategies on a motivational construct in a larger engineering class. More specifically, the second study focused on understanding change in students' participation in two instructional strategies (i.e., reflective thinking and teamwork) and students' achievement goals. Further, the study investigated the unique contribution of instructional strategies on students' academic performance and changes in achievement goals. I used stepwise hierarchical regression,

simultaneous regression, and repeated measures ANOVA to analyze the data. The results indicated a significant and positive change in students' teamwork behaviors and reflection specificity from the beginning of the semester to the end of the semester. Further, there was a non-significant change in students' performance-approach and performance-avoidance from the beginning of the semester to the end of the semester. However, results showed a significant adverse effect on the students' mastery approach. Moreover, teamwork behaviors appeared as the most significant predictor of students' academic performance and changes in approach goals.

The third study focused on investigating the role of the same two instructional strategies on students' academic performance and multiple motivational constructs (i.e., self-efficacy, task value, and engagement). I used structural equation modeling, and repeated measures ANOVA to analyze the data. The results indicated a significant decline in all motivational constructs except for social engagement. Also, similar to study 2, teamwork behaviors was the most significant predictor of students' academic performance, changes in self-efficacy beliefs, and task value. Moreover, engagement appeared as a significant predictor of self-efficacy beliefs and task value.

In this dissertation study, I used an empirical approach to evaluate the instructional strategies by integrating them with a psychological model of achievement goals, self-efficacy, task-value, and engagement. The study advances the literature of engineering education by addressing the literature gap of studying the relative effectiveness of instructional strategies in a real classroom. Moreover, it provides additional evidence that aligns with the ICAP hypothesis. Further, with this study, I offered a validated engagement scale with four distinct dimensions for engineering classes.

CHAPTER 1. **DISSERTATION OVERVIEW**

Introduction

In the recent past, engineering education researchers and practitioners have focused on introducing student-centered instructional strategies in engineering classrooms. The premise of these instructional strategies was rooted in engaging students in the learning process through meaningful learning activities (Prince, 2004). In research efforts for the evidence of the student-centered instructional strategies, researchers looked for an alternative method to traditional lecture-based teaching where students were the passive receiver of the information (Prince, 2004). Such existing studies have reported the evidence in favor of the effectiveness of various instructional strategies such as collaborative teamwork (e.g., Terenzini, Cabrera, Colbeck, Parente, & Bjorklund, 2001), cooperative students' projects (e.g., Zakaria, Chin, & Daud, 2010), think-pair-share (e.g., Kothiyal, Majumdar, Murthy, & Iyer, 2013), exit tickets (e.g., Green, 2016), and concept maps (Darmofal, Soderholm, & Brodeur, 2002). To explore the effectiveness of specific activities, researchers have typically used the pairwise comparison of two approaches (i.e., student-centered vs. traditional) as the research design (Streveler & Menekse, 2017). However, there are very few research studies that compared the relative effectiveness of multiple student-centered activities on students' learning outcomes.

Besides, the most common objective of such a comparison was to determine the effects of student-centered instructional strategies on students' learning and performance (Slavin, 1996). Although it is essential to understand the role of instructional strategy on students' performance, there are other important non-cognitive factors to this information. For example, information on students' motivation, engagement, goals, resistance to student-centered learning, or impact on soft skills is equally important. In an engineering context, most studies have looked at the role or relationship of various motivational constructs in predicting students' academic performance. However, the literature with an integrative role of instructional strategy is less explored.

In sum, while it is important to understand the effectiveness of an instructional strategy in a learning context, by far, the literature is sparse on two factors. 1) The relative effectiveness of different student-centered learning strategies on students' performance (Streveler & Menekse, 2017), and 2) studying the impact of such strategies on multiple motivational constructs when introduced in an engineering classroom.

Accordingly, my goal in this dissertation study was to explore the role of different instructional strategies on engineering students' both academic performance and motivation. In this dissertation, the focus was on understanding three important facets: 1) the relationship between engineering students' motivation and instructional strategies, 2) the effect of these instructional strategies on students' learning outcomes and motivation, and the 3) change in engineering students' motivation from pre to post use of instructional strategies. I argue that identifying these relationships will help engineering instructors to understand the relative effectiveness of each instructional strategy, and understand variations in students' motivation based on student-centered learning strategies. Also, it will help them to incorporate appropriate instructional strategies in engineering courses, which could help in enhancing students' motivation.

Background

In this dissertation, I present three studies that collectively explore the role of different instructional strategies on engineering students' academic performance and motivation. Figure 1.1 below describes the theoretical framework of the dissertation. There are three major constructs of this theoretical framework 1) self-regulated learning, 2) Interactive, Constructive, Active, Passive (ICAP) framework, and 3) motivational constructs.

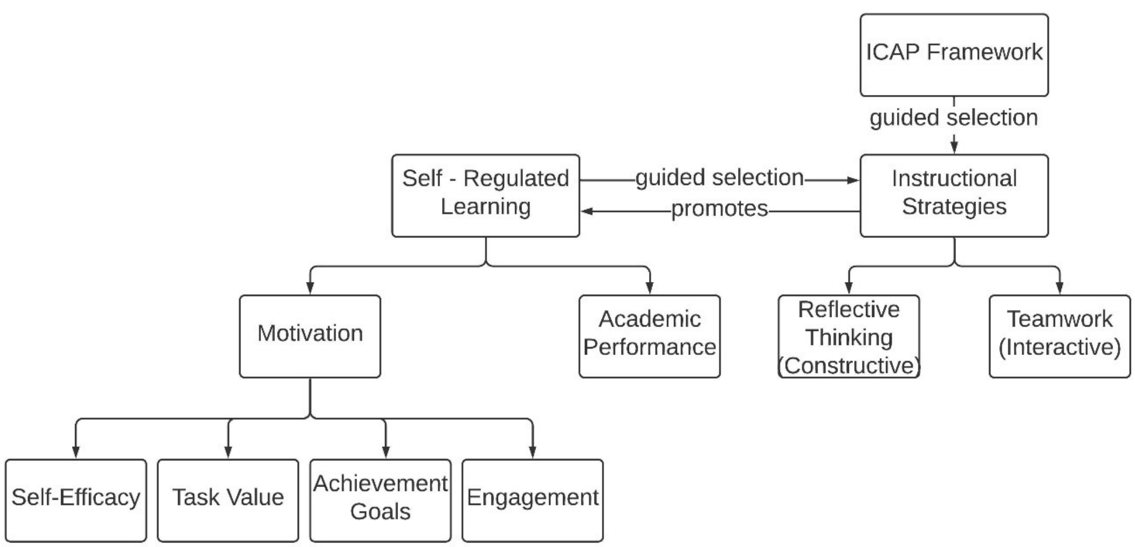

Figure 1.1. The theoretical framework of the dissertation

In each study, the relevant literature is explored. However, the basic premise of the literature review revolved around the theoretical foundation of the selection and implementation of two strategies, motivational constructs, and their relationship with students' learning and performance.

In this dissertation study, I used self-regulated learning as a lens to achieve three goals 1) select the appropriate instructional strategies that promote self-regulation in students, 2) to evaluate the effect of these instructional strategies on key sources of motivation in self-regulated learning, and 3) to understand the role of the selected instructional strategies on students' academic performance. In addition, I used the ICAP framework to guide in the selection of different instructional strategies.

Self-regulated learning, instructional strategies, and academic performance

Self-regulation in academic context refers to the proactive use of the self-directive process to transform mental abilities into academic skills (Zimmerman & Schunk, 1989). In this process, students continuously monitor their progress and outcomes towards a goal and accordingly redirect unsuccessful efforts (Zimmerman & Schunk, 2001). Students use this process to master their learning by taking the initiative, showing perseverance, and adaptive skills (Zimmerman & Schunk, 2001).

Self-regulation is a key concept in students' learning and performance and is often associated with students' academic achievement (Zimmerman, 1990). Prior research studies suggested three fundamental components through which self-regulation was associated with students' performance and achievement: 1) Self-regulated learners reflect on their learning experience (Zimmerman & Martinez-Pons, 1986). 2) Self-regulated students use cognitive engagement to learn and master course material (Corno & Mandinach, 1983). 3) Self-regulated students monitor and control their effort (Corno, 1986). These three components suggest that self-regulated students use an array of processes to demonstrate their participation and optimize their learning, effectiveness, and performance (Zimmerman & Kitsantas, 2005).

Existing research on self-regulated learning have suggested that students with better self-regulation participate in instructional activities, monitor their progress, and are more effective as learners (Zimmerman & Schunk, 2008). Moreover, such studies guided the premise of introducing various interventions, teaching pedagogies, and instructional strategies in the classes to help students in their learning process (e.g., Zimmerman, Bonner, & Kovach, 1996).

Prior research studies suggested that in most cases, instructional interventions for promoting self-regulation in students were designed and introduced to promote two kinds of competences in students. 1) social competence, 2) personal competence (Zimmerman & Kitsantas, 2005). Social competence refers to students' ability to manage and work with peers, perform in team and group tasks, and maintain a good and communicative relationship with peers, mentors, and professors. Such students learn from vicarious experiences, see the viewpoints of their peers, and work with them to achieve the shared and collective goal (Cho, Demei, & Laffey, 2010; Zimmerman, 1989). Personal competence refers to students' ability to reflect on their learning processes, and they are self-motivational in nature. Such students show the self-awareness process and regulate themselves accordingly (Zimmerman & Kitsantas, 2005). Prior research studies also suggest that students acquire these competencies by sustaining their self-beliefs, working with their peers, and adjusting their learning processes (Zimmerman & Kitsantas, 2005).

In prior research studies, instructional strategies have been discussed in the context of both personal competence and social competence. In this dissertation, these two competencies became the primary source of inspiration for the selection of two instructional strategies. In prior research studies, social competence is often associated with strategies such as project-based learning (English & Kitsantas, 2013), group work (Cho et al., 2010; Järvelä & Järvenoja, 2011), and peer instruction (Roscoe & Chi, 2007). For personal competence, there is evidence of using reflective thinking (Jenson, 2011; Schunk & Zimmerman, 1998), problem-based learning (Hung, 2011), goal-setting, and planning (Pintrich, 2000b). I, for this study, selected the two instructional strategies as teamwork behaviors (social competence), and reflective thinking (personal competence). I evaluated students' participation in these two strategies and used self-regulation as a lens to study their role in students' academic performance and motivation.

Self-regulated learning and motivation

In addition to students' academic performance, and participation in instructional strategies for both personal and social competence, self-regulated learning has focused on students' motivational and affective functioning (Boekaerts, Zeidner, & Pintrich, 1999). Motivational processes help students to initiate and guide their efforts to self-regulate the learning process (Zimmerman & Schunk, 2008). Research studies revealed that students' with better self-regulation abilities set better goals, monitor, and adjust their processes in a timely and appropriate manner and overcome deficient processes efficiently (Zimmerman & Schunk, 2008). Also, students with high motivation are relatively more persuasive towards their learning process, progress, and outcomes (Bouffard-Bouchard, Parent, & Larivee, 1991). Such students show higher effort towards learning a new task (Schunk, Hanson, & Cox, 1987), are persistent towards their learning (Schunk, 1985), and show greater satisfaction and affect (Zimmerman & Kitsantas, 1999).

Zimmerman & Schunk (2008) described key sources of motivation in self-regulated learning, such as self-efficacy, task values, interests, goal orientation, outcome expectancy, and future time perspective. They suggested that these motivational constructs could be associated with self-regulated learning in four possible ways, which are: 1) as a precursor to self-regulation, 2) as a mediator to self-regulation, 3) as a concomitant of self-regulation outcomes, and 4) a primary outcome of self-regulation. For this dissertation study, I focused on four motivational constructs and studied the impact of students' participation in instructional strategies on these four constructs. The used constructs are 1) self-efficacy beliefs, 2) task value, 3) achievement goals, and 4) engagement. Existing research studies have associated these all four motivational constructs with self-regulated learning in all four possible ways of being a precursor, mediator, concomitant, or exclusive outcome.

Self-efficacy beliefs refer to students' judgments about their capabilities to attain their goals (Bandura, 1997). These judgments allow the students to organize and act on their action plans, which eventually lead to the desired outcomes (Pajares & Schunk, 2001). The self-efficacy beliefs helped students in putting efforts, staying persistent and actively participate in class activities (Pajares & Schunk, 2001). Researchers have associated self-efficacy beliefs with self-regulated learning as being a precursor, mediator, and an exclusive outcome (Zimmerman & Schunk, 2008). Moreover, the prior research studies reported that engaging students in self-regulated activities could lead to improving their self-efficacy concomitantly with students' academic performance (Schunk, 1998). Further, the efficacy beliefs can be based on four sources 1) past performance (prior experience and outcome on certain tasks), 2) vicarious experience (social comparison with peers), 3) verbal and social persuasions (persuasions by peers or teachers), and 4) psychological states (emotional state students' experience towards tasks). These four sources can trigger different self-regulatory behavior in students (Zimmerman & Schunk, 2008). Based on these connections between self-efficacy beliefs, self-regulation, and academic performance, it is important to undertake this construct and study its impact in an engineering class context.

The second construct used in this dissertation study is task value. According to expectancy-value theory (e.g., Eccles & Adler, 1983; Wigfield & Eccles, 2000) task value refers to students' belief that academic task is relevant, important, useful, and worth pursuing. Such beliefs are important to direct students' effort in self-regulating their learning (Battle & Wigfield, 2003). Prior research suggested that students see the value of task from four perspectives (Wigfield & Eccles, 2000): 1) how important it is to participate and do well in the task, 2) what intrinsic gains they may get from doing the task, 3) how useful is the task especially in their future work, 4) how much effort and time will be needed to complete the task. Based on these perspectives, task value could be a precursor, mediator, and an outcome of self-regulated learning (Zimmerman & Schunk, 2008). For example as a precursor, if students find a value in doing or participating in an activity, they will choose to do it. However if students see too much effort and time, in comparison to importance and gains, they most likely will not engage in such activities (Battle & Wigfield, 2003). Similarly, Pintrich & De Groot (1990) reported a mediating role of task value in students' self-regulation and the use of cognitive strategies. Moreover, Wolters, Shirley, & Pintrich's (1996) study indicated that task value is a concomitant outcome motivational role in self-regulated learning. They found that students' self-evaluations positively predicts their task values and self-regulatory strategies. Given these connections of task value and self-regulation, I opted to use task value as a second motivational construct in this study.

Achievement goals (Ames, 1992; Elliot & Church, 1997), refers to students' purpose of engaging in a specific task. This purpose helps students to take a proactive approach to engage in specific academic tasks to attain or avoid their desired outcome. In prior research studies, achievement goals were categorized with approach and avoidance distinction. Four types of achievement goals were commonly studied, which are mastery approach, performance approach, mastery avoidance, and performance-avoidance (Elliot & Church, 1997). In mastery goals (approach and avoidance), students' main focus is on developing competence in an academic task, while in performance goals (approach and avoidance), they focus on showing competence relative to their peers (Elliot, 1999; Elliot & Harackiewicz, 1996). Fryer & Elliot (2008) suggested that mastery goals represent an important aspect of self-regulation. These goals allow students to plan and use specific strategies for attaining or avoiding the outcomes. This positionality indicates that achievement goals could be precursor, and concomitant outcome of student use of self-regulated learning processes (Zimmerman & Schunk, 2008). For example, Grant & Dweck (2003) reported that strong learning goals are associated with students' selection of learning strategies and efforts. Such students also showed perseverance and persistence in quickly recovering from poor performance. I believe that due to these naturalistic alignments of achievement goals with self-regulation, adding them in the study will give a more thorough understanding of these connections in an engineering context.

Students' engagement is a multidimensional construct that refers to students' interaction with the context and adapting to variations in the contextual properties (Connell, 1990). Such interactions impact students' academic achievement and behavior (Fredricks, Blumenfeld, & Paris, 2004). These interactions provide students the information about their competence and enhance their adaptive skills (Eccles, Wigfield, & Schiefele, 1998). In other words, students self-regulate themselves and use cognitive strategies to show their adaptive behavior (Pintrich & De Groot, 1990). Prior research studies generally supported three aspects of engagement which are: behavioral (involvement, and attention to class activities), emotional (value learning, and showing positive reaction towards teachers, peers, and activities), and cognitive (willingness to put effort into understanding and to master the concepts) engagement (e.g., Fredricks et al., 2004). However, recent studies indicated the fourth aspect of social engagement (social interaction with peers and maintaining a relationship while learning), which proved to be an integral component of engagement (M.-T. Wang, Fredricks, Ye, Hofkens, & Linn, 2016). In prior research studies, engagement, and specifically, cognitive engagement, was associated with self-regulation and self-efficacy beliefs (Fredricks et al., 2004). Also, students' engagement appeared as a strong predictor of students' choice of strategies and performance (Pintrich & De Groot, 1990). Considering the role of engagement as both a precursor and an outcome of the self-regulation strategies, I used the multidimensional engagement construct as the fourth motivational construct.

ICAP framework

In addition to promoting personal and social competence using a self-regulation lens, in this dissertation study, I used the ICAP framework (Chi, 2009), which guided the selection of instructional strategies. Chi (2009) provided a framework to differentiate the use of active, constructive, and interactive modes in student-centered learning strategies and their resultant behaviors by the observable (overt) characteristics. In this framework, passive refers to the state when students are a passive listener of the information and are not involved in any physical processing activity. Active mode refers to the state when the student is attentive to classwork by physically doing something (e.g., taking notes). Constructive refers to producing some overt outputs. This mode involves creating new knowledge based on existing information (e.g., drawing a diagram). Interactive, in addition to active and constructive behaviors, refer to social interaction with another person such as peer, teacher, or parent, who is involved in the co-construction process (e.g., collaborating on a project). The term interactive is about engaging in not only the conversations but also getting connected by getting feedback, guidance, or scaffolding (Chi, 2009). In addition to the provided differentiation between the four modes, and their processes, the framework also generated and proved the hypothesis for learning stating that "interactive activities are more likely to produce better learning than constructive activities, which in turn might be better than active activities, which are better than being passive" (Chi, 2009, p. 73). However, there is limited literature that explored the hypothesis (comparison of interactive vs. constructive) in classroom settings (Menekse, Stump, Krause, & Chi, 2013). Also, there is an extensive literature which showed that small groups based interactive method might not necessarily promote greater learning when compared with individual learning (Lou et al., 1996; Menekse et al., 2013). These studies suggest that there can be other factors such as motivational and engagement factors that may contribute to students' learning (Barron, 2003; Chi & Menekse, 2015). This limited evaluation of the ICAP hypothesis in the engineering classroom guided me to explore this hypothesis. In addition, I used the framework to verify the results with motivational and engagement factors. In this study, I focused on using the ICAP framework as a second lens to understand the role of interactive and constructive activities on students' performance and motivation.

Based on the ICAP hypothesis in this dissertation study, I focused on using the two strategies, which involve students in different modes of learning. The two instructional strategies used in this dissertation study are teamwork behaviors and reflective thinking. The teamwork behaviors involved students in interactive activities, while reflective thinking allowed students to be engaged in constructive activities. With this dissertation, I evaluated the ICAP hypothesis in real engineering classroom setting for both students' learning and motivation.

Data collection process

For all three studies, the data were collected in an entire semester from engineering students for multiple aspects of the research design constructs.

For study 1, the data were collected in a required engineering course from 52 sophomore students. Students initially completed a self-efficacy survey. Further, they provided their individual reflections for each lecture during the entire semester. Also, students' academic performance was measured through three course exams conducted at different times in the semester. Figure 1.2 describes the data collection process of the study.

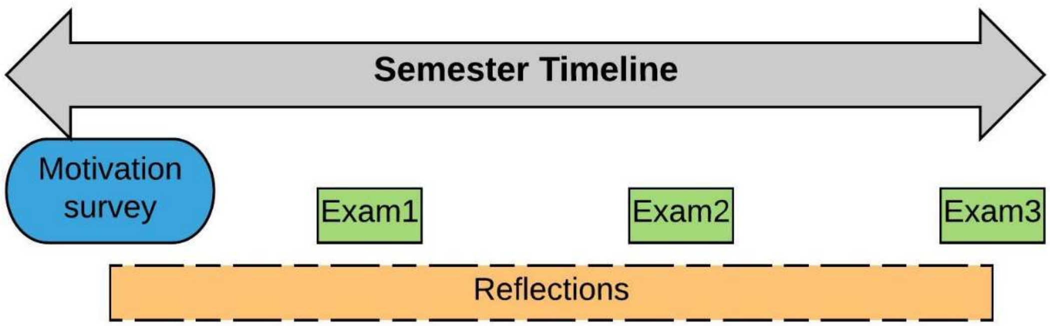

Figure 1.2. Data collection timeline of study 1

For studies 2 and 3, data were collected from a required first-year engineering course from 120 students. Similar to study 1, students participated in the data collection of multiple constructs. In addition to pre-post motivation surveys, students submitted reflections in 26 lectures and completed their peers' evaluations at four-time points. Students' academic performance was measured using their exams score in three exams. Figure 1.3 describes the data collection timeline for both studies.

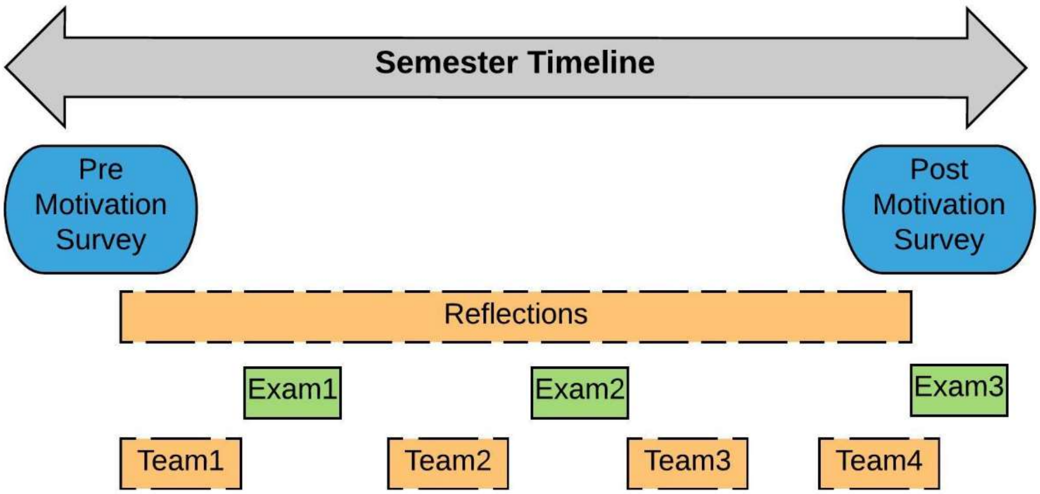

Figure 1.3. Data collection timeline of study 2 and 3

Instruments: Validity and limitations

In this dissertation study, collectively for all three studies, I collected the data from five aspects. These aspects are 1) motivational surveys, 2) reflective thinking, 3) teamwork behaviors, 4) academic performance, and 5) prior success. For each of these aspects, I used an instrument to ensure the use of appropriate data collection methods with minimal bias.

Motivational surveys

Students self-reported their motivation on four constructs, i.e., self-efficacy, task value, achievement goals, and engagement.

For self-efficacy and task value, I used the sub-scales of Motivated Strategies for Learning Questionnaire – MSLQ (Pintrich, Smith, Duncan, & Mckeachie, 1991). The survey instrument is designed to measure students' academic motivational orientations. Also, MSLQ is one of the most acceptable and widely used instrument designed to measure students' self-regulated learning (e.g., Dinsmore, Alexander, & Loughlin, 2008; Zimmerman, 2008). Also, the survey instrument has been widely used in undergraduate and especially engineering education studies to explore students' self-efficacy beliefs and task value (e.g., Honicke & Broadbent, 2016; Mamaril, Usher, Li, Economy, & Kennedy, 2016). Based on these facts, the MSLQ appeared as a valid choice to collect the data on students' academic self-efficacy and task value. Further, I used the items without modification to preserve the validity of the sub-scales.

In addition to the MSLQ survey on self-efficacy and task value, I collected the data on achievement goals using the Achievement Goal Questionnaire-Revised – (AGQ-R) survey instrument (Elliot & Murayama, 2008). I collected the data on three types of achievement goals: 1) mastery goals, 2) performance goals, and 3) performance-avoidance. Similar to MSLQ, the AGQ-R survey has been extensively used in engineering education and is considered a valid and reliable instrument for the purpose (e.g., Ranellucci, Hall, & Goetz, 2015). Also, I used survey items without any modification to keep the validity intact.

Further, to collect data on students' engagement, I used the modified multidimensional engagement instrument, "The Math and Science Engagement Scales" (Wang et al., 2016). The instrument is validated and extensively used in the K-12 context. However, it is not used for engineering students. I choose the instrument as it captures and collects data on four dimensions of engagement, which are behavioral, emotional, cognitive, and social. As I modified the engagement instrument for engineering classes, the confirmation of the validation of the survey was an essential aspect. Appendix B has the results of the validation of the instrument in an engineering context.

Although I used the validated and commonly used instruments to collect the motivation data, these all instruments rely on students' self-reported evidence only. As these all instruments are contextual, so the factors such as the nature of the course, university, and teaching strategies could influence students' responses. Besides, students report their motivation introspectively or retrospectively where they could make generalizations about what they believe they will do or did in a situation. These generalizations could be influenced by students' ability to relate the questions with their experience and learning in a conscious manner (Roth, Ogrin, & Schmitz, 2016). Similar to all surveys, these generalizations could have an impact on the validity of the instruments.

Reflective thinking

To collect data on reflective thinking, prior research studies suggest the use of various methods that collect students' reflection in a textual form (e.g., discussion board, wikis, and surveys). I used CourseMIRROR application (Fan, Luo, Menekse, Litman, & Wang, 2015; Luo, Liu, & Litman, 2016), which prompts students to reflect on each lecture from two perspectives muddiest point, and point of interest. I particularly used the application as it uses Natural Language

Processing (NLP) algorithms to summarize reflections for each lecture. These summaries are made available to both students and teachers and could be a source of continuous feedback.
These collected reflections for both perspectives are converted into equivalent quality or specificity score using a rubric (Heo, Anwar, & Menekse, 2018; Menekse, Stump, Krause, & Chi, 2011). To reduce the bias and ensure validity, two human raters independently read and evaluated each reflection. These raters used the rubric to convert the reflections into the specificity score for both perspectives. There was a good agreement between the two coders, as κ (MP) = .617, and κ (POI) = .652 (Altman, 1990). Also, to ensure the reliability, the data was collected multiple times (after each lecture) and quantified to preserve the nature of the study in an authentic way. I used humans' assigned reflection specificity score as a measure of reflective thinking.

Teamwork behaviors

Prior research studies suggest that students' teamwork effectiveness measures can be inferred from their teamwork behaviors and attitudes (Britton, Simper, Leger, & Stephenson, 2017). In this context of data collection regarding student teamwork behaviors, there were four possible ways: 1) measuring performance in teamwork using a questionnaire, or product evaluation (e.g., Mumford, Van Iddekinge, Morgeson, & Campion, 2008; Stevens & Campion, 1994, 1999), 2) self-report of students' teamwork effectiveness on a survey (e.g., Wang, MacCann, Zhuang, Liu, & Roberts, 2009), 3) peer-evaluation of students teamwork effectiveness (e.g., Cestone, Levine, & Lane, 2008), 4) process data such as observation, or teacher-reported evidence of team effectiveness (e.g., Zhuang, MacCann, Wang, Liu, & Roberts, 2008). Based on these four ways, no one measure could fully evaluate students' teamwork behaviors. Consequently, in this dissertation study, I decided to use students' peer evaluation as a proxy measure of students' teamwork behaviors.

To collect the data on students' teamwork behaviors, using peer evaluation, I used the CATME Smarter Teamwork peer evaluation tool (Loignon et al., 2017; Loughry, Ohland, & DeWayne Moore, 2007; Ohland et al., 2012). Students' evaluated their peers on 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. To ensure the validity and reliability of this measure, each student was trained using CATME training modules to evaluate appropriately. To minimize the bias, multiple peers (members of the team) evaluated each student. Also, in this study, the data was collected on multiple time points (after each milestone).

Academic performance

To collect the data on students' academic performance, in all three studies of the dissertation, I used students' exam scores (three exams). There are other measures (e.g., score of problem sets, and assignments), which could have been used. However, in most cases, the other assessments were based on team performance and is not a true measure of students' individual performance. Also, for studies 2 and 3, team scores did not vary for individual members of the teams and thus showed the minimal difference. Besides, the exams in all three studies are graded by the instructional team without any involvement of the research team. The instructional teams graded the exams using standard-based grading (Hylton & Diefes-Dux, 2016) and learning objectives. Although exam scores have the limitation of covering only one aspect of students' grades, the criteria of standard-based grading ensured the validity of exams being used as measure with minimal bias.

Prior success

To collect the data on students' prior success, in this dissertation study (especially for study 2 and 3), I have used students' SAT scores. For those students, who did not have SAT scores, I converted their ACT scores into SATs by using a concordance table (College Board, 2018). The purpose of the SAT or ACT is to determine the students' readiness for college. However, it provides a common data point to compare all the students. Although many other measures could have been used for prior success such as students' high school grades or their GPA, these measures were not based on a single standard, and thus could have introduced a bias. As SAT and ACT are standardized tests (test uniformly, and in a consistent manner), it is possible to compare the relative performance of individual students without much bias. Also, due to the uniformity and consistent way of tests, they appeared as a more reliable indicator of students' prior success. It is noteworthy that many schools and universities are now eliminating the need to have SAT and other similar standardized tests for admission. In the absence of such information, a university or course-based initial evaluation of students' concepts, graded on a standardized rubric could be used. However, in this study, to reduce the bias of individual evaluations, only the SAT (or ACT converted to SAT) score has been used.

Chapters' organization

This dissertation study comprises three interrelated research studies. The details of these studies are summarized in Figure 1.4.

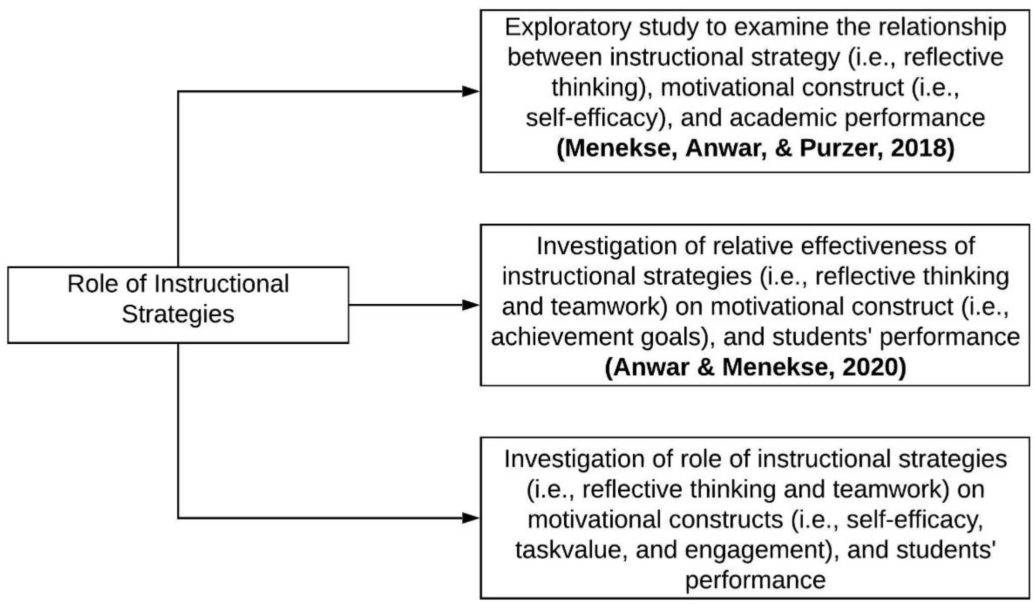

Figure 1.4. Summary of each paper in the dissertation

Each research study is fundamentally characterized by its research questions. However, the overarching goal was three-fold: 1) determining the relationship between students' motivation and instructional strategies, 2) relative effectiveness of each instructional strategy on students' performance and motivation, and 3) the role of instructional strategies in predicting engineering students' motivation and academic performance.

Overall these studies, addressed the following research questions:

1. What is the relationship between motivation, instructional strategy, and students' performance?
2. How do students' reflection quality, teamwork behaviors, and motivation change over time (during a semester)?

3. How do instructional strategies predict engineering students' academic performance and changes in motivation?

In this dissertation study, in each paper, described in a separate chapter, I approached each of these goals through their distinct research questions, literature review, and methods. However, it is important to note that I followed an incremental exploratory research design, where each study informs the need for the next one. Also, each study adds a new dimension to the previous study.

Chapter 2 describes the first study in this dissertation, which focused on doing exploratory analysis on determining the relationship between one motivational construct (self-efficacy), and one instructional strategy (reflective thinking). The study also explored the role of self-efficacy and students' reflection behaviors on their learning outcomes. The correlation and multiple linear regression analysis shed light on these roles and relationships. This preliminary study helps to understand the motivational construct and instructional strategy. The results of this study guided the need for further studies that could establish relationships in the context of multiple strategies on a larger sample. A version of this chapter is already published as a chapter in a book titled "*Self-Efficacy in Instructional Technology Contexts.*"

Based on the results and guidelines of the first study, I focused on the second research goal. I evaluated the relative effectiveness and unique contribution of instructional strategies in predicting students' academic performance (details reported in chapter 3). Further, the study also investigated the unique contribution of two instructional strategies (i.e., reflective thinking, and teamwork) to predict changes in students' achievement goals. The study used stepwise hierarchical and simultaneous multiple regressions to answer the questions. Further, the study used multivariate repeated measures ANOVA to determine the change in students' participation behaviors and motivation. The results of this study guided the need for using other motivational constructs and conducting further analysis with multiple motivational constructs in the analysis. This chapter is a reproduced version of the recent publication in the "*International Journal of Engineering Education.*

In chapter 4, I focused on the second and third research goals in the context of multiple motivational constructs. The motivational constructs used in this study were self-efficacy, task value, and engagement. The study determines the unique contribution of instructional strategies to predict changes in these motivational constructs. Further, the study examines the role of different instructional strategies in predicting engineering students' motivation using multiple constructs and academic performance. In this study, I used stepwise hierarchical and simultaneous multiple regressions to answer the questions regarding the unique contributions of instructional strategies. Further, I used Structural Equation Modeling (SEM) to determine the role of these instructional strategies on students' performance and motivation.

In chapter 5, I present additional analysis. The chapter describes the results of an SEM analysis conducted to see the relationship of three motivational constructs and their effect on students' participation in instructional strategies and academic performances. I conducted this analysis as existing studies describe motivational constructs as a pre-cursor to students' participatory behavior in learning activities.

Finally, chapter 6 provided the conclusion of this dissertation study, by shedding light on the results of each study in a collective way. Chapter 6 also describes the limitations and future directions of this dissertation.

The appendices of the study include the survey instrument used to collect the data, the results of the validation of the engagement section of the survey, and reprint rights obtained from the respective bodies for re-producing the first and the second study.

Contribution in a broader spectrum

There are various broader contributions of this dissertation. First, this study is among a few research studies that address the relative effectiveness of multiple student-centered instructional strategies in engineering classroom settings. Most studies typically focused on the effectiveness of a single active instructional strategy in comparison to a traditional approach. However, this study is preliminary in nature and answers another important question for instructors that which of the different strategies promote students' participation and eventually is a better predictor of their academic performance. This comprehensive understanding can help instructors to design their courses for better student' engagement and motivation.

Second, few studies associated students' participation in activities related to an instructional strategy with students' motivation. However, very few studies studied the impact of multiple instructional strategies and multiple motivational constructs collectively. This dissertation advances the literature by utilizing multiple constructs and strategies together. This multiple and collective use helps the researchers and instructors to understand the learning context of these instructional strategies better and will improve the understanding of how students approach and regulate their participation.

Third, earlier studies in mathematics and science indicated that self-regulated learning interventions produced successful outcomes in a classroom setting (Zimmerman & Schunk, 2008). However, such research in the context of engineering students was sparse. This research study provides informative results not only on the use of these instructional strategies but also on their impact in a classroom setting.

Fourth, this study is amongst the few studies that evaluated the ICAP hypothesis in real classroom settings for engineering students. The results of this study will provide guidelines to instructors for creating learning activities that help students to show interactive, constructive, and active behaviors, which may result in skillful engineers.

Lastly, one contribution of this dissertation is in the form of a validated engagement scale for measuring engineering students' engagement from four aspects as behavioral, emotional, social, and cognitive engagement. This scale can help future researchers to study students' engagement in class.

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CHAPTER 2. **UNDERSTANDING THE RELATIONSHIP BETWEEN SELF-EFFICACY, REFLECTIONS AND STUDENTS' LEARNING**

Menekse, M., Anwar, S., & Purzer, S. (2018). Self-Efficacy and Mobile Learning Technologies: A Case Study of CourseMIRROR. In C. B. Hodges (Ed.), *Self-Efficacy in Instructional Technology Contexts* (pp. 57–74). Springer.

Introduction

Educational technologies are considered as essential components of teaching and learning at every stage of the curriculum across grade levels. Technology-enhanced learning environments, including simulations, adaptive tutors, virtual labs, learning management systems, video games, and mobile applications, offer a range of features to enhance learning and engagement through evidence-based practices. Lately, there has been a growing surge of mobile applications and technologies that are developed for instructional use. The most common mobile learning technologies are designed as tools to deliver content and enhance students' understanding of domain-specific concepts, or used as tools to facilitate course management, notetaking, or communication between the instructional team and among students. Some examples of domain-specific applications include Math Duel (Kim, 2016), and PhotoMath (Webel & Otten, 2015); course management applications such as Class Dojo (Blevins & Muilenburg, 2013; Hammonds, Matherson, Wilson, & Wright, 2013; O'Brien & Aguinaga, 2014), Blackboard Learn learning management system – LMS (Ashok, 2011; Suk Hwang & Vrongistinos, 2012), and JDLX ((Tang, Zhou, & Chen, 2015); language learning applications such as Duolingo (Ahmed, 2016; Munday, 2016; von Ahn, 2013); and notetaking and organization applications such as Evernote (Barile, 2011; Schepman, Rodway, Beattie, & Lambert, 2012). Also, some mobile technologies are designed to enable virtual learning by expanding or creating changes in the learning environments, for example, virtual field trips (Kravcik, Kaibel, Specht, & Terrenghi, 2004; Spicer & Stratford, 2001), create new learning environments (Crowther, 2007; Graham, 2006; Sharples, Arnedillo-Sánchez, Milrad, & Vavoula, 2009; Zurita & Nussbaum, 2004), and make critical but cumbersome practices more efficient through text processing abilities (Aljohani & Davis, 2013; C.-M. Chen & Chen, 2009; Hwang & Chang, 2011; Roschelle, 2003). While there is a great interest in developing and utilizing mobile learning technologies, some studies argued the adverse aspects of such technologies to improve learning. One critique is that although mobile technologies are engaging, they are not effective in enhancing student learning (Sharples, 2006). Another one is that mobile technologies are efficient at delivering content, but it does not facilitate learning (Sharples et al., 2009). A third critique is that implementing mobile technologies in classrooms may weaken the social interactions among students and between students and their instructors (Gikas & Grant, 2013). These critiques argue that to be effective in supporting learning, mobile applications should enrich the interactions between instructors and learners and enhance learner engagement and experience without interfering with it (Beale, 2006). Moreover, the design of mobile learning technologies should consider not only the engagement of individual students but also take into account all stakeholders in the classroom (Sharples et al., 2009). In this chapter, we describe a mobile learning technology, called CourseMIRROR, which is designed to support interaction between students and instructors and to enhance learner experience. Specifically, CourseMIRROR (Mobile In-situ Reflections and Review with Optimized Rubrics) is developed to scaffold students to reflect on their learning and challenges they face in the lecture. This application also provides the summary of reflections via natural language processing (NLP) algorithms and help instructors to recognize the most common student reflections. In this way, CourseMIRROR is targeted to enhance the learning experience by improving learners' motivation, engagement, and learning outcomes by streamlining self-reflections and peer learning on mobile devices. In this study, we specifically use the lens of self-efficacy theory to examine the relationship between students' self-efficacy, their reflection behaviors, and learning outcomes. The next section presents a review of research on self-efficacy in the light of academic achievement; reflection; and mobile learning technologies. The third section presents a research study of CourseMIRROR implementation in a college level class.

Self-efficacy as the theoretical framework

Self-efficacy is a multidimensional construct that indicates the ways people feel, thinks, and behaves in certain situations (Bandura, 1977; Elias & Loomis, 2002; Pajares & Schunk, 2001). Prior research showed that students' self-efficacy plays a substantial role in their decision-making processes, achievement goals, and academic achievement across domains (e.g., Bandura, 1997; Schunk & Swartz, 1993). Self-efficacy is the key determinant of coping behavior, effort, and sustainability to face the obstacles and aversive experiences (Bandura, 1977; Jex & Bliese, 1999). Individuals with high self-efficacy approach difficult tasks as challenges to be mastered and develop an intrinsic interest in tasks (Pajares & Schunk, 2001). Such people recover from failures and setbacks and attribute failure to insufficient effort or acquirable skills (Bandura, 1977; Pajares & Schunk, 2001). In contrast, individuals with low self-efficacy beliefs doubt their capabilities and consider difficult tasks as threats (e.g., Purzer, 2011). Such individuals not only give up quickly but are also not resilient and are slow to recover from their failures (Bandura, 1977; Pajares & Schunk, 2001; Schunk, 1985).

Self-efficacy is personal beliefs about the capability to produce the outcomes and desired level of performance. These beliefs determine how people feel, think, motivate themselves, and behave. It is imperative to note that self-efficacy is not be confused with self-confidence as confidence is the strength of the belief in personal abilities, while efficacy is based on both the level of attainment and strength of belief to attain the level (Pajares, 1996). These beliefs further strengthen the way people accomplish tasks as ones with higher self-efficacy take difficult tasks as challenges to be mastered (Pajares & Schunk, 2001) as compared to people with lower self-efficacy who consider such tasks as threats to be avoided which result in low aspirations and weak commitments. These diverse effects of self-efficacy beliefs are produced through four major psychological processes, which are: cognitive (thinking processes to draw on from knowledge to construct new options, weight and integrate predictive factors, test and revise judgments, and remember the effect of employed factors), motivational (choice of actions, intensity, and persistent with goals of causal attributions, outcome expectancies, and cognitive), affective (coping capabilities and emotional reactions experienced under challenging situations), and selection processes (choices made for personal development and environment) (Bandura, 1989, 1994). Self-efficacy theory further describes that people's beliefs about their efficacy can be built based on four sources of influence (Bandura, 1977, 1994; Schunk et al., 1987) which are:

1. Past performances and mastery experiences: The result of prior experiences on certain tasks is the most influential source of these believes as individuals gauge the effects of their actions, and their interpretations guide them to build stronger beliefs (Bandura, 1994). Success in such cases where help to raise self-efficacy, the failure lower it down and thus has important

implications for increasing students' achievement in an academic environment (Bandura & Schunk, 1981).

2. Vicarious experiences: Observing the performance of others, especially those who appear to be similar to themselves or are in similar situations. The sources of information, though, are weaker than results of mastery experience but are valuable when people lack prior experience or are uncertain about their capabilities (Bandura & Schunk, 1981; Schunk, 1985). Vicarious experience also involves social comparisons with others, such as peer modeling, to develop one's self-perceptions of competence (Schunk, 1985).

3. Verbal and social persuasions from others such as peers, teachers, and family members: The sources of efficacy information are weaker than mastery or vicarious experience, but persuaders can play an essential role in the development of self-efficacy beliefs (Pajares & Zeldin, 1999; Zeldin & Pajares, 2000). Positive persuasions encourage and empower the self-efficacy beliefs (Bandura, 1986, 1989).

4. States of psychological arousal and anxiety towards particular domains or tasks such as anxiety, stress, arousal, fatigue, and mood state: People can gauge their self-efficacy beliefs by the emotional state they experience as they contemplate an action (Bandura, 1997). These emotional reactions thus provide the cues for success or failure of an outcome.

Self-efficacy and academic achievement

Schunk et al. (1987) argued that self-efficacy primarily supports academic achievement and persistence in academic situations. Self-efficacy requires students to take into account factors such as what they will need to learn, what knowledge and skills are required as prerequisites for this learning, the degree to which the prerequisite information is retained, rehearsing the material to be learned, past experiences of similar skills, the time required for learning, and how they shall monitor their learning (Schunk, 1996b). When faced with obstacles, self-efficacy of a student is the key determinant of coping behavior and the level of effort (Bandura, 1977; Jex & Bliese, 1999).

Accordingly, self-efficacy helps students to motivate themselves and improve their competence (Schunk, 1996b) and attain the desired outcomes. These beliefs also mediate students' academic achievement and have discriminant validity in predicting their learning outcomes (Zimmerman, 2000). Hodges, Stackpole-Hodges, & Cox (2008) described academic self-efficacy as the confidence and belief to perform in learning situations. Prior research studies indicated that individuals might form their academic self-efficacy based on several factors, which include their general opinion about themselves or their beliefs and prior experiences about specific domains related to subjects or skills. These beliefs can be based on their ability and confidence to solve mathematics problems (Hackett & Betz, 1989), or perform communication-related tasks such as reading or writing (Shell, Colvin, & Bruning, 1995). Lent, Brown, & Larkin (1984) examined the relation of self-efficacy to students' persistence and success in science and engineering college majors. They found a strong connection between higher self-efficacy and higher grades. Further, it was indicated that students with relatively higher self-efficacy beliefs persisted longer in technical and scientific majors. Multon, Brown, & Lent (1991) conducted a meta-analysis of 36 academic self-efficacy studies and found an average effect size of 0.38 (Cohen's d) for the relationship between self-efficacy and academic achievement, representing 14% variance in academic performance of students. It is critical to note that self-efficacy is a context-specific construct. For example, one might have low self-efficacy in one area of engineering, such as applying physics principles to design a mechanical system but have high self-efficacy in another area such as using an engineering design process to develop the same system (Yasar, Baker, Krause, & Roberts, 2007). Therefore, it is essential to understand the context when evaluating the students' self-efficacy (Purzer, 2011).

Self-efficacy and reflection behaviors

Reflection is a fundamental cognitive process for all learning experiences that require active engagement with the task (Menekse, Stump, Krause, & Chi, 2011; Schön, 1983). According to Dewey (1933), reflection requires persistence of engagement with task or problem, and past experience is vital for future suggestions. Also, Dewey (1933) argued that reflection must intend to combine experience with current understanding to enable better decisions in the future. According to Bandura's (1986) social cognitive theory, self-referent thoughts mediates between knowledge and actions, and through self-reflection, individuals evaluate their own experiences and thought processes. These self-evaluated reflections inform self-efficacy as they describe the capabilities to organize and execute the courses of actions required to manage prospective situations (Bandura, 1997; Pajares, 1996). Reflection can allow students to recognize their mastery experiences and vicarious experiences by making sense of their prior learning experiences, explore their cognition and self-beliefs, alter their thinking and behavior by observing others in similar situations, and engage themselves in self-evaluation. In this way by using self-efficacy motivators and reflections, self-beliefs can be strengthened by engaging in self-regulatory strategies (Bandura, 1989), enhancing individuals' perceptions of their competence (Meece, Wigfield, & Eccles, 1990), or improving their performance in an academic subject (Marsh, Walker, & Debus, 1991). Various studies have established the relationship between self-efficacy and reflection behaviors (Krogstie & Krogstie, 2016; Moradkhani, Raygan, & Moein, 2017; Phan, 2007; Phan, 2014; Seggelen - Damen & Dam, 2016; Yost, 2006). A path analytical study (Phan, 2007) involving second-year university students yielded evidence attesting to the positive effects of self-efficacy on reflection ($\rightarrow$: $\beta = 0.38$) and understanding ($\rightarrow$: $\beta = 0.43$). Similarly, Moradkhani et al. (2017), using multiple regression, found that metacognitive reflection was the only predictor of self-efficacy in teachers. Overall, these studies highlight the importance of the relationship between self-efficacy and reflection behaviors.

Self-efficacy and mobile learning technologies

There have been significant changes in how instruction is delivered in and out of classroom settings with the recent breakthroughs in educational technologies. Accordingly, as information technologies, communication software, and social media became widespread at each level of education, research on self-efficacy is also changing. Various studies investigated the relationship between computer technology and self-efficacy beliefs. The studies reported self-efficacy as an integral component for the use of the computer-related technologies in education (e.g., Celik & Yesilyurt, 2013) and forming Information and Communication Technology (ICT) expertise (Davies, 2002). Few studies investigated the effect of game-based learning and students' self-efficacy beliefs (Meluso, Zheng, Spires, & Lester, 2012; Shank & Cotten, 2014), and found that there has been a significant increase in self-efficacy beliefs and learning outcomes using game-based learning environment. Accordingly, the rapid rise of mobile technologies in the past decade transformed every aspect of our daily lives and redefined interactions and behaviors across mediums. A recent survey indicates that 95% of undergraduate students in the USA own at least one mobile device, and the projections imply ownership levels will increase steadily (Chen, Seilhamer, Bennett, & Bauer, 2015). As an educational technology tool, developments in mobile technologies are significantly shaping both formal and informal learning environments.

Furthermore, the distinct modalities of smart devices (such as instant and constant internet connection, camera, microphone, and various sensors) provide valuable tools for students and instructors. Also, these modalities and increased ownership levels of mobile devices present opportunities and challenges to integrating their use into the classroom strategically.

Current research studies on mobile technologies take two directions: First, studies to evaluate the effectiveness of specific mobile applications to enhance students' learning or engagement; and second, studies to indicate the effectiveness of incorporating mobile learning technologies in educational settings. The first direction of literature focuses on the research and development of mobile applications. These applications can be classified into four broad categories: 1) domain or subject-specific applications, 2) classroom management applications, 3) language learning applications, and 4) other applications. The second direction of literature studies explores the effect of incorporating mobile learning technologies in education settings. Sung, Chang, & Liu (2016) reviewed several studies to indicate that mobile computing support both traditional style lecture and innovative teaching methods such as game-based learning. Lan, Sung, & Chang (2007) emphasized the importance of peer interaction and used mobile devices supported peer-assisted learning (MPAL) system and found the system useful to improve collaboration and motivation. Roschelle et al. (2010) compared Technology-mediated, Peer-Assisted Learning (TechPALS) and a desktop product and found that students in TechPALS performed better than the other group.

Klopfer, Sheldon, Perry, and Chen (2012) investigated the use of UbiqGames— educational games and reported that students get engaged by the mobile games and are interested in learning more about the content topics. Hwang & Tsai (2011) reviewed mobile learning studies, published between 2001 and 2010, and found that most of these studies focused on language arts, engineering, and computer technology in higher education. Wong & Looi (2011) studied the influence of mobile devices on seamless learning and suggested the framework for efficient use. Seamless learning refers that students can learn in various scenarios and are easily able to switch between these scenarios or contexts. On the other hand, relatively few studies exist that explored the relationship between mobile technologies and self-efficacy beliefs (Achterkamp, Hermens, & Vollenbroek-Hutten, 2016; Al-Emran, Elsherif, & Shaalan, 2016; I.-S. Chen, 2017; Kenny, Van Neste-Kenny, Burton, Park, & Qayyum, 2012; Sha, Looi, Chen, Seow, & Wong, 2012; H.-Y. Sung, Hwang, Liu, & Chiu, 2014). Sha et al. (2012) found that student motivation could account for student engagement with the use of mobile devices as cognitive, metacognitive, and motivational tools.

Kenny et al. (2012) studied the use of mobile devices by nursing faculty and students for learning and teaching purposes. Using the exploratory factor analysis, they found the mobile self-efficacy of students and teachers is related to the potential use of mobile technology in teaching and learning. The self-efficacy score also showed that both faculty and students be confident in the use of mobile technologies and their engagement in learning. Park et al. (2012) used the Technology Acceptance Model (TAM) and showed that mobile learning self-efficacy was significant in affecting user attitude. Also, mobile learning self-efficacy has a significant relationship with perceived ease of technology use. Yang (2012) investigated the attitudes and self-efficacy of using mobile learning devices and found that the quick access attained through mobile learning devices boost students' motivation to learn. Further, this access also helps in increasing students' self-efficacy beliefs about concepts, material, and other technology-related information. However, none of these studies explored the relationship between self-efficacy and learning outcomes by using the context of mobile learning technologies. The limited literature to examine self-efficacy and mobile learning technologies indicate the need for more research studies. This research gap reveals that though rich literature is available on understanding self-efficacy and its relationship with learning environments and students' learning, further exploration is needed in new technologies. To address the mentioned gap, the next section presents the CourseMIRROR mobile technology (Fan et al., 2015; Luo, Fan, Menekse, Wang, & Litman, 2015), as well as a classroom study that was conducted to explore the relationship between students' self-efficacy and reflection behaviors using this application.

CourseMIRROR: Mobile In-situ Reflections and Review with Optimized Rubrics

We developed CourseMIRROR mobile technology to design engaging mobile interfaces for collecting high-quality reflections in classrooms. We used the idea of "reflection prompts" while developing the system. Reflection prompts refer to questions that allow students to metacognitively monitor their learning experiences and share it with their instructors, and in some cases, with their peers as well. Prior studies in different domains showed that reflective activities benefit students by enhancing their learning outcomes. Based on the prior research on reflection prompts, we aimed four primary design goals: 1) provide students a convenient and efficient way to compose and submit reflection responses; 2) encourage and help students to create specific and pedagogically valuable reflections; 3) facilitate instructors to make sense of students' written reflections efficiently in large classrooms; and 4) assist students in reading their classmates' reflections for peer learning (Fan et al., 2015; Fan, Luo, Menekse, Litman, & Wang, 2017; Luo et al., 2015). With these four guiding design principles, we developed CourseMIRROR mobile learning system that uses Natural Language Processing (NLP) algorithms to enhance classroom instructor-student interactions via streamlined and scaffolded reflection prompts. CourseMIRROR can remind students to submit written reflections after each lecture and collect such reflections in a scalable manner. Furthermore, CourseMIRROR summarizes the reflections and presents the most common ones to both instructors and students. Figure 2.1 shows the interfaces of CourseMIRROR.

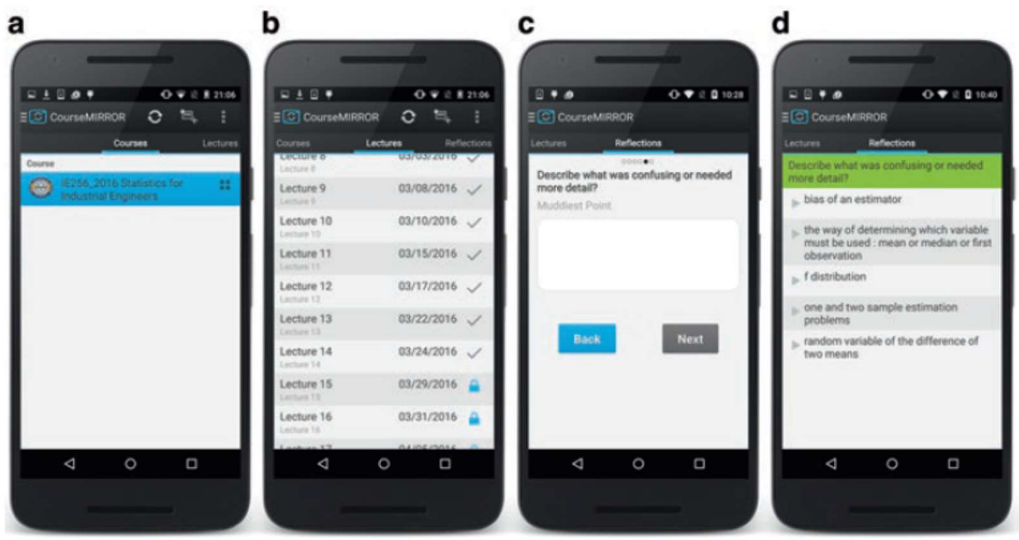

Figure 2.1. Primary interfaces of CourseMIRROR: (a) course list, (b) lecture list, (c) reflection writing page, and (d) reflection summary and sharing page

Once a student logs into CourseMIRROR after creating a username and password (user information is stored in our server database), she/he can first access the enrolled courses (Figure 2.1a). By clicking the course item, the student can go to the corresponding lectures (Figure 2.1b). Clicking the details button on the right side of each course item will redirect the user to the homepage of the corresponding course. In the list of the lectures (Figure 2.1b), the student can find the lectures for which she/he can submit reflections. The status icon on the right side of each lecture item shows the status of the lecture (e.g., open for reflection, reflection submitted, and upcoming lectures). For lectures that are open for reflection, clicking the lecture item will lead to the reflection submission page where the student can start writing reflections (Figure 2.1c) using the

CourseMIRROR reflection writing page. At the end of each lecture, students receive push notifications on their mobile devices to remind them to write reflections for the corresponding lecture. Once submitted, the data are stored in the database, at which point we use NLP techniques to generate summaries of the student reflections. The summaries are shared with both instructors and students on both PCs and the CourseMIRROR app (Figure 2.1d). We piloted CourseMIRROR in multiple classrooms with college students across science and engineering classes. Specifically, CourseMIRROR has been implemented in 14 different classes and used by more than 1000 students. Our primary findings so far indicate: 1) Students are willing to submit reflections in a timely manner; 2) active reminders via emails and push notifications to increase the response rate; 3) generating reflections benefit students by encouraging them to revisit key concepts of the course; 4) students enjoy reading the summaries based on their classmates' reflections and find summaries beneficial, and 5) students benefit from the reflection and feedback cycle enabled by CourseMIRROR (Fan et al., 2015, 2017; Heo et al., 2018; Luo et al., 2015). In one of these classroom CourseMIRROR implementations, we explored the relationship between students' self-efficacy beliefs, reflection behaviors, and learning outcomes. The specific research questions were:

RQ1. Do students with high academic self-efficacy beliefs generate high-quality reflections?

RQ2. To what degree do students' self-efficacy beliefs and reflection quality scores predict their learning outcomes?

In the next section, we described the implementation and reported our findings.

Implementation of CourseMIRROR in an engineering classroom

Participants

Fifty-two sophomore engineering students participated in this study. These participants were taking the required engineering class about engineering statistics. The main topics covered in this course include hypothesis testing, random variables, and probability distributions, statistical inference, the goodness of fit, decision making, and building empirical models. Students were given surveys at the beginning of the semester, they used the CourseMIRROR mobile app during the semester, and we also collected their exam scores after the semester ends.

Measures

Self-efficacy survey

We used the Motivated Strategies for Learning Questionnaire – MSLQ (Pintrich, Smith, Duncan, & Mckeachie, 1991). The MSLQ was designed to measure students' use of learning strategies and their motivational orientations (Duncan & McKeachie, 2005; Pintrich et al., 1991). The full version consists of 81 items with a total of 15 subscales (nine learning strategies and six motivation subscales), and the scales can also be used individually. The MSLQ uses a Likert scale with seven options (i.e., 1—Not at all true of me, 7—Very true of me). Based on our research goals, we used the self-efficacy subscale. The self-efficacy subscale includes eight items. All students were asked to complete the survey in the first week of the semester. We chose MSLQ for our research purposes because it has been commonly used to measure academic self-efficacy across studies in educational psychology, learning sciences, and educational technology (e.g., (Bong, 2002; Klassen, Krawchuk, & Rajani, 2008; Lodewyk & Winne, 2005). Also, the self-efficacy subscale of the MSLQ has excellent internal consistency (Cronbach's $\alpha = 0.93$).

Learning outcomes score

The learning outcomes score included first, second, and final exams for all students. The maximum score for each exam was 100, and the minimum was zero. The course instructor prepared the exams with no involvement from the research team, and she, with her teaching assistants, graded all of the exams.

We calculated the learning outcomes score, which resembled the instructor's method of the course grade calculation and was computed by adding 30% of exam 1, 30% of exam 2, and 40% of the final exam for each student.

Reflections

Students were prompted by the CourseMIRROR application to reflect on their experiences after each class during the semester. There were two reflection prompts: the first prompt was asking about the "point of interest," and the second prompt was asking about the "muddiest point." Specifically, the point of interest prompt was to "describe what you found most interesting in today's class," and the muddiest point prompt was "describe what was confusing or needed more detail." Each reflection was coded for the quality by two raters. The reflection quality indicates the completeness and details in one's reflection. The coding schema followed a scale from 0 to 4 to indicate the degree of reflection quality. This coding schema was developed based on the one used in Menekse et al. (2011) study. There were a total of 1142 reflections (721 for the point of interest and 721 for the muddiest point). Two raters coded all these reflections, and Cohen's Kappa was 0.66. Based on the guidelines from Altman (1990), kappa of 0.66 indicates a substantial strength of agreement. Furthermore, since $p < 0.001$, our kappa coefficient is statistically significantly different from zero.

Analysis and results

Self-efficacy and reflections

The first set of analyses was conducted to understand the relationship between self-efficacy and reflections by using Pearson product-moment correlation. Coefficients were computed among two reflection scores (point of interest and muddiest point), the number of reflections submitted by each student, and self-efficacy scores for each student. We used Holm's sequential Bonferroni method to control for Type 1 error. The results presented in Table 2.1 show that two out of the six correlations were statistically significant. The correlation between the point of interest and muddiest point reflection qualities was significant, as well as the correlation between self-efficacy scores and the total number of reflections submitted by each student. The other correlations were not significant.

Table 2.1. Correlations among reflection variables and self-efficacy score (N = 52)

	Number of reflections	Self-efficacy score	Point of Interest quality score
Self-efficacy score	0.34*		
Point of Interest quality score	0.21	0.22	
Muddiest point quality score	0.10	0.22	0.35*

**p< 0.01*

Self-efficacy, reflections, and learning

We were also interested in understanding the role of students' self-efficacy and their reflection behaviors on their learning outcomes scores. Multiple linear regression was conducted with four predictors (self-efficacy score, the point of interest quality, muddiest point quality, and number of reflections), while the dependent variable was the learning outcomes score. We used a stepwise regression method to explore the best combination of predictors. Based on the results, the best model excluded the point of interest quality score but kept the rest of the predictors. The linear combinations of these three predictors were significantly related to learning outcomes score, $F(3, 48) = 25.58$, $p < 0.001$. The R^2 value was 0.62, indicating that 62% of the variance of the learning outcomes score can be accounted for by the linear combination of predictors. Table 2.2 shows bivariate and partial correlations. All the bivariate and partial correlations were statistically significant.

Table 2.2. Bivariate and partial correlations of the predictors with learning outcomes score

Predictors	Bivariate coefficients	Partial coefficients
Self-efficacy score	0.63**	0.57**
Number of reflections	0.62**	0.56**
Muddies point quality score	0.29*	0.30*

** p< 0.05, ** p <0.01*

Conclusion

Studies over decades indicate that self-efficacy is a key construct to understand academic achievement for all students at each grade level. Students' perceptions of efficacy play a major role in their metacognitive monitoring and decision-making processes. Further evidence also shows that learning environments influence students' self-efficacy beliefs and their behaviors. While there is a rich literature on understanding the mechanisms of self-efficacy and its role in academic achievement, research on self-efficacy continues to be an area of interest as the new learning technologies emerge. Specifically, the rapid rise of mobile technologies in the past decade transformed every aspect of our daily lives and redefined interactions and behaviors across mediums. Prior research indicates that the learning environment plays a role in changing students' self-efficacy beliefs (Lorsbach & Jinks, 1999).

Breakthroughs and new developments in educational technology also transform the learning environments. These changes in learning environments necessitate studying how these new educational technologies influence the relationship between academic self-efficacy and learning outcomes.

Furthermore, prior research studies underlined the critical role of reflection on learning and self-efficacy. However, there are only a few applications that are being developed to monitor students' reflection behaviors. These applications were commonly associated with the web-application domain, such as classroom management system tools, including discussion board, wikis, and blogs (Mclaughlin, 1991; Suk Hwang & Vrongistinos, 2012), and weblogs (Wopereis, Sloep, & Poortman, 2010). Due to the novelty of using mobile applications and technology for self-reflection, little evidence is available in that respect (Verbert, Duval, Klerkx, Govaerts, & Santos, 2013). Accordingly, the relationship between the use of educational technology, self-efficacy, and students' learning outcomes is less explored in the literature. Hodges (2008) explored this gap in the literature to reflect the role of self-efficacy in computer and information technology-based environments. He observed this shortcoming in online learning environments. Hodges (2008) reiterated that self-efficacy beliefs are context-specific (Bandura, 1997), and any situational change needs careful consideration. The situational changes include shifts in the mode of education and training, which are evident with the use of educational technologies. Further, he suggested that with the increased use of technology, self-efficacy needs to be examined within technology-enhanced environments to understand and investigate the possible factors that may affect academic achievement with the use of different modes to deliver instruction. With our study, we provided a new set of findings to understand this relationship between students' self-efficacy beliefs and their learning outcomes while utilizing unique learning technologies to facilitate student learning. This chapter primarily presented the role of technology-based learning environments on students' self-efficacy beliefs and their academic achievements. Likewise, this chapter reviewed the use of mobile learning technologies and their relation to students' self-efficacy beliefs. Further, we identified that literature explores the effect of introducing mobile application in curriculum or using mobile technology in class, but lacks studies that investigate the relationship between this new learning environments and students' self-efficacy. This explored gap opens venues for new research directions in the area of mobile learning technologies and self-efficacy. As an example, the chapter introduced the study findings based on the implementation of CourseMIRROR mobile learning technology in an engineering classroom.

CourseMIRROR is a mobile application designed to collect students' reflections prompts and generates phrase-based summaries using NLP algorithms. The study investigated the relationship between students' self-efficacy, reflection behaviors, and learning outcomes. The results showed that students' self-efficacy beliefs, their reflection on confusing concepts, and the number of reflections submitted by students were significant predictors of their learning outcomes score. Overall, 62% of the variance of the learning outcomes score can be accounted for by the linear combination of these three predictors. Furthermore, there was a significant correlation between students' self-efficacy scores and the number of reflections that they submitted throughout the semester. These findings indicate that students' perception of their efficacy is related to their reflection behaviors.

CHAPTER 3. **CONTRIBUTIONS OF REFLECTIONS AND TEAMWORK BEHAVIORS ON ENGINEERING STUDENTS' PERFORMANCE AND ACHIEVEMENT GOALS**

Anwar, S., & Menekse, M. (2020). Unique contributions of individual reflections and teamwork on engineering students' academic performance and achievement goals. *International Journal of Engineering Education*, *36*(3), 1018–1033.

Abstract

Prior research studies in engineering education have 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 evaluations 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 behaviors 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.

Introduction

Over the decades, education researchers have focused on integrating different instructional strategies in college classrooms to enhance student engagement and achievement. Prior research studies supported that active involvement is essential for improving students' understanding of fundamental Science, Technology, Engineering, and Mathematics (STEM) concepts (Basham & Marino, 2013; Chi & Wylie, 2014; Fang, bin Daud, Al Haddad, & Mohd-Yusof, 2017; M. Prince, 2004). 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 (Hyun, Ediger, & Lee, 2017; Lumpkin, Achen, & Dodd, 2015; M. Prince, 2004) such as project-based learning (Alves, Mesquita, Moreira, & Fernandes, 2012; Gómez-Pablos, del Pozo, & Muñoz-Repiso, 2017; Han, Capraro, & Capraro, 2015), reflective thinking (Ghanizadeh, 2017; Menekse et al., 2011; Travers, Morisano, & Locke, 2015), and collaborative teamwork (Fidalgo-Blanco, Sein-Echaluce, García-Peñalvo, & Conde, 2015; Figl, 2010). Also, to explore the relative effectiveness of different instructional strategies on student learning, Chi (Chi, 2009) 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) (Chi & Menekse, 2015; Menekse et al., 2013).

Similarly, prior research studies 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

(Riemer, 2003). 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 (Butler & Winne, 1995; Kierstead, 1999). Prior studies on engineering education have used both personal competence (e.g., reflecting on your experiences), and social competence (e.g., being an effective team member) as approaches to enhance students' learning (Riemer, 2003). Prior studies described being an effective team member as an essential skill for all engineers (Menekse, Purzer, & Heo, 2019; NAE, 2004), and it is included as a required core competency in engineering education (Crawley, Malmqvist, Lucas, & Brodeur, 2011).

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:

RQ1. What is the unique contribution of two instructional strategies (i.e., reflective thinking, and teamwork) to predict students' academic performance?

RQ2. What is the unique contribution of two instructional strategies (i.e., reflective thinking, and teamwork) to predict students' achievement goal gains?

RQ3. How do students' reflection specificity and teamwork behaviors change during a semester?

RQ4. 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.

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 (Ames, 1992; Pintrich, 2000a). 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.

Reflective thinking and collaborative teamwork

Prior research studies defined reflective thinking as an active and persistent cognitive process of analyzing and describing beliefs about knowledge (Dewey, 1933). Thus, reflection is a process that consists of judgment and reaction (Zimmerman, 1990, 2002). Rodgers (2002) 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 happens 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 make connections with new knowledge. Prior research studies showed that prompting students to reflect on their learning experiences can help them to identify their confusion and make connections among different concepts (Boud, Keogh, & Walker, 1985; Davies, 2012).

Also, some studies suggested that reflection best happens in collaborative learning environments (Demissie, 2015; Phan, 2007). Collaborative learning environments allow students to work in small teams for a common goal, listen to others' opinions, have discussions, and receive feedback (Johnson, Johnson, & Smith, 1998). 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 (Dierdorff & Ellington, 2012), foster higher-order thinking of students (Palincsar, 1998), and learning the concepts better (Alves et al., 2012). Furthermore, teamwork behaviors can facilitate students' self-regulation due to explicit peer feedback (Schunk, 1996a; Webb & Palincsar, 1996), discussions to promote planning and evaluation of tasks (Davis, 2003), and encourage social interactions in classrooms (Järvelä, Hurme, & Järvenoja, 2011; Springer, Stanne, & Donovan, 1999).

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 (Nevgi, Virtanen, & Niemi, 2006). 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.

Self-regulated learning (SRL)

Prior research studies define SRL as a deliberate process that requires judgment and adaptation (Butler & Winne, 1995). This process has three important components that are relevant to students' performance: 1) students' behavior of monitoring and controlling their effort (Corno, 1986), 2) students' ability to reflect on their learning experiences and prior knowledge (Zimmerman & Martinez-Pons, 1986), and 3) students' use of cognitive strategies to learn and understand the material (Corno & Mandinach, 1983). 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 (Zimmerman & Schunk, 2008). The premise of the SRL theory suggests that if introduced in classrooms, students not only show better performance and achievement through an ongoing experiential development but can also attain competency at both personal and social levels (Riemer, 2003; Torrente et al., 2014). Students acquire these competencies by sustaining beliefs about their abilities, and while working with their peers (Zimmerman & Kitsantas, 2005). They understand the difficulty of learning tasks by seeing the viewpoints of their peers and regulate their effort to accomplish their set goals (Zimmerman & Schunk, 2003, p. 66).

Prior research studies have suggested various instructional strategies for personal competence and social competence. For example, to promote personal competence, the prior research studies showed that reflective thinking (Jenson, 2011; Schunk & Zimmerman, 1998), problem-based learning (Hung, 2011), goal-setting, and planning (Pintrich, 2000b) were effective. Also, to promote social competence, the prior research studies showed the use of project-based learning (English & Kitsantas, 2013), group work (Cho et al., 2010; Järvelä & Järvenoja, 2011), and peer instruction (Roscoe & Chi, 2007) 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 (Michalsky & Kramarski, 2015; Stefanou, Stolk, Prince, Chen, & Lord, 2013). 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.

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 (Chi, 2009). The four modes are interactive, constructive, active, and passive (Chi & Wylie, 2014). 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 (Chi, 2009). 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 (Chi, 2009). The term interactive refers to engaging students in not only the conversations but also getting connected by receiving or providing feedback, guidance, or scaffolding (Chi, 2009). 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 (Chi, 2009). 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 (Menekse et al., 2013).

However, there is good literature that showed this suggested hypothesis might not always be accurate, especially for the comparison of interactive versus constructive activities (Chi & Menekse, 2015; Lou et al., 1996; Menekse et al., 2013). 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 (Barron, 2003; Chi & Menekse, 2015). Besides, not many studies explored the role of interactive versus constructive activities on student success in classroom settings (e.g., Menekse et al., 2013). 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 (Chi & Menekse, 2015; Menekse et al., 2013). 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.

Achievement goals

Most goal orientation theorists connected achievement goal orientation with judgment and improvement in one's competence (Ames & Archer, 1988; Dweck, 1986; Harackiewicz, Barron, Pintrich, Elliot, & Thrash, 2002). The achievement goal theory is also driven by students' motivation and competence-based aims (Archer, 1994). Based on the evaluation of personal competence, two distinctive goal categories were identified as mastery and performance goals (Dweck, 1986). 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 (Dweck, 1986; Senko, 2016). The performance goals are relative goals which are formed by using the perception of competence relative to the performance of others (Ames & Archer, 1988; Dweck, 1986). Students make interpersonal and normative comparisons to define their performance goals. Both of these kinds of 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 (Heo et al., 2018; Standage & Treasure, 2002). Researchers of achievement goal theory also introduced the approach-avoidance distinction to this theory (Elliot & Church, 1997). 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 (Wentzel & Miele, 2009, p. 77). Similarly, in the mastery approach, students strive to learn and improve their skills (Elliot, 1999; Pintrich, 2000b).

Research on achievement goals showed that changes in these goals have an impact on students' learning (Blackwell, Trzesniewski, & Dweck, 2007). Also, students with strong performance and mastery goals frequently used learning strategies and improved their performance (Grant & Dweck, 2003). These use of strategies and improvements indicated students' proactive approach and adjustments in the process by self-regulating themselves (Schunk & Zimmerman, 1998; Zimmerman & Schunk, 1989). Prior research studies also suggested an integration of achievement goal approach to the social cognitive model of self-regulation (Fryer & Elliot, 2008), and have shown the positive relationship between achievement goals and self-regulation strategies (Miller, Behrens, Greene, & Newman, 1993). Similarly, Zimmerman & Schunk (Zimmerman & Schunk, 2008) 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 (Miller et al., 1993; Pintrich, 2000b). 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 (Zimmerman & Schunk, 2008). 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.

Research methods

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 3.1 shows the demographic information of the participants by race and gender.

Table 3.1. 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

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 (Fan et al., 2015, 2017; Luo, Liu, Liu, & Litman, 2018) was used for students' reflection, and 2) CATME Smarter Teamwork (Loignon et al., 2017; Loughry et al., 2007; Ohland et al., 2012) for peers' evaluation in collaborative teamwork.

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 (Luo et al., 2016). 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 (Heo et al., 2018; Menekse et al., 2011). 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) = .617, and κ (POI) = .652 (Altman, 1990).

Teamwork was a mandatory component of this class and CATME (Comprehensive Assessment of Team Member Effectiveness) Smarter Teamwork (Loignon et al., 2017; Loughry et al., 2007; Ohland et al., 2012) 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 (Elliot & Murayama, 2008) 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.

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 3.2 indicates the structure of the dataset.

Table 3.2. 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

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 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 accounts 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.

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.

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 3.3 presents the steps to determine the order of the sets.

Table 3.3. 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	.095		.165		.413	
Reflection-Spec	.006		.015		.002	
P-Success	.083		.029		.015	
Step 2						
Team-Behaviors &Reflection-Spec		.014		.014		.005
Team-Behaviors & P-Success		.066		.038		.000

ΔR^2 represents the changes in R^2

For all three exams, the teamwork behaviors data accounts 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 3.4.

Table 3.4. Summary of stepwise 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	.085	.085	.176	.176	.363	.363
Team-Behaviors & P-Success	.163	.087	.203	.028		
Team-Behaviors, P-Success & Reflection-Spec	.178	.015	.214	.011		
Team-Behaviors & Reflection-Spec					.373	.009
Team-Behaviors, Reflection-Spec & P-Success					.374	.002

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 3.5shows the significant predictors for each exam.

Table 3.5. 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	.017**	.288**	.277**
Exam2				
	No coefficient is significant			
Exam3				
	C	12.472*	.598*	.217*
	H	14.606**	.655**	.282**

**p<0.05, **p<.01; sr^2 indicates the % of variance uniquely explained by the predictor*

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 .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 3.6 summarizes the results.

Table 3.6. Summary of simultaneous regression analysis for the unique contribution of teamwork behaviors, reflection specificity, and prior success to predict exam scores

	Exam 1	Exam 2	Exam 3
	R^2	R^2	R^2
All sets	.178	.214	.374
Team-Behaviors & Reflection-Spec	.107	.190	.358
Team-Behaviors & P-Success	.152	.203	.441
Reflection-Spec & P-Success	.104	.075	.023

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.

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 (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 3.7shows the variances to determine the order of the sets.

Table 3.7. Variances to predict exam scores – Determination of order of sets

Predictors	Mastery Gains		Performance Gains		Avoidance Gains	
	R^2	ΔR^2	R^2	ΔR^2	R^2	ΔR^2
Step 1						
Avg-Team-Behaviors	.032		.081		.020	
Avg-Reflection-Spec	.021		.011		.035	
P-Success	.000		.036		.036	
Step 2						
Avg-Team-Behaviors & Avg-Reflection-Spec		.026		.056		
Avg-Team-Behaviors & P-Success		.000		.033		
P-Success & Avg-Team-Behaviors						.016
P-Success & Avg-Reflection-Spec						.054

ΔR^2 represents the changes in R^2

In the first step, the teamwork behaviors data accounts for the most variance to predict both the approach category gains, i.e., mastery gains, and performance gains. For avoidance gains, prior success accounts 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 3.8.

Table 3.8. 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	.036	.036	.086	.086		
Avg-Team-Behaviors & Avg-Reflection-Spec	.068	.032	.106	.020		
Avg-Team-Behaviors, Avg-Reflection-Spec & P-Success	.068	.000	.142	.036		
P-Success					.036	.036
P-Success & Avg-Reflection-Spec					.090	.054
P-Success, Avg-Reflection-Spec & Avg-Team-Behaviors					.108	.018

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 account for the most variance to predict approach categories. In contrast, reflection specificity accounts 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 3.9 provides a summary of the results.

Table 3.9. 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	.068	.142	.108
Avg-Team-Behaviors & Avg-Reflection-Spec	.057	.092	.056
Avg-Team-Behaviors & P-Success	.036	.120	.051
Avg-Reflection-Spec & P-Success	.024	.057	.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 accounts for most contribution to predict students' avoidance behaviors. Teamwork behaviors was also a better predictor of students' performance behaviors than mastery behaviors.

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 3.10 indicates the results of repeated measures ANOVA.

Table 3.10. Results of changes in teamwork behaviors and reflection specificity

	Mauchly's W	Huynh-Feldt ε	Effect Size (η^2)
Team-Behaviors			
C	.874**	.901	.112
I	.854**	.885	.170
K	.802**	.846	.079
E	.888**	.913	.071
H	.843**	.877	.040
Reflection-Spec			
MP	.991**	1.000	.378
POI	.966**	.987	.263

*$p<0.05$, **$p<.01$

Huynh-Feldt values indicate that for Contribution to teamwork (C) dimension of teamwork behaviors data with $F(1.802, 203.603) = 14.260$, $p< .001$ 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 $F(1.771, 200.077) = 23.089$, $p< .001$; for Keeping team on track (K) dimension with $F(1.692, 191.168) = 9.654$, $p< .001$, and for Expecting quality (E) dimension with $F(1.826, 206.295) = 8.675$, $p< .001$, 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 $F(1.754, 198.151) = 4.747$, $p = .013$, we only observed significant mean difference from time points one to three. POI with values $F(1.975,183.641) = 33.195$, $p< .001$ 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.

Table 3.11 shows the mean difference of each CATME dimensions and aspects of reflection data.

Similarly, for reflection specificity score, Huynh-Feldt values indicated, MP with values $F(2, 186) = 56.477$, $p < .001$ 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 $F(1.975,183.641) = 33.195$, $p < .001$ 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.

Table 3.11. 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	.230**	.247**	.017
I	.255**	.294**	.040
K	.169**	.201**	.032
E	.179**	.197**	.018
H	.081	.162**	.080
Reflection-Spec			
MP	.486**	.562**	.076
POI	.263**	.289**	.026

**p<0.05, **p<0.01*

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 3.12indicates the result of multivariate repeated-measures ANOVA.

Huynh-Feldt values indicate that in mastery approach $F(1.886, 175.392) = 26.368$, $p < .001$, 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.

Table 3.12. Repeated-measures ANOVA for achievement goals (changes from pre to post)

	Mauchly's W	Huynh-Feldt ε	Effect Size η^2
Mastery Approach	.833	.871	.217
Performance Approach	.755	.815	.006
Performance Avoidance	.764	.821	.004

*$p<0.05$, **$p<.01$

Huynh-Feldt values indicate that for performance approach $F(1.630, 154.843) = .531$, $p = .553$ there is no significant mean difference between pre and post-performance approach. Huynh-Feldt values indicate that for performance avoidance $F(1.641, 155.934) = .420$, $p = .618$, 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.

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 behaviors were 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 behaviors are 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 research studies on the ICAP hypothesis showed contrary or null results (Chi & Menekse, 2015; Lou et al., 1996; Menekse et al., 2013). However, our study results confirmed the ICAP hypothesis (Chi, 2009; Chi & Wylie, 2014) in a classroom setting. These results provided some evidence that interactive activities could promote higher performance than constructive activities (Chi & Menekse, 2015; Chi & Wylie, 2014). 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 stepwise 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 (Elliot, 1999). Also, similar to existing studies, results showed that reflections help students to develop achievement goals towards avoiding failures (Elliot & Harackiewicz, 1996; Heo et al., 2018). 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 (Elliot & Harackiewicz, 1996). 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 (Blair & Razza, 2007; Brutus & Donia, 2010; Ramdass & Zimmerman, 2011). For example, Ramdass & Zimmerman (Ramdass & Zimmerman, 2011) 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 (Brutus & Donia, 2010) 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 results of performance-related goals could be due to the sample of engineering students in this study. They might have already established performance-related goals and motivation (Ames & Archer, 1988).

Overall this study provided valuable information about the role of the instructional strategies on students' achievement goals and academic performances (Vogt, 2008). 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.

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 (Elliot & Murayama, 2008) 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 research studies also indicate that students' self-reports are valid indicators of their abilities, e.g., (Marsh et al., 2018; Xu, 2018). 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.

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. Also, 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.

CHAPTER 4. **ROLE OF INSTRUCTIONAL STRATEGIES ON ENGINEERING STUDENTS' ENGAGEMENT, SELF-EFFICACY, TASK VALUE, AND ACADEMIC PERFORMANCE**

Abstract

Prior research studies suggested the use of student-centered instructional strategies to enhance students' learning outcomes and motivation. However, limited literature studied the role of more than one instructional strategy when introduced in a single class. In this paper, we focused on students' participation in activities related to two instructional strategies, i.e., reflective thinking, and teamwork behaviors in an engineering classroom setting. We studied the role of these strategies on students' academic performance, and changes in motivational constructs while accounting for students' prior success. We used three motivational constructs, which are self-efficacy beliefs, task value, and engagement (measured on four scales of behavioral, emotional, social, and cognitive engagement). One hundred twenty students participated in this semester-long study. Data included a total of 3530 individual reflections in 26 lectures and peer evaluation of teamwork behaviors at four-time points. Besides, we recorded students' performance on three exams. Students also provided information on motivational constructs both at the beginning and at the end of the semester. We used students' standardized test scores as a measure of their prior academic success. The paper addressed two research questions. The first question focused on the nature of change in motivational constructs using repeated-measures ANOVA. Moreover, the question determined the unique role of each instructional strategy in predicting that change using hierarchical and simultaneous regression. The second question focused on understanding the relationship between instructional strategies, academic performance, and changes in motivational constructs using the full structural equation model (SEM). The results indicated a decline in all motivational constructs from pre to post. However, the decline was not significant for social engagement. Further, teamwork behaviors accounted for the most variance in predicting changes in students' motivational constructs. Also, reflection specificity appeared as a second-best contributor to changes in students' self-efficacy, task value, and emotional engagement. The results of SEM also showed that teamwork behaviors significantly and positively relate to academic performance. Further, teamwork behaviors showed a positive and significant indirect effect of changes in students' self-efficacy and task value. However, the SEM results indicated

non-significant impacts of reflection specificity on students' academic performance and changes in motivational constructs. These results also align with the ICAP hypothesis, which suggests that interactive activities are likely to promote better academic performance compared to constructive activities.

Introduction

In response to various calls for the Science, Technology, Engineering and Mathematics (STEM) education reforms (e.g., AAAS, 2010), many studies explored the impact of student-centered instructional strategies in college classrooms (Borrego, Froyd, & Hall, 2010; Prince & Felder, 2006). Research studies outline the use of a broad range of these instructional strategies, for example, think pair share, generating concept maps, or exit tickets. The primary premise of introducing these instructional strategies was based on the principle that students construct their knowledge and do not merely absorb information, as explained in the lecture (Prince & Felder, 2006). Prior research supports that when instructors began using student-centered strategies, students' were engaged, and also their academic performance improved (Kaplan, Middleton, Urdan, & Midgley, 2002; Kothiyal et al., 2013; Turner & Patrick, 2004). Also, such instructional strategies helped students to use good self-regulation strategies (e.g., Michalsky & Kramarski, 2015) and often improved the retention rate of students in STEM degrees and careers (Prince & Felder, 2006). In sum, prior research indicated that these instructional strategies actively engage students in their learning process, and as a result, when compared with the traditional approaches, were associated with better learning outcomes, and improved regulation and motivation. However, these active strategies were often only compared with the traditional approaches, which also resulted in students' resistance to actively engaging with a learning activity, and lack of students' motivation to adopt such methods (Borrego et al., 2010; Finelli, Daly, & Richardson, 2014). This lack of motivation is more evident when students are not appropriately engaged, or when they do not see the value in the use of such strategies (Gauci, Dantas, Williams, & Kemm, 2009). Although there are studies that have focused on the role of an instructional strategy on students' motivation, there is a lack of empirical studies that explored the relative effectiveness of more than one instructional strategy in real classroom settings (Streveler & Menekse, 2017).

In this paper, we explored the role of two instructional strategies, i.e., reflective thinking, and collaborative teamwork on engineering students' academic performance and motivation. We used the self-regulation and ICAP framework lens to select the two student-centered learning strategies.

Prior research studies associated self-regulation based interventions with two kinds of competences (personal and social competence). These competencies could also lead to better learning outcomes and performance (Riemer, 2003). In personal competence, students adjust their learning processes in the light of their self-beliefs, and motivation. Such students develop an ability to reflect on their processes and show self-awareness (Zimmerman & Kitsantas, 2005). A common example of such competence includes reflective thinking (Jenson, 2011; Schunk & Zimmerman, 1998), problem-based learning (Hung, 2011), goal-setting, and planning (Pintrich, 2000b). In social competence, students' social and vicarious experiences help them to regulate and monitor their performance (Zimmerman, 1989). Such students develop an ability to manage and work with peers, perform in team and group tasks, and maintain a good and communicative relationship with peers, mentors, and professors. A common example of social competence interventions includes project-based learning (English & Kitsantas, 2013), group work (Cho et al., 2010; Järvelä & Järvenoja, 2011), and peer instruction (Roscoe & Chi, 2007). One major factor in selecting the two strategies is derived from these two competencies, and we selected reflective thinking as an approach to develop personal competence and teamwork behaviors for social competence.

In addition to self-regulated learning, the Interactive Constructive Active Passive (ICAP) framework (Chi, 2009) guided the selection process of these two strategies. This framework helps to differentiate the use of active, constructive, and interactive modes in student-centered learning strategies and their resultant behaviors by the observable (overt) characteristics. With the framework, the passive mode suggests that students are a passive listener of information and shows no physical processing activity behaviors. Active mode indicates that the student is actively engaged and is attentive in class. Also, the student is physically involved by doing something (e.g., taking notes). In constructive mode, students are producing overt outputs by creating new knowledge based on existing information (e.g., drawing a diagram). Also, in interactive mode, the student is not only producing overt outputs but is also socially engaged and interacting with another person to co-create knowledge (e.g., collaborating on a project). The ICAP framework hypothesizes that "interactive activities are most likely to produce better learning than constructive activities, which in turn might be better than active activities, which are better than being passive" (Chi, 2009, p. 73). However, there is limited literature that explored the hypothesis (comparison of interactive vs. constructive) in classroom settings (Menekse et al., 2013). Also, there is an extensive literature which showed that small groups based interactive method might not necessarily promote greater learning when compared with individual learning (Lou et al., 1996; Menekse et al., 2013). In this study, We focused on using the ICAP framework as a second lens to select the instructional strategies, where reflective thinking is constructive, and teamwork behaviors are referring to interactive mode. We also used the framework to verify the results with motivational and engagement factors.

We concurrently introduced the instructional strategies in a required engineering course. We studied the relative effectiveness of these two instructional strategies on changes in engineering students' motivation. We also studied the relationship of these instructional strategies with students' academic performance and changes in motivational constructs. We measured the students' motivation using students' self-efficacy beliefs, task value, and engagement. More specifically, in this semester-long study, we addressed the following research questions:

> RQ1: What are the unique contributions of two instructional strategies (i.e., reflective thinking, and teamwork) to predict changes in students' self-efficacy beliefs, task value, and engagement?
>
> RQ2: How do students' participation in instructional strategies relate to their academic performance and changes in their motivational constructs (self-efficacy, task value, and engagement)?

The next sections present the literature review, followed by research methods, results, and discussion and conclusion with the implications of this study.

Literature review

Self-regulated learning refers to the process adopted by learners to activate and sustain cognitions, affects, and behaviors. Self-regulated learners direct their behaviors systematically towards the attainment of learning goals and academic outcomes (Schunk & Ertmer, 2000).

An often associated construct with students' self-regulation is the use of instructional interventions that promote active participation. The instructional activities help students in their learning process, academic achievement, and could be associated with students' development as self-regulated learners (Stefanou et al., 2013). Student-centered instructional strategies help the learners to regulate their learning process and eventually perform better (e.g., Loyens, Magda, & Rikers, 2008; Rezaee & Mosalanejad, 2015).

Prior studies suggested that student-centered instructional strategies not only impact students' cognitive behaviors but also stimulate their motivations (Stefanou et al., 2013). For example, Alexander & Wade (2000) argued that relevant and meaningful instructional strategies and associated tasks are conducive to students' active involvement in learning, and help them to develop self-regulation skills and motivational behaviors. However, it is also important to note that different student-centered learning approaches may result in different outcomes for both cognitive and motivational behaviors (Stefanou et al., 2013; Vermunt & Vermetten, 2004). Although research studies have explored the outcomes based on instructional strategies in the context of self-regulated learning (Stefanou et al., 2013), such literature is sparse with the simultaneous introduction of multiple instructional strategies. Also, it is vital to study how different instructional contexts build on other factors, such as students' prior knowledge and their beliefs about their learning (Pintrich, 2000b). Prior research studies suggested that instructional strategies and the context can activate or change students' beliefs on their capabilities, expectations, behaviors, and engagement (Vermunt and Vermetten, 2004).

Considering the sparsity of studies on multiple instructional strategies, and their role on multiple facets of students' motivation, self-regulation, and academic performance, this study brings these pieces together in a study designed in a required engineering class. The motivational constructs included in this study are self-efficacy, task value, and engagement.

Self-efficacy, self-regulated learning, and academic performance

A critical construct that usually accompanied the discussion of learners' self-regulation is the concept of self-efficacy, which broadly acted as an interface between learners' motivation, cognition, and performance. Self-efficacy is defined as personal beliefs about the capability to produce the outcomes and desired level of performance (Bandura, 1977, 1997). In Bandura's perspective, self-efficacy beliefs have trait-like situational components that can be dependent mostly on four variables, such as recent or past performances, vicarious experiences, interpersonal persuasions, and psychological state (Bandura, 1977).

In the case of students' learning, the definition of self-efficacy connects these beliefs with students' self-regulated capabilities (Pajares, 2008; Zimmerman & Schunk, 2008). Zimmerman &

Schunk (2008) have suggested that self-efficacy beliefs are precursor, mediators, and are in a natural relationship with self-regulated learning, which allows students to use more cognitive and metacognitive strategies. These students also monitor their work, persist longer, engage themselves in more effective self-regulatory strategies, and bravely confront the academic challenges (Bandura & Schunk, 1981; Zimmerman & Schunk, 2008).

Students with stronger self-beliefs about their capability, participate in learning tasks (derived from instructional strategies) regardless of their past performance (Pajares, 2008; Schunk & Ertmer, 2000). Previous research studies have reported the evolution of self-efficacy beliefs during a semester with mixed results about the direction of the self-efficacy change. For example, Maricuțoiu & Sulea (2019), in their semester-long study, have reported an increase in students' self-efficacy beliefs during the semester. Their study also suggested a mediating effect of the evolution of students' self-efficacy beliefs on students' engagement in the learning tasks. In contrast, Papinczak, Young, Groves, & Haynes, (2008) reported a decline in students' self-efficacy beliefs after being engaged using project-based instructional strategy. Similarly, students' self-efficacy beliefs of undergraduate students in STEM courses have been associated with their academic achievement and performance (Hutchison, Follman, Sumpter, & Bodner, 2006; Lent, Brown, & Larkin, 1987; Purzer, 2011). For example, Hutchison et al. (2006) reported self-efficacy beliefs as an essential factor in explaining first-year engineering students' achievement, persistence, and interest.

Considering the above factors, prior research studies confirm the importance of self-efficacy beliefs as an essential motivation variable in connection with instructional strategies, students' academic performance, and self-regulated learning theory.

Task value, self-regulated learning, and academic performance

Another essential construct associated with students' self-regulation, learning, and participation in learning tasks is task value (Zimmerman & Schunk, 2008). Task value refers to students' beliefs about the importance and value of the task (Eccles & Wigfield, 2002). This motivational construct describes students' reasons for doing a task (Pintrich & De Groot, 1990).

Prior research studies found a strong connection between task value and self-regulated learning (Pintrich & De Groot, 1990), where task value helps to promote and sustain self-regulated learning (Pintrich, 1999). Zimmerman & Schunk (2008) have suggested that task values are precursor, mediator, and are in a natural relationship with self-regulated learning, which allows students to employ more strategies to regulate their learning behavior.

Although value-related constructs are less studied than other motivational constructs (Jones, Paretti, Hein, & Knott, 2010), research studies indicated that students who believe that task is valuable and exciting, use the metacognitive approach and cognitive strategies frequently (Zimmerman & Schunk, 2008). These students also exert more effort to manage and achieve their goals (Eccles & Adler, 1983). Also, prior research studies support that task value has the primary effect on students' use of learning strategies, participation in activities, and performance (Neuville, Frenay, & Bourgeois, 2007). However, these effects have mixed direction of the effect. For example, Jones et al. (2010) described a decrease in first-year engineering students' value-related beliefs. On the contrary, Meece, Wigfield, & Eccles (1990) found task value as a positive predictor of students' performance in a mathematics course. Also, these results are established with the use of student-centered learning based instruction. For example, Nie & Lau (2010) described the student-centered learning instructional strategies as a significant predictor of students' task value and achievement. Considering the mixed direction of effect, it is essential to add the task-value construct in a study on students' motivation along with self-beliefs

Based on the role of task value and being a relatively less studied construct to students' self-regulated learning and performance, this study considers both expectancy and value-related beliefs as important motivation variables.

Engagement, beliefs, and academic performance

Prior studies suggested that engaged students self-regulate their goals, participate in activities, and are attentive to their learning (Christenson, Reschly, & Wylie, 2012). Both students' self-efficacy and task value beliefs help students to understand the meanings of their learning experiences in the context of their achievements (Schunk, Pintrich, & Meece, 2008). These meanings also help students to value their engagement in their learning tasks (Liem, Lau, & Nie, 2008).

In the past, researchers have used engagement both as a meta and multidimensional construct. As a meta construct, engagement includes the meaning of participation and is associated with motivational constructs such as self-efficacy, task value, and interest (Fredricks et al., 2004). As a multidimensional construct, studies have reported behavioral, emotional, and cognitive aspects of engagement (Appleton, Christenson, & Furlong, 2008; Elbers, 2003). Recently, research studies introduced the social or community engagement dimension in an academic context. Social engagement describes students' active participation in a social group or a team (Avison, McLeod, & Pescosolido, 2007). However, limited literature has used engagement with its four dimensions in an academic context, which suggests the need for studies, specifically in the engineering context.

Also, studies on meaningful learning and instructional strategies advocate student involvement as an essential component. For example, Smith, Sheppard, Johnson, & Johnson (2005) suggested the use of classroom pedagogies that invoke better interaction and engagement among students. They suggested that such pedagogies, when engaging students, will have a lasting impact on students' achievement, especially when they learn complex materials.

Considering the literature evidence of students' engagement with other motivational constructs (self-efficacy, task value), instructional strategies, and academic performance, we used a four-dimensional engagement construct to evaluate engagement relationships with instructional strategies. We also use engagement factors to evaluate its connection with other motivational constructs and students' academic performance.

In summary, prior studies confirm the importance of the use of strategies for self-regulation skills, engaging students in the learning process, and change in their motivation, especially self-efficacy beliefs and task value. However, there is also a need for a study that 1) examines the role of multiple instructional strategies in a single classroom, and 2) examines multiple motivational factors (e.g., self-efficacy, task value, and engagement) with instructional strategies on students' achievement in an engineering course context. Hence, in this study, we use self-regulated learning as a theoretical lens to select the two instructional strategies. Further, we use the self-regulated learning lens to study the relationships between students' participation in learning activities, academic performance, and motivations described by their self-efficacy, task value, and engagement.

Methods

Participants

The sample of the study consisted of 120 first-year engineering students enrolled in an introductory engineering course in a large public university located in the Midwest United States.

The students' are randomly placed in different sections of the first year engineering course. We collected the data from one section of the course. As most of the incoming freshmen students undertake the course as a required course, the course was a good venue to understand the relationship of instructional strategies with motivational constructs. Also, the course revolved around the fundamental programming concepts using MATLAB and the development of mathematical models to solve engineering problems. The programming concepts are essential for engineering major students and relatively hard in nature, which allows understanding students' behaviors and participation in instructional strategies in a meaningful way. Table 4.1. describes the gender, and race/ethnicity information of the participating students. 83.33 % of students were male, and 16.67% were female. Also, 21.67% of the total participated students were international, 61.67% were white American, and 16.67% belonged to underrepresented minorities.

Table 4.1. Demographics information of students

	No of students	Percentage
Gender		
Male	100	83
Female	20	17
Race/Ethnicity		
American Indian or Alaskan	0	0
Asian American	9	8
Black or African American	2	2
Hispanic or Latinx	2	2
Native Hawaiian	1	1
White or European American	74	62
Two or more races	6	5
International	26	22

Data collection and instruments

We collected the data for five aspects required to answer the research questions. These aspects are:

1. Students' reflection measured by reflection specificity on the scale of 0-4.
2. Students' teamwork behaviors measured using students' peer evaluations on a scale of 1-5.
3. Students' self-reported motivation on three constructs (i.e., self-efficacy, task value, and engagement) measured using surveys on a scale of 1-6.
4. Students' prior success measured using SAT score.

5. Students' academic performance in an engineering course measured using three exam scores.

We used multiple instruments to collect the data. We used the mobile application "CourseMIRROR" (Fan et al., 2015; Luo et al., 2016) to collect students' reflection on two aspects 1) muddiest point, and 2) point of interest. For each lecture, students were prompted to reply to two questions. For the muddiest point, we prompted the students to "Describe what was confusing or needed more detail?" For the point of interest, we asked them to "Describe what you found most interesting in today's lecture?" We collected students' reflections in 26 lectures comprising of 3430 student reflections in total (~55% completion rate). The students voluntarily participated in the reflection process. As the collected reflections were in textual form, we converted them into a score based on a rubric of reflection specificity (Heo et al., 2018; Menekse et al., 2011). The students could get a score from 0 to 4, where 0 indicates an irrelevant reflection, while 4 indicates a specific reflection. We employed two raters independently to convert the reflections into the reflection specificity score for both MP and POI. There was a good agreement between the two raters, as κ (MP) = .617, and κ (POI) = .652 (Altman, 1990).

The teamwork behaviors data were collected using CATME (Comprehensive Assessment of Team Member Effectiveness) Smarter Teamwork (Loignon et al., 2017; Loughry et al., 2007; Ohland et al., 2012) peer evaluation tool. The data were collected at four-time points, after each milestone (96.5% average completion rate) on five dimensions of CATME which are 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.

We used the Qualtrics survey system to collect the data on all motivational constructs in a pre and post manner. For self-efficacy and task value, we used the subscales of Motivated Strategies for Learning Questionnaire (MSLQ) Survey (Pintrich et al., 1991). For the engagement, we used a validated and extensively used instrument "The Math and Science Engagement Scales" in K-12 classes (Wang et al., 2016). We modified this engagement instrument for engineering classes, and thus, it is essential to validate this revised instrument before conducting any further analysis (as explained in Appendix B). The students' engagement scales include the subscales of behavior, social, cognitive, and emotional engagement. The measures of students' motivation were collected twice in the semester, i.e., once at the beginning of the semester and once at the end of the semester. The data was collected using 6-Likert scale value (95.5% average completion rate), where one indicated "strongly disagree," and six indicated "strongly agree." Please refer to Appendix A for survey items.

For the students' prior success, we used SAT scores. For students who had only ACT scores, we converted their ACT scores into SAT scores using standardized calculations. As SAT and ACT are standardized tests (test uniformly, and in a consistent manner), they can help to compare the relative performance of individual students without bias of individual evaluations. Also, these scores, due to their nature and requirement of admission, are a more reliable indicator of students' prior success.

To collect the data of students' academic performance in the course as the fifth aspect, we used the score of three exams. The maximum score for each exam was 120. Although each exam focused on the different content aspect of the course, there was no difference in the format of each exam. The teaching assistants and instructor graded the exams without any involvement from the research team.

Procedure and data analysis

Before analyzing the data, we reverse coded all the negatively worded items (~10 items). This step of conversion helped to bring all the data on the same scale. Further, we evaluated the issues related to outliers, skewness, kurtosis, multi-collinearity, singularity, and missing data. For all the surveys, all three measures of central tendency mean, median, and mode were roughly the same for all the aspects, and no outlier was found. Skewness and kurtosis values were below or close to 1, which indicated no issues on skewness and kurtosis. Also, the r values between various aspects were less than .90, which indicated no multicollinearity or singularity issues between constructs. As the data had less than 5% missing values, we used the mean imputation method to replace the missing values before conducting the analysis. Also, based on the Confirmatory Factor Analysis (see Appendix B for CFA results), in this paper, we used the revised engagement factors (with 19 items instead of 23).

To address the first research question, first, we conducted multivariate repeated measures of ANOVA to understand the effect of instructional strategies on students' self-efficacy beliefs, task value, and engagement scales. We used Mauchly's Test of sphericity and values of epsilons to determine the sphericity assumptions. In case of violations, we adjusted the degrees of freedom accordingly.

Also, we conducted hierarchical multiple regression analysis to determine which strategy accounts for most variance, and simultaneous regression analysis to determine the unique contribution of each strategy in predicting changes in students' motivational constructs. To do these analyses, we calculated changes in students' self-efficacy beliefs, task value, and engagement, respectively, from pre to post-implementation of instructional strategies. For calculating these changes, we took the average of the pre-scale and post-scale and subtracted the pre-scale average from the post average. For example, self-efficacy change = average (post-self-efficacy items) – average (pre-self-efficacy items). Similarly, we calculated the task value change and engagement change for each subscale. Besides, we took the average of each dimension of reflective thinking (average (MP), and average (POI)); and teamwork behaviors (average (C), average (K), average (I), average (E), and average (H)).

To address the second research question, we conducted a general full structural equation model (SEM) between instructional strategies, exam scores, and students' changes in motivational constructs, while accounting for students' prior success. We used all three exams as a measure of students' academic performance. To assess these relationships of strategies, performance, and changes in motivations, we tested an SEM model based on the correlation matrix. We determine the results on variance and covariance estimation.

For testing the fitness of the model, we considered multiple goodnesses of fit indices. These indices include Root Mean Square Error of Approximation (RMSEA), Standardized Root Mean Square Residual (SRMR), Comparative Fit Index (CFI), Non-Normed Fit Index (NNFI), Goodness of Fit Index (GFI), and Incremental Fit Index (IFI). According to the literature, the values of above 0.90 for CFI, GFI, NNFI, and IFI are indicative of a good model (Hu & Bentler, 1999). Besides, the values of RMSEA and SRMR below 0.10 are adequate (Browne & Cudeck, 1993) with a good fit of below 0.08, and excellent fit being with values below 0.05 (Hu & Bentler, 1999).

In the full model SEM, we have one endogenous (prior success), and six exogenous variables namely reflection specificity (2 indicators), teamwork behaviors (5 indicators), academic performance (3 indicators), self-efficacy (1 indicator), task value (1 indicator), and engagement (4 indicators). In the SEM analysis, it is essential to handle the exogenous and endogenous variables with one indicator. In our case, these are prior-success, changes in self-efficacy, and changes in task value. We modeled these variables by fixing the factor loadings to one, and error variance to zero. The notable point is that single item constructs are reported to lack measures of internal consistency (reliability). However, studies indicated that single-item measures are sufficient and, in cases more robust (e.g., students' GPA, or an average of scale measures to ensure parsimonious model) than the scale measures (Hyland & Sodergren, 1996; Wanous, Reichers, & Hudy, 1997).

A critical aspect of conducting SEM is the sample size. Prior research studies support the use of a large sample size to conduct SEM analysis and have various recommendations, but usually, $N > 100$ is the minimum sample size for conducting SEM (Anderson & Gerbing, 1988; Tabachnick & Fidell, 2001; Tinsley & Tinsley, 1987). Also, prior research studies suggested the criteria for using a ratio of 5 -10 cases per variable where variables can have multiple indicators (Bentler & Chou, 1987; Nunnally & Bernstein, 1967). Based on these recommendations, the sample size of 120 students indicates a sufficient sample size to conduct the SEM analysis. Considering the four scales of engagement as different indicators under one latent construct, we have a total of 7 latent variables, which requires 35 – 70 students' responses to conduct a reliable SEM analysis. A sample of 120 students thus gives an adequate sample size for the SEM analysis.

We used LISREL 10.20 to conduct the SEM analysis using a 95% confidence interval. Also, we used IBM SPSS Statistics (v.26) to conduct the reliability, correlation, descriptive statistics, repeated measures ANOVA, and regression analysis.

Results

RQ1: What are the unique contribution of two instructional strategies (i.e., reflective thinking, and teamwork) to predict changes in students' self-efficacy beliefs, task value, and engagement?

At first, we determined the direction of change in students ' self-efficacy, task value, and engagement from the beginning of the semester to the end of the semester. We used a multivariate repeated-measures ANOVA. We conducted repeated measures by two-time points and on multi-item self-efficacy, task value, and along four dimensions of engagement.

We used Mauchly's W test of sphericity. The epsilons (ε), which are estimates of the degree of sphericity. We found that epsilons were less than 1.0, indicating the sphericity assumptions were violated except for cognitive engagement. In the cognitive engagement, the value was close to 1, and also, the test was non-significant, indicating that sphericity was not violated. To adjust the degrees of freedom, we used Greenhouse-Geisser adjustment if epsilon was less than 0.75, and

Huynh-Feldt epsilon adjustments otherwise. Table 4.2 and Table 4.3 indicates the results of repeated measures ANOVA.

Table 4.2. Adjustment and descriptive statistics of self-efficacy, task value, and engagement

	Pre		Post					
	M	*SE*	*M*	*SE*	*W*	ε	*df*	χ^2
Self-efficacy	4.853	.066	4.341	.072	.785	.914	9	28.435**
Task value	4.867	.064	4.180	.085	.438	.713	14	96.601**
Engagement								
Behavioral	5.251	.045	4.982	.052	.741	.912	9	35.122**
Emotional	4.501	.083	3.883	.082	.709	.883	9	40.338**
Social	5.019	.049	4.954	.047	.679	.900	9	45.446**
Cognitive	5.119	.049	4.889	.050	.911	.965	8	10.978

**p<0.05, **p<0.01*

Table 4.3. Repeated measures ANOVA for changes in self-efficacy, task value, and engagement

	F (1,119)	*p*	η^2	Mean Differences Pre to post
Self-efficacy	57.945	< .001**	.327	.512**
Task value	98.726	< .001**	.453	.687**
Engagement				
Behavioral	40.143	< .001**	.252	.270**
Emotional	65.552	< .001**	.345	.618**
Social	1.713	.193	.014	.066
Cognitive	24.307	< .001**	.170	.231**

**p<0.05, **p<0.01*

The results based on adjusted values indicate significant mean difference between pre and post self-efficacy $F(1, 119) = 57.945$, $p< .001$, task value $F(1, 119) = 98.726$, $p< .001$, behavioral $F(1, 119) = 40.123$, $p< .001$, emotional $F(1, 119) =65.552$, $p< .001$, and cognitive engagement $F(1, 119) = 24.307$, $p< .001$. The pairwise comparison based on time indicates a significant decline in all of these from pre to post. The effect sizes show medium to large effect. However, the results indicate a non-significant mean difference between pre and post social engagement $F(1, 119) = 1.713$, $p< .001$. Overall, the results indicate that there is a significant negative difference in students' self-efficacy beliefs, task value, and behavioral, emotional, and cognitive engagement. In sum, these results indicate an observable adverse effect on all motivational constructs except social engagement. These adverse effects are also visible in graphs, as shown in Figures 4.1 (A- F).

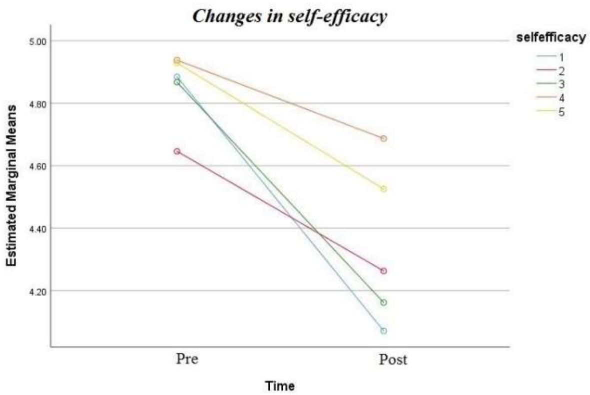

Fig 4.1 (A)

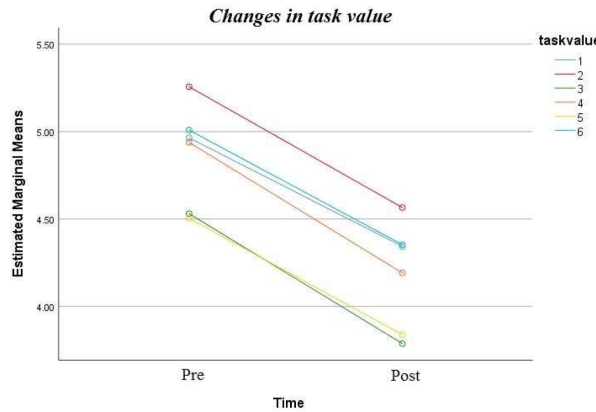

Fig 4.1 (B)

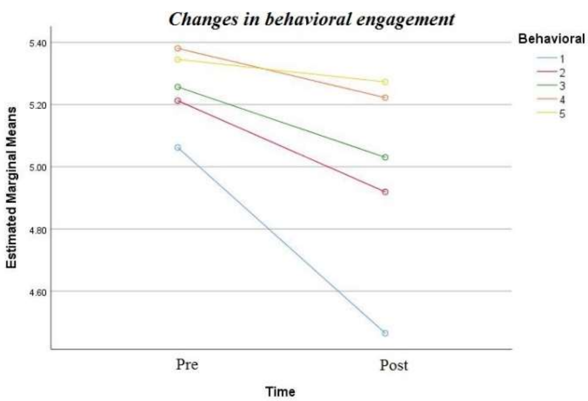

Fig 4.1 (C)

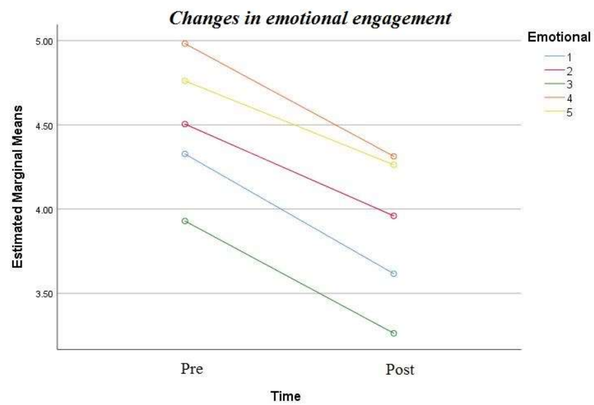

Fig 4.1 (D)

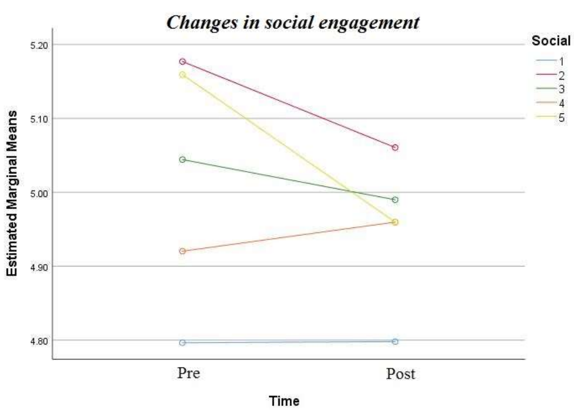

Fig 4.1 (E)

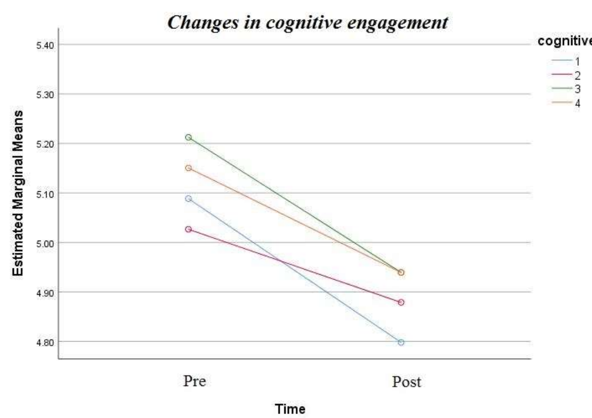

Fig 4.1 (F)

Figure 4.1(A- F). Changes in motivational constructs

To further elaborate on the question, we used the change in students' motivational constructs, which include self-efficacy beliefs, task value, and engagement changes (behavioral, emotional, social, cognitive) as dependent variables. We used stepwise hierarchical regression analysis to explore that which instructional strategy accounts for most variance while predicting changes in motivational construct. We also accounted for students' prior success. Besides, we also used simultaneous analysis to determine the unique contribution of students' overall reflection specificity (Reflection-Spec), overall teamwork behaviors (Team-Beh), and prior success (P-Success) to predict motivational changes in the course.

In this stepwise process, we used a two-step process to determine the order of the sets. At first, 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 used the value of change in R^2 to determine the variable, which adds the most variance and predictability in the model. Table 4.4 shows the variances to determine the order of the sets.

Table 4.4. Variances to predict exam scores – Determination of order of sets

	SE		TV		BE		EE		SoE		CE	
	R^2	ΔR^2	R^2	ΔR^2	R^2	ΔR^2	R^2	ΔR^2	R^2	ΔR^2	R^2	ΔR^2
Step 1												
Team-Beh	.106		.034		.079		.070		.046		.031	
Reflection-Spec	.011		.027		.007		.002		.001		.015	
P-Success	.003		.000		.025		.000		.004		.031	
Step 2												
Team-Beh & Reflection-Spec		.010		.021		.001		.000		.005		.009
Team-Beh & P-Success		.012		.002		.028		.000		.002		.027

SE = Self-efficacy; TV = Task value; BE = Behavioral engagement; EE = Emotional engagement; SoE = Social engagement, CE = Cognitive engagement.

In the first step, teamwork behaviors account for the most variance to predict self-efficacy, task value, and all four scales (behavioral, emotional, social, and cognitive) of engagement change. In the second step, the results of changes in R^2 indicated that for self-efficacy, behavioral engagement, and cognitive engagement, the order of good model was teamwork behaviors, prior success, and reflection specificity. For the other motivational changes (i.e., task value, emotional engagement, and social engagement), teamwork behaviors, reflection specificity, and prior success made the order. The results of the regression analysis to predict changes in motivational constructs are presented in Table 4.5.

Table 4.5. Summary of stepwise hierarchical regression analysis relating teamwork behaviors, prior success, and reflection specificity to motivational changes

	SE		TV		BE		EE		SoE		CE	
	R^2	ΔR^2	R^2	ΔR^2	R^2	ΔR^2	R^2	ΔR^2	R^2	ΔR^2	R^2	ΔR^2
Team-Beh	.069	.069	.032	.032	.086	.086	.064	.064	.058	.058	.034	.034
Team-Beh & *Second Set**	.085	.015	.041	.009	.114	.028	.067	.003	.062	.004	.059	.025
Team-Beh, Reflection-Spec & P-Success	.101	.016	.043	.002	.116	.002	.067	.000	.062	.000	.074	.014

SE = Self-efficacy; TV = Task value; BE = Behavioral engagement; EE = Emotional engagement; SoE = Social engagement, CE = Cognitive engagement.

* *Second Set is P-Success for self-efficacy, behavioral engagement, and cognitive engagement, while Second Set is Reflection-Spec for task value, emotional engagement, and social engagement*

The results of the changes in R^2 indicates that teamwork behaviors account for 6.9% of the variance to predict changes in students' self-efficacy, 3.2% variance to predict changes in task value, 8.6% variance to predict changes in behavioral engagement, 6.4% variance to predict changes in emotional engagement, 5.8% variance to predict changes in social engagement, and 3.4% variance to predict changes in cognitive engagement. The reflection specificity accounts for an additional 1.6% of the variance to predict self-efficacy change, 0.9% variance to predict task value change, 0.2% variance to predict changes in behavioral engagement, 0.3% variance to predict changes in emotional engagement, 0.4% variance to predict changes in social engagement, and 1.4% variance to predict changes in cognitive engagement.

The prior success data additionally accounts for 1.5% variance to predict self-efficacy change, 0.2% variance to predict task value change, 2.8% variance to predict changes in behavioral engagement, and 2.5% variance to predict changes in cognitive engagement. However, prior success does not account for any variance to predict changes in emotional and social engagement. The results of stepwise hierarchical regression indicate that students' teamwork behaviors account for the most variance to predict all motivational changes.

To determine the unique contribution of each of these sets to predict changes in self-efficacy, task value, and all four scales (behavioral, emotional, social, and cognitive), we further conducted simultaneous regression analysis. Table 4.6 provides a summary of the results.

Table 4.6. Summary of simultaneous regression analysis for the unique contribution of teamwork behaviors, reflection specificity, and prior success to predict changes in students' motivation

	ΔR^2					
	SE	TV	BE	EE	SoE	CE
All sets	.101	.043	.116	.067	.062	.074
Team-Beh & P-Success	.090	.034	.114	.063	.057	.061
Team-Beh & Reflection-Spec	.112	.053	.081	.071	.053	.040
Reflection-Spec & P-Success	.019	.010	.035	.005	.004	.054

SE = Self-efficacy; TV = Task value; BE = Behavioral engagement; EE = Emotional engagement; SoE = Social engagement, CE = Cognitive engagement.

The results of simultaneous regression analysis indicate that teamwork behaviors have the unique contribution of 8.20%, 3.30%, 8.10%, 6.20%, 5.80%, and 2.00% to predict changes in self-efficacy, task value, behavioral, emotional, social and cognitive engagement, respectively. Similarly, reflection specificity uniquely accounts for 1.10%, 0.90%, 0.20%, 0.40%, 0.50%, and 1.30% to predict changes in self-efficacy, task value, behavioral, emotional, social and cognitive engagement, respectively. Prior success account for 1.10%, -1.00%, 3.50%, -0.40%, 0.90%, and 3.40% to predict changes in self-efficacy, task value, behavioral, emotional, social and cognitive engagement, respectively. Overall, the results indicate that teamwork behaviors account for the most contribution predicting the changes in motivational constructs except changes in cognitive engagement. For changes in cognitive engagement, students' prior success accounts for most contributions. Also, students' prior success indicates the negative contribution to changes in students' task value and emotional engagement.

RQ2: How the students' participation in instructional strategies relates to their academic performance and changes in their motivational constructs (self-efficacy, task value, and engagement)?

To answer the question and broadly assess the relationships between instructional strategies, academic performance, and changes in self-efficacy beliefs, task value, and engagement while accounting for students' prior performance, we tested a general structural equation model (SEM) using the full model approach. The SEM was based on variance and covariance matrices estimation, and all variables of interest were evaluated simultaneously (Byrne, 1998).

At first, we calculated the descriptive statistics and factor reliabilities of the data for the constructs of the survey are presented in Table 4.7.

Table 4.7. Descriptive statistics of the instructional strategies, and achievement constructs

Constructs	No of items	Reliability	Mean	Variance	Min	Max
P-Success	1	-	1984.67	20388.317	1560	2320
Reflection-Spec	2	.747	2.811	.002	2.781	2.842
Team-Beh	5	.949	4.033	.003	3.969	4.081
Acad-Performance	3	.754	94.484	51.265	87.380	101.699
Self-efficacy	1	.531*	-.5116	.542	-2.65	1.20
Task value	1	.599*	-.6871	.574	-3.00	1.17
Engagement	4	.714	-.2699	.054	-.618	-.066

**calculated correlation between pre average and post average*

We calculated the factor reliabilities using Cronbach's alpha. For single indicator factors (i.e., prior success, self-efficacy, task value), we did not use the Cronbach's alpha. However, for self-efficacy and task value, we used test-retest reliability on average of pre-scale, and on average of post-scale (as discussed in Weir, 2005). For each item, the descriptive statistics are based on item-based statistics.

We formed the hypothesized model based on the temporal and research-based evidence, as presented in Figure 4.2. A theoretical hypothesized model depicting the relations between prior success, instructional strategies, academic performance, and changes in motivational constructsFor example, Liu, Andre, & Greenbowe (2008) showed that students' prior success contributed towards their participation in the instructional strategy of computer simulations. Also, in studies, students' prior success is used both as a controlling factor and predecessor to their achievement outcomes (e.g., Phan, 2014). Further studies indicated that students who participate in instructional strategies show excellent academic achievement (e.g., Callahan, 2008; Johnson, Johnson, & Smith, 1998). Based on the temporal evidence, we conducted the post surveys of students' motivation at the end of the semester, while the three exams were spread across the semester. We place the changes in motivation as the last set of the full model. We used structural equation modeling (SEM) and assessed how well this hypothesized model fits the data from a representative sample of first-year engineering students in the context of performance in a required engineering course.

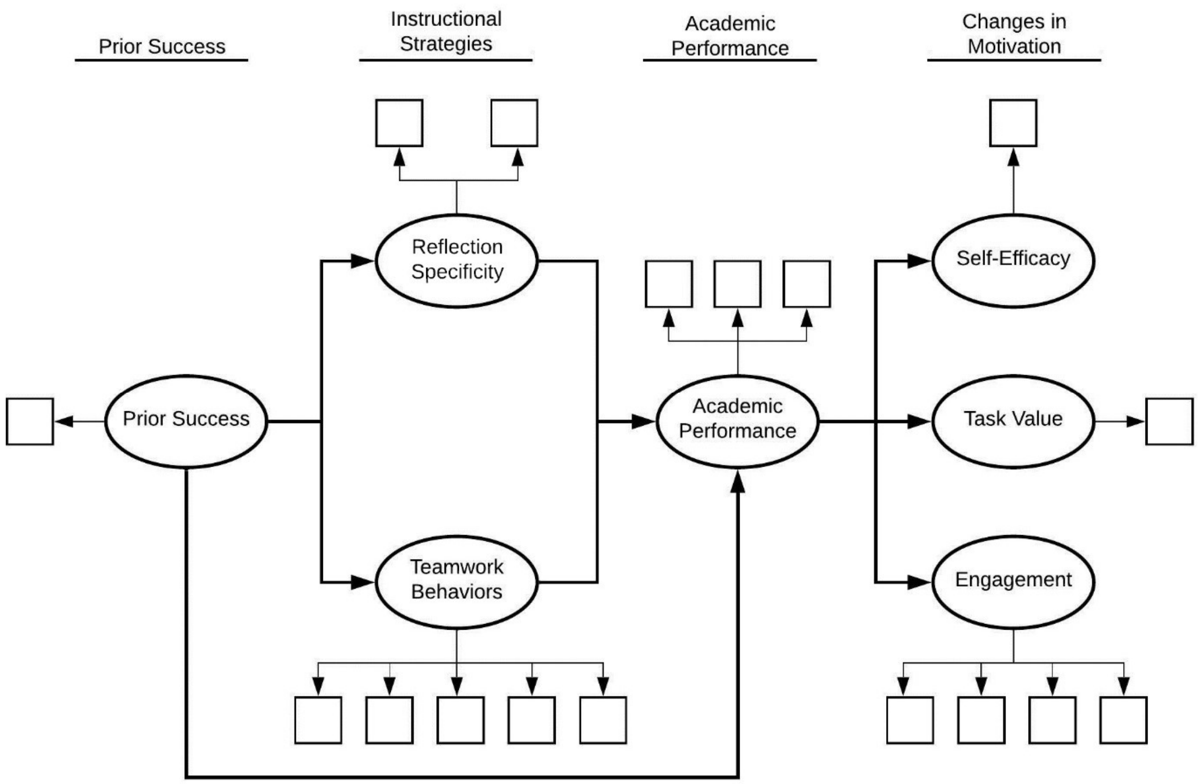

Figure 4.2. A theoretical hypothesized model depicting the relations between prior success, instructional strategies, academic performance, and changes in motivational constructs

In the hypothesized model, we have one exogenous variable (Prior Success) with one indicator and six endogenous variables. We classified these endogenous variables into three categories: 1) Instructional strategies, which include reflection specificity – 2 indicators, and teamwork behaviors – 5 indicators, 2) Academic performance – 3 indicators, and 3) Changes in motivational constructs, which includes changes in self-efficacy – 1 indicator, changes in task value – 1 indicator, and changes in engagement – 4 indicators to represent the four subscales of behavioral, emotional, social, and cognitive engagement with a total of 120 observations.

The preliminary analysis indicates that all the factor loadings, factor variances, covariance, and error variances were significant at $p < .05$. The test of the hypothesized model showed that general structure modeling was not a good fit. Although $\chi 2(114) = 265.743$, $p=0.000$, which is an indication of an adequate model, the goodness of fit indices indicates a non-adequate model. The Non-Normed Fit Index (NNFI) = 0.830, Incremental Fit Index (IFI) = 0.860, and Comparative Fit

Index (CFI) = 0.857 were less than 0.95 and not close to 0.90 needed for good fit of the model. Also, Root Mean Square Error of Approximation (RMSEA) = 0.105, and Standardized Root Mean Square Residual (SRMR) = 0.108, which were greater than the cutoff of 0.1, and indicates a need of modification in the model.

Based on the modification indices, and maximum modification index, we revised the model by estimating regression and error variances in five steps. Table 4.8 represents the changes at each step in the model.

Table 4.8. Results of the structural analyses for estimation at each step

Models Estimations	df	$\chi 2$	p	RMSEA	SRMR	CFI	IFI	NNFI
1. β (5,4)	113	219.716	<.001	0.0887	0.101	0.900	0.902	0.879
2. β (4,6)	112	197.608	<.001	0.0798	0.0743	0.919	0.921	0.902
3. Ɛ (3,6)	111	179.626	<.001	0.0718	0.0731	0.935	0.937	0.921
4. Ɛ (5,10)	110	167.935	<.001	0.0662	0.0726	0.945	0.947	0.933
5. β (5,6)	109	155.761	.002*	0.0598	0.0661	0.956	0.957	0.945

$p<0.05$

The re-specified fitted model, based on five estimations, indicates a good fit of the model. The $\chi 2(109) = 155.761$, p=0.002, which is an indication of an adequate and significant model. The goodness of fit indices also indicates a good model fit. The Non-Normed Fit Index (NNFI) = 0.945, Incremental Fit Index (IFI) = 0.957, and Comparative Fit Index (CFI) = 0.956, were greater than or close to 0.95 which is an indication of an excellent fit. The Root Mean Square Error of Approximation (RMSEA) = 0.0598 and Standardized Root Mean Square Residual (SRMR) = 0.0661, both were less than 0.08, which confirm the adequacy of the fitted model, without the need of further modification. The completely standardized regression coefficients are presented in Figure 4.3. Based on the five estimations, we included three new regression links in the hypothesized model. They are 1) from self-efficacy to task value, 2) from engagement to self-efficacy, and 3) from engagement to task value.

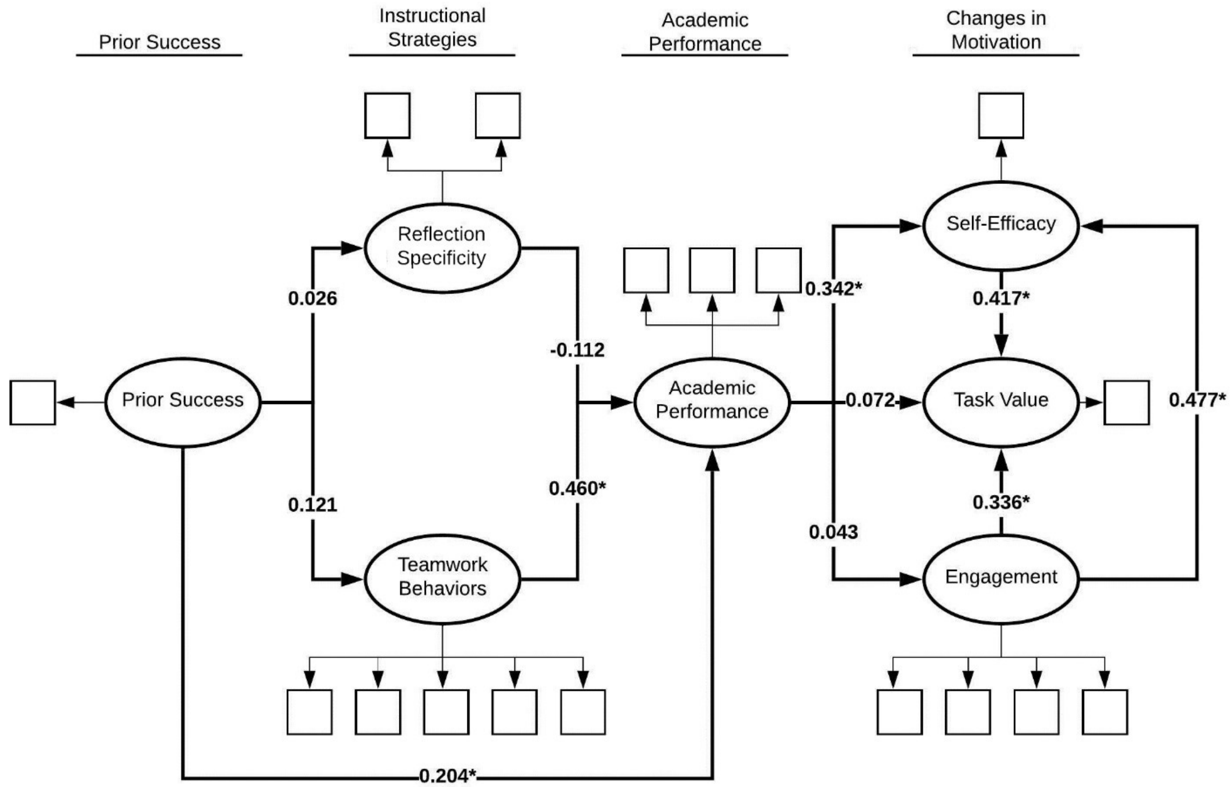

Figure 4.3. Structural model of instructional strategies in predicting students' academic performance, and changes in motivational constructs

As seen in Figure 4.3, there is no suppression effect in the model. Besides, it is essential to note the significant regression coefficients in Figure 4.3, denoted by *. The coefficient between prior success and academic performance is both positive and significant. This positive – significant regression coefficient indicates that the increase in prior success could increase the mean of academic performance. With a one-unit standardized increase in the prior success, while holding other variables constant in the model, the academic performance will increase by 0.204 units. Similarly, the regression coefficients between teamwork behaviors and academic performance are also both positive and significant, which indicates a positive correlation between the two. Also, one unit increase in teamwork behaviors accounts for a 0.460 increase in academic performance. One noteworthy aspect is that although teamwork behaviors accounted for some predictability for students' academic performance, the reflection specificity shows a non-significant relationship with academic performance.

It is also important to note that out of the three motivational changes (i.e., self-efficacy, task value, and engagement), the only significant relationship was between academic performance and the change in self-efficacy. The direction of this relationship is positive, which means that students who performed better have a greater change in self-efficacy beliefs. However, such a relationship cannot be established for changes in task value and engagement. It is also important to note that this relationship shows an indirect effect (Indirect effect = 0.167) of teamwork behaviors on changes in self-efficacy beliefs mediated through academic performance.

The model re-specification required estimation of three regression coefficients, and all of them are positive and significant. Changes in students' engagement are related to both task value and self-efficacy. Moreover, changes in self-efficacy are related to task value. Based on these estimations, we see an indirect effect of academic performance on task value (Indirect effect = 0.238) mediated through changes in self-efficacy. Also, there is an indirect effect of teamwork behaviors on changes in task value mediated through both academic performance and self-efficacy (Indirect effect = 0.109).

In addition to regression coefficients as depicted in Figure 4.3, please refer to Table 4.9 for parameter estimates of factor loadings, co-variances, and error variances based on the completely standardized solution.

Table 4.9. Parameters of SEM fitted model - Factor loadings, co-variances, and error variances

Var	PS	REF	TEAM	AP	SE	TV	ENG
	Factor Loadings						
PS1	1.000	--	--	--	--	--	--
POI	--	.404	--	--	--	--	--
MP	--	1.500	--	--	--	--	--
C	--	--	.958	--	--	--	--
I	--	--	.879	--	--	--	--
K	--	--	.917	--	--	--	--
E	--	--	.847	--	--	--	--
H	--	--	.886	--	--	--	--
Exam1	--	--	--	.748	--	--	--
Exam2	--	--	--	.795	--	--	--
Exam3	--	--	--	.647	--	--	--
SE1	--	--	--	--	1.000	--	--
TV1	--	--	--	--	--	1.000	--
ENG1	--	--	--	--	--	--	.630
ENG2	--	--	--	--	--	--	.651
ENG3	--	--	--	--	--	--	.585
ENG4	--	--	--	--	--	--	.760

	REF	TEAM	AP	SE	TV	ENG	PS
	Factor Co-variance						
REF	1.000	--	--	--	--	--	--
TEAM	.003	1.000	--	--	--	--	--
AP	-.105	.485	1.000	--	--	--	--
SE	-.035	.175	.362	1.000	--	--	--
TV	-.025	.115	.238	.608	1.000	--	--
ENG	-.005	.021	.043	.492	.544	1.000	--
PS	.026	.121	.257	.093	.061	.011	1.000

	POI	MP	C	I	K	E	H	Exam1	Exam2	Exam3	ENG1	ENG2	ENG3	ENG4
	Error Variances*													
	.837	-1.25	.082	.228	.159	.282	.216	.441	.368	.582	.603	.576	.657	.422
E			-.082											
Exam3					-.111									

Note: Completely standardized solution

Abbreviations are Prior Success (PS), Reflection (REF), Point of Interest (POI), Muddiest Point (MP), Teamwork Behaviors (TEAM), Contribution to teamwork (C), Interaction with teammates (I), Keeping the team on track (K), Expecting quality (E), Having relevant knowledge, skills, and abilities (H), Academic Performance (AP), Self-Efficacy (SE), Task Value (TV), Engagement (ENG).

** The matrix is diagonal*

Overall, these results indicate a positive and significant regression of prior success and teamwork behaviors with students' academic performance. Also, self-efficacy appeared as a mediator between academic performance and task value. Moreover, the academic performance showed to be a significant mediator between teamwork behaviors and changes in self-efficacy beliefs.

Discussion

We designed a semester-long study to investigate the role of instructional strategies on changes in students' motivational constructs (self-efficacy beliefs, task value, and engagement). We used self-regulated learning theory as a lens to design the study, choose the instructional strategies that could promote self-regulation by improving students' personal and social competence, and interpret results. The two chosen instructional strategies were reflecting on the learning experience and participation in teamwork. We observed students' behaviors in the activities associated with these learning strategies. Further, we chose the motivational constructs of students' self-efficacy beliefs, task value, and engagement. We used these constructs based on their connection with students' self-regulation skills and academic performance.

The first research question evaluated two aspects 1) direction of changes in students' motivational constructs, and 2) the unique role of instructional strategies in predicting those changes. The first aspect was based on existing studies which showed a mixed direction of change in students' motivational constructs when engaged in instructional strategies based activities (e.g., Jones et al., 2010; Maricuțoiu & Sulea, 2019; Meece et al., 1990; Papinczak et al., 2008). We measured the change in student self-efficacy, task value, and engagement from the beginning of the semester to the end of the semester. In the case of first-year engineering students, we observed a decline in students' motivational constructs of self-efficacy; task value; and behavioral, emotional, cognitive engagement. These results are noteworthy as we engaged students in student-centered learning strategies (i.e., reflective thinking and teamwork behaviors) where these strategies targeted to improve self-regulation in students. However, these results are contrary to some studies on self-efficacy and task value, which shows improved motivation (e.g., Maricuțoiu & Sulea, 2019; Meece et al., 1990). Schaffer, Chen, Zhu, & Oakes (2012) suggested that students show improved motivation (particularly self-efficacy) if they have a positive experience; otherwise, a stressful experience could lead to a decline. Consequently, in this study, the reasons for such a decline in motivation could be related to not fulfilling students' expectations about the course. In general, students when come to engineering discipline, they have higher level of motivation (Geraedts, van de Groep, & Hueting, 2015). These higher levels of motivation could be due to their performance in high school, getting higher scores in standardized tests, and getting admission to one of their top choice university. However, the course content (e.g., programming concepts) could be challenging for them. The intrinsically hard nature of programming concepts (Guzdial, 2004), inability to solve problems, and not being able to see the relevance of the course with their future goals or major could cause frustration and stress in students.

In addition to students' expectations, experience in the course and instructional strategies could be another reason for the decline in motivation. Most first-year engineering courses focus on engaging students in teamwork behaviors or other student-centered learning strategies. Students with variant learning styles and not understanding its impact on their learning could find teamwork as irrelevant and difficult to manage (Nordstrom & Korpelainen, 2011). Such students can also question their individual learning in the course and may experience negative feelings. These results require the investigation of students' experiences in such strategies. Future investigations are essential to explore whether participation in such activities causing stress or frustration for students? This literature evidence leads to another vital question, which strategies are more effective and less stressful for students?

The above question led us to the second aspect of this question, where we investigated the unique contribution of two instructional strategies on predicting changes in students' motivational constructs while accounting for their prior success. Although previous studies and Bandura's framework for self-efficacy beliefs sources (Bandura, 1997) have indicated that students' past performance or success can be the most influential source (Hutchison et al., 2006), our results showed that teamwork behaviors accounted for the most variance in predicting the changes in students' self-efficacy beliefs, task value, engagement (except cognitive engagement). Student reflection specificity accounted for the second-most variance for changes in self-efficacy, task value, and emotional engagement. For changes in cognitive engagement, students' prior success appeared as the most significant predictor. Besides, the results also confirmed the negative relationship of task value with student's prior success (Eccles et al., 1983).

The design of the above question and literature-based evidence led us to answer the second question of investigating the relationships between instructional strategies, students' academic performance, and changes in motivational constructs. We used SEM analysis using the full model approach. The results indicate that students' prior success and teamwork behaviors are the significant predictors of students' academic performance. Also, teamwork behaviors have a mediated path to predicting changes in students' self-efficacy beliefs through academic performance. Findings show that academic performance has a positive path towards predicting change in students 'self-efficacy beliefs and mediated paths to predict changes in task value. These results are interesting as two of the four sources that influence self-efficacy beliefs (Bandura & Schunk, 1981) and based on interactions and social experience, i.e., vicarious experience and verbal persuasions. Vicarious experiences and both verbal and social persuasions suggest an influential role of peers in students' self-efficacy beliefs. Although more studies are required to understand the role of independent sources, this study confirms that teamwork behaviors can be an influential source of students' self-efficacy beliefs. Another noteworthy aspect is that students' prior success also showed a significant indirect effect on changes in students' self-efficacy beliefs. This indirect outcome confirms that students' mastery experiences (another influence source) can gauge students' self-efficacy beliefs. In addition to teamwork, changes in engagement predict both changes in self-efficacy and changes in task value positively.

Collectively when studied the unique contribution of instructional strategies on predicting changes in students' motivation, reflection specificity accounted for some variance for changes in self-efficacy, task value, and emotional engagement. However, the results of the SEM analysis showed contradictory results, and no direct relationship could be established. We looked for the indirect effect of reflection specificity in predicting these three changes and found very minimal and negative indirect effects (Indirect effects = -0.040, -0.027, -0.003, respectively). These results indicate the need for further evaluations as literature shows that failure of an outcome in motivational constructs can be associated with students' emotional state and stress.

These results are novel, as no previous study has studied the simultaneous role of two instructional strategies on students' academic achievement and academic performance in a single engineering class.

Limitations and future directions

Based on the discussion of the results, the study has several limitations and corresponding future directions. First, the study has collected the data from one section of a first-year engineering class, which resulted in a relatively small sample size. Although the data was collected on multiple constructs and shows ample power to conduct valid and reliable analysis, however, future studies can focus on a larger sample size in multiple classrooms to increase generalizability and statistical power. Future studies could also focus on multi-institutional data to have ample diverse samples for such investigations.

Second, as the focus of this study was on instructional strategies participation, we did not investigate the direct effect of predicting academic performance using motivational constructs. A future study can be designed to focus precisely on the role of motivational constructs to predict engineering students' academic performance, specifically with a four-dimensional engagement construct.

Also, although we choose the instructional strategies under the premise of self-regulation learning, it would have been a good addition to have data on students' self-regulation process using MSLQ scales. This would have helped us to see the impact of these instructional strategies on students' self-regulation. A future study could be designed to investigate the direct impact of students' participation in instructional strategies and their self-regulation measures.

Besides, although we collected the data of students' participation in instructional strategies at various time points, we did not account for time-based analysis. A future study may use a time series analysis for time-based variations in the data set.

Although we formed our hypothesized SEM model based on literature and temporal evidence, however, another aspect of research could be on evaluating other full models using SEM analysis. For example, we could use the student' pre-motivational constructs in predicting their academic performance (see chapter 5) or post motivational constructs. As we see in an analysis that changes in engagement predict changes in students' self-efficacy beliefs and task value, a future model could investigate the relationship between different motivational constructs.

In this study, we heavily relied on surveys and students' self-reported evidence of self-efficacy, task value, and engagement. We did not include any process data such as classroom observation for triangulation of our results. A future investigation may include an in-depth analysis of process data, especially related to students' engagement and behaviors in student-centered learning strategies. Such analysis may help us to understand students' resistance or stress factors.

Conclusion

This study examined the potential influence of two instructional strategies on students' academic performance and changes in self-efficacy, task value, and engagement. Given the uniqueness of introducing two instructional strategies simultaneously in the model, this study is the first one that tested the relational pattern of the variables mentioned above collectively using hierarchical and simultaneous regression, and as a full model using SEM analysis.

Overall, this study provides unique and valuable information in the context of engineering students. The results are evidence of several positive outcomes and implications. First, being the first study that investigates the role of multiple instructional strategies the study highlights the questions on the design of learning environment in first-year engineering courses including 1) which strategies are more suitable for students' learning, and 2) to what extent we ask students to participate in activities related to such strategies which do not result in fear or stress for the students. Second, the study confirms the decisive role of teamwork behaviors and students' prior success in predicting students' academic performance for engineering students. Third, the study informs that even with multiple instructional strategies, students' teamwork behaviors account for most variability in predicting students' academic performance, which also confirms that interactive activities lead to better academic performance (Chi, 2009; Menekse et al., 2013). Fourth, the study showed that teamwork behaviors

also accounts for positive and significant variance in predicting changes in students' self-efficacy beliefs through the mediating role of academic performance. Fifth, the study showed that while reflection specification accounts for some variance to predict changes in self-efficacy, task value, and emotional engagement, when put in the collective model, these results do not hold. Fifth, the study showed that changes in students' engagement could predict the variance in the change of self-efficacy and task value beliefs.

The combined analysis of self-efficacy, task value, engagement, instructional strategies, and academic performance provides an initial analysis of their relationships. However, many aspects of these results indicate the need for more studies in the context of the relative effectiveness of different instructional strategies on engineering students' motivation and performance.

CHAPTER 5. **FURTHER ANALYSIS**

In this further analysis section, the focus is on addressing the following research question: RQ1: How do students' self-efficacy beliefs, task value, and engagement are related and predict students' participation in instructional strategies and academic performances?

Procedure and data analysis

Before analyzing the data, I reverse coded all the negatively worded items (~10 items). Further, I evaluated the issues related to outliers, skewness, kurtosis, multi-collinearity, singularity, and missing data. For all the surveys, all three measures of central tendency mean, median, and mode were roughly the same for all the aspects, and no outlier was found. Skewness and kurtosis values were below or close to 1, which indicated no issues on skewness and kurtosis. Also, the r values between various aspects were less than .90, which indicated no multicollinearity or singularity issues between constructs. As the data had less than 5% missing values, I used the mean imputation method to replace the missing values before conducting the analysis.

To address the research questions, I conducted structural equation modeling (SEM) analysis using a full model method between students' surveys of motivational constructs, instructional strategies, and exam scores while accounting for students' prior success. I used all three exams as a measure of students' academic performance. I explored a general structural equation model based on the correlation matrix and examined results on variance and covariance estimations. I considered multiple goodnesses of fit indices to evaluate the fitness of the model, which include Root Mean Square Error of Approximation (RMSEA), Comparative Fit Index (CFI), and Incremental Fit Index (IFI). As the data had less than 5% missing values, I used the mean imputation method to replace the missing values before conducting the analysis.

For this analysis, I looked for the adequacy of sample size on the criteria of using a ratio of 5 -10 cases per variable where variables can have multiple indicators (Bentler & Chou, 1987; Nunnally & Bernstein, 1967). As I considered the four scales of engagement as different latent variables, and I have a total of 10 latent variables, which requires 50 – 100 students' responses to conduct a reliable SEM analysis. A sample of 120 students gives an adequate sample size for this SEM analysis.

I used LISREL 10.20 to conduct the CFA and SEM analysis of the data using a 95% confidence interval. Also, I used IBM SPSS Statistics (v.26) to conduct reliability, correlation, descriptive statistics.

In this analysis, I used students' self-reported motivation in pre surveys to assess the relationship between the motivational constructs and their effect on students' participation in instructional strategies and academic performances. For using the valid and parsimonious analysis, I prepared the data based on the results of multiple fitted models. I converted the data into a parsimonious model by dropping or combining the highly dependent indicators (parcels) for the latent variables. These forms of composite indicators have been widely used in existing literature (e.g., Byrne, 1998; Deci & Ryan, 2002; Levesque, Zuehlke, Stanek, & Ryan, 2004) and is considered as a valid procedure for more parsimonious model fitting (e.g., Vallerand, 1997). I used the revised engagement factors based on the re-specified CFA model (see Appendix B). Based on the fittings for the parsimonious models, there was no change made to behavioral engagement, cognitive engagement, reflection, and academic performance indicators. However, I made following changes to the indicators of the other factors:

1) Prior success – I kept the single indicator. However, being the exogenous variable with one indicator in the model, I modeled it by fixing the factor loading to one, and error variance to zero.
2) Self-efficacy – I converted into three indicators by combining the fourth and fifth indicators into one indicator and dropping the third indicator based on its high dependency with other indicators.
3) Task value – I converted into three indicators by combining the first and fourth indicators and combining the third and fifth indicators. Besides, I dropped the second indicator.
4) Emotional engagement – I converted into three indicators by combining first, fifth, and sixth indicators.
5) Social engagement – I converted into four indicators by dropping the fifth indicator.
6) Teamwork behaviors – I converted into two indicators by combining I and H dimensions. I also dropped the C and K dimensions from the SEM analysis.

Results

RQ1: How do students' self-efficacy beliefs, task value, engagement, instructional strategies, and academic performance are related?

To answer the question and broadly assess the relationships between the prior success, pre-motivational constructs (self-efficacy beliefs, task value, and engagement), instructional strategies participation, and engineering students' academic performances, I tested a general structural equation model (SEM) using the full model approach. The SEM was based on variance and covariance matrices estimation, and all variables of interest were evaluated simultaneously (Byrne, 1998).

At first, I calculated the descriptive statistics and factor reliabilities of the data for the constructs of the survey are presented in Table 5.1. The factor reliabilities were calculated using Cronbach's alpha. The descriptive statistics are based on item-based statistics.

Table 5.1. Descriptive statistics of the pre-motivational, instructional strategies, and achievement constructs based on the parsimonious model

Constructs	Reliability	Mean	Variance	Min	Max
Self-efficacy	.825	4.823	.013	4.696	4.911
Task Value	.820	4.826	.072	4.518	5.009
Engagement					
Behavioral	.782	5.251	.016	5.062	5.381
Emotional	.801	4.375	.159	3.929	4.690
Social	.709	5.014	.031	4.797	5.177
Cognitive	.697	5.119	.006	5.027	5.212
Reflection	.747	2.811	.002	2.781	2.842
Teamwork	.886	4.066	.000	4.060	4.073
Academic Performance	.754	94.484	51.265	87.380	101.699

I formed the hypothesized model based on the temporal and research-based evidence, as presented in Figure 5.1. For example, Liem, Lau, & Nie, (2008) used students' prior achievement score both as a controlling factor and predecessor to establish the relationship of students' self-efficacy and task value beliefs with their achievement outcomes (also see Eccles & Adler, 1983; Zimmerman et al., 1992). Also, their hypothesized and fitted model suggested a partial mediation relationship between students' engagement/disengagement and their self-efficacy and task value to predict achievement outcomes (also see Jones, Johnson, & Campbell, 2015). I used temporal (i.e., time of occurrence of the two strategies) evidence to place the two instructional strategies in the model. Also, I wanted to see the results of directly predicting students' academic performance using their participation behaviors in the instructional strategies. I used structural equation modeling (SEM) and assessed how well this hypothesized model fits the data from a sample of first-year engineering students in the context of performance in a required engineering course.

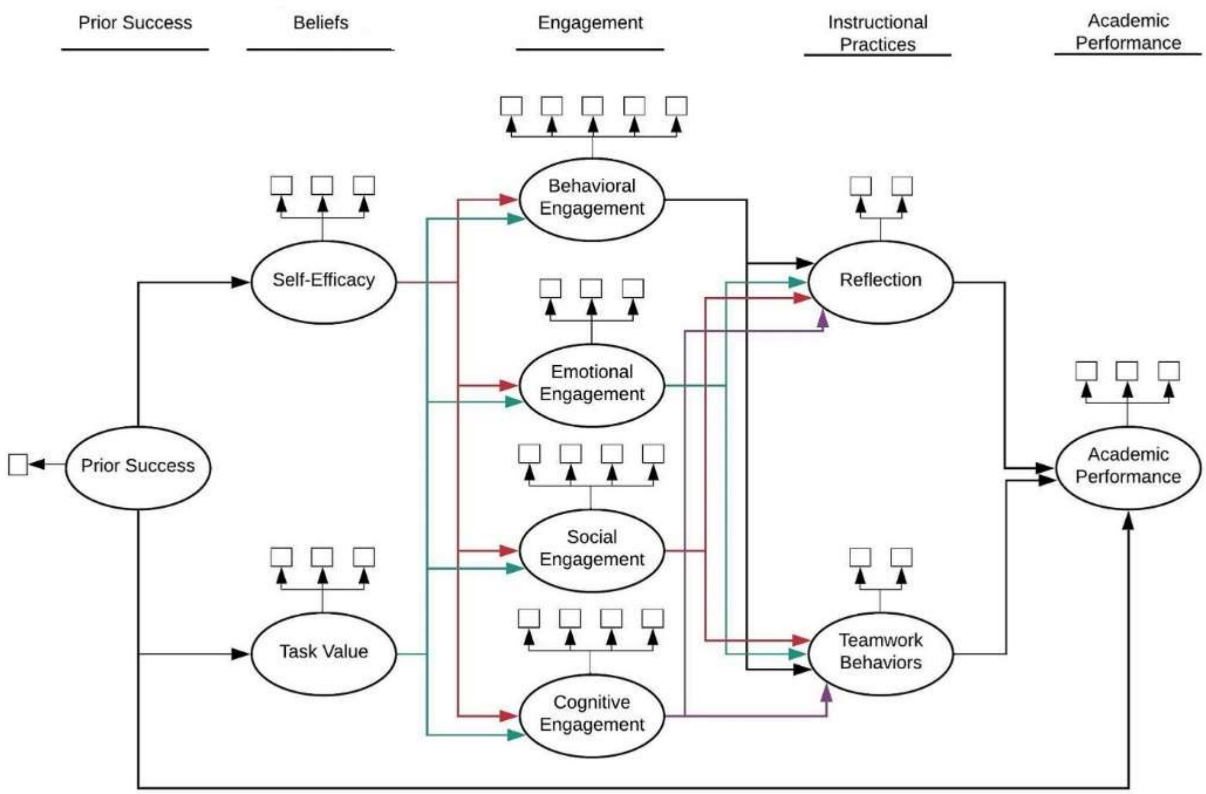

Figure 5.1. A theoretical hypothesized model depicting the relations between prior success, task value, self-efficacy, engagement, instructional strategies, and academic performance

In the hypothesized model, I have one exogenous variable (Prior Success) with one indicator and nine endogenous variables. I classified these endogenous variables into four categories: 1) Expectancy beliefs, which includes self-efficacy – 3 indicators, and task value – 3 indicators. 2) An engagement that includes four subscales of behavioral – 5 indicators, emotional – 3 indicators, social – 4 indicators, cognitive engagement – 4 indicators. 3) Instructional strategies, which include reflection – 2 indicators, and teamwork behaviors – 2 indicators. 4) Academic performance – 3 indicators with a total of 120 observations.

The preliminary analysis indicates that some factor loadings were non-significant. However, all the factor variances, covariance, and error variances (except for teamwork behaviors1) were significant at $p < .05$. The test of the hypothesized model showed that general structure modeling was not a good fit. Although $\chi2(385) = 779.330$, p=0.000, which is an indication of an adequate model, the goodness of fit indices indicates a non-adequate model. The Non-Normed Fit Index (NNFI) = 0.724, Incremental Fit Index (IFI) = 0.763, and Comparative Fit Index (CFI) = 0.756 were less than 0.90 and not even close to 0.85. Although Root Mean Square Error of Approximation (RMSEA) = 0.0924, which was less than the cutoff of 0.1, Standardized Root Mean Square Residual (SRMR) = 0.178, which indicates a need of modification in the model.

Based on the modification indices, and maximum modification index, I revised the model by estimating regression and error variances in ten steps. In each step, I looked for the modification that causes maximum modification without changing the structure of the model-based n completely standardized solution. Table 5.2 represents the changes at each step in the model.

Table 5.2. Results of the structural analyses for estimation at each step

Models Estimations	df	χ2	p	RMSEA	SRMR	CFI	IFI	NNFI
β (2,5)	384	658.698	<.001*	0.0772	0.0855	0.830	0.835	0.807
Ɛ (22,12)	383	642.970	<.001*	0.0752	0.0848	0.839	0.844	0.817
Ɛ (15,13)	382	629.871	<.001*	0.0735	0.0825	0.847	0.851	0.825
Ɛ (17,16)	381	618.747	<.001*	0.0721	0.0802	0.853	0.858	0.832
Ɛ (18,11)	380	606.129	<.001*	0.0704	0.0809	0.860	0.865	0.840
Ɛ (22,3)	379	589.631	<.001*	0.0681	0.0801	0.870	0.874	0.850
Ɛ (6,3)	378	580.571	<.001*	0.0668	0.0815	0.875	0.879	0.856
Ɛ (20,9)	377	560.655	<.001*	0.0637	0.0817	0.886	0.890	0.869
Ɛ (5,4)	376	547.997	<.001*	0.0617	0.0803	0.894	0.897	0.877
Ɛ (5,3)	375	540.365	<.001*	0.0606	0.0794	0.900	0.903	0.881

*$p<0.05$

The re-specified fitted model, based on ten estimations, indicates a good fit of the model. The $\chi2(375) = 540.365$, $p<0.001$, which is an indication of an adequate and significant model. The goodness of fit indices also indicates a good model fit. The Non-Normed Fit Index (NNFI) = 0.881, Incremental Fit Index (IFI) = 0.903, and Comparative Fit Index (CFI) = 0.900, were greater than or close to 0.90 which is an indication of an adequate fit. The Root Mean Square Error of Approximation (RMSEA) = 0.0606 and Standardized Root Mean Square Residual (SRMR) = 0.0794, both were less than 0.08, which confirm the adequacy of the fitted model, without the need of further modification. The completely standardized regression coefficients are presented in Figure 5.2.

As seen in Figure 5.2, the regression coefficient between self-efficacy beliefs and engagement constructs are positive and significant. Although the regression coefficients between task value and engagement constructs are significant, they are negative. This negative relationship could mean two things that 1) when students report higher task value, their engagement declines, or 2) the direction of the relationship is opposite, which means that engagement impacts task value positively, while task value negatively impacts engagement. This relationship is also confirmed with the estimated regression coefficient between social engagement and task value. This estimated regression is positive and significant, which indicates that an increase in social engagement, positively impacts students' task value. Also, these values are higher than 1.00 indicates a suppression effect in the model due to self-efficacy beliefs and task value. For both task value and self-efficacy, they probably covary highly with other predictors and shares the predicted variability, which is reflected through the suppression effect.

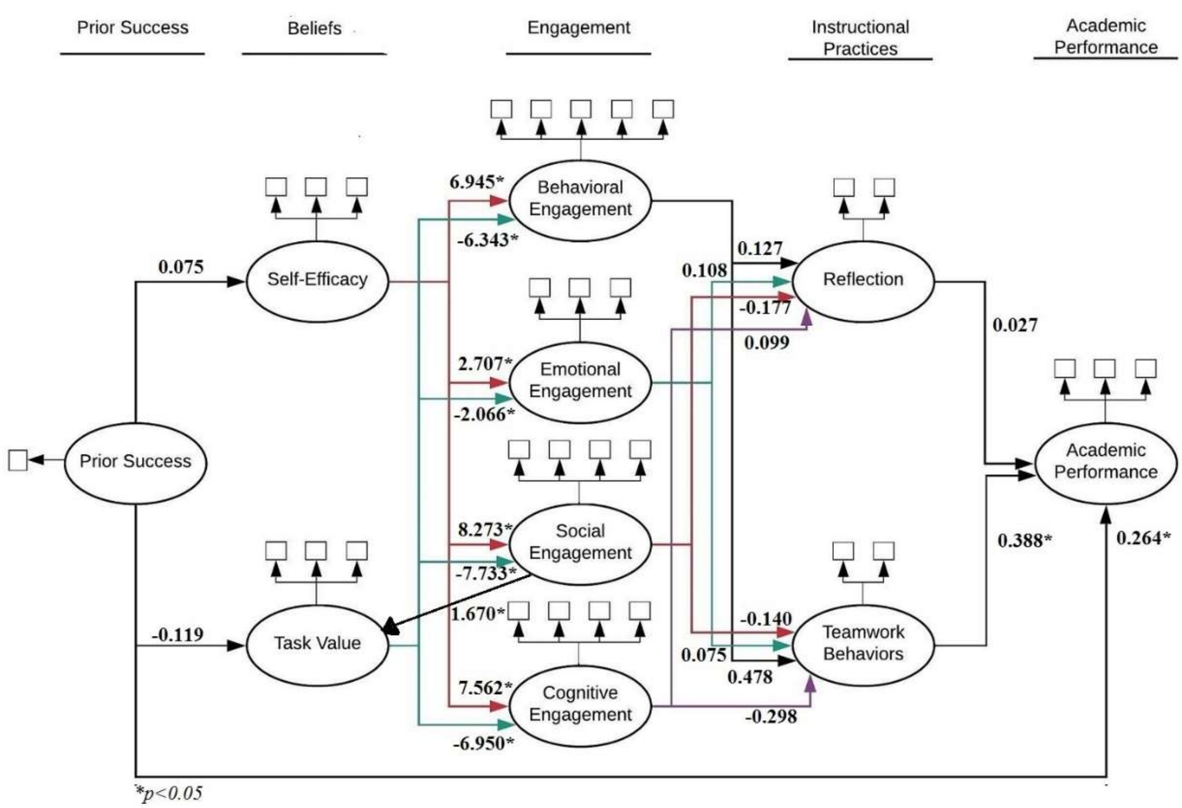

Figure 5.2. Structural model of self-efficacy, task value, engagement, instructional strategies in predicting students' academic performance

Also, for task value, the opposite direction of balance (as estimated between social engagement to task value) could cause the true negative indirect effects and hence is represented by the suppression. Two important and significant regression coefficients need to be noted 1) regression between teamwork behaviors and students' academic performance, and 2) students' prior success and academic performance. Although, as predicted, teamwork behaviors show a positive regression with academic performance, the regression between reflection and academic performance are non-significant. Please refer to Table 5.3 and Table 5.4 for parameter estimates of factor loadings, covariance, and error variances based on the completely standardized solution.

The results indicate that students' prior success and teamwork behaviors are a significant predictor of students' academic performance. Findings show that self-efficacy has a positive path towards predicting students' teamwork behaviors, and reflection behaviors, while task value indicates a negative path towards both instructional strategies. These results confirm the existing studies' results on self-efficacy beliefs, where self-efficacy was found to predict some team behaviors (Purzer, 2011). Also, students' engagement showed a mediation, while students' self-efficacy and task value showed a suppression effect on students' participation in the instructional strategies and eventually on their academic performance. This suppression effect indicates that both of these constructs as a precursor increases the predictive validity of other variables in the model. The simultaneous nature of analysis indicates that the engagement has a negative relationship with task value. However, engagement acts as a mediator between students' self-efficacy beliefs, participation in instructional strategies activities, and academic performance. Another noteworthy aspect is the nature of the relationship between engagement and instructional strategies. The most surprising negative relationship was between social engagement and teamwork behaviors, which indicated that where students reported more social engagement, the peer evaluation indicated poor participation of the team members. Similarly, students' cognitive engagement has a negative relationship with both instructional strategies. Overall, these results indicate a positive and significant regression of prior success and teamwork behaviors with students' academic performance.

These results are novel, as no previous study has studied the simultaneous role of two instructional strategies on both students' motivation and academic achievement in a single engineering class.

Table 5.3. Factor loadings and covariance of the fitted SEM model

	Factor Loadings									
Var	PS	SE	TV	BEH	EMO	SOC	COG	REF	TEAM	AP
PS1	1.000	--	--	--	--	--	--	--	--	--
SE1	--	.710	--	--	--	--	--	--	--	--
SE2	--	.789	--	--	--	--	--	--	--	--
SE3	--	.820	--	--	--	--	--	--	--	--
TV1	--	--	.615	--	--	--	--	--	--	--
TV2	--	--	.697	--	--	--	--	--	--	--
TV3	--	--	.827	--	--	--	--	--	--	--
BEH1	--	--	--	.634	--	--	--	--	--	--
BEH2	--	--	--	.741	--	--	--	--	--	--
BEH3	--	--	--	.694	--	--	--	--	--	--
BEH4	--	--	--	.517	--	--	--	--	--	--
BEH5	--	--	--	.634	--	--	--	--	--	--
EMO1	--	--	--	--	.833	--	--	--	--	--
EMO2	--	--	--	--	.786	--	--	--	--	--
EMO3	--	--	--	--	.659	--	--	--	--	--
SOC1	--	--	--	--	--	.635	--	--	--	--
SOC2	--	--	--	--	--	.557	--	--	--	--
SOC3	--	--	--	--	--	.528	--	--	--	--
SOC4	--	--	--	--	--	.618	--	--	--	--
COG1	--	--	--	--	--	--	.715	--	--	--
COG2	--	--	--	--	--	--	.543	--	--	--
COG3	--	--	--	--	--	--	.545	--	--	--
COG4	--	--	--	--	--	--	.583	--	--	--
POI	--	--	--	--	--	--	--	1.381	--	--
MP	--	--	--	--	--	--	--	0.453	--	--
TEAM1	--	--	--	--	--	--	--	--	1.045	--
TEAM2	--	--	--	--	--	--	--	--	.759	--
Exam1	--	--	--	--	--	--	--	--	--	.751
Exam2	--	--	--	--	--	--	--	--	--	.761
Exam3	--	--	--	--	--	--	--	--	--	.670

	Factor Co-variance								
	SE	TV	BEH	EMO	SOC	COG	REF	TEAM	AP
SE	1.000	--	--	--	--	--	--	--	--
TV	.992	1.000	--	--	--	--	--	--	--
BEH	.652	.549	1.000	--	--	--	--	--	--
EMO	.656	.620	.629	1.000	--	--	--	--	--
SOC	.599	.515	.897	.558	1.000	--	--	--	--
COG	.666	.553	1.112	.658	.954	1.000	--	--	--
REF	.114	.101	.147	.154	.092	.143	1.000	--	--
TEAM	.078	.072	.068	.102	.046	.149	.026	1.000	--
AP	.053	.048	.057	.061	.049	.090	.040	.391	1.000
PS	.075	.065	.102	.066	.110	.109	.012	.006	.267

Note: Completely standardized solution

Abbreviations are Prior Success (PS), Self-Efficacy (SE), Task Value (TV), Behavioral Engagement (BEH), Emotional Engagement (EMO), Social Engagement (SOC), Cognitive Engagement (COG), Reflection (REF), Point of Interest (POI), Muddiest Point (MP), Teamwork Behaviors (TEAM), Academic Performance (AP). The numbers corresponding indicate the used parcel

Table 5.4. Error variances of the fitted SEM model

Var	SE1	SE2	SE3	TV1	TV2	TV3	BEH1	BEH2	BEH3	BEH4	BEH5	EMO1	EMO2	EMO3	SOC1	SOC2	SOC3	SOC4	COG1	COG2	COG3	COG4	POI	MP	TEAM1	TEAM2	Exa m1	Exa m2	Exa m3
SE1	0.5	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--
SE2	--	0.38	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--
SE3	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--
TV1	--	--	--	0.62	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--
TV2	--	--	--	0.23	0.51	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--
TV3	--	--	--	--	--	0.32	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--
BEH1	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--
BEH2	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--
BEH3	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--
BEH4	--	--	--	--	--	--	--	--	--	0.738	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--
BEH5	--	--	--	--	--	--	--	--	--	--	0.598	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--
EMO1	--	--	--	--	--	--	--	--	--	--	--	0.306	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--
EMO2	--	--	--	--	--	--	--	--	--	--	--	--	0.383	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--
EMO3	--	--	--	--	--	--	--	--	--	--	--	--	--	0.565	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--
SOC1	--	--	--	--	--	--	--	--	--	--	--	--	0.17	--	0.597	--	--	--	--	--	--	--	--	--	--	--	--	--	--
SOC2	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	0.689	--	--	--	--	--	--	--	--	--	--	--	--	--
SOC3	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	0.252	0.721	--	--	--	--	--	--	--	--	--	--	--	--
SOC4	--	--	--	--	--	--	--	--	--	--	0.193	--	--	--	--	--	--	0.618	--	--	--	--	--	--	--	--	--	--	--
COG1	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	0.489	--	--	--	--	--	--	--	--	--	--
COG2	--	--	--	--	--	--	--	--	0.168	--	--	--	--	--	--	--	--	--		0.705	--	--	--	--	--	--	--	--	--
COG3	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	0.703	--	--	--	--	--	--	--	--
COG4	--	--	0.18	--	--	--	--	--	--	--	--	0.209	--	--	--	--	--	--	--	--	--	0.66	--	--	--	--	--	--	--
POI	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	-0.91	--	--	--	--	--	--
MP	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	0.795	--	--	--	--	--
TEAM1	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	-0.092	--	--	--	--
TEAM2	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	0.424	--	--	--
Exam1	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	0.44	--	--
Exam2	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	0.41	--
Exam3	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	0.55

Note: Completely standardized solution

Abbreviations are Prior Success (PS), Self-Efficacy (SE), Task Value (TV), Behavioral Engagement (BEH), Emotional Engagement (EMO), Social Engagement (SOC), Cognitive Engagement (COG), Reflection (REF), Teamwork Behaviors (TEAM), Academic Performance (AP). The numbers corresponding indicate the used parcel

CHAPTER 6. **DISCUSSION AND CONCLUSION**

Overview and summary

This dissertation includes three inter-related studies that together describe the role of instructional strategies on students' performance and motivational constructs. Each study determined relationships between students' participation in instructional activities, students' self-reported motivation, and students' academic performance. Each chapter of this dissertation provided a unique insight into the role and relationship between these sources of information. Accordingly, the combined results of all three studies elaborate on the full picture on the relationships and role of multiple instructional strategies, and multiple motivational constructs.

The theoretical foundation of self-regulated learning and the ICAP framework guided this dissertation study. The self-regulated learning provided the lens to select the instructional strategies under the premise of engaging students that promote both personal and social competence. Besides, the ICAP framework suggests that interactive activities could promote better learning and behaviors than constructive activities (Chi, 2009; Chi & Wylie, 2014). Based on these two lenses, I selected the strategies of reflective thinking (personal competence, can be classified as constructive based on the ICAP framework), and teamwork behaviors (social competence, can be classified as interactive based on the ICAP framework). The reflective thinking participation was determined based on the evaluation of the reflection specificity, while teamwork behaviors were based on peer evaluation of team members of each student.

Further, self-regulated learning also helped in deciding the key motivational constructs. Students' motivational processes play a pivotal role in guiding students' efforts and participation to self-regulate their learning (Zimmerman & Schunk, 2008). I selected the motivational constructs that have literature evidence to be in a strong relationship with self-regulated learning. The motivational constructs are self-efficacy, task value, achievement goals, and engagement. These constructs have evidence to be associated with self-regulated learning in four possible functional ways 1) as a precursor, 2) as a mediator, 3) as a concomitant outcome, 4) direct outcome (Zimmerman & Schunk, 2008). It is also noteworthy that the prior research studies suggested that self-regulation processes and instructional strategies require additional time and effort from students. It is thus important that the instructor involves students through diligent practice in required tasks so to motivate students (especially passive learners) to spend that extra effort (Zimmerman & Schunk, 2008). In these semester-long studies, students were asked to participate in reflective thinking activity multiple times during the course (after each class for study 1, and 26 times for study 2 & 3). Further, students evaluated their team members four times in the semester (study 2, and 3).

In this chapter, I am providing a summary of each study individually. Further, I am discussing the future directions of the research, and conclusion.

Study 1: Relationship between motivation and instructional strategy

This exploratory study investigated the relationship between instructional strategy (i.e., reflective thinking) and a motivational construct (i.e., self-efficacy). Further, the study also investigated their collective effect on predicting students' academic learning outcomes.

The analysis was conducted in two stages. At first, the analysis was conducted to understand the relationship between self-efficacy and reflections by using Pearson product-moment correlation. Coefficients were computed between reflections scores (aka reflection specificity) from two aspects (i.e., muddiest point, and point of interest), the number of reflections submitted by each student, and self-efficacy score. The correlations between self-efficacy score and number of reflections; and MP quality score and POI quality score were significant.

In addition to correlations, multiple linear regression was performed with four predictor variables such as self-efficacy score, POI quality score, MP quality score, and the number of reflections. The students' learning outcomes score was the dependent variable. POI quality score was excluded from the model based on the stepwise regression method to explore the best combination of predictors. The results indicated that 62% variance of the learning outcomes could be accounted for by the linear combination of the predictors. Further, all the bivariate and partial correlations found significant in the analysis.

Overall, these results indicated that students' perceptions of their efficacy are related to their reflection specificity. However, it is important to understand these relationships with other motivational constructs and also with more than one instructional strategy.

Study 2: Unique contribution of instructional strategies on motivation and performance

In this study, the focus was on identifying the unique contributions of students' participation in different instructional strategies (i.e., individual reflections and teamwork) while predicting their academic performance and changes in achievement goals. The goal was approached using two dimensions of analysis 1) the analysis was conducted to determine the changes and direction of change in both instructional strategies participation, and achievement goals, 2) measure the relative and unique contribution of each strategy while accounting for students' prior success on both performance and achievement goals.

To answer the first dimension, repeated measures ANOVAs were conducted, which indicate that both students' reflection specificity and teamwork behaviors improved over time in a semester. The results indicate that the diligent practice of participating in activities helps students to show improved participation in both teamwork behaviors and reflection writing. However, there was a non-significant difference from pre to post in performance-approach and performance-avoidance goals. Also, there was a significant decline in students' mastery approach. These results indicate that keeping other non-studied factors constant; there is an effect of self-regulated interventions on students' achievement goals. Besides, the results also indicate that students' self-regulatory processes and motivation are associated, and in this case, they may have an indirect or conflicting relationship (Zimmerman & Schunk, 2008). These results guided the need for understanding these relationships with other motivational constructs.

For the second dimension of understanding the unique contribution of instructional strategies, I used step-wise hierarchical and simultaneous regression analyses. The results indicate that students' teamwork participation behaviors were the strongest predictors of their academic performance in the exams. Also, teamwork behavior had a better contribution than other constructs in predicting students' approach (mastery and performance) goals. Reflection specificity was a better predictor of students' avoidance goals. These results confirm the ICAP hypothesis that interactive activities play a significant contribution in predicting students' learning and behavior than constructive activities. Besides, as approach goals orientations focus on mastering task and learning, teamwork participation can be associated with students' understanding and mastering. Similarly, reflective thinking and understanding muddiest and interesting concepts of lectures can help to understand students' reasons for avoiding learning or misunderstandings in general.

Overall the study informed the unique contribution of each instructional strategy on one motivational construct, i.e., achievement goals. However, this study also set the stage of another study to understand these relationships for multiple motivational constructs.

Study 3: Role of instructional strategies on motivation and performance

The focus of the third study is to understand the role of two instructional strategies on students' academic performance and changes in multiple motivational constructs. The motivational constructs include students' self-efficacy beliefs, task value, and engagement. I approached this study using three forms of analysis 1) the analysis was conducted to determine the changes and direction of change in both instructional strategies participation, and motivational constructs, 2) measure the relative and unique contribution of each strategy while accounting for students' prior success on changes in motivational constructs, and 3) understanding relationships between these constructs when studied collectively.

For the first form of analysis, I conducted repeated-measures ANOVAs. Although there was a non-significant difference from pre to post in social engagement, there was a significant decline from pre to post in self-efficacy, task value, behavioral engagement, emotional engagement, and cognitive engagement. Similar to achievement goals (as discussed in study 2), these results indicate that there was a change in students' motivational constructs from pre to post. This result led me to understand this relationship further. For more elaborate understanding, I approached the second form of analysis and conducted hierarchical and simultaneous regression analysis. This analysis helped me to explore the relationship between instructional strategies and students' motivation changes. Similar to the analysis with achievement goals (as studied in study 2), the results indicate that teamwork behaviors accounted for the most variance in predicting changes in students' motivational constructs.

For the form of analysis, I focused on understanding the relationship between instructional strategies, academic performance, and changes in motivational constructs in a collective way. I used a full model structural equation modeling (SEM) analysis. The results associated teamwork behaviors with academic performance, self-efficacy, and task value. These results confirm that self-regulated learning processes can result in successful outcomes in a classroom setting (Zimmerman & Schunk, 2008). Moreover, the results indicate that self-efficacy and task value are the concomitant outcomes of teamwork activities due to the significant indirect effect of teamwork behaviors on them.

Considering the four sources that influence self-efficacy beliefs (Bandura & Schunk, 1981), two of the influence sources are vicarious experience and verbal persuasions. Vicarious experiences suggest that peers can be an influential source of students' self-efficacy beliefs due to social comparisons. Also, verbal and social persuasions by peers, such as in teamwork, can play an important role in students' self-efficacy beliefs. Although more studies are required to understand the role of independent sources, these results confirm the influential source of teamwork behaviors on students' self-efficacy beliefs in the light of vicarious experiences, and verbal persuasions (Bandura, 1977, 1994). Another noteworthy aspect is that students' prior success also showed a significant indirect effect on changes in students' self-efficacy beliefs. This indirect outcome confirms that students' mastery experiences (another influence source) can gauge students' self-efficacy beliefs.

Besides, the SEM analysis revealed a non-significant impact of reflection specificity on students' academic performance and changes in motivational constructs. These results indicate the need for further evaluations as literature shows that failure of an outcome in motivational constructs can be associated with students' emotional state and stress.

Collectively these three studies show five (4 positive and 1 negative) major results. The positive result includes: 1) motivational beliefs, personal, & social competence, and learning are associated. 2) the ability to self-regulate can help students in achieving their desired learning outcomes. 3) deliberate practice can help students' to acquire the desired competence. 4) confirms that in the context of first-year engineering students, interactive activities lead to better academic performance (confirmation of ICAP hypothesis). The negative results highlight that students' motivation is declining post the use of instructional strategies, especially in the context of the first-year engineering course. This decline in students' motivation could be due to three possible reasons of high prior motivation, learning style, and course design and environment.

Prior research studies suggest that in general, incoming engineering students have a high level of motivation (Geraedts et al., 2015). These higher levels of motivation could be due to their performance in high school, getting higher scores in standardized tests, and getting admission to one of their top choice university. However, college and course experiences can alter these motivational beliefs (Hofer, 1994). Specifically, the studied first-year engineering course includes programming in MATLAB, which is intrinsically hard to learn (Guzdial, 2004). The hard nature of programming concepts could cause frustration in students' during the process of learning and activities. This frustration may be doubled if they do not get their anticipated outcome (e.g., assignment score), and start dreading doing the course.

Another possible reason for the decline in students' motivation could be due to the non-matching of their personal learning style with the nature of course activities (Larkin & Budny, 2005). For example, in this study, the course had a major graded component that required students to work in teams. Students with variant learning styles and not understanding its impact on their learning could find teamwork as irrelevant and difficult to manage (Nordstrom & Korpelainen, 2011). When the major portion of the course asks students to work in teams, they may start questioning their individual learning and lose their interest.

Also, the course design and execution could be another reason for the decline in students' motivation. The course was designed with the flipped lecture, where students have to see a video for a module before coming to class. The class time is spent mostly in discussions, and students working in teams. Students could feel that course is demanding too much of their in and out of class time. In such a situation, students' minds could compete for what is worthy of their time and attention and cause a decline. Also, in general, in engineering classes, students want to work on artifacts that are interesting and relevant to them (Guzdial, 2004) or which is closer or in line with their anticipated major. Students' aspirations, expectations for their futures are very important for them, and they want these connections in courses (Husman, Derryberry, Crowson, & Lomax, 2004). Absence to see such connections, and outcomes could lead them to question the relevance of the course, and eventually can cause a decline in their motivation towards the course. Another important facet of course design is the relevance of classwork with exams. In the current course, students give their paper and pencil based exams in a big hall on a week day night. This process of conducting the exams could be overwhelming, and exhausting due to both the nature and timings. The paper and pencil exam is probably more syntax focused and doesn't necessarily test students' ability to program. Also, the timings of the exam may clash with the learning style of some students, causing a decline in their motivation towards the course.

Implications

The collective results of three studies where informed about the relationships between these constructs, also highlight the effect of these strategies on individual motivational constructs. This comprehensive understanding can be a guide to engineering instructors and curriculum designers to consider instructional strategies according to the context, and which proves to more effective and less stressful for students.

For engineering education instructors, especially for first-year engineering education instructors, this study highlights the questions on the design of the learning environment and points towards two important questions:

1) Which strategies are more suitable for students' learning?

2) To what extent we ask students to participate in activities related to such strategies that do not result in fear or stress for the students?

The first implication is that instructors need to decide instructional strategies according to the course requirements and needs of the course. The studied first year engineering course is designed with a project-based learning approach, with a lot of emphasis on teamwork. Also, a good final grade chunk is due to the team tasks. Where this approach may help students to get the ability to work in a team, the overuse could be the reason for demotivating students. For example, students are bound to complete peer evaluations at four-time points, which probably is overburdening, and taking away the autonomy as is graded activity. In the light of results, although peer evaluations improved over time, that could be due to the fact that the first evaluation happen in the beginning of the team project when students might not be fully aware of their teammates and their strengths. Doing an evaluation without knowing the team members could be stressful, or they could find it unnecessary. Moreover, it is important that instructors use teamwork for tasks, which absolutely require the teamwork and not for each activity.

Also, the reason for the decline in students' motivation could be due to the structure and allocation of rewards in the course. One feasible way to overcome the situation could be to involve students in teamwork, without penalizing them. Also, instructors should use strategies without an evident difference in the grading of two different strategies.

Another important aspect of the instructional strategy is the instructor's motivation and appropriate use of the strategy. For example, the reflective thinking strategy required that instructor read summaries of students' reflections and use them as a tool of formative assessment by addressing students' concerns in subsequent lectures. If students' do not see the feedback aspect or teachers' motivation towards the use of an instructional strategy, they may not perceive the learning environment as supportive. This perception of a non-supportive environment could also lead to demotivation of students. Instructors, in the future implementation of first-year engineering courses, may reflect on what may make their classroom environment supportive and how they may add or improve the components of feedback and formative assessment.

In this course, the use of second instructional strategy as was done in a simultaneous manner, with an added technology, probably could cause an overuse of technology tools in class. Students are using multiple technology systems, including learning management systems, CATME, Qualtrics for surveys, hot seat, or discussion forums. When another component was added, with the use of another technology, that besides having a purpose, may cause stress in students. In the future, instructors may decide to use the technology tools and teaching strategies, with a balance.

Further, as a first-year engineering course has a component of programming in MATLAB, the instructor may use strategies that align with programming and problem-solving. The programming concepts are known to be intrinsically hard in nature. The over-emphasis on syntax than semantics and logic building could cause stress in students. In addition, students may not find programming errors as their friend. The inability to deal with failure may cause a spirit crash. Instructors may help students by designing the course with more emphasis on programming than coding (syntax focused). In the same realm, in the future, the instructor may choose to conduct the exams, which test students' ability to program and logic building and do not necessarily test their ability to produce the correct syntax.

In addition, instructors can conduct motivation and learning style surveys at the beginning of the semester to understand their students. This may help instructors to develop a teaching strategy that is according to the learning style of the students. Also, with this approach, instructors may teach the concepts to students within a familiar and relevant context.

Limitations and future directions

There are several limitations and future directions of this dissertation, which are described in individual chapters. However, this section discusses the overarching limitations and future directions.

This dissertation was conducted in one section of an engineering course. This particular sample selection led to a relatively small sample size (52 students in the first study and 120 students in second and third study) and limited context. As motivational constructs (especially self-efficacy and engagement) are context-specific, the results might be different for a larger sample. A future study can encompass the context of multiple engineering courses with a larger sample.

It is noteworthy that these results might be inflated due to the variation in the requirement of two instructional 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. Although we countered this limitation by collecting data at multiple time points, however, future studies can be designed with minimal embedded bias.

Also, in this dissertation, the focus was to understand the role and relationships between self-regulated learning based instructional strategies and motivational constructs. The studies collectively did not include gender, ethnicity, and other demographics information based variations in these constructs. Similarly, other aspects of students' diversity, such as cultural or socio-economic variations, were not in the scope of the study. A future study could be designed that addresses the potential differences between students' participation based on demographic factors.

Also, several other aspects of analysis, such as the direct effect of predicting academic performance using motivational constructs is not discussed in this dissertation. Also, the results indicate that engagement emerges as a predictor of self-efficacy beliefs and task value. This could be a venue for future studies that understands the role of engagement in predicting students' participation and motivational behaviors.

Moreover, I did not use all four motivational constructs together in the SEM model. A future study can address this limitation of combining all four motivational constructs with instructional strategies and academic performance.

In addition, in this study, data, especially motivational constructs, were based on students' self-reported evidence of their motivation in both pre and post case. The used surveys may not provide the concrete evidence on what was happening in the class that could highlight students' use of self-regulating learning practices. Therefore, in future studies, the use of process data (e.g., observation data, field notes) could help to understand and triangulate the results.

Also, although I used self-regulated learning theory and ICAP as a lens to design the study and interpret the results, I lacked data on students' self-reported evidence of self-regulation.

Similarly, I did not have students' information about their viewpoint of instructional strategies introduced in the course and their participation. Also, a future study could be designed to investigate the direct impact of students' participation in instructional strategies and their self-regulation measures.

Other theories, such as self-determination theory (Deci & Ryan, 2002), provides a mechanism to evaluate the student-centered learning strategies and also helps to understand students' intrinsic and extrinsic motivation. Future studies can combine students' viewpoints about how much autonomy, competence, and relatedness (self-determination aspects) these strategies provided to them with motivational constructs. Also, a future study may combine the self-determination theory with self-regulated learning to understand the role of these instructional strategies.

Also, this studied followed a correlational research design and did not employ a quasi-experimental or experimental design. Future studies can address this limitation by designing and executing such studies.

The results of these studies raised two important questions. 1) Which strategies are more effective and less stressful for students? 2) Are we overburdening students (e.g., Hedberg, 2009), which is causing stress and negative emotions, leading to declining in students' most motivational constructs based on the end of semester surveys? For example, Su (2016) suggested that overburdening the cognitive load can lead to learning anxiety and a negative impact on students' motivation. Future studies may account for students' emotions' and especially the effort and time students need to be successful.

Conclusion

Overall, this dissertation study provided novel explorations on the relationships between two instructional strategies, four motivational constructs, and engineering students' academic performance. The role and relative contribution of different student-centered learning instructional strategies on students' learning in a classroom setting is understudied (Streveler & Menekse, 2017). Also, very few studies combined multiple motivational constructs with student-centered learning strategies. These collective constructs, incremental explorations, the choice of methods made this dissertation original and resourceful.

Also, this dissertation study informs that motivational belief, personal, and social competence, and learning are associated. The ability to self-regulate can help students in achieving their desired learning outcomes. Also, deliberate practice can help students' to acquire the desired competence.

One unique contribution of this study is in providing a validated four-dimensional engagement scale with 19 items for engineering students (see Appendix B). Although the validation of the instrument was not part of the research goals, the nature of the studies required its validation as this is the first time this scale was used in the engineering education context.

The results of this dissertation share similarities and align with existing studies on motivational constructs and self-regulation learning. However, the results in contrast to four possible functional ways of relationships, describe a definite relationship of self-efficacy, task value, and achievement goals with self-regulated interventions. These results could be a venue for future studies.

Finally, the ICAP framework was understudied and less evaluated in a real classroom setting (Menekse et al., 2013). This dissertation study is amongst the few studies that evaluated and confirmed the ICAP hypothesis in engineering context in a single classroom.

Closing acknowledgments

Thank you to all students who participated in this dissertation study. Also a special thank you to the reviewers, and members of the editorial board of Springer Nature, and International Journal of Engineering Education for helping in revising the manuscripts.

APPENDIX A. SURVEY

Name & Last Name ___________________________________ Date_______________

Instructions: We are interested in your thoughts and feelings about this class and engineering classes in general. Please answer these questions as honestly as you can. This is not graded, and there are **no right or wrong answers**. Read each sentence and mark the choice that shows how much you agree with it.

Answer all questions using the following scale:

Strongly Disagree	Disagree	Somewhat Disagree	Somewhat Agree	Agree	Strongly Agree

Note: Subtitles were not shared with students

Mastery approach

1. I am striving to understand the content as thoroughly as possible.
2. My goal is to learn as much as possible.
3. My aim is to completely master the material presented in this class.

Performance Approach

4. My goal is to perform better than the other students.
5. My aim is to perform well relative to other students.
6. I am striving to do well compared to other students.

Performance Avoidance

7. My aim is to avoid doing worse than other students.
8. I am striving to avoid performing worse than others.
9. My goal is to avoid performing poorly compared to others.

Task value (MSLQ)

10. I think I will be able to use what I learn in this course in other courses.
11. It is important for me to learn the course material in this class.
12. I am very interested in the content area of this course.
13. I think the course material in this class is useful for me to learn.
14. I like the subject matter of this course.

15. Understanding the subject matter of this course is very important to me.

Self-Efficacy (MSLQ)

16. I believe I will receive an excellent grade in this class.

17. I am confident I can understand the most complex material presented by the instructor in this course.
18. I am confident I can do an excellent job on the assignments and tests in this course.
19. I am certain I can master the skills being taught in this class.
20. Considering the difficulty of this course, the teacher, and my skills, I think I will do well in this class.

Engagement - Behavioral

21. I stay focused in engineering classes.
22. I put effort into learning engineering.
23. I keep trying even if something is hard in engineering.
24. I complete my engineering homework assignments on time.
25. I do other things when I am supposed to be paying attention in engineering classes. (R)
26. If I do not understand a task in engineering, I give up right away. (R)

Engagement - Emotional

27. I look forward to the engineering class.
28. I enjoy learning new things about engineering.
29. I feel good when I am in engineering classes.
30. I think that the engineering classes are boring. (R)
31. I do not want to be in engineering classes. (R)
32. I often feel down when I am in engineering classes. (R)

Engagement - Social

33. I think about others' ideas and add my opinion in engineering classes.
34. I try to understand other people's ideas in engineering classes.
35. I work with classmates to come up with ways to solve problems in engineering classes.
36. I do not care about other people's ideas in engineering assignments. (R)
37. When working with others in engineering, I do not share my ideas. (R)
38. I do not like working with my classmates in engineering classes. (R)

Engagement - Cognitive

39. I go through the work that I do for engineering classes and make sure that it is right.
40. I try to connect what I am learning in engineering classes to things I have learned before.

41. I try to understand my mistakes when I get something wrong in engineering classes.
42. I would rather be told the answer in engineering than have to figure it out myself. (R)
43. When work is hard in engineering, I only study the easy parts. (R)

APPENDIX B. VALIDATING THE ENGAGEMENT INSTRUMENT IN UNDERGRADUATE ENGINEERING CONTEXT

INTRODUCTION

In this dissertation study, for evaluating students' engagement, especially in Chapter 4, I used a validated and extensively used instrument in K-12 classes (Wang et al., 2016). However, the engagement instrument is not used in undergraduate engineering courses. Also, I modified this engagement instrument for engineering classes. Consequently, it is essential to validate this revised instrument before conducting any further analysis. The students' engagement scales of this study includes the subscales of behavior, social, cognitive, and emotional engagement. The measures of students' motivation and engagement were collected twice in the semester, i.e., once at the beginning of the semester and once at the end of the semester. The data was collected using 6-Likert scale value, where one indicated "strongly disagree," and six indicated "strongly agree." Please refer to Appendix A for survey items.

More specifically, I addressed the following research question:

RQ1. What is the relationship between the observed measures of engagement items (~23 items) and their constructs?

PROCEDURE AND DATA ANALYSIS

Before analyzing the data, I reverse coded all the negatively worded items (~10 items). Further, I evaluated the issues related to outliers, skewness, kurtosis, multi-collinearity, singularity, and missing data. For all the subscales, all three measures of central tendency mean, median, and mode were roughly the same, and no outlier was found. Skewness and kurtosis values were below or close to 1, which indicated no issues on skewness and kurtosis.

I conducted a Confirmatory Factor Analysis (CFA) to validate the engagement instrument for engineering students. The CFA is a confirmatory technique to validate the instrument supported by logic and theory (Schreiber, Nora, Stage, Barlow, & King, 2006). The version of the instrument was already validated in the original study (Wang et al., 2016) for K-12 students. However, as I modified the survey for engineering students, CFA appeared as the most appropriate technique, which allows testing the existing hypothesis of a relationship between observed variables and their latent constructs (Suhr, 2006). Also, prior research studies support the aggregation of pre and post data into one single data point for survey validation (Levesque-Bristol & Richards, 2014), so I aggregated the engagement survey responses for this question into a single dataset (N = 240). The missing data of an engagement survey comprised 28 out of 240 entries, which was less than 5% of the data. Based on these results and randomness of the missing data, I used the mean imputation method to impute the missing values before conducting the CFA analysis.

For testing the fitness of the model, I considered multiple goodnesses of fit indices. These indices include Root Mean Square Error of Approximation (RMSEA), Standardized Root Mean Square Residual (SRMR), Comparative Fit Index (CFI), Non-Normed Fit Index (NNFI), Goodness of Fit Index (GFI), and Incremental Fit Index (IFI). According to the literature, the values of above 0.90 for CFI, GFI, NNFI, and IFI are indicative of a good model (Hu & Bentler, 1999). Besides, the values of RMSEA and SRMR below 0.10 are adequate (Browne & Cudeck, 1993) with a good fit of below 0.08, and excellent fit being with values below 0.05 (Hu & Bentler, 1999). Also, I used the significance tests for factor loadings, where I used significant factor loadings with standardized coefficients of above 0.30 as good measures of the underlying construct (Hatcher, 2005).

RESULTS

At first, I calculated the descriptive statistics and factor reliabilities of the data for the constructs of the survey are presented in Table B.1. The factor reliabilities were calculated using Cronbach's alpha. The descriptive statistics are based on item-based statistics.

Table B.1. Descriptive statistics of the survey constructs for engagement survey

Constructs	Reliability	Mean	Variance	Min	Max
Behavioral	.758	5.006	.123	4.410	5.311
Emotional	.878	4.359	.272	3.618	5.094
Social	.754	4.982	.013	4.797	5.123
Cognitive	.734	4.910	.055	4.505	5.085

To answer the question, I created the CFA model on all 240 responses (combined pre and post data set) and evaluated the extent to which the hypothesized model was a good fit to the observed data. I used a priori that: a) response to engagement can be explained by four factors, b) Each item would have a non-zero loading on the burnout factor it was designed to measure, and zero loadings on all other factors, c) the four factors would be correlated, and d) measurement error terms would be uncorrelated. All analysis was based on covariance matrices. The analysis in this study was run to explore the goodness of the fit of the model.

A preliminary analysis was conducted on the fit of the hypothesized model. The results indicated that Behavior5, Emotion2, Social4, and Cognitive4 appeared as poor items (see Appendix A for the text of the items). Except for Emotion2, all other items were negatively worded questions. All other factor loadings, factor variances, covariance, and error variances were significant at $p < .05$. For all these items, in the initial model, the factor loading was not significant, and also communalities indicated their values below 0.3, which was the cutoff value to identify the poor item. Besides, the goodness of fit statistics indicated the significant and higher value of chi-square $\chi 2(224) = 703.13$, $p = 0.0000$. As Chi-square is extremely sensitive to the deviation between reproduced and actual correlation matrix, I used other goodness of fit indicators as well. The Goodness of Fit Index (GFI) = 0.784, Non-Normed Fit Index (NNFI) = 0.787, Incremental Fit Index (IFI) =0.813, and Comparative Fit Index (CFI)=0.811 are less than 0.90, which indicates the absence of good model. Although Standardized Root Mean Square Residual (SRMR)=0.0801, and Root Mean Square Error of Approximation (RMSEA) = 0.094 were under 0.10, but in the light of GFI, NNFI, IFI, and IFI values which are indicative of not a good fit, I modified the model. As the presence of poor items was evident, I decided to improve the model without poor items.

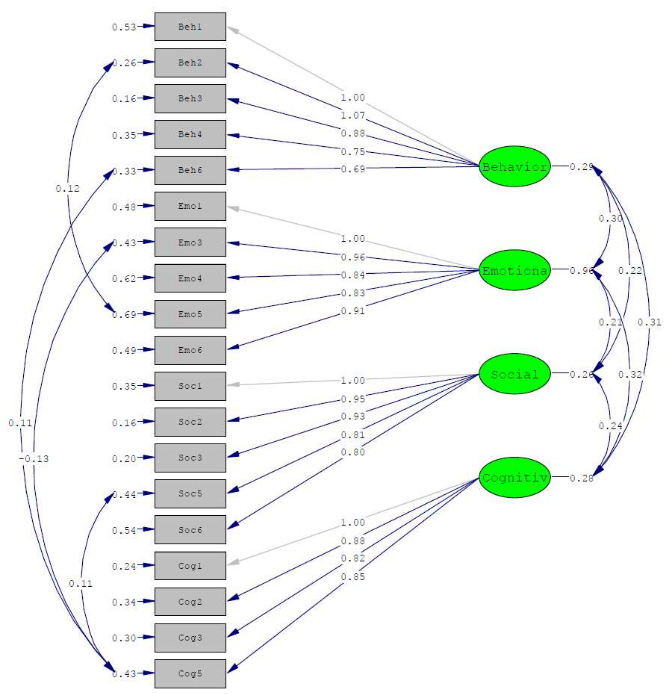

Figure B.1. Fitted CFA Model of Re-specified Version

I re-specified the model without four items (Behavior5, Emotion2, Social4, and Cognitive4), changing the number of items to 19 from 23. The re-specified model indicates that all factor loading, factor variances, covariance, and error variances are significant at $p < .05$. The model was improved in four steps, where the error variances were estimated, as shown in Table B.2. The estimated error variances were based on the modification index and model appropriateness. The fitted model is shown in Figure B.1. Please refer to Table B.3 for parameter estimates based on the completely standardized solution.

Table B.2. The goodness of fit indicators of estimated models

	$\chi 2$	df	RMSEA	SRMR	CFI	IFI	NNFI	GFI
Error_var(Cog5,Beh6)	390.82	145	.084	.0614	.885	.886	.864	.858
Error_var(Cog5, Soc5)	369.53	144	.081	.0596	.894	.895	.874	.864
Error_var(Cog5,Emo3)	353.36	143	.078	.0589	.901	.902	.882	.869
Error_var(Emo5, Beh2)	336.91	142	.076	.0580	.908	.910	.890	.872

The achieved model indicated a lower value of Chi-square $\chi 2(142) = 336.91$, $p = 0.0000$. The goodness of fit indicators was improved and showed adequate fit with values as with values CFI = 0.908, IFI = 0.910, which were greater than 0.90, and both NNFI and GFI got very close to 0.9. The RMSEA =0.076, SRMR = 0.0580, which was under 0.08. The results of the CFA indicated an excellent fit between the proposed model and the observed data.

With these results, the validated survey instrument has 19 items instead of the 23 items which effectively mapped on their construct. This result is particularly interesting due to two reasons: First, although existing studies describe engagement as a multidimensional construct (Appleton et al., 2008), there are not many studies that have used the different and all aspects of engagement in their investigations. Specifically, studies have often not used social engagement as a construct of engagement. Second, there are not much-validated instruments that capture the four dimensions of engagement for engineering undergraduate students. Existing instruments (e.g., Student Engagement Instrument – SEI (Appleton, Christenson, Kim, & Reschly, 2006) uses fewer dimensions and generally focus on cognitive and affective engagement.

Table B.3. Parameters of CFA Fitted Model

	Factor Loadings				Error Variances				
Observed variable	Behavioral	Emotional	Social	Cognitive	Construct	Behavioral	Emotional	Social	Cognitive
Beh1	0.599	--	--	--	Behavioral	1.000	--	--	--
Beh2	0.752	--	--	--	Emotional	0.571	1.000	--	--
Beh3	0.768	--	--	--	Social	0.794	0.412	1.000	--
Beh4	0.566	--	--	--	Cognitive	1.066	0.611	0.897	1.000
Beh6	0.544	--	--	--					
Emo1	--	0.817	--	--					
Emo3	--	0.824	--	--					
Emo4	--	0.721	--	--					
Emo5	--	0.701	--	--					
Emo6	--	0.785	--	--					
Soc1	--	--	0.653	--					
Soc2	--	--	0.767	--					
Soc3	--	--	0.721	--					
Soc5	--	--	0.527	--					
Soc6	--	--	0.483	--					
Cog1	--	--	--	0.732					
Cog2	--	--	--	0.625					
Cog3	--	--	--	0.621					
Cog5	--	--	--	0.569					

Note: Completely standardized solution

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Chapter 4
Self-efficacy and Mobile Learning Technologies: A Case Study of CourseMIRROR

Muhsin Menekse, Saira Anwar, and Senay Purzer

Introduction

Educational technologies are considered as essential components of teaching and learning at every stage of curriculum across grade levels. Technology-enhanced learning environments including simulations, adaptive tutors, virtual labs, learning management systems, video games, and mobile applications offer a range of features to enhance learning and engagement through evidence-based practices. Lately, there has been a growing surge of mobile applications and technologies that are developed for instructional use.

The most common mobile learning technologies are designed as tools to deliver content and enhance students' understanding of domain specific concepts, or used as tools to facilititate course management, notetaking, or communication between instructional team and/or among students. Some examples of domain specific applications include *Math Duel* (Kim, 2016) and *PhotoMath* (Webel & Otten, 2015); course management applications such as *Class Dojo* (Blevins & Muilenburg, 2013; Hammonds, Matherson, Wilson, & Wright, 2013; O'Brien & Aguinaga, 2014), *Blackboard Learn* learning management system (LMS) (Ashok, 2011; Suk Hwang & Vrongistinos, 2012), and *JDLX* (Tang, Zhou, & Chen, 2015); language learning applications such as *Duolingo* (Ahmed, 2016; Munday, 2016; von Ahn,

M. Menekse (✉)
School of Engineering Education, College of Engineering, Purdue University,
West Lafayette, IN, USA

Department of Curriculum and Instruction, College of Education, Purdue University,
West Lafayette, IN, USA
e-mail: menekse@purdue.edu

S. Anwar · S. Purzer
School of Engineering Education, College of Engineering, Purdue University,
West Lafayette, IN, USA
e-mail: anwars@purdue.edu; purzer@purdue.edu

C. B. Hodges (ed.), *Self-Efficacy in Instructional Technology Contexts*,
https://doi.org/10.1007/978-3-319-99858-9_4

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Anwar, S., & Menekse, M. (2020). Unique contributions of individual reflections and teamwork on engineering students' academic performance and achievement goals. *International Journal of Engineering Education*, *36*(3), 1018–1033.

Gmail **Saira Anwar <sairaanwar@gmail.com>**

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International Journal of Engineering Education Vol. 36, No. 3, pp. 1018–1033, 2020
Printed in Great Britain

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

SAIRA ANWAR
School of Engineering Education, Purdue University, West Lafayette, IN, USA. E-mail: anwars@purdue.edu

MUHSIN MENEKSE
School of Engineering Education, and Department of Curriculum and Instruction, Purdue University, West Lafayette, IN, USA.
E-mail: menekse@purdue.edu

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

* Accepted 4 January 2020.

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PUBLICATIONS

JOURNAL ARTICLES (Published or Under-Review)

1. **Anwar, S.,** Menekse, M., Guzey, S., & Bryan, L.A. (under review). Exploring the role of an integrated life science and engineering unit on 6th grade students' science learning outcomes. Submitted to *Journal of Research in Science Teaching*
2. Kadir, K., Menekse, M., & **Anwar, S.** (under review). Pre-College STEM content needs and mid-college academic success. Submitted to *Higher Education Research & Development.*
3. Kadir, K., Menekse, M., & **Anwar, S.** (under review). Engineering students' perceived needs as predictors of their mid-college academic success. Submitted to *European Journal of Engineering Education.*
4. **Anwar, S.,** & Menekse, M. (under review). Review and use of post-secondary observation protocols. Submitted to the *Review of Education.*
5. Menekse, M., **Anwar, S.,** & Akdemir, Z. (2020). Relative effectiveness of specific versus general reflection prompts on engineering students' academic performance and engagement. *The Journal of Experimental Education.*
6. **Anwar, S**., & Menekse, M. (2020). Unique contributions of individual reflections and teamwork on engineering students' academic performance and achievement goals. *International Journal of Engineering Education*, *36*(3), 1018–1033.
7. Menekse, M., Zheng, X. and **Anwar, S.** (2020). Computer science students' perceived needs for support and their academic performance by gender and residency: An exploratory study, *Journal of Applied Research in Higher Education*. https://doi.org/10.1108/JARHE-07-2019-0194
8. **Anwar, S.,** Bascou, N.A, Menekse, M., & Kardgar, A. (2019) A systematic review of studies on educational robotics. *Journal of Pre-College Engineering Education Research*, *9*(2), Article 2. https://doi.org/10.7771/2157-9288.1223
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1. **Anwar, S.,** Menekse, M., & Guzey, S. (in preparation). Students' performance and motivation: A comparison of two middle school corporations.
2. **Anwar, S.,** Menekse, M., & Guzey, S. (in preparation). Relationship between middle school students' engagement, situated interest, and academic performance.
3. **Anwar, S.,** Menekse, M., & Butt, A. A. (in preparation). Development and validation of the survey instrument to evaluate the user experience of educational technologies.

BOOK CHAPTER

1. Menekse, M., **Anwar, S**., & Purzer, S. (2018). Self-efficacy and mobile learning technologies: A case study of courseMIRROR. In C. B. Hodges (Ed.), *Self-efficacy in instructional technology contexts*, Springer Nature Switzerland AG.

PEER-REVIEWED CONFERENCE PROCEEDINGS

1. **Anwar, S.**, Menekse, M., Butt, A.A. (2020). Perceived motivational constructs and engineering students' academic performance. *127th Annual Conference & Exposition, American Society of Engineering Education*. Montreal, Canada.
2. **Anwar, S**., Menekse, M., Guzey, S., Bogan, V., Genc, U. & Bryan, L. (2020). Role of engagement in predicting students' performance in an Integrated Life STEM Unit. *127th Annual Conference & Exposition, American Society of Engineering Education*. Montreal, Canada.

3. Butt, A.A., **Anwar, S.**, & Menekse, M. (2020). Work in Progress: First–year engineering students' study strategies and their academic performance. *127th Annual Conference & Exposition, American Society of Engineering Education*. Montreal, Canada.
4. **Anwar, S.**, Menekse, M., & Butt, A.A. (2020, in press). Unique contributions of reflective thinking and teamwork behaviors on engineering students' academic performance. *Proceedings of the American Educational Research Association (AERA)*, San Francisco, CA.
5. **Anwar, S**., & Menekse, M. (2019). Impact of the educational technology-based learning environment on students' achievement goals, motivational constructs, and engagement. *ICER'19 Proceedings of the 2019 ACM Conference on International Computing Education Research (pp. 321-322)*, Toronto, Canada.
6. **Anwar, S**., & Menekse, M. (2019). Engineering students' self-reflections, teamwork behaviors, and academic performances. *126th Annual Conference & Exposition, American Society of Engineering Education*. Tampa, Florida.
7. **Anwar, S**., Menekse, M., Guzey, S., Bogan, V.L., Burnett, S.C., & Jung, J.Y. (2019). Effect of integrated life science units on middle school students' engagement. *126th Annual Conference & Exposition, American Society of Engineering Education n*. Tampa, Florida.
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19. **Anwar, S**., Mumtaz, M. (2010). GOF design patterns in web-based educational societies portal, In *Proceedings of 11th National Research Conference, SZABIST*, Islamabad, Pakistan
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