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The Relationship Between Engineering Students' Achievement Goals, Reflection Behaviors, and Learning Outcomes*

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Prior studies have shown that students' achievement goals play a key role in their learning strategies, decision-making processes, and learning outcomes. However, a majority of these studies were conducted with undergraduate psychology students. Thus, there is a need to explore the role of students' achievement goals on their reflection behaviors and learning outcomes in different fields, including engineering education. Based on our literature review in engineering education, there are a limited number of studies that investigated the relationship between achievement goals and students' learning outcomes. Therefore, we conducted this exploratory research study to investigate the relationship between achievement goals, reflection behaviors, and learning outcomes of engineering students. We used the Achievement Goal Questionnaire-Revised (AGQ-R) scale to measure 69 sophomore engineering students' achievement goals. Six response variables were included: average reflection quality, the total number of reflections submitted, two exam scores, the final exam score, and the total weighted learning outcomes. Based on our analyses, we found that the mastery approach was significantly related to the total number of reflections, the final exam score, and the total weighted learning outcome variables. The performance approach was also significantly related to the final exam and total weighted learning outcome. Mastery avoidance was significantly related to the total number of reflections, the second exam, and the total weighted learning outcome. Finally, performance avoidance was significantly related to the second exam, final exam, and the total weighted learning outcome. Overall, our findings are informative to researchers in the engineering education field for better understanding students' learning strategies, reflection behaviors, and learning outcomes relating to their goal orientation. Thus, this study provides benefits to researchers and other stakeholders such as faculty members or administrators in engineering education to develop more effective intervention programs that positively impact student motivation and their learning strategies as well as learning outcomes.

Keywords: achievement goals; reflection; engineering education; mobile learning

1. Introduction

Students form their achievement goals based on their motivation and prior experience with related courses and domains [1–3]. These achievement goals, along with the instructional strategies, affect students' learning strategies and outcomes [4, 5]. Although some educational psychology studies have shown that there is a significant relationship between achievement goals, learning strategies, and learning outcomes, we observed that this relationship had not been explored in the field of engineering education. In this study, we investigated the relationship between engineering students' achievement goals, their reflection behaviors, and learning outcomes by conducting a semester-long study in an Industrial Engineering class. This research is primarily focused on the following research questions:

1. How are achievement goals related to engineering students' reflection behaviors?
2. What is the relationship between achievement goals and learning outcomes?

In this paper, we introduce the achievement goal theory and its relationship to the reflection process, and how these constructs affect the learning outcomes. Next, we discuss the previous research studies in engineering education that investigated students' motivation. In the methods section, we explain the procedure that we used for data collection and data analyses. In the results section, we present the findings based on our statistical analysis.

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Table 1. Summary of Achievement Goals

Achievement Goal	Definition
Mastery Approach	Focuses on learning and understanding materials.
Performance Approach	Focuses on performing well compared to others, ego-involved.
Mastery Avoidance	Focuses on avoiding failure of learning or understanding.
Performance Avoidance	Focuses on avoiding performing worse than others.

In the conclusion section, we discuss the implications of our findings and future research directions.

1.1 Achievement goal theory, reflection, and self-regulated learning

Achievement goal theory considers that an individual's motivation is driven by a specific purpose [4, 6], and encompasses various types of beliefs that are related to goals [7]. Achievement goal theory incorporates both affective and cognitive factors of goal-directed behavior [4, 5]. Accordingly, this theory can be considered as an integrating theory that provides a profound framework to explain students' goal-directed behavior to enhance learning outcomes.

Mastery and performance goals are the fundamental constructs of achievement goal theory that has been extensively discussed in the prior literature [4–7]. The mastery goal focuses on learning and understanding materials, whereas the performance goal focuses on performing well compared to others, as it involves an individual's ego [6]. These different goals influence students' achievement in different ways based on their self-regulation strategies and learning processes [6–9]. Researchers, later on, adopted the 'approach versus avoidance' distinction into achievement goal theory to better explain performance goal-related results [1]. For instance, Wolters argued that performance-avoidance goals may be associated with negative academic outcomes, whereas performance-approach goals are considered beneficial in some cases to enhance learning outcomes [1]. On the other hand, mastery approach is most often associated with intrinsic motivation, higher engagement, and interest [10]. However, findings from different research studies on these constructs are rarely congruent. The researchers included different variables as a measure of response or to the evaluation criteria that they used to categorize performance goal or mastery goal with the approach and avoidance distinction [1, 2, 11–13]. Elliot and McGregor found that the performance approach was a significant predictor of students' learning outcome(s) [10]. Other studies found that mastery approach affected intrinsic motivation [3, 14]. Also, some of the previous studies found a positive correlation between these elaborated achievement goal orientations and self-regulated learning (SRL) behaviors [12, 15]. On the contrary, Elliot and Moller analyzed previous research studies regarding the relationship between SRL and performance approach [12] and found that there was no significant relationship between SRL and performance approach. However, they also suggested the results might be affected by a difference in perspective about performance approach. That is, researchers have had different perspectives on performance approach regarding student's learning due to a difference in focus by researchers when evaluating goal orientation. Definitions of achievement goals are summarized in Table 1.

Researchers have shown that achievement goals and SRL behaviors are essential components in understanding students' learning processes. In classrooms with a learner-centered approach, reflection is considered as one of the key learning strategies [16, 17]. Zimmerman provided a specific structure of reflection which consists of self-judgment and self-reaction for SRL [2]. In his study, self-judgment includes two sub-components which are self-evaluation and causal attribution. Self-evaluation refers to that learner's evaluation of their performance based on any standard, such as their previous performance, peer's performance, or any criteria set by instructors. Causal attribution occurs when the learners think about what caused errors or success. Self-reaction includes self-satisfaction and adaptive/defensive responses. Self-satisfaction indicates the positive emotion that learners experience whereas adaptive/defensive responses are the affective responses when learners experience failure. In other words, based on Zimmerman's study, learners can experience two different stages; they can either experience the sense of satisfaction when they perceive that they are doing well in the class, or they experience the sense of failure or frustration when they think that they are not doing well in the class. In this case, they could either become defensive to protect their self-image or be adaptive to improve their learning strategy.

Therefore, reflection is one of the critical components of SRL. Indeed, research studies on reflection have shown that the quality of self-reflection is significantly related to students' learning outcomes [16, 18]. For example, Lee and Hutchinson examined the effect of self-reflection facilitated by questions on learning and found that the quality of the reflection positively correlated with student learning [19].

Many research studies indicated the importance of student achievement goals and reflection behaviors in understanding their learning processes. Despite much-established evidence in the educational psychology field, we observed that achievement goal theory had not been explored in engineering education. And there is currently little understanding of how engineering students' achievement goals relate to their learning outcomes of engineering concepts. Therefore, the goal of this study is to explore the relationship between achievement goals, reflection behavior, and engineering students' learning outcomes. In the next section, we examine previous research studies that examined engineering students' motivation, particularly regarding the achievement goals.

1.2 Prior research on engineering students' motivation and learning strategies

Prior studies in engineering education explored motivation constructs and their relationships to students' learning strategies and learning outcomes. Based on our review of the literature focusing on journal articles that were published recently (2010–2017), we found thirteen studies that investigated motivational constructs (see Table 2). We categorized these studies based on the motivation constructs they used. The motivation constructs focused on these studies are self-efficacy, intrinsic motivation, self-regulation, achievement goals, and expectancy-value.

Some studies considered achievement goals as the motivational constructs and explored their effectiveness on learning [21, 23, 27, 31]. Most of these studies investigated motivational constructs regarding students' learning strategies and engagement but did not explore the achievement goals themselves and the relationship with learning outcomes or any learning strategy. Nelson, Shell, Husman, Fishman, and Soh (2015) [27] was the only study that considered students' learning outcomes, and they found that the students who underachieved in technical and non-engineering foundation courses at the beginning of their engineering degree programs were less successful in their upper-level engineering courses. These researchers used a learner-centered approach to find specific learning profiles based on motivation, goal orientation and self-

Table 2. Engineering Education Studies Focusing on Motivational Constructs

Citation	Constructs Used	Instrument/Measure
French, Immekus, and Oakes [20]	Intrinsic motivation	The Academic Intrinsic Motivation Scale (AIMS) survey
Galand, Raucent, and Frenay [21]	Self-efficacy, mastery goal, performance goal, self-regulation	Survey*
Haase, Chen, Sheppard, Kolmos, and Mejlgaard [22]	Intrinsic motivation	The Academic Pathways of People Learning Engineering Survey (APPLES)
Hardre, Siddique, and Smith [23]	Mastery goal, performance goal, self-efficacy	Survey*
Hilpert, Husman, Stump, Kim, Chung, and Duggan [24]	Self-regulation	The Future Time Perspective Scale (FTPS) survey
Jones, Osborne, Paretti, and Matusovich [25]	Autonomy, utility value, self-efficacy	MUSIC (eMpowerment, Usefulness, Success, Interest, Caring) Model of Academic Motivation survey
Lawanto, Butler, Cartier, Santoso, and Goodridge [26]	Self-regulation, metacognition	Survey*
Nelson, Shell, Husman, Fishman, and Soh [27]	Self-regulation, mastery approach, performance approach	Student Perceptions of Classroom Knowledge Building (SPOCK) scale, a survey from Shell and Soh's study [37]
Panchal, Adesope, and Malak [28]	Expectancy-value	Survey*
Purzer [29]	Self-efficacy	Discourse data**
Stump, Husman, and Corby [30]	Intelligence beliefs, self-efficacy	The Implicit Theories of Intelligence (ITI) scale survey, SPOCK scale, the Motivated Strategies for Learning Questionnaire (MSLQ) survey
Szewckyk-Zakrzewska and Avsec [31]	Mastery goal	Survey*

* Researchers developed and used their own surveys. ** Study used discourse data instead of surveys.

regulation using the Student Perception of Classroom Knowledge Building (SPOCK) scale. They suggested that students' goal orientation and related beliefs could influence the way students regulate their learning in engineering courses. The authors found that a majority of underachieving engineering students had maladaptive profiles which influenced their learning and goals, resulting in lower grades compared to students who had adaptive profiles. Hardre, Siddique, and Smith [23] presented a systematic approach to model and validated interactions among multiple motivational characteristics of junior and senior students. The authors found factors and pathways that showed the role of multiple motivational characteristics to model students' course engagement, career efficacy, and success expectations.

There are other engineering education studies that explored the effect of intrinsic motivation on students' academic achievement, persistence [20] and achieved skills [22]. French, Immekus, and Oakes examined students' success and persistence both in their major and in their university experience by conducting hierarchical linear and logistic regression analysis [20]. This study showed that intrinsic motivation was positively correlated with students' persistence in their engineering major. Haase, Chen, Sheppard, Kolmos, and Mejlgaard studied the first year engineering students in the U.S. and Denmark to investigate two skill sets: InterPersonal and Professional (IPP) skills and Mathematics and Science (M/S) skills. They found intrinsic motivation played a significant role in student success [22].

The other prevalent motivation construct used in the studies was self-efficacy [21, 23, 25, 29, 30].
Purzer investigated the relationship between the nature of team discourse and its effect on self-efficacy and learning using a sequential mixed methods approach [29]. She reported a moderate positive correlation between students' self-efficacy and support-oriented discourse. Further, Jones, Osbone, Paretti, and Matusovich investigated the relationship of the eMpowerment, Usefulness, Success, Interest, and Caring (MUSIC) components of academic motivation to students' engineering identification, sense of program belongingness, engineering utility, and expectancy along with self-efficacy beliefs [25]. The authors observed the extent to which students' engineering identification and motivational beliefs affected their course effort, course grades, choice of major, and career goals. The reported the significant effect of MUSIC components with engineering identification, program belongingness, and expectancy but that was in the context of course usefulness and interest and did not measure the effect on achieved learning outcomes.

Finally, we observed that self-regulation was explored as a learning strategy [21, 24, 26, 27]. For instance, Lawanto, Butler, Cartier, Santaso, and Goodridge used the SRL framework in an engineering design project to investigate task interpretation and strategy use among the first-year engineering students [26]. The authors examined high and low performing students for their interpretation of tasks and their use of cognitive and metacognitive strategies. They reported that compared to low-performing students, high-performing students had greater awareness and used monitoring and fix-up strategies more, both in the design process and in project management.

As discussed above, several constructs were used to explain engineering students' motivation and learning strategies. However, none of them used achievement goal theory to explain students' learning strategies or learning outcomes. It was also found that there is a limited number of studies on reflection itself. Thus, this study explores engineering students' achievement goals and their relationship with reflection behaviors and learning outcomes.

2. Method

2.1 Participants

The data was collected from 69 students (23 females, 46 males) from a fundamental statistics class for sophomore industrial engineering students over one 12-week semester at a public university. Ages ranged from 19–21. The course was chosen because it was a required course for all industrial engineering students; thus, we expected that the sample we collected would well-represent the entire industrial engineering student population in the university.

2.2 Instruments

We used the Achievement Goal Questionnaire-Revised (AGQ-R) survey revised by Elliot and Murayama [14]. The AGQ-R has been used extensively in the literature and has been shown to be a valid and reliable instrument. The survey consists of four subcategories; mastery approach goal (Cronbach's $\alpha = 0.84$), mastery avoidance goal (Cronbach's $\alpha = 0.88$), performance approach goal (Cronbach's $\alpha = 0.92$), and performance avoidance goal (Cronbach's $\alpha = 0.94$). A total of twelve survey items were provided, and a 5-point Likert scale was used for each item (1: Strongly disagree, 5: Strongly Agree). The researchers used the survey items without any modification to preserve the validity of the original survey.

Students' reflection behavior was collected through a mobile application called CourseMIRROR (Course Mobile In-situ Reflections and Review with Optimized Rubrics), which was developed by the CourseMIRROR research team for both iOS and Android smart devices [32, 33]. CourseMIRROR combines the benefits of mobile application and reflections. In addition, it was designed to create an interactive environment between students and faculty in a large classroom.

The CourseMIRROR application has multiple features. At the end of each lecture, students receive the server-side push notifications on their mobile devices to remind them for writing reflections. The application allows users (faculty and students) to login using their specific credentials and access the application. The application allows the users to access their registered or enrolled courses. Students can access the lectures of the selected course. The application interfaces allow the students to write their reflection for the currently open for reflection lecture. Once submitted, CourseMIRROR collects students' reflections and uses Natural Language Processing (NLP) algorithms to create phrase-based text summaries of responses. In the current study, we used students' original reflection data collected via CourseMIRROR instead of the summary of reflection data that was processed by NLP algorithm as the original data as we were more interested in each student's reflection behavior. For the reflection, students were asked to reflect on the parts of the lecture that they felt were confusing or difficult.

Students' reflection quality was measured based on a scoring rubric, which ranged from 0 to 4. The quality indicated the completeness and details in one's reflection. Accordingly, our coding schema for the reflections followed the scale to specify the degree of depth or quality of reflections. The original version of this flowchart was developed by Menekse and his colleagues [40]. The total number of reflections was also measured to find if students were consistently involved in reflection behavior throughout the semester. Fig. 1 shows the flowchart for coding the reflection quality.

The learning measures included first, second, and final exams for all students. The maximum score for each exam was 100, and the minimum was zero. Each exam included a combination of short answer, multiple-choice and true-false type questions. All exams were developed, administrated, and graded by the course instructor and her teaching assistants. The authors of this study had no involvement in this process.

2.3 Procedure

The survey data were collected at the beginning of the semester, prior to any data collection for reflections or learning outcomes. Students' reflection data were collected for 21 lectures throughout the academic semester. Students submitted their reflection via CourseMIRROR during the semester which

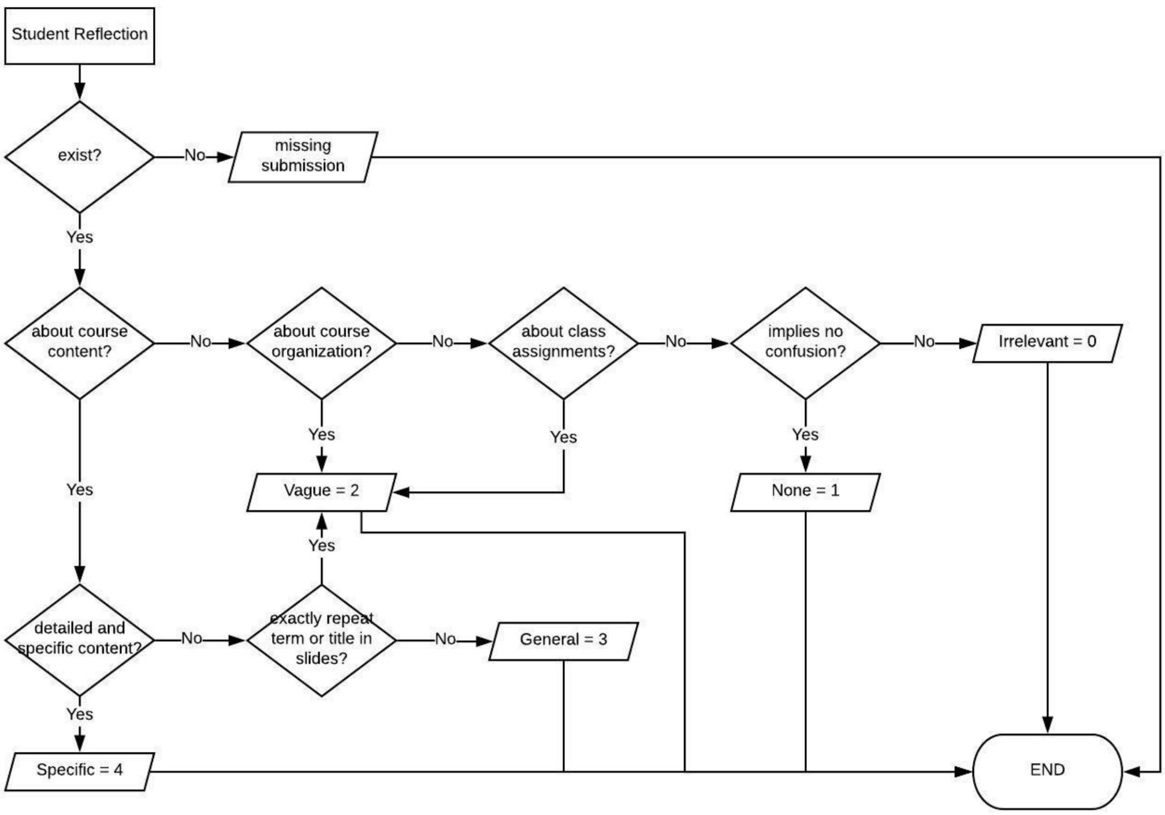

Fig. 1. Flowchart for Coding Students' Reflections.

lasted for 12 weeks. The two exams and the final exam scores were used as learning outcome measures. The total weighted learning outcome was included as well. Students' average reflection quality was measured based on the rubric above (Fig. 1). Two independent raters coded students' reflection, and Cohen's kappa was 0.66, which indicated that there was a substantial strength of agreement based on the guidelines from Altman [34]. We used students' average reflection quality for this study because we were interested in the relationship between students' achievement goals and the overall reflection quality.

2.4 Analysis

To explore the relationship between each achievement goal, and participants' reflection behavior and learning outcome, six variables were included as response variables: (1) average reflection quality; (2) total number of reflections; (3) exam 1; (4) exam 2; (5) final exam; and (6) total weighted learning outcome (exam 1*.3+ exam 2*.3 + final exam*.4). Below is the summary of descriptive statistics for each variable. Multiple separate bivariate regression analyses were conducted to explore the relationship between each achievement goal and each response variable. Each achievement goal was included separately based on the suggestion of Elliot and Murayama [14]. That is, achievement goals share the same dimensions, and thus there is a correlation among achievement goals. Therefore, the authors argued that each achievement goal should be assessed separately to measure the effect of each achievement goal accurately [14].

Using Statistical Package for the Social Science (SPSS) software, normality and homoscedasticity were tested to determine if any assumption was violated for regression analysis prior to performing regression analyses. The Shapiro-Wilk test was chosen to check the normality. Homoscedasticity was checked with scatter plots using standardized residuals, and standardized predicted responsive variable values. We found that normality was violated for most of the models. Scatter plots of homoscedasticity check also indicated that most of the models violated the assumption. As a result, we proceeded with data transformation [35]. Thus, for this study, we performed three different analysis procedures and compared the results. First, parametric bivariate linear regression analyses were conducted. After data transformation, we ran the parametric bivariate linear regression analyses and compared the results. Finally, Generalized Linear Regression analyses were conducted as General Linear Models (GLMs) do not have to meet the normality assumption [35].

3. Results

The results from the twenty-four-parametric bivariate linear regression models indicated that we had significance from some of the response variables with each goal orientation. First, the results indicated that mastery approach was positively related to the total number of reflections, final exam, and total weighted learning outcome. Performance approach was also positively related to the final exam and total weighted learning outcome, however, not related to any reflection behavior variables. The relationship between performance approach and exam score variables (the final exam, the total weighted learning outcome) were stronger than those between mastery approach and the exam scores, as they had greater effect sizes. Mastery avoidance, similar to mastery approach, was significantly related to both the total number of reflections and the final exam. Performance avoidance, similar to performance approach, was significantly related to exam 2, the final exam, and the total weighted learning outcome variables, however, there was no relationship between any reflection behavior variables. The results from the parametric bivariate linear regression analyses before data transformation are summarized in Table 4.

The transformation function for the data transformation was explored using JMP, a software program for statistical discovery developed by SAS [36]. The type of transformation was chosen based on the lowest log-likelihood value and the Akaike Information Criterion (AIC) value for the

Table 3. Descriptive Statistics of Average Reflection Quality, Total Number of Reflections, Exam 1, Exam 2, Final Exam, and Total Weighted Learning Outcome

	Average Reflection Quality	**Total Number of Reflections**	**Exam 1**	**Exam 2**	**Final Exam**	**Total Weighted Learning outcome**
Mean	2.21	12.45	81.06	77.17	75.87	566.36
SD	0.50	5.77	14.37	14.30	11.64	78.33
Min	1.0	1	39	34	46	329.10
Max	3.5	22	105	102	98	694.50
Missing	0	0	2	5	2	8
N	69	69	67	64	67	61

Table 4. Results from Regression Analysis for the Effects of Mastery Approach, Performance Approach, Mastery Avoidance, and Performance Avoidance on Each Response Variable

Variable	*F*	*p*	η_{p^2}
Mastery approach			
average reflection quality	$F(1,65) = 0.006$	0.940	0.000
total number of reflections	$F(1,65) = 5.268$	0.025*	0.075
exam 1	$F(1,63) = 1.100$	0.298	0.017
exam 2	$F(1,60) = 2.398$	0.127	0.038
final exam	$F(1,63) = 6.458$	0.014*	0.093
total weighted learning outcome	$F(1,57) = 4.228$	0.044*	0.069
Performance approach			
average reflection quality	$F(1,65) = 0.773$	0.382	0.012
total number of reflections	$F(1,65) = 1.148$	0.288	0.017
exam 1	$F(1,65) = 0.303$	0.584	0.005
exam 2	$F(1,60) = 2.126$	0.150	0.034
final exam	$F(1,63) = 11.409$	0.001**	0.153
total weighted learning outcome	$F(1,57) = 5.299$	0.025*	0.085
Mastery avoidance			
average reflection quality	$F(1,65) = 0.061$	0.805	0.001
total number of reflections	$F(1,65) = 23.605$	0.000**	0.266
exam 1	$F(1,63) = 1.244$	0.269	0.019
exam 2	$F(1,60) = 6.437$	0.014*	0.097
final exam	$F(1,63) = 8.573$	0.005**	0.120
total weighted learning outcome	$F(1,57) = 3.382$	0.071	0.056
Performance Avoidance			
average reflection quality	$F(1,65) = 1.115$	0.295	0.017
total number of reflections	$F(1,65) = 1.773$	0.188	0.027
exam 1	$F(1,63) = 0.141$	0.708	0.002
exam 2	$F(1,60) = 7.537$	0.008**	0.112
final exam	$F(1,63) = 5.861$	0.018*	0.085
total weighted learning outcome	$F(1,57) = 5.638$	0.021*	0.090

$^*p < 0.05$, $^{**}p < 0.01$.

response variables [35, 37]. The AIC values give an estimate of how much the model can fit the data. Thus, the AIC value was used for model selection over Bayesian Information Criterion (BIC) value [35, 37–39]. Beta distribution fit the data of response variables, and thus response variables were transformed to fall into the range from 0 to 1 [40]. Then, regression analyses proceeded with transformed variables. Normality and the homoscedasticity assumption check were conducted as well. The results indicated that some of the models kept the assumptions after the transformation. However, the results indicated that the *p*-values or the effect sizes from any model were not improved. We also conducted GLM analyses and compared the results with the ones from the previous analysis. However, the *p* values and effect size remained the same as from the previous parametric bivariate linear regression analyses.

As illustrated above, the significance or the effect sizes for some of the models have not improved even after the beta distribution fit all of the distribution of response variables. The results from GLM analyses were not improved either as they remained the same as the results of bivariate regression analyses. One possible explanation for why the results were not improved is that the data of both explanatory variables and response variables were clustered, meaning that students were clustered to a few (scores) points. For instance, there were students who had the same score for the mastery approach as they did for average reflection quality and the final exam. As a consequence, normality and homoscedasticity assumptions may not be appropriate to analyze the data.

4. Discussion

Achievement goal theory incorporates both affective and cognitive factors of goal-directed behavior. Accordingly, achievement goal theory can be considered as an integrating theory that provides a profound framework to explain students' goal-directed behavior to enhance learning in classroom settings. Mastery goal and performance goal are the key constructs of this theory that have been discussed by researchers in educational psychology. Later on, the researchers have adopted the distinction between approach and avoidance and incorporated the negative academic outcomes especially to better explain performance-avoidance goal related results. Thus, we used the approach and avoidance distinction for mastery and performance goal in this study. We administered the AGQ-R survey at the beginning of the semester prior to any other data collection for all four categories without any modification. In addition, we collected student reflections as it has been an essential component of understanding students' learning experiences and self-evaluation of their performance. We used the mobile application CourseMIRROR to collect students reflection and calculated the reflection quality scores based on the scoring rubric (Fig. 1). We explored these constructs and their relationship with engineering students' learning outcomes by using their exam scores.

We used three analysis procedures to compare the results: (1) parametric bivariate linear regression analysis, (2) parametric bivariate linear regression analysis after data transformation, and (3) generalized linear regression analysis. The results indicated that there were significant effects of students' mastery approach on their reflection behaviors, final exams, and total weighted learning outcomes. A performance approach had significant effects on the final exam and the total weighted learning outcome. Although our results of mastery approach and performance approach had a limited significance of effect on some of the response variables, the results still align with findings from prior research studies [1, 3, 10, 11, 14], which is performance approach is positively correlated with learning outcome and mastery approach is positively correlated with students' learning strategies. Our results indicated that mastery approach had a significant correlation with a few learning outcomes, yet, performance approach still had the stronger correlation with learning outcomes. Therefore, our research study adds the empirical evidence that supports the previous findings regarding achievement goals from educational psychology field. On the other hand, it is interesting that our results with mastery avoidance and performance avoidance had some significant relationship with exam scores. Moreover, mastery avoidance was significantly related to the total number of reflection. Research studies on mastery avoidance or performance avoidance are relatively scarce compared to mastery approach or performance approach. Thus, our research findings on those avoidance orientations could give us the direction for the future research studies, which is exploring mastery avoidance and performance avoidance with learning strategies more in detail.

There are some limitations concerning research design in this study. Since this is an exploratory study with a limited sample size, the statistical impact of results may be weaker than the one from explanatory studies. Also, the data set included students' reflections on one course and in one semester. Future studies in different classes across different institutions are needed to make stronger claims for our findings.

5. Conclusions

The overarching goal of this study was to investigate the relationships between achievement goals, reflection behavior, and learning outcomes of industrial engineering students. We observed that students achievement goals and reflection behaviors are less explored in the field of engineering education. As prior studies have argued that achievement goals and reflection behaviors are essential components in understanding the decision-making and learning processes, it is important to explore how engineering students' achievement goals relate to their learning outcomes in real classroom settings. With this study, we addressed this scarcity in engineering education and the need for research studies focusing on achievement goal theory, engineering students' reflection behaviors and learning outcomes.

The results and limitations provide us with several directions for future research studies. First, explanatory studies with a larger sample size can be performed to have a stronger impact on the statistical significance of the relationship between engineering students' achievement goals, learning strategies (such as reflection behavior), and learning outcomes. Second, longitudinal research studies may be conducted to measure the long-term effect of achievement goal on students' learning strategies and learning outcomes across multiple semesters. Third, additional variables can be included to more thoroughly understand the relationship between achievement goals, reflection behavior, and learning outcome(s). Engagement, interest towards course material, and self-efficacy are the examples of the variables. Fourth, as mentioned in the discussion section, mastery avoidance and performance avoidance could be explored more in detail regarding the learning strategies, learning outcome, and with approach orientations as well. Thus, it is possible to conduct a research study by interviewing students to find students' goal orientation more in detail. Last, the future studies may use a more elaborated scoring rubric to measure the reflection quality.

Overall, this study provides benefits to the stakeholders such as faculty members or administrators in engineering education as it is the first study which explored the relationships among achievement goals, reflection behaviors, and learning outcomes for engineering students. This study facilitates the development of ideas for more effective intervention programs that positively impact student motivation and their learning strategies as well as learning outcomes.

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