# Investigating Motivation and Self-Regulated Learning for Students in a Fundamental Engineering Course

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## Abstract

Motivation and self-regulated learning (SRL) are two interconnected constructs that are critical for student learning, especially for those in challenging fundamental engineering courses such as Thermodynamics. Each of these elements are integral to the learning process and typically impact one another, as fostering motivation can lead to improved self-regulatory skills. SRL is described as a cyclical process where students plan, set goals, monitor learning, and reflect to further plan learning strategies. These strategies require further investigation as they are increasingly important to integrate within the classroom, especially for challenging STEM-based courses. By specifically fostering motivation and SRL, students can engage more effectively with the material, leading to improved learning outcomes. To investigate these components of the learning process in engineering, we collected self-report measures of achievement goal orientation (motivation), general self-efficacy (motivation), and motivated strategies for learning (SRL) for 146 undergraduate engineering students in Thermodynamics.

To better understand (1) the interconnected nature of these constructs for students and (2) the self-regulatory and motivational profiles of students who might exist within this engineering classroom, we conducted a cluster analysis based on students' self-reported SRL strategies and their achievement goal orientation (motivation). The cluster analysis was conducted with 146 Thermodynamics students who responded to these questionnaires for the Spring 2023 semester at a university in the Southeastern United States. We identified 4 student clusters that emerged from our *k*-means cluster analysis. By identifying these different groups, we can better understand the possible archetypes of students in Thermodynamics classrooms based on self-perceptions of SRL and motivation.

We then conducted a Kruskal-Wallis test to determine if there were median differences between clusters for self-reported general self-efficacy, another motivation construct. Consistent with the literature, we identified that there were statistically significant median differences between the student clusters. This study shows a significant difference between each of these clusters, indicating a need for educators to address the varied student needs within the engineering classroom. By understanding the types of students who might be in our classrooms, we can better adapt instructional decision-making to more accurately address the motivational and self-regulatory needs of our students.

**Keywords:** self-regulated learning, motivation, improved learning outcomes, instructional decision-making, cluster analysis

## Introduction

To investigate student engagement in engineering courses, it is beneficial to understand the varied components that comprise student experience and behavior [1] especially as learning in STEM (Science, Technology, engineering and Math) includes challenging coursework [2]. This research is a part of an NSF grant #2225208, which specifically addresses the elements contributing to the relatively low retention rates in engineering [3]-[6]. To effectively address retention rates while simultaneously acknowledging the stress of increased international competition and demand for engineering careers [7], [8], this research investigates the compatible constructs of motivation and self-regulated learning to provide insight regarding student experiences [5], [9], [10]. Based on Winne and Hadwin's model of SRL [11], [12] there are several internal and external factors impacting a student's SRL. For the purposes of this study, we investigate motivation as an internal factor of SRL. For the external factor, students in this course engaged in multiple attempt testing to foster metacognitive SRL via reflection between exams.

Additionally, motivation and SRL positively contribute to learning achievement in STEM courses [7]. For example, when investigating gifted students' motivation compared to typical achieving students, gifted students displayed a statistically significantly higher score for each motivation subscale compared to non-gifted students while demonstrating the positive impacts of self-regulated learning amongst students [13]. Furthermore, in 73 intervention studies conducted during a scoping review, 63% of the SRL interventions were positively correlated with students' performance [14].

Therefore, the purpose of this study is to investigate (1) the interconnected nature of metacognitive self-regulated learning and motivation for students and (2) the self-regulatory and motivational profiles of students within this engineering classroom.

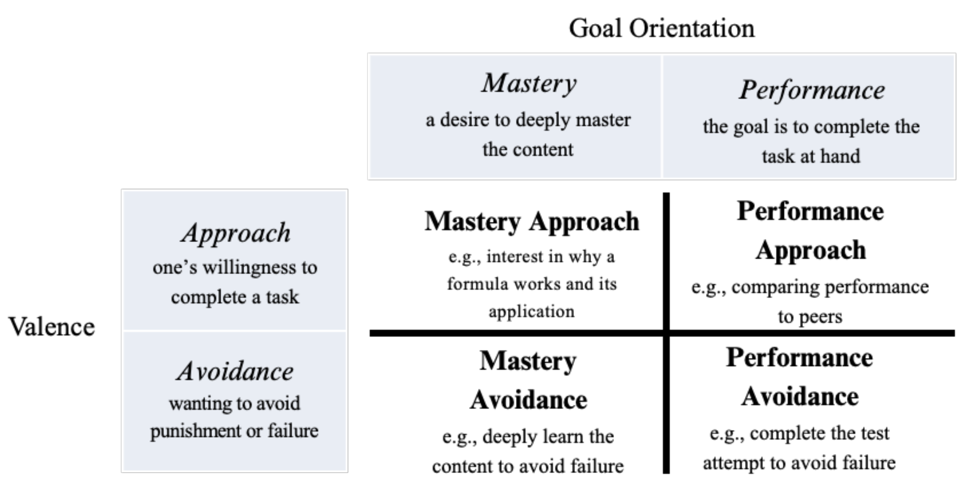
**Theoretical Frameworks**

For this study, we base our research on theories of motivation and SRL. Motivation is a multi-faceted construct that engages both one's beliefs about themselves, as well as how one approaches various tasks [15]. *Self-efficacy* is understood to be the beliefs that one holds regarding their capability to engage in the appropriate behaviors to complete a task or achieve a goal [16]. Therefore, self-efficacy serves as a key component of any individual's willingness to learn and to be motivated to approach a task. This construct, in conjunction with *achievement goal theory* [17], provides an integrative understanding of how a student might approach a specific task (e.g., studying in a fundamental engineering course) by identifying the orientation an individual has towards understanding a learning task.

Achievement goal orientation outlines the nature of goals students set for their learning. The framework includes a 2x2 matrix with two dimensions (Figure 1). The first focuses on one's motivation to learn: *mastery* (learning to deeply understand the material) and *performance* (learning to complete a task). The other dimension is paired with *approach* (a student's willingness to approach a task) and *avoidance* (a student's tendency to avoid a task or a consequence). As seen in Figure 1, the framework outlines four goal orientation profiles: mastery-approach, mastery-avoidance, performance-approach, and performance-avoidance. *Mastery approach* often indicates that students are reporting higher levels of wanting to master the content for the purposes of learning the material more deeply. *Performance approach* indicates that students report that they are willing to complete the task with the goal of achieving better outcomes than their peers comparatively. *Mastery avoidance* typically includes a desire to master the content, and students might be driven to complete their work to avoid consequences or failures. And finally, *performance avoidance* indicates students are completing tasks to avoid failure as compared to other students in their courses. Students receive a score for each self-reported dimension. Typically, students with a strong *mastery approach* goal orientation tend to learn deeply and are intrinsically motivated [18], whereas students who have a stronger *performance approach or avoidance* goal orientation might not engage in metacognitive practices, and lead to a more surface-level motivational engagement [18].

Not only do students' motivation to succeed impact their success in foundational engineering courses, fostering self-regulated learning can benefit student outcomes as well [19]. Self-regulated learning is an iterative process that engages students in (1) task understanding, (2) goal setting and planning (for a learning or study-based task), (3) performing (the act of studying), and (4) reflecting (on performance or effective strategies) [12], [20]. Self-regulated learning benefits student growth by promoting a process that deepens learning and bolsters metacognitive practices [19] (e.g., reflecting on one's own learning to better understand how to study better in the future). By investigating metacognitive self-regulated learning in the context of motivation, we can begin to create a more holistic view of student engagement, motivation, and learning [9].

**Figure 1.** Achievement goal theory matrix [21].




## Methods

As Thermodynamics is a challenging fundamental engineering course, students must use various learning strategies to persist in the program [22]. This study is part of an NSF grant that aims to support student engagement in undergraduate engineering education to be equitable and inclusive. Oftentimes, these engineering courses can provide roadblocks to students due to their motivation orientation, their beliefs in their ability to do well in the course, and the self-regulated learning (or lack thereof) utilized within the classroom. To address the external factors that impact SRL, the course instructor implemented multiple attempt testing (MAT). Multiple attempt testing allows for students to engage in metacognitive monitoring, reflect on their learning from the previous test, plan/practice appropriately, and then perform the test again. Students were able to take up to 3 attempts on every test.

In a Thermodynamics course at a large public university in the Southeast United States, 146 students ($n$=146) responded to the following measures to investigate their self-reported motivation: the General Self Efficacy (GSE) Scale ($.76 \leq \alpha \leq .90$) [23] the Achievement Goal Questionnaire – Revised (AGQ-R) [21] ($\alpha = .84$ [mastery-approach]; $\alpha = .88$ [mastery-avoidance]; $\alpha = .92$ [performance-approach]; $\alpha = .94$ [performance-avoidance], and the metacognitive self-regulation scale of the Motivated Self-Regulated Learning Questionnaire (MSLQ) ($\alpha = .79$; [24]).

The General Self-Efficacy Measure [23] is on a scale from 1-4 [Not True at All (1), Hardly True (2), Moderately True (3), and Exactly True (4)] with a sum score for the whole measure. The AGQ-R [21] is on a Likert scale from 1-5 [Strongly Disagree (1) to Strongly Agree (5)]. Each goal orientation is the sum of three specific questions associated with it (mastery-approach: 1, 3, 7; mastery-avoidance: 5, 9, 11; performance-approach: 2, 4, 8; and performance-avoidance: 6, 10, 12). The Metacognitive Self-Regulation Measure of the MSLQ [24] is on a scale from 1-7 [Not true at all of me (1) to Very true of me (7)]. The scores for the MSLQ are then averaged. Students completed the measures towards the end of the course, and the study was approved by the International Review Board (IRB).

**Results**

To better understand the manner in which students report their motivation and self-regulated learning, we asked the following research questions: (1) Are there distinct profiles that emerge when investigating student self-reported goal orientation and metacognitive self-regulated learning? (2) If so, are there significant differences in self-reported self-efficacy for these clusters?

*Research Question 1*
For the first research question, we ran two types of cluster analyses (as performed in [25]) on student self-reported responses to the MSLQ and each dimension of the AGQ-R (see above and Table 1). First, we ran hierarchical clustering to identify the number of clusters, followed by $k$-means clustering. By clustering these survey responses, we aimed to investigate the relationship between one's metacognitive self-regulated learning strategies, as well as their achievement goal orientation. As the AGQ-R is a measure that has four constructs that are not mutually exclusive, if they score high in one category, that does not automatically indicate that they will score low on another. Therefore, by conducting a cluster analysis, we will be able to identify whether clear groups emerge to investigate the relationship between student's reported 4 achievement goal orientation scores and metacognitive self-regulation in the classroom.

After standardizing the variables via Z-Scores in SPSS, we started with hierarchical clustering using Ward's method to determine the change in agglomeration coefficients (AC). The ACs indicated a 3- to 5-cluster solution would be appropriate. Based on the elbow method, we decided to test three groups first, and then four groups using $k$-means clustering. To justify our choice of cluster solution, we compared our cluster based on the sample sizes per cluster and comparing means between standardized variables in the cluster analysis [26]. For the four-cluster solution, the iteration histories reached .00. The number of cases were slightly imbalanced, yet provided clear insight about the distinct types of students that might be in the engineering classroom we investigated.

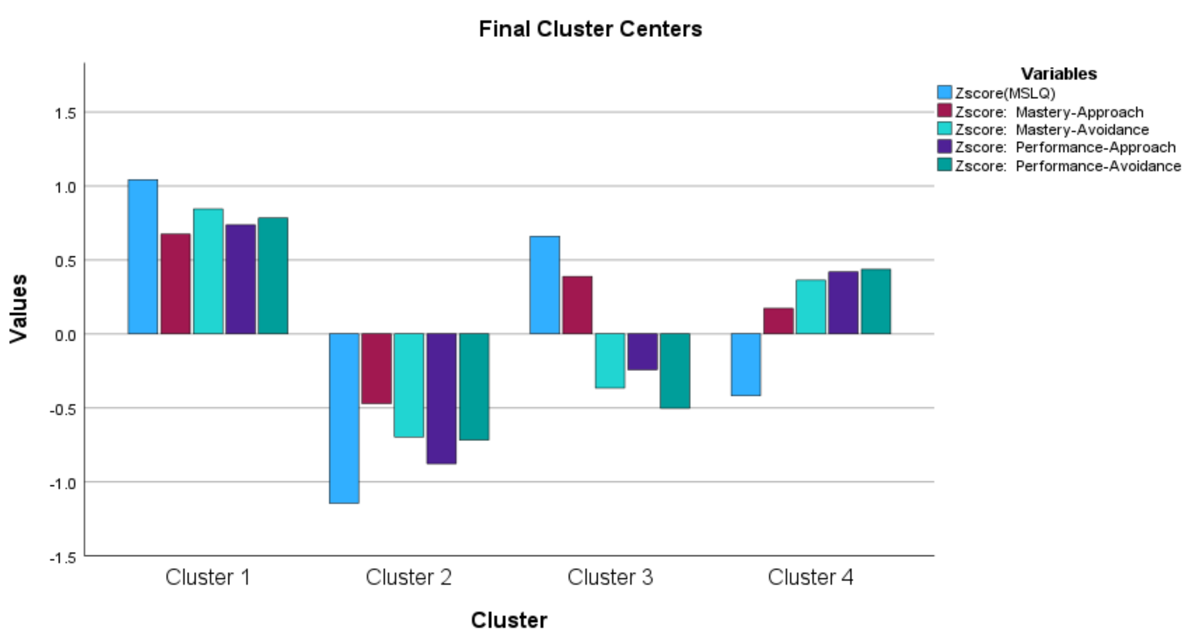
The following measures were utilized to create the clusters: each goal orientation of the AGQ-R, and the Motivated Learning Strategies Questionnaire. Table 1 includes each questionnaire, their minimums and maximums for each measure, and the average score for the students who volunteered to complete the survey in the Thermodynamics course.

**Table 1.** The AGQ-R and MSLQ measures used for the *k*-means cluster analysis.

| Measure | Alpha Level | Minimum Score | Maximum Score | Mean |
|---|---|---|---|---|
| Mastery-approach (AGQ-R) | α = .84 | 3 | 15 | 11.78 |
| Mastery-avoidance (AGQ-R) | α = .94 | 3 | 15 | 10.41 |
| Performance-approach (AGQ-R) | α = .92 | 3 | 15 | 11.05 |
| Performance-avoidance (AGQ-R) | α = .94 | 3 | 15 | 10.99 |
| Metacognitive Self-Regulation (MSLQ) | α = .79 | 1 | 7 | 4.48 |

The four main groups that emerged were: (1) High All Achievement Goals and High SRL (*n*=34), (2) Low All Achievement Goals and Low SRL (*n*=20), (3) Deep-Level Motivation and High SRL (*n*=24), and (4) Surface-Level Motivation and Low SRL (*n*=68) (Figure 2).

**Figure 2.** Four-Solution *k*-means clusters for the MSLQ and the AGQ-R (mastery approach, mastery avoidance, performance approach, and performance avoidance).



Cluster 1: High All Achievement Goals and High SRL (*n*=34) indicate that all factors were higher on average in all categories, suggesting that these students demonstrated using self-regulated learning skills. Additionally, all the achievement goal orientation dimensions had a high score, demonstrating a possible lack of clarity regarding the reason for their motivation in the course. Students who report high levels of SRL and high levels of all goal orientations might desire to both master the content and get a good grade in comparison to their peers.

Cluster 2: Low All Achievement Goals and Low SRL (*n*=20) demonstrate students reported lower scores for all of their responses, indicating they might struggle with SRL and motivation in their coursework. Similarly, to Cluster 1, there could be a lack of clarity around their motivational goals.

Cluster 3: Deep-Level Motivation and High SRL (*n*=24) is named as such because only the mastery approach and SRL is high in this category. Mastery approach typically indicates that a student desires to learn the material to deepen their understanding of the content, spurring on the use of metacognitive learning strategies [8], [18], [27]. Therefore, the pairing of High metacognitive SRL is unsurprising and may indicate that these students are effective self-regulators.

Cluster 4: Surface-Level Motivation and Low SRL (*n*=68) shows lower scores for all dimensions of the AGQ-R than Cluster 1, but also shows an inverse relationship with the MSLQ, demonstrating high levels of all goal orientations, but low use of self-regulation. Of note, both of the performance components of the AGQ-R are higher than the other dimensions, and therefore, named to be Surface-Level Motivation as performance tends to be associated with completing a learning task without seeking depth of knowledge [18], [28].

*Research Question 2*

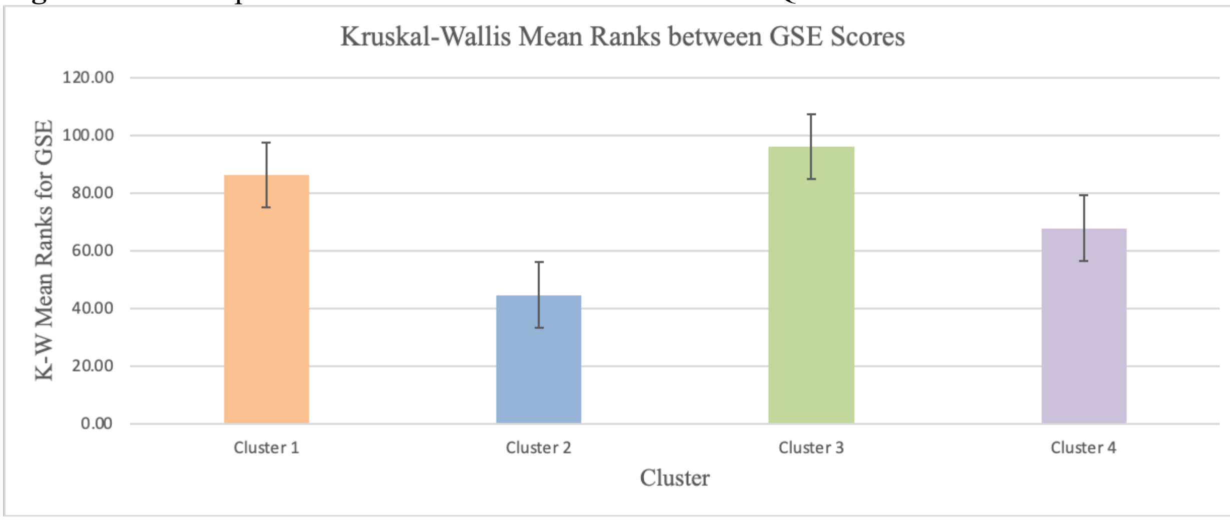
As clusters emerged, we investigated whether there were significant differences between these clusters as it pertains to self-efficacy (i.e., a student's belief they would do well in a course). Due to the unequal cluster sizes, a Kruskal-Wallis non-parametric test was run to determine if there were median differences between each cluster's self-efficacy score, another motivation construct.

The results revealed a statistically significant difference between clusters, with (3) Deep-Level Motivation and High SRL as the highest mean rank of 96.08, then (1) High All Achievement Goals and High SRL, (2) Low All Achievement Goals and Low SRL, with (4) Surface-Level Motivation and Low SRL as the lowest [$H(3) = 20.758$, $p < .001$].

**Table 2**. Mean Rank score for General Self-Efficacy by SRL-AGQ-R Cluster

| | | ***N*** | **Mean Rank** |
|---|---|---|---|
| **GSE** | 1 | 34 | 86.22 |
| | 2 | 20 | 44.53 |
| | 3 | 24 | 96.08 |
| | 4 | 68 | 67.69 |

**Figure 3.** Bar Graph of Kruskal-Wallis Results for SRL-AGQ-R Clusters




## Discussion

This study investigated the relationships between engineering students' self-reported motivational constructs and self-regulated learning in a Thermodynamics course that implemented multiple test attempts, a pedagogical adaptation to enhance metacognitive SRL practices in the classroom. We conducted a cluster analysis using student responses to the questionnaires; four clear clusters emerged. Consistent with the literature [29], the surface-level motivation and low-SRL cluster (Cluster 4) demonstrate that there is a relationship between students who engage in externally motivated activities and report low levels of using metacognitive self-regulated learning strategies. As this is the largest group (*n*=68), accounting for 45.67% of students in this course, it is helpful for the researcher teams to identify interweaving metacognitive strategies (e.g., pedagogical activities that promote metacognition). Additionally, students reported higher scores for the performance component of the achievement goal orientation construct; these students will be motivated to complete the work, but their goal will often be to complete the task instead of mastering the course material. These results indicate establishing methods and activities in the classroom, such as multiple attempt testing, might promote deeper learning strategies. These activities foster students' self-regulation and motivation, but at different self-reported levels.

Furthermore, Deep-Level and High SRL (Cluster 3) is one of the smaller groups, comprising only 13.69% of the class. As this group reported higher scores for a mastery goal orientation and SRL, it is expected that this group had the highest mean rank, demonstrating that these students had higher self-efficacy scores. Implications are to encourage educators to foster student metacognitive SRL strategies, as students' beliefs about their ability to do well in a course was significantly higher for students with high self-reported metacognitive self-regulated learning. Additionally, this profile exhibits student self-report scores of seeking mastery of the content, which is associated with deeper learning [9], [18]. As students *master* content in a fundamental engineering course such as Thermodynamics, they can effectively carry that knowledge with them to future courses, a beneficial skill to advance well in engineering degrees.

## Conclusion & Future Directions

These results demonstrate the relationships between SRL and motivation constructs (e.g., achievement goal orientation and self-efficacy) and provide a more holistic overview of students who might be in an engineering course early in their pursuit of an undergraduate degree. The clusters that emerged underscore the importance of differentiated instruction to enhance metacognitive SRL and motivation. Students who report low SRL also tend to report lower motivation, comprising almost half of the respondents in a Thermodynamics course as high SRL and motivation can lead to stronger outcomes and deeper learning [13], [14], [18].

Future studies will deepen the investigation of these clusters by identifying the relationship between these clusters and student perceptions of effectiveness for the pedagogical intervention. These data will help us adapt instructional design and decision-making [30] to more effectively foster student motivation and SRL. In this course in particular, the course instructor has already implemented multiple attempt testing to engage with reflection and metacognitive practices. Further investigation will review the perception of these activities by cluster in this class, while also analyzing the relationship to course grades.

Furthermore, as this project is for mechanical and aerospace engineering, the researchers hope to expand the project to other branches of engineering (e.g., computer engineering, civil engineering). To more holistically understand engineering students, the researchers will conduct interviews to have a more comprehensive understanding of student engagement with pedagogical differentiation, motivational constructs, their metacognitive self-regulated learning strategies, and their experiences as an undergraduate engineering student.

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