Understanding the Factors that Promote Students' Learning in Thermodynamics

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Abstract

Thermodynamics is an important subject in engineering training and forms the basis of pure engineering sciences. However, the performance of students in thermodynamics nationwide is poor. Not all students with high GPAs (>3.0) are able to pass thermodynamics on the first attempt. This study seeks to understand the correlation between the success rate in the Fundamentals of Thermodynamics (MEEN241) and the following dependent variables: General Physics (PHYS241), combined quizzes and reading quizzes, homework, tests, midterm examination, final examination, and prior GPA. We also designed assignments and assessments to capture acquired skills. These items test high-level thinking skills such as applying a thermodynamic principle to illuminate a problem. The research question this study tries to answer is, "How does success in quizzes and reading quizzes and prior knowledge in thermodynamics (PHYS241) impact the success rate in MEEN241?" To answer this question, we designed a machine-learning algorithm that is made up of decision trees, random forest ensemble, and Naïve Bayes classifiers that take as input the academic data of students (N=111) enrolled in MEEN241. The machine-learning algorithm makes the prediction by popular vote. The machine-learning model has an accuracy of 86.49%. The class recall is, respectively, 90.48 and 81.25%, for true pass and true failed. The class precision is, respectively, 86.36 and 86.67%, for predicated pass and predicted fail. Combined quizzes and reading quizzes is the root node in six out of seven classifiers, while PHYS241 was eliminated because the information content was less than the 0.1 threshold. These results show that success in RRQ impacts positively on the success rate in MEEN241 while also showing that prior knowledge in the form of PHYS241 has no influence on the success rate in MEEN241. This study suggests that students' success depends on developing and constantly improving good pedagogy and good study habits.

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Introduction

Engineering students' poor performance in thermodynamics is chronic, prevalent, intolerable, and resistant to change (Dukhan & Schumack, 2013; Dukhan, 2016). The historic average success rate in MEEN241, Fundamentals of Thermodynamics, is 54.6% (Akangah, Parrish, Ofori-Boadu, & Davis, 2018), meaning that a significant number of students fail the class each semester. Karimi and Manteufel identified four categories of students who failed: (i) students who neither attend class regularly nor complete assigned homework, (ii) students who appeared engaged but their efforts did not result in significant learning and as a result did poorly on exams, (iii) students with poor conceptual understanding of the material, and (iv) students with weak conceptual understanding of thermodynamics (2014).

Although PHYS241, General Physics I, is not a prerequisite to MEEN241, the mechanical engineering (ME) curriculum is structured so that students usually take PHYS241 prior to MEEN241. However, some students do not follow the prescribed curriculum and take MEEN241 before PHYS241. The ME undergraduate student handbook describes PHYS241 as "a calculus-based physics course that covers the fundamental principles of Newtonian mechanics, heat, and thermodynamics" (Mechanical Engineering Department, 2017).

About 59% of students enrolled in the MEEN241 class passed PHYS241, and the rest either failed or have not taken the course. It is therefore important to understand how prior knowledge in thermodynamics, PHYS241, helps or hinders learning and, specifically, how this prior knowledge impacts the success rate in MEEN241. This knowledge will help instructors more appropriately design instructions (Ambrose, Bridges, DiPietro, Lovett, & Norman, 2010).

After surveying important literature on pedagogy, Lin, Yen, Liang, Chiu, and Guo (2016) found that pedagogical methods and students' cognitive ability influence how they learn complex and abstract scientific concepts. Reasoning is an important human ability. Students use reasoning ability to draw conclusions and to solve problems, and this ability is a good predictor of academic achievement (Bhat, 2016). Hiebert and Grouws (2007) argue that developing students' quantitative reasoning skills requires providing them with opportunities to learn by allowing students to struggle with understanding important concepts and persisting in problem solving. Dukhan (2016) and Dukhan and Schumack (2013) identify three main learning issues that students have in thermodynamics: 1) conceptual difficulties, 2) struggle with integrating concepts and principles, and 3) not recognizing the relevance of thermodynamic principles in solving problems. Dukhan further reports that many instructors have implemented several instructional strategies; however, students' performance in thermodynamics continues to be poor and unacceptable (2016).

In this study, we aim to elucidate the importance of prior knowledge and well-designed assignments and assessments in promoting students' conceptual understanding of thermodynamics. We also seek to assess their ability to integrate known concepts and principles in solving thermodynamic problems. The aims of this study are (i) assign reading lessons to students to facilitate the learning of thermodynamic concepts and principles; (ii) assign quizzes and reading quizzes (RRQ) that are designed to assess acquired skills such as understanding of thermodynamic concepts, outlining thermodynamic problems, stating relevant assumptions, drawing schematics, drawing process diagrams, using calculus to derive equations, working from fundamental principles to solve problems, and working in consistent units; (iii) collect data on students' performance in PHYS241; and (iv) collect data on homework, quizzes, reading quizzes, midterm exams, etc. conducted during the semester. We developed a machine-learning model to answer the research question: "How does success in RRQ and prior knowledge in thermodynamics, PHYS241 General Physics, impact the success rate in MEEN241?"

Methods

Participants

The 111 participants were college students in an introductory thermodynamics class MEEN241, Fundamentals of Thermodynamics, during fall 2016 and spring 2017 semesters. We collected the academic records of these students, randomized the data, and assigned a random three-digit number to the resulting data. At the start of each semester, we collected students' GPAs and the letter grades of students in PHYS241. Scores in the following course tasks were compiled at the end of the semester: homework (HW), quiz (Q), reading quiz (RQ), tests (T), midterm (MT), final examination (FE), and cumulative weighted average (CWA). We combined the Q and RQ to obtain RRQ.

Materials

For this study, we designed and assigned concept-intensive materials as reading lessons for the students. Students take notes as they read through the assigned lesson, and these notes could be used on the RQ that is based on the reading lesson. We also designed Q, RQ, and T to assess acquired skills such as defining concepts, framing problems, stating relevant assumptions, drawing schematics, drawing process diagrams, working from fundamental principles, and working in consistent units. These assessments test high-level thinking skills such as applying a thermodynamic principle to illuminate a problem.

Procedure

Data Summary. We assigned various weights to assignments and assessments. These weights are summarized in Table 1, which also summarizes the frequency of various assignments and assessments along with students' success in these assignments and assessments

Table 1. Weights assigned to various assignments and assessments.

ASSIGNMENTS & ASSESSMENTS			STUDENTS' SUCCESS	
Types	Weights	Frequency	Predictor Variables	%Success Rate
HWs	10%	30	HW	83.78
RQ	5%	14	RQQ	63.1
Q	15%	16	MT	63.06
MT	20%	3	T	76.58
T	20%	6	FE	24.32
FE	30%	3	GPA (High, Ave, Low)	53.15; 45.95; 0.90
			PHYS241	59.46
			MEEN241 Pass-Rate	56.76

To pass MEEN241, a student must achieve a minimum CWA of 60% as well as a minimum of 60% in any assignment or assessment to pass that assignment or assessment. It is not mandatory to pass all course assignments and assessments to pass MEEN241. For this study, we defined a high GPA as greater than or equal to 3.0, an average GPA is defined as less than 3.0 but greater than or equal to 2.0, and a low GPA as less than 2.0.

Data Analysis. This study attempts to understand the relationship between the success rate in MEEN241 and the dependent variables: General Physics (PHYS241), combined quizzes and reading quizzes, homework, tests, midterm examination, final examination, and students' prior GPA. To answer the research question, we used the RapidMiner data analytics platform to develop a machine learning model that consists of three algorithms—decision tree, random forest, and Naïve Bayes. RapidMiner (2017) is an integrated extendable environment for machine learning, data mining, text mining, and predictive analytics platform and has an excellent drag and drop graphics capability. It has powerful algorithms capable of solving many analytics problems. RapidMiner comes as a free or commercial version. We used the free version in this study.

We ranked the attributes by information gain as shown in Table 2. Information gain is based on the reduction in entropy after a dataset is split on an attribute and is a measure of a reduction in uncertainty. Information gain measures the association between inputs and outputs and measures the relevance of an attribute. Entropy is a probabilistic measure of uncertainty or ignorance.

Table 2. Attributes ranked by information gain.

Attributes	Information Gain
RRQ	0.288
FE	0.241
MT	0.186
T	0.161
GPA	0.136
HW	0.069
PHYS241	0.042

Because the information gain of HW and PHYS241 is less than the threshold value of 0.1, we subsequently dropped them. We examined the correlation between the remaining attributes and did not find a strong correlation. We designed three classifiers that take these attributes as inputs to predict the success rate in MEEN241. Prediction is based on the voting system. Figure 1 shows the basic concept.

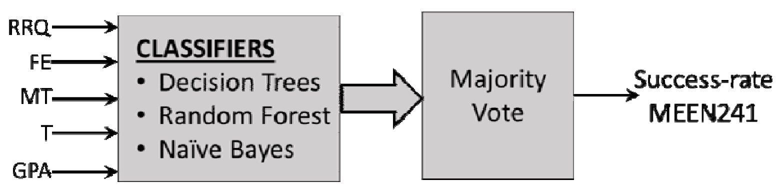


Figure 1. Conceptual model to predict success rate in MEEN241.

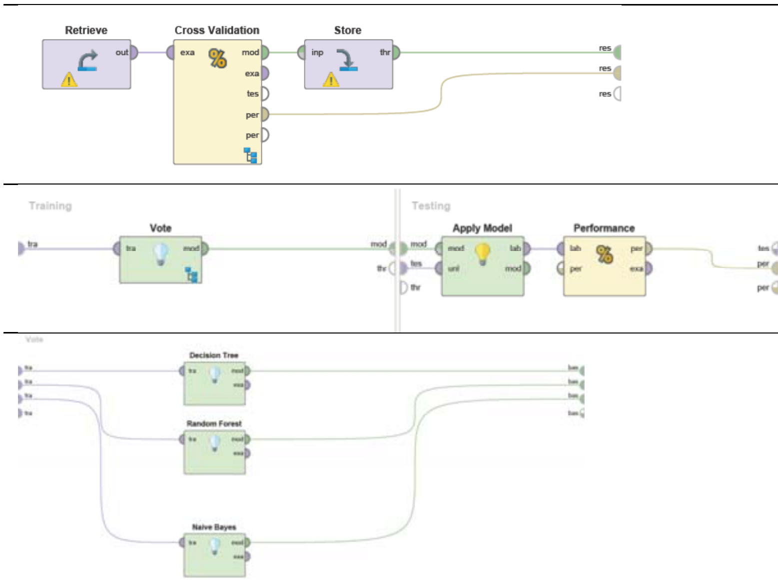
Decision Tree (DT) with Cross-Validation. We optimized the DT with respect to maximum depth, criterion, apply pre-pruning, and apply pruning. We obtained the optimized parameters as maximum depth of the decision tree: 6; criterion: accuracy; apply pre-pruning: true; and apply pruning: false. This model includes three subsets, derived by using a linear sampling method. In the cross-validation method, we used two subsets for training the DT and one subset for testing.

A minimum 0.1 Gini index gain, a measure of impurity or entropy of a node based on observed probabilities, was used. A confidence of 0.1 was used in making predictions based on the decision tree. This parameter specifies the confidence level used for the pessimistic error calculation of pruning (RapidMiner, 2014). The pessimistic pruning method uses pessimistic statistical correlation test (Quinlan, 1993).

Random Forest Classifier. A random forest classifier generates several DT ensembles, and it does not overfit model to data. In a case of a classification problem, the classifier outputs the class that is the mode of the classes, and in the case of a regression problem, it outputs the mean prediction of the individual trees. The classic bootstrap method was used in this study, where three subsets were created at random with replacements from the original data. RapidMiner randomly selects the variables and decides on the best split to the node. This method does not prune the trees. We applied a minimal Gini index of 0.1 and a confidence of 0.1.

Naïve Bayes Classifier. The Naïve Bayes classifiers are a family of simple “probabilistic classifiers” and denote a supervised learning method in addition to a statistical method for classification. The method applies the Bayes’ theorem with strong (naïve) independence assumptions between the attributes. It assumes a certain probabilistic model to calculate uncertainty about the model in a vigorous way by determining probabilities of the outcomes. It is capable of solving diagnostic and predictive problems. Bayesian classification provides practical learning algorithms and can combine prior knowledge with observed data. It calculates explicit probabilities for hypothesis and it is robust to noise in the input data.

The process diagrams for the ensemble algorithm are shown in Figure 2.



(a) Ensembled Machine Learning Model

(b) Vote, Apply model and Performance operators embedded in the Cross Validation operators

(c) Decision Tree, Random Forest and Naïve Bayes operators within the Vote operator

Figure 2. Ensembled machine learning model comprising decision tree, random forest and Naïve Bayes methods.

Results

Data Summary

The boxplot distributions of the dependent variables are shown in Figure 3.

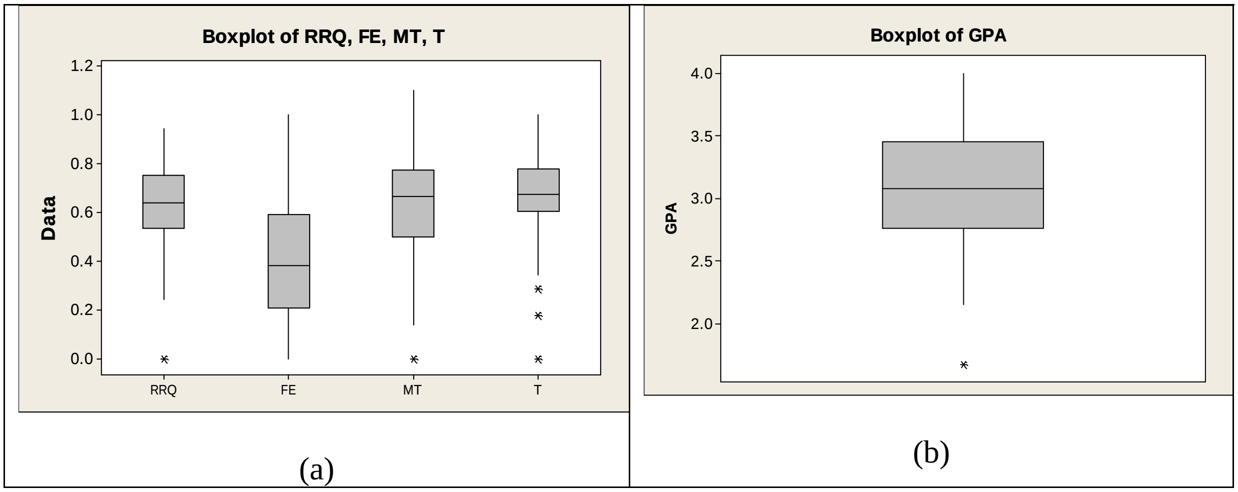


Figure 3. Distribution of students' data: (a) Assignments and assessments, (b) GPA.

Confusion Matrix

The confusion matrix is shown in Table 3.

Table 3. Confusion matrix of ensembled machine-learning algorithm.

	True PASS	True FAILED	Class Precision
Predicated PASS	57	9	86.36%
Predicated FAILED	6	39	86.67%
Class Recall	90.48%	81.25%	

The machine-learning model has an accuracy of 86.49%. The class recall or sensitivity are 90.48% and 81.25%, respectively, for true pass and true failed. The class recall, which is expressed as a percentage, is defined as the ratio of relevant instances that have been retrieved over the total amount of relevant instances. The class precision or positive dependent value is 86.36% and 86.67%, respectively, for predicated pass and predicated failed. The class precision is defined as the ratio of relevant instances among the retrieved instances.

Results from Modeling

Decision Tree Algorithm. Figure 4 shows a schematic of the details of the decision tree. The highest node, RRQ, in the tree is the root node and represents the attribute with the lowest entropy or uncertainty. The tree is built by first determining which attribute can best separate an impure node into children (internal) nodes that are purer than the parent node. This attribute is then used to split the node. The children nodes are FE and T. This process is repeated until a node is pure or too small to be split further, producing the leaf nodes—FAILED and PASS. A number of different criteria can be employed in this calculation; however, the Gini index criterion is used in this study.

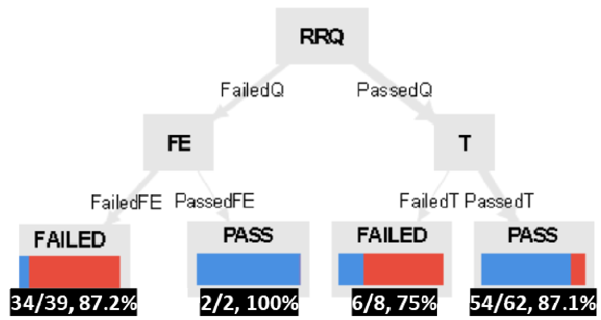
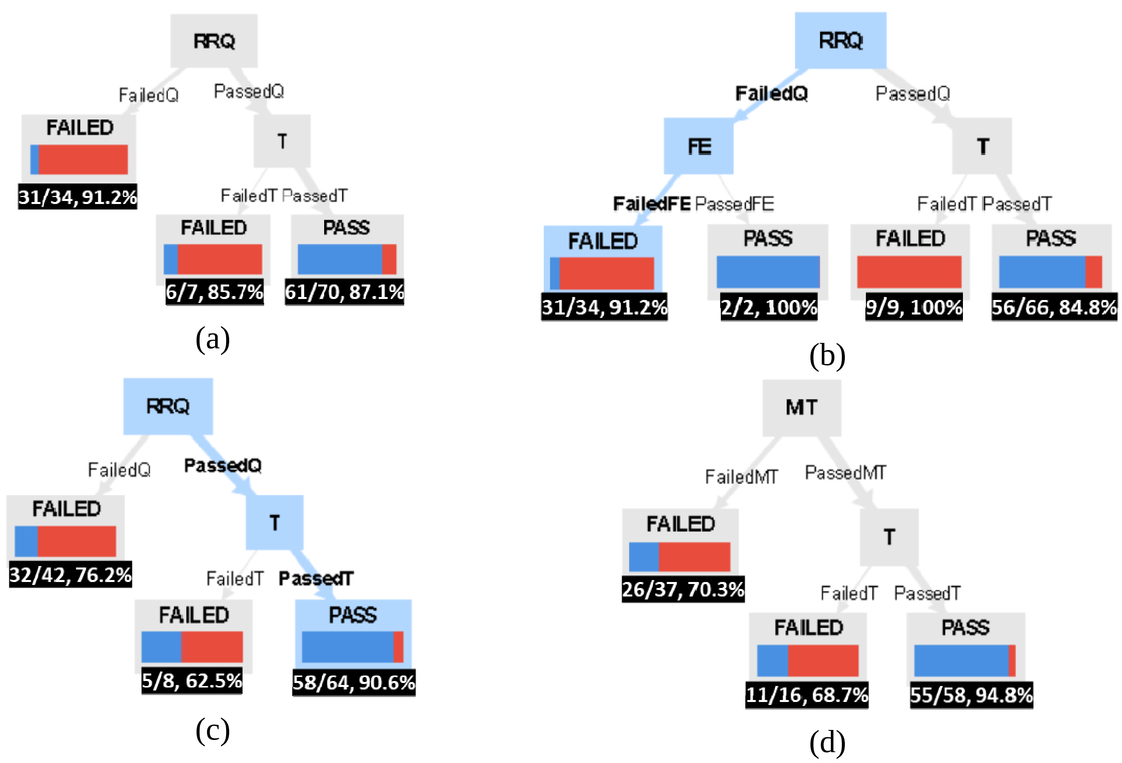
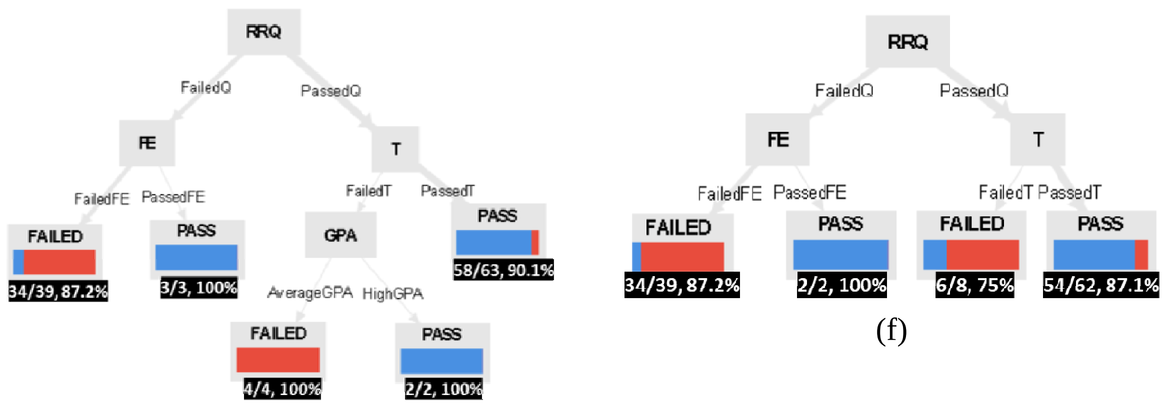


Figure 4. Decision tree with cross-validation.

The class label of an impure leaf is obtained from the highest occurring value of the target variable or class and this value is indicated beneath the leaf node. The decision tree predicts that out of 62 students who passed both RRQ and T, 54 students (87.1%) passed MEEN241. Of the 8 students who passed RRQ but failed T, 6 (75%) failed MEEN241. Similar analysis could be conducted for the other branches.

Random Forest Decision Tree Ensemble. Figure 5 shows six (a-f) different decision trees generated for this study, using stratified sampling with three subsets to guarantee that the distribution of the class in the subsets is the same as that in the whole dataset.





(e) (f)

Figure 5. Random forest decision tree ensemble.

Of the six random forest decision trees, five have RRQ as the root node while the remaining tree has MT as the root node. Taking the decision tree (e) as an example, the two students who passed RRQ, failed T, and have high GPA also passed MEEN241. More than half of 111 students (53.15%) have GPAs equal or greater than 3.0. Furthermore, all students with an average GPA who passed RRQ and failed T also failed MEEN241. However, the number of students with high or average GPAs who passed or failed MEEN241, respectively, are too small to draw any conclusions.

Discussion

This research looks at the manner by which the dependent variables GPA, RRQ, T, MT, and PHYS241 affect the success rate in MEEN241. Class assignments and assessments were thus designed in line with the problem-solving approach shown in the course textbook (Cengel & Boles, 2002). Resources such as teaching assistants and the instructor's office hours were also accessible to students to promote learning. In addition, students periodically received reading assignments.

A machine-learning algorithm to explore the relationship between dependent variables and success rate in MEEN241 was developed. The model has a good accuracy of 86.49%. The model correctly predicted 57 true pass out of 63 cases and correctly predicted 39 true failed out of 48 cases. In this study, we seek to understand the impact of the dependent variables on the success rate in MEEN241. Therefore, a model with a high class recall and precision is needed. The class recall is, respectively, 90.48 and 81.25%, for true pass and true failed. The class precision is, respectively, 86.36 and 86.67%, for predicted pass and predicted failed. Although a high class precision for predicted pass is needed, the difference is statistically insignificant.

The information content in HW and PHYS241 are uncertain and, as a result, their information gain is less than the threshold of 0.1. This discovery was found to be quite alarming. Akangah et al. determined that HW assignments were not helpful because students usually either copied from the solution manual or did not complete assigned HW (2018).

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This finding contradicts the general belief among school leaders, teachers, and parents that homework is a useful educational tool (Falch & Rønning, 2011). HW is influenced by many factors and effective HW design can promote student learning (Pelletier & Normore, 2007; Planchard, Daniel, Maroo, Mishra, & McLean, 2015; Bas, Senturk, & Cigerci, 2017). HW assignments are given for tutorial purposes, such as offering students with the chance of reviewing or practicing material that has already been presented in the class. When students copy from the solution manual or fail to submit their HW, they circumvent the process and the system fails. When students struggle with grasping important concepts and persisting in problem solving, they develop reasoning skills and that promotes academic achievement (Bhat, 2016; Hiebert & Grouws, (2007).

It was determined, however, that prior knowledge in PHYS241 has no influence on the success rate in MEEN241. Even though the curriculum of PHYS241 deals with some of the basic concepts in thermodynamics such as heat and should impact the passing rate in MEEN241, it does not do so. This finding is in accordance with conclusions made in Akangah et al. (2018). The information gain in PHSY241 (~0.042) is low, and there is no association between success in PHSY241 and success in MEEN241. Ambrose et al. (2010) concluded that students' prior knowledge can help or hinder their learning, but the data in this work does not support this conclusion, suggesting that course content in PHYS241 has no relevance to thermodynamics. We suggest a curriculum review to understand this discrepancy.

The research results indicate that success in RRQ positively impacts the success rate in MEEN241. RRQ has the highest frequency of testing among the dependent variables. We observed the effect of frequent classroom teaching on student achievement. Many researchers agreed that, when done right, frequent testing helps students retain concepts longer (Bangert-Drowns, Kulik, & Kulik, 1991; De Paola, & Scoppa, 2011; Karpicke, 2012; Carpenter, 2012; Einstein, Mullet, & Harrison, 2012).

The information gain in GPA is higher than the threshold value of 0.1; however, the information gain is not high, and GPA is therefore not a very useful attribute for predicting the success rate in MEEN241. GPA is not a root node and only made it as a branch node in one out of six decision trees. GPA is a very vital parameter employed in admissions and job recruitment decisions among others. Notwithstanding all these, several studies have indicated that GPA can easily be predisposed to reporting biases (Felton & Koper, 2005), tenure of faculty members (Karimi & Manteufel, 2013), student-faculty interaction and desire to excel in college (Lambert, Rocconi, Ribera, Miller, & Dong, 2012), students engaging in part-time work during the semester (Dundes & Marx, 2006). As a result of these influences on GPA, it is therefore not surprising that GPA is not the most important factor in predicting who passes MEEN241.

Conclusions

This paper assesses the correlation between the success rate in MEEN241 (56.76%) and the following dependent variables: General Physics (PHYS241), combined quizzes and reading quizzes, homework, tests, midterm examination, final examination, and students' prior GPA.

We used the entropy method to rank the dependent variables and eliminated variables with information gain less than the threshold of 0.1. The resulting dependent variables are T, MT, FE, GPA, and RRQ.

Class assignments and assessments were designed to evaluate acquired skills such as understanding of thermodynamic concepts, framing problems, stating relevant assumptions, drawing schematics, drawing process diagrams, using calculus, working from fundamental principles, and working in consistent units. These assignments and assessments test high-level thinking skills such as applying a thermodynamic principle to illuminate a problem. The problem-solving method is built on the strategy described in the textbook. Reading assignments were given frequently, followed by RQ.

A machine-learning model was developed to answer the research question: "How does success in RRQ and prior knowledge in PHYS241 impact the success rate in MEEN241? The model has good accuracy, class recall, and class precision. The models were, however, found to be slightly better at predicting success rate than fail rate. This capability is welcome as we seek to understand the effects of the dependent variables on the success rate in MEEN241.

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