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RESEARCH ARTICLE

A Data-Driven Approach to Engineering Instruction: Exploring Learning Styles, Study Habits, and Machine Learning

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ABSTRACT This study examined the impact of learning style and study habit alignment on the academic success of engineering students. Over a 16-week semester, 72 students from Process Engineering and Electronic Engineering programs at the Universidad de Los Llanos participated in this study. They completed the Learning Styles Index questionnaire on the first day of class, and each week, teaching methods and class activities were aligned with one of the four learning dimensions of the Felder-Silverman Learning Styles Model. Lesson 1 focused on one side of a learning dimension, lesson 2 on the opposite side, and the tutorial session incorporated both. Quizzes and engagement surveys assessed short-term academic performance, whereas midterm and final exam results measured long-term performance. Paired t-tests, Cohen's effect size, and two-way ANOVA showed that aligning teaching methods with learning styles improved students'short-term exam scores and engagement. However, multiple regression analysis indicated that study habits (specifically time spent studying, frequency, and scores on a custom-developed study quality survey) were much stronger predictors of midterm and final exam performance. Several machine learning models, including Random Forest and Voting Ensemble, were tested to predict academic performance using study behavior data. Voting Ensemble was found to be the strongest model, explaining 83% of the variance in final exam scores, with a mean absolute error of 3.18. Our findings suggest that, while learning style alignment improves short-term engagement and comprehension, effective study habits and time management play a more important role in long-term academic success.

INDEX TERMS Academic performance, engineering instruction, ensemble methods, Felder-Silverman learning styles model (FSLSM), machine learning (ML), predictive modeling.

I. INTRODUCTION

In the era of Artificial Intelligence (AI) and machine learning, the ability to mine vast amounts of student data

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presents university educators with unprecedented opportunities to adapt their teaching methodologies. Machine learning involves the development of algorithms that are learned from data to make decisions or predictions. This advancement raises an important question in the context of engineering education: What is the most valuable data that can be collected to develop the most effective teaching strategies Answering this question could significantly improve student performance and prepare them for their future careers as engineers. This effort aligns with Sustainable Development Goal 4 of UNESCO's Incheon Declaration for Education 2030, which calls for equitable quality education and lifelong learning opportunities for all [1].

One issue that has divided scholars, educators, and policymakers is the concept of learning styles, which refers to individuals' specific preferences for how they receive and process information, and how they respond cognitively and behaviorally to certain learning tasks [2]. These preferences are often categorized into several models, including the VARK model [3], Kolb's Experiential Learning Theory (ELT) [4], Honey and Mumford's learning styles [5], Gardner's multiple intelligences [6], Dunn and Dunn's learning styles model [7], Grasha-Riechmann's Student Learning Styles Scales [8], and the Felder-Silverman Learning Styles Model (FSLSM) [9].

These models are no longer new ideas in the literature. However, if the idea that students have specific learning styles is true, AI and machine learning can be built around this concept to improve educational outcomes. For example, Latham et al. [10] developed a Conversational Intelligent Tutoring System (CITS) that predicted learning styles with accuracies ranging from 61% to 100%, whereas Hasan et al. [11] achieved 97.56% accuracy in identifying learning styles using the Extreme Gradient Boosting (XGBoost) machine learning library. However, the existence of learning styles remains a controversial topic.

Learning styles advocates argue that tailoring instruction to preferred learning styles improves the quality of education and can create more effective and engaging learning experiences for students [12], [13]. Tailoring instructional styles to students' learning preferences has also been shown to reduce stress levels [14], resulting in more positive feedback from students about their teachers, [15] and increased student satisfaction in e-learning environments [16].

Opponents argue that there is insufficient empirical evidence and rigorous research to justify the widespread use of learning styles in education [17], [18], [19], [20]. Furthermore, some studies have indicated that aligning teaching methods with learning styles can lead to negative learning outcomes [21]. The meshing hypothesis, introduced by Pashler et al. [22], posits that students achieve optimal learning outcomes when instruction is tailored to their preferred learning style. To experimentally validate this hypothesis, they argue that specific evidence is needed: a cross-interaction between learning style and instructional method, showing that certain instructional methods benefit specific groups, but not others. However, their literature review revealed that very few studies have employed appropriate methodologies to test this hypothesis.

Beyond learning styles, are there other educational factors that deserve greater attention to improve educational outcomes Savage et al. [23] demonstrated that intrinsic motivation is a key factor in higher academic performance, suggesting that motivation is closely linked to engagement in learning activities. This perspective raises another important question: should educators prioritize increasing student satisfaction and engagement during lectures, labs, and tutorials, as several studies suggest [24], [25], [26], [27]?

Perhaps, the key to academic success lies in students' study habits: the methods, frequency, and intensity with which they study. Entwistle and Peterson [28] argued that a deep and strategic approach to studying is far more effective than simply aligning instruction with learning styles. Similarly, Rabia et al. [29] highlighted the role of consistent and well-structured study habits in achieving academic success regardless of learning style preferences. Heffler [30] also points out that while learning styles may affect how students allocate their study time, they do not necessarily improve their academic performance.

By identifying the key factors that influence academic success, AI and machine learning can be employed to make accurate predictions, allowing universities and faculty to intervene early with at-risk students and to provide targeted support. These predictions can also help institutions allocate resources more effectively in areas such as instructional design, academic advice, and curriculum development. Therefore, the use of machine learning to predict student performance over the past two years has been a topic of great interest. Doz et al. [31] used random forest regression and fuzzy logic to predict performance and achieved an R^2 of 0.391 for the national assessment scores. Nachouki et al. [32] developed a CGPA prediction model with over 92% accuracy using Random Forest (RF) based on high school and key course grades. Asthana et al. [33] demonstrated that learning coefficients derived from adaptive assessments can serve as dynamic predictors, with their linear regression model achieving a 97% accuracy in predicting academic performance.

These debates about the factors that most influence academic success and how they can be used to predict performance are necessary to advance the field of engineering education. To contribute to this discussion, we designed our study to test the following hypotheses.

1. Adapting teaching methods to students' preferred learning styles will improve retention and understanding in the short term, as measured by weekly tests, but not in the long term, as measured by midterm and final exam results.
2. Aligning teaching methods with students' learning styles will result in greater student engagement and

satisfaction but will not have a significant effect on long-term academic success.
3. Tutorials that integrate teaching methodologies from both sides of each learning dimension in the FSLSM (e.g., Active and Reflective in the AR weeks, Sensing and Intuitive in the SI weeks) will result in the highest academic performance and student engagement compared to lectures that focus on only one side of a learning dimension.
4. Study quality and habits have the greatest influence on academic performance, and these data will be the most effective in predicting midterm and final exam grades through machine learning.

Testing these hypotheses makes our study unique, as it combines an analysis of learning style alignment with a comprehensive assessment of students' study behaviors, using machine learning models to directly compare their respective impacts on academic success. This integrated approach offers new insights into how teaching methods and student habits contribute to the long-term outcomes of engineering education.

The structure of this paper is organized as follows: Section II details the design of the study, explaining the logic behind each statistical test, and the setup of the regression and prediction models employed. Section III presents and interprets the findings of these analyses, contextualizing them within the existing literature, and exploring their implications for teaching practices in engineering education. Section IV concludes the paper by summarizing the main findings and providing future research directions.

Table 1 provides a list of the nomenclatures that were used frequently in this article for ease of reference.

TABLE 1. Terms and abbreviations used in this study.

AI	Artificial Intelligence
FSLM	Felder-Silverman Learning Styles Model
AR	Active/Reflective
SI	Sensing/Intuitive
VB	Visual/Verbal
SG	Sequential/Global
ANOVA	ANalysis Of VAriance
ILS	Index of Learning Styles
ESS	Engagement and Satisfaction Survey
HSD	Turkey´s Honest Significant Difference
VIF	Variance Inflation Factor
SQS	Study Quality Survey
Moodle	Modular Object-Orientated Dynamic Learning Environment
KNN	K-Nearest Neighbors
SVM	Support Vector Machines
VE	Voting Ensemble
MSE	Mean Square Error
RMSE	Root Mean Square Error
MAE	Mean Absolute Error
R^2	R-squared
SCV	Standard Deviation of Cross-Validation
MCV	Mean Cross-Validation

II. METHODOLOGY

This section outlines the research design, data collection procedures, and analytical techniques used to explore the relationships among learning styles, study habits, and academic performance.

A. PARTICIPANTS AND STUDY DESIGN

Our study involved 72 fourth-year engineering students from the Universidad de Los Llanos, Villavicencio, Colombia. Among the participants, 42 were enrolled in the electronic engineering program, and 30 in the process engineering program. during the 16-week semester, from September to December 2023. To validate the adequacy of this sample size, statistical power analyses were conducted with a significance level ($\alpha = 0.05$) and power threshold ($1-\beta = 0.80$), demonstrating that the sample size was sufficient to detect medium to large effect sizes in the statistical analyses, including paired t-tests, ANOVA, regression models, and mixed-effects models.

Initially, 102 students participated in the study, but only 86 attended all lectures and tutorials. To maintain consistency and data integrity, only the 72 students who attended all classes during the semester and scored 1–5 or 7–11 on the Index of Learning Styles (ILS) survey were included in the final dataset. Students who scored 6, indicating a balanced preference, and those who did not attend all classes were excluded to ensure that the analysis accurately reflected the influence of learning style on academic performance. All students completed and signed consent forms prior to the start of the study, which was approved by the university's research and ethics board.

On the first day of class, students completed a Spanish-language paper version of the ILS questionnaire, which consists of 44 questions with answers marked as either 'a' or 'b.' Each set of 11 questions corresponds to one of the four learning dimensions of the FSLSM. The FSLSM was chosen for our study because it is the learning model most targeted at engineering students [9]. Scores were calculated on a scale of 0 to 11 for each dimension, where 11 indicated a strong preference for one side of the dimension and 0 indicated a preference for the opposite side. For example, in the Active/Reflective (AR) dimension, a score of 11 indicates a highly active learning student, while a score of 0 indicates a highly reflective learning student. Scores from 0 to 5 were labeled as right-side students of a dimension and scores from 6 to 11 as left-side of a dimension students.

The first dimension, AR, differentiates between students who prefer to actively engage with information through discussions, group work, or hands-on experiences (active), and those who favor introspection and individual reflection before interacting with the material (reflective). Active students excel in collaborative environments, where they can physically engage with the content, whereas reflective students perform better when they think independently [9].

The second dimension, Sensing/Intuitive (SI), identifies students based on their preference for types of information.

Sensing students favor concrete, practical details, and enjoy real-world applications of knowledge. They respond well to structured information and preferred consistency in their learning environments. Conversely, intuitive students are drawn to abstract theories, conceptual information, and innovative ideas. They often prefer exploring possibilities and connections rather than sticking to conventional or routine tasks. This dimension is important in engineering education, where both hands-on experimentation and theoretical understanding are required [9].

The third dimension, Visual/Verbal (VB), pertains to the sensory modality through which students best receive information. Visual learners retain and understand content more effectively when presented through diagrams, flowcharts, and other visual resources, while verbal learners respond better to written and spoken explanations, such as lectures or textual information. This distinction highlights the importance of incorporating both visual and verbal instruction methods to accommodate diverse preferences [9].

The final dimension, Sequential/Global (SG), describes how students progress in learning. Sequential learners prefer to present information in a linear, step-by-step manner, progressively building their understanding. They excel when the content is logically structured, allowing them to build on prior knowledge incrementally. By contrast, global learners comprehend information holistically and make intuitive connections. They may struggle with step-by-step learning, but excel when they grasp the big picture or broader context of the material before delving into specifics. Global learners benefit from seeing the end goal or wider context of the subject matter before focusing on its details [9].

Standardized protocols were established to administer all data collection instruments and assessments to ensure the thoroughness of the data collection process and to minimize potential biases. Each session included quizzes and surveys distributed immediately following the instructional activities, ensuring consistent timing and reducing the risk of memory bias. The instruments were designed to measure engagement, study behaviors, and learning outcomes in a uniform manner across the 16-week semester. The midterm and final exams were given outside of normal class time to ensure that they did not interfere with the rotating structure of teaching methodologies or affect the balance in the number of classes allocated to each learning dimension, thereby avoiding procedural bias that could influence the consistency and fairness of the study design. Variability in the data collection environment was minimized by adhering to a consistent schedule and process.

Selection bias was addressed using strict inclusion criteria, as only students who attended all classes and demonstrated clear preferences in the ILS survey were included in the final dataset. Excluding students with balanced preferences (scores of six on the ILS scale) ensured the clarity of the matched and mismatched conditions in the analyses. Additionally, students who did not meet the attendance requirement were excluded to maintain data integrity and to ensure that the dataset accurately reflected the effects of the instructional methods.

To further mitigate bias, all data were anonymized and processed using automated systems to eliminate manual errors. Questions within the surveys were balanced between positively and negatively worded items to reduce the risk of response bias such as acquiescence or social desirability effects. These measures ensured that the data collection process was systematic and objective, thus providing a reliable foundation for the study's analyses and conclusions.

With a robust data collection framework in place, this study implemented a structured instructional design focused on aligning teaching methodologies with learning styles. Each week of the semester focused on one of the four learning dimensions of the FSLSM, with two lecture sessions and one tutorial session, each lasting two hours. The first lecture session focused on one side of the learning dimension (e.g., Active for AR), the second lecture session focused on the opposite side (e.g., Reflective for AR), and the tutorial session combined teaching methodology and classroom activities from both sides of each dimension. This was rotated every four weeks, so the AR dimension was tested at weeks 1, 5, 9, and 13; the SI dimension at weeks 2, 6, 10, and 14; the VB dimension at weeks 3, 7, 11, and 15; and the SG dimension at weeks 4, 8, 12, and 16. The midterm and final exams were conducted outside the normal class time.

The selection of teaching methodology and classroom activities was guided by the course outlines of electronic engineering and process engineering courses and was supported by relevant academic literature.

For the AR dimension, we borrowed ideas from Freeman et al. [34] and Prince et al. [35]. Active instruction, which included group discussions and laboratory work, was incorporated into the first lecture to promote engagement and the immediate application of concepts, while reflective instruction involved the use of reflective journals and individual problem-solving assignments, allowing time for contemplation before applying the taught material. For the SI dimension, we developed teaching methods and classroom activities using the work of Felder and Silverman [36]. Sensory instruction included laboratory experiments and real-world case studies to engage students in hands-on, detail-oriented tasks. Conceptual discussions and open-ended design tasks were conducted to foster creativity and forward thinking.

For the VB dimension, we drew our ideas from Schneider et al. [37]. For visual instruction, multimedia presentations, diagrams, and flowcharts were used to explain complex concepts, whereas verbal instruction included detailed reading assignments and group discussions. For the SG dimension, ideas were taken from the work of Prince and Felder [38], where sequential instruction used structured problem sets and flowcharts to understand the material in a logical and systematic way, whereas global instruction involved overviews and interdisciplinary projects.

A complete breakdown of each week is provided, including topics taught, teaching methodology, and class activities (see Appendix A). In both engineering courses, there was a midterm exam in week five and a final exam at the end of week 16.

B. QUIZ AND ENGAGEMENT SURVEY DEVELOPMENT

At the end of each lesson and tutorial, the students were allotted 10 minutes to answer a quiz. The quizzes were designed to assess retention and comprehension of the material covered in each teaching session. This allowed us to statistically measure the effect of the fit and mismatch of the teaching methodology with students' learning styles as well as the correlation with their exam scores. For the purposes of our study, we defined retention as students' ability to recall the information they have learned, and comprehension as the ability to understand the meanings or concepts of the material. Based on the work of Maya et al. [39], the quizzes used a combination of multiple-choice questions (MCQs) and short-answer questions.

MCQs were used to assess students' recognition memory and understanding of key concepts, whereas short-answer questions assessed their ability to apply and synthesize new information. Each quiz consisted of six multiple-choice questions worth one point each and two short-answer questions worth two points each, for a total of 10 points.

Following the questionnaire, students were given five minutes to complete the Engagement and Satisfaction Survey (ESS). This survey was developed to assess how the students felt about each teaching session. The survey, shown in Appendix B, consisted of 10 questions, with responses scored on a Likert scale from "Strongly Disagree" with a value of 1 point to "Strongly Agree" with a value of 5 points. The points were summed to obtain a range of 10–50 points.

Guided by the literature on educational assessment and measuring student engagement [40], [41], the survey was designed to assess several aspects of engagement and satisfaction, including clarity of material, relevance of activities, effectiveness of teaching methods, and overall student motivation.

While the Likert scale provides a straightforward and widely accepted method for capturing subjective perceptions, such scales are subject to potential response biases, including central tendency bias and acquiescence bias. These biases can affect the interpretation of data by influencing the way students respond to questions, particularly if they tend to avoid extreme options or agree with statements, regardless of their true feelings. To mitigate these limitations, the survey was carefully designed to include a balanced set of positively and negatively worded questions to minimize the likelihood of patterned or biased responses. Additionally, the large sample size and consistent administration of the survey across all class sessions helped ensure reliable and interpretable data.

The results of this survey served as a feedback tool to improve teaching and as a source of data for statistical analysis. This also allowed us to measure the correlation between student engagement and satisfaction with their midterm and exam grades to test Hypothesis 4.

C. STATISICAL ANALYSIS

To test Hypotheses 1 and 2, we conducted paired t-tests to assess the effect of matched and mismatched teaching methodologies on student performance and engagement across the four dimensions of the FSLSM learning styles. The goal was to determine whether students performed better and engaged more when the instructional approach was aligned with their preferred learning style.

In this analysis, a match condition was defined as when the student's learning style matched the instructional approach used (e.g., active learning for an active learner identified by the ILS), whereas a mismatch condition occurred when the instructional method did not align with the student's learning style.

In addition to paired t-tests, effect sizes were calculated to assess the magnitude of differences. Cohen's d was used to measure the effect size, which represents the difference between the two means in terms of standard deviations.

In this case, the mean difference refers to the average score difference between the match and non-match conditions for each student, while the standard deviation of the differences represents the variation of those differences across the dataset.

Effect size calculations were performed separately for each learning dimension and for quiz and engagement scores. This analysis was conducted using Python 3.11, with numpy and scipy.stats libraries for data processing and statistical calculations.

To complement the paired t-tests, independent t-tests were conducted to analyze differences in quiz scores and engagement scores between the matching and non-matching conditions. While paired t-tests focused on within-student comparisons, independent t-tests examined performance differences across groups, thus providing a broader perspective on instructional alignment.

Independent t-tests were used, as they allowed for a direct comparison of aggregated quiz performance and engagement scores, validating the findings of paired t-tests at the group level. This dual approach ensured a comprehensive analysis by capturing both individual-level variability and broader population trends, thus enhancing the robustness and generalizability of the results.

The next part of our study was to further test Hypothesis 1 against the argument put forward by Pashler et al. [22], which states that the only way to validate the learning styles hypothesis is to demonstrate a crossover interaction between learning style and instructional method. This means that the instructional method that produces the best learning outcomes should vary depending on the student's learning style, leading to a crossover in performance when the data are graphed. To test this, a two-way ANOVA was conducted for each learning dimension, with two factors: the students' specific learning style (e.g., active vs. reflective) and the instructional method used (Lecture 1 vs. Lecture 2). The main focus of the analysis was the interaction term, as a significant interaction indicates that the most effective instructional method depends on the student's learning style.

Following the ANOVA analysis, interaction plots were created using Python 3.11 to visually assess the presence of cross-class interactions. In these plots, quiz scores are placed on the y-axis and teaching methods on the x-axis, with separate lines representing each learning style. A cross-class interaction would be confirmed if the lines cross, indicating that different teaching methods were more effective for different learning styles.

Mixed-effects models were employed to analyze the quiz and engagement scores under matching and non-matching conditions. The fixed effect in these models was the instructional alignment condition (MatchStatus: Matching vs. Non-Matching), while random effects were included for StudentID to account for repeated measures within the students. Separate models were constructed for the quiz and engagement scores to examine the impact of instructional alignment on these outcomes while adjusting for individual variability. The models were implemented using Restricted Maximum Likelihood (REML) estimation, providing estimates for fixed effects (condition) and random effects (StudentID variance). This approach ensured that both between- and within-subject correlations were accounted for in the analysis.

StudentID was included as a random effect to account for individual differences in students' baseline performance and engagement, which remained constant across the different conditions. This adjustment ensured that variations in scores were correctly attributed to instructional alignment (matching vs. non-matching) rather than to inherent differences between students. By treating each student as their own "group" with unique characteristics, the model focused on the effects of instructional conditions without bias. This approach enhances the accuracy and reliability of the analysis by acknowledging that students are not the same, and prevents misattribution of variability in the data.

The use of mixed-effects models was justified by the hierarchical structure of the data, with repeated measures nested within individual students across weeks and under instructional conditions. These models complemented the paired t-tests, independent t-tests, and Two-Way ANOVA by corroborating the findings, accounting for individual variability, generalizing the results, and extending the analysis depth. Unlike t-tests, mixed-effects models explicitly adjust for baseline differences between students (random intercepts) and potential variability in responses to instructional conditions. By addressing dependencies in the data, mixed-effects models strengthened the generalizability of the results, ensuring that the observed effects of instructional alignment were not artifacts of unaccounted within-subjects correlations. Furthermore, while Two-Way ANOVA focused on the interaction effects between learning styles and instructional methods, mixed-effects models incorporated individual differences as random effects, offering a more comprehensive understanding of the data. This dual approach strengthened the overall reliability of the study's findings.

The next part of our study aimed to test Hypothesis 3 by analyzing whether students performed better on the quizzes and showed higher engagement during tutorial sessions, which combined teaching methodologies from both sides of a learning dimension, compared to lectures that focused exclusively on one side. The hypothesis for both analyses was that integrating both teaching styles into the tutoring environment would result in higher exam scores and engagement than lectures that did or did not match students' preferred learning styles.

The quiz and engagement scores were compared under three conditions: matched, unmatched, and tutorial across the four learning dimensions of the FSLSM. The analysis was performed using Python 3.11, including pandas for data manipulation, statsmodels to perform statistical tests, and scipy for post hoc analysis. For the quiz and engagement scores, a repeated measures ANOVA was used to assess the differences between these three conditions within each learning dimension. This method controls for individual variability when comparing different teaching methods for the same group of students. Data were reformatted to a long format for analysis, and the AnovaRM function from the statsmodels library was used to perform repeated measures ANOVA.

Post-hoc comparisons were performed using Tukey's Honest Significant Difference (HSD) test from the statsmodels.stats.multicomp module to identify statistically significant differences between the conditions. This test was used to make pairwise comparisons between conditions (match vs. Tutorial, Match vs. No Match, Tutorial vs. no match) considering multiple testing.

D. FACTORS THAT AFFECT ACADEMIC PERFORMANCE

To assess the relationship between quiz and engagement scores under various instructional conditions (match, mismatch, and tutorial) and their impact on midterm and final exam performance, we used multiple linear regression and RF models.

Based on the students' learning styles across the four learning dimensions, averages were calculated for weeks 1-4 for midterm predictions and weeks 5-16 for final exam predictions.

We used multiple linear regression with the Python 3.11 scikit-learn library to analyze the predictive power of quiz scores and engagement in midterm exam performance. Each model used average scores from the match, mismatch, and tutorial quizzes. as independent variables and midterm and final exam scores as dependent variables. We further analyzed engagement scores, following the same methodology, by calculating averages of match, mismatch, and tutorial conditions to predict midterm and exam results. To address any potential multicollinearity between the predictors, we calculated the Variance Inflation Factor (VIF) using the statistics models library.

We applied Random Forest after multiple linear regressions to capture possible non-linear errors. relationships between quiz scores and exam performance, which the linear model might have missed. We used pandas for data manipulation, scikit-learn to implement the regression model, and Random Forest regressor for ensemble models; to evaluate performance, we used mean_squared_error and ^{r} score.

To test Hypothesis 4, this part of our study explored the relationship between students' study habits and their performance on midterm and final exams. The data collected included exam scores, Study Quality Survey (SQS) scores, and Moodle logs of total time and frequency spent studying. The goal was to determine how study quality, frequency of study sessions, and time spent studying before and after the midterm exam predicted academic success. The SQS assessed the effectiveness of students' study habits across multiple dimensions. It consists of 10 questions scored on a 5-point Likert scale, addressing aspects of study behavior such as study duration, consistency, review practices, and use of additional resources such as professor-provided readings. The total possible score ranged from 10 to 50 points, with higher scores indicating better study habits. The survey was administered thrice: on the first day of class, before the midterm exam, and after the midterm exam. The average score of these three points was used in the analysis, providing a stable and representative measure of study habits throughout the semester. All the SQS questions are presented in Appendix C.

The students recorded the time they spent studying and the frequency of their study sessions using the university's Moodle platform. The frequency of study sessions was calculated as the number of days per week that the students engaged in study activities. These data provided information about the consistency and distribution of study time before and after the midterm exam.

While the SQS provided valuable data on students' study habits, the use of a Likert scale introduced certain limitations that could influence the interpretation of the data. Response biases, such as social desirability bias, may have led some students to overreport positive study behaviors to align with their perceived expectations. Additionally, the ordinal nature of Likert-scale data can limit its sensitivity in capturing subtle differences in study habits. To address these constraints, the survey questions were carefully crafted to minimize leading language and ensure clarity. Furthermore, averaging the scores across the three time points helped reduce the potential variability caused by isolated instances of inconsistent responses, providing a more reliable measure of students' study habits over time. These measures ensured that the SQS scores remained meaningful in predicting academic success.

We used multiple regression analysis to quantify the extent to which study habits influenced midterm and final exam scores, compared to the learning style alignment models. Two regression models were developed: one regressing midterm exam scores on study quality, frequency of study sessions, and time spent studying before the midterm exam and one regressing final exam scores on study quality, frequency of study sessions, and time spent studying after the midterm exam. Multiple regression analysis allowed us to assess the combined effect of these study behaviors on exam performance, providing a direct comparison to the multiple linear regression models used for learning style alignment.

E. PREDICTIVE MODELING OF ACADEMIC PERFORMANCE

Our study tested several machine learning models to predict midterm and final exam scores using Moodle logs of study frequency and amount, as well as SQS data including scores for each question. The goal was to further test Hypothesis 4, which posits that study habits are the strongest predictors of academic success in both the midterm and final exams. The goal was to identify the best-performing models for making predictions and to determine the key drivers of academic performance.

First, we tested tree-based models, including bagging regressors, Decision Trees, and Random Forest, as these models are well suited for handling complex, non-linear relationships and providing insights into feature importances. We used pandas for data manipulation, scikit-learn for model implementation, and matplotlib for visualization. Specifically, for the Bagging model, we employed BaggingRegressor from the sklearn.ensemble module, along with DecisionTreeRegressor from sklearn.tree. The Bagging model was used to reduce the variance by averaging multiple decision trees, thereby providing more stable predictions. For the Decision Tree model implemented using DecisionTreeRegressor from sklearn.tree, the focus was on interpretability and understanding the decision-making process behind the predictions. The Random Forest model, implemented with RandomForestRegressor from sklearn.ensemble, was used for its robustness, as it creates an ensemble of decision trees to improve accuracy and reduce overfitting. For all tree-based models, hyperparameter tuning was performed using RandomizedSearchCV from sklearn.model_selection, optimizing parameters such as n_estimators, max_depth, and min_samples_split. Five-way cross-validation was used to evaluate the model performance on different data splits and avoid overfitting.

Next, we tested instance-based models such as k-nearest neighbors (KNN) and Support Vector Machines (SVM). For these models, we used pandas for data handling, scikit-learn for model implementation, and StandardScaler from sklearn.preprocessing to scale input features. The KNN model was implemented using KNeighborsRegressor from sklearn.neighbors, with the number of neighbors (n_neighbors) tuned to optimize the performance. KNN was chosen for its ability to make predictions based on instance similarity, making it a valuable model for understanding how closely related study behaviors predict academic success. The SVM model was implemented using Support Vector Regression (SVR) from sklearn.svm with a Radial Basis Function (RBF) kernel to capture non-linear relationships between study behaviors and test scores. Hyperparameter tuning was performed using RandomizedSearchCV, with parameters such as C (regularization strength) and gamma (kernel coefficient) optimized to ensure that the models were generalized well. Both models were evaluated using a five-way cross-validation to ensure consistency in comparisons across different data subsets.

We also tested a Voting Regressor that combined predictions from RandomForestRegressor, Ridge, Lasso, and ElasticNet to provide a balanced and robust prediction. Voting Ensemble (VE) was implemented using sklearn.ensemble *'s*VotingRegressor, with fine-tuning performed using RandomizedSearchCV to optimize hyperparameters for each individual model. This ensemble approach enabled us to leverage the strengths of each component model, with the final prediction being the average of the individual model results. Cross-validation was applied to ensure that the VE model provided consistent performance for different subsets of the data.

For all the models, we employed a consistent set of metrics to assess their predictive performance. These metrics included the mean square error (MSE), root mean square error (RMSE), mean absolute error (MAE), and R-squared (R^2). The MSE was used to quantify the mean square difference between the predicted and actual exam scores, providing a general idea of the model's accuracy. The RMSE was calculated to present this error in the same units as the exam scores, making it more interpretable. MAE represents the mean magnitude of prediction errors, offering a more intuitive understanding of how far off the predictions were on average. Finally, R^2 was used to assess how much of the variance in the midterm and final exam scores was explained by the model. These metrics were calculated separately for midterm and final-exam predictions, allowing for a comprehensive comparison of model performance at different stages of the semester.

Feature importance was calculated for models that offer this functionality, specifically the Random Forest and VE models. Feature importance was used to understand the relative impact of each study's behavior on predicting academic performance. The RandomForestRegressor and tree-based components within the Voting Regressor, both from the sklearn.ensemble library, were used to rank features based on their importance to the predictions. For models such as KNN, SVM, and Bagging Regressor, feature importance was not applicable, as these models do not inherently offer such functionality. In these cases, the performance was evaluated based on predictive accuracy alone.

III. RESULTS AND DISCUSSIONS

This section presents and discusses the key findings of our study by examining the influence of learning styles, study habits, and predictive models on academic performance. The results are then discussed in the context of the engineering education literature. More detailed explanations for Tables 2–10, including definitions of parameters and interpretation of results, are provided in Appendix D.

A. SAMPLE SIZE AND STATISTICAL POWER

The sample size of 72 participants represented the eligible population of fourth-year engineering students enrolled in two programs at the Universidad de Los Llanos during the study semester. To ensure data consistency and reliability, only students who completed all sessions and met the specific criteria for the ILS survey, as detailed in the Methodology section, were included. Statistical power analyses were conducted to confirm the adequacy of the sample size for the various analyses. These calculations were performed using the standard thresholds for significance ($\alpha = 0.05$) and power ($1-\beta = 0.80$). The results demonstrated that the sample size was sufficient for detecting medium to large effects across the statistical methods employed.

For paired t-tests, the power analysis indicated that a sample size of 34 participants was required to detect a moderate effect size ($d = 0.5$), whereas 15 participants were sufficient to detect a large effect size ($d = 0.8$). The sample size of 72 participants exceeded these thresholds, ensuring robust power for these analyses. For ANOVA, which examined the interaction effects between learning styles and instructional methods, the required sample size for medium effects ($f = 0.25$) was 34 participants and for large effects ($f = 0.4$) was 15 participants. Thus, the sample size exceeded these requirements, providing confidence in the validity of the results.

In regression analyses, which were employed to predict academic performance, the power analysis revealed that 33 participants were required to detect small effect sizes ($f^2 = 0.02$) and 16 participants were sufficient for medium effects ($f^2 = 0.15$). The inclusion of 72 participants satisfied these requirements, ensuring that the analysis could detect meaningful effects. Mixed-effects models, used to account for repeated measures over 16 weeks, further increased the statistical power by leveraging repeated observations. These models incorporate both fixed and random effects, enhancing precision and reducing variability, making them well suited for smaller sample sizes.

The machine learning models employed in this study, including ensemble methods such as voting regressors and RF, were validated for dataset size using five-fold cross-validation. This approach ensures that the models are trained and tested on independent subsets, thereby enhancing their generalizability. Additionally, the feature-to-sample ratio remained within acceptable limits, with fewer than 15 predictors, including study behaviors, such as time spent studying, session frequency, and SQS scores. These factors mitigated the risk of overfitting even with a modest sample size.

Although larger datasets could further improve generalizability, the findings align with prior studies in educational research that successfully applied machine learning to datasets of similar or smaller sizes. Studies by Nachouki et al. [32] and Asthana et al. [33] demonstrated successful academic performance predictions using datasets of comparable or smaller sizes, and the sample size and robust statistical techniques used in this study ensured that the results were both reliable and meaningful. Future research involving larger and more diverse populations could extend the generalizability of these findings; however, the current study still provides valuable insights into the relationship between learning styles, study behaviors, and academic performance in engineering education.

B. STATISTICAL ANALYSES

Having established the adequacy of the sample size and robustness of the statistical methods, the results of the analyses are presented. As shown in Table 2, the paired t-test revealed significant differences in quiz and engagement scores between the matched and mismatched instructional methods across all four learning dimensions. In the AR dimension, active learners showed statistically significant improvements in quiz scores ($t = 4.04$, $p = 0.0002$) and engagement scores ($t = 5.79$, $p = 8.56 \times 10-7$) when the instructional method matched their learning style. Reflective learners also demonstrated substantial improvements in quiz scores ($t = 8.94$, $p = 7.92 \times 10-10$) and engagement scores ($t = 5.04$, $p = 2.26 \times 10-5$) under matching conditions.

TABLE 2. Scores and p-values for questionnaire and engagement scores.

Learning Dim	Learning style	Quiz t-score	p-value	Eng t-score	p-value
AR	Active	4.04	2.00 x 10^{-4}	5.79	8.56 x 10^{-7}
	Reflective	8.94	7.92 x 10^{-10}	5.04	2.26 x 10^{-5}
SI	Sensing	7.95	4.09x10-10	8.90	1.76 x 10^{-9}
	Intuitive	5.74	5.51 x 10^{-6}	3.95	5.70 x 10^{-4}
VB	Visual	3.13	3.30 x 10^{-3}	7.87	1.21 x 10^{-9}
	Verbal	4.94	2.74 x 10^{-5}	3.74	8.00 x 10^{-4}
SG	Sequential	3.26	2.70 x 10^{-3}	3.16	3.4 x 10^{-3}
	Global	8.18	6.53 x 10^{-10}	5.23	6.54 x 10^{-6}

A similar trend was observed in the SI dimension, where sensory-perceptive students performed better on quizzes ($t = 7.95$, $p = 4.09 \times 10-10$), and intuitive students also showed significant improvements ($t = 5.74$, $p = 5.51 \times 10-6$) under pairing conditions. These results were also consistent across the VB and SG dimensions, where both types of students within each dimension performed better when the instructional method was aligned with their learning-style preferences.

As shown in Figure 1, Cohen's d effect size analysis demonstrated moderate-to-large effects across most dimensions, with 95% confidence intervals, confirming the robustness of these effects. In the AR dimension, active learners exhibited a moderate effect on quiz scores (Cohen's d = 0.62, 95% CI: 0.19, 1.05), and a moderate to large effect on engagement scores (Cohen's d = 0.71, 95% CI: 0.19, 1.24). The confidence intervals, particularly for engagement scores, suggest that the effect of matching instructional methods on learning styles is consistently moderate to high for active learners. Reflective students showed large effects on test scores (Cohen's d = 1.63; 95% CI: 1.08, 2.17) and engagement scores (Cohen's d = 0.92; 95% CI: 0.41, 1.44), with confidence intervals indicating the high reliability of these effects.

In the SI dimension, sensory learners exhibited large effect sizes for test scores (Cohen's d = 1.17, 95% CI: 0.65, 1.70), whereas intuitive learners showed large effects (Cohen's d = 1.13, 95% CI: 0.62, 1.65). The wide confidence intervals, while still significant, suggest some variation in effect sizes but maintain the conclusion that matching instructional methods yields substantial improvements. Moderate-to-large effect sizes were observed in the VB and SG dimensions, with confidence intervals reinforcing the consistency of the observed effects. Visual learners had a large effect size for engagement scores (Cohen's d = 1.39, 95% CI: 0.83, 1.96), indicating a strong effect of the matched instruction.

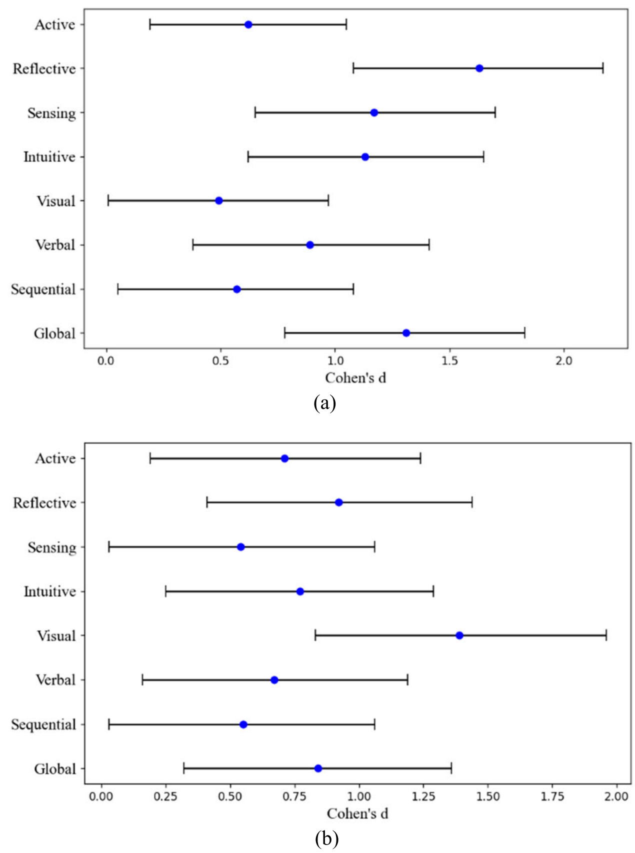

FIGURE 1. Cohen's D for questionnaire (a) and engagement scores (b) with 95% confidence intervals.

The 95% confidence intervals, particularly for test scores, indicate the precision of the effect size estimates, highlighting the reliability of the improvements observed when instruction was tailored to students' learning style. This also suggests that while there is some variability, the positive impact of tailoring instruction on learning style is consistently observed across all dimensions of learning.

An independent t-test was conducted to compare quiz scores between the matching and non-matching conditions. The null hypothesis H_o stated that there was no difference in mean quiz scores and engagement scores between the two conditions, while the alternative hypothesis H_A posited that the mean quiz scores and engagement scores for the matching condition would differ, specifically being higher than those for the non-matching condition. A two-tailed t-test was used to evaluate differences between groups.

The analysis yielded a t-statistic of $t = 18.95$ and a p-value of $p < 1.49 \times 10^{-74}$ indicating an extremely statistically significant difference between the two conditions. The mean quiz score for the matching condition was 8.63, compared to 7.62 for the non-matching condition. Similarly, for engagement scores, the analysis yielded a t-statistic of $t = 17.7$ and a p-value of $p < 7.03 \times 10^{-66}$, also demonstrating a highly significant difference. The mean engagement score for the matching condition was 17.13, compared to 12.56 for the non-matching condition. These results provide strong evidence that instructional alignment with students' preferred learning styles significantly enhances both their short-term quiz performance and student engagement.

A two-way ANOVA confirmed significant interaction effects between learning style and instructional method across all dimensions, as shown in Figure 2.

In the AR dimension, a highly significant interaction effect ($F(1,572) = 115.51$, $p < 0.0001$) indicated that active students performed better in lesson 1 (activity-focused instruction), whereas reflective students performed better in lesson 2 (reflection-focused instruction). These results confirm the learning styles hypothesis, as the optimal instructional method depends on students' style.

In the SI dimension, the interaction effect was also significant ($F(1,572) = 122.45$, $p < 0.0001$), with sensory learners performing better in Lesson 1 and intuitive learners performing better in Lesson 2. Similar interaction effects were observed in the VB ($F(1, 572) = 59.86$, $p < 0.0001$) and SG ($F(1,572) = 89.51$, $p < 0.0001$) dimensions, confirming Hypothesis 1 that students perform better when instructional methods are aligned with their learning styles.

A central aspect of Pashler et al.'s argument [22] is that, for the learning styles hypothesis to be validated, studies must demonstrate a cross-class interaction, whereby students with different learning styles achieve the best results when the instructional method aligns with their style, while others achieve the best results with a different method. We believe that our study meets the criteria for validating the learning-style hypothesis. The results of our two-way ANOVA showed significant cross-class interactions across all four learning dimensions in the FSLSM. In each case, students performed best when the instructional method matched their learning style, while those with a different learning style performed best when the opposite method was used.

The mixed-effects models revealed significant differences in both the quiz and engagement scores between the matching and non-matching conditions. For quiz scores, the fixed effect of instructional alignment indicated that students in the matching condition scored, on average, 1.01 points higher than those in the non-matching condition. Similarly, engagement scores were 4.57 points higher, on average, under matching conditions compared to the non-matching condition. Both effects were highly statistically significant,

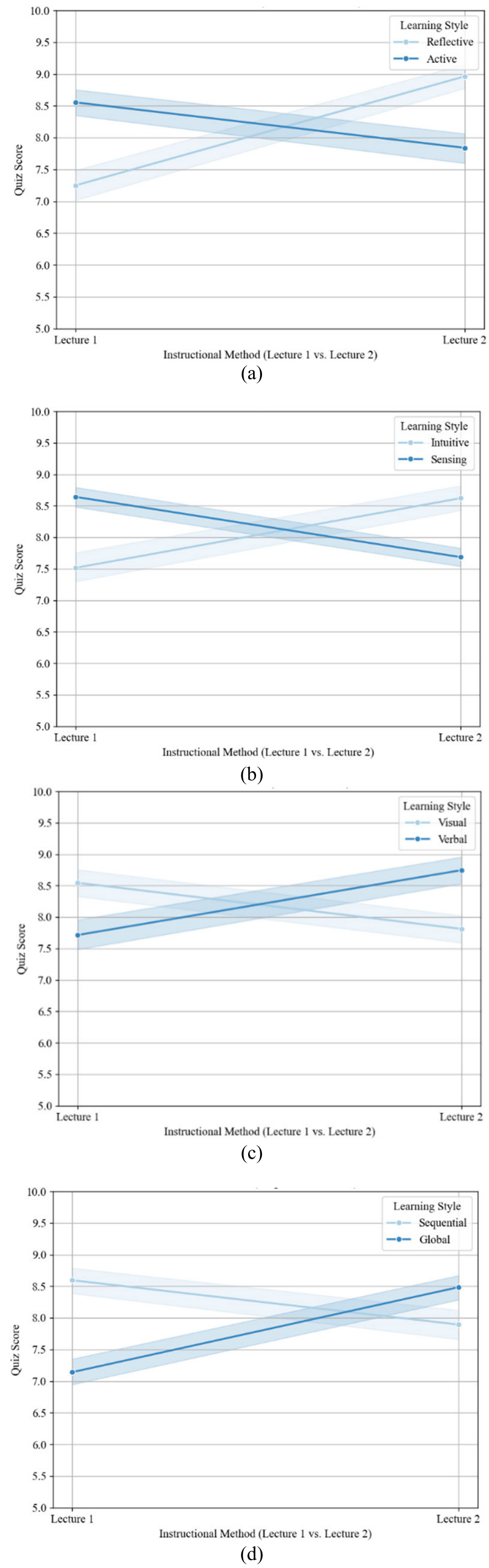

FIGURE 2. Interaction effects graphed for each learning dimension between learning style and instructional method in Lecture 1 vs. Lecture 2.

confirming that aligning instructional methods with students' preferred learning styles positively influenced their short-term academic performance and engagement.

These findings are consistent with the results of paired and independent t-tests, corroborating the conclusion that instructional alignment enhances learning outcomes. However, the mixed-effects models extended these results by accounting for individual differences in students' baseline performance and engagement levels through random effects for Student-ID. This adjustment ensured that the observed effects of matching instructional methods were not confounded by the inherent variability between students, thus strengthening the validity of the findings.

The incorporation of mixed-effects models also provided a deeper understanding of the data structure. By modeling both within-subject correlations and between-subject variability, the analysis confirmed that the observed differences were generalized across the population. Furthermore, these models complemented the Two-Way ANOVA by emphasizing the role of individual differences, while confirming the broader trends observed in the interaction effects between instructional methods and learning styles.

However, although our results support the meshing hypothesis in our specific educational context, it is important to note that these findings cannot necessarily be generalized to all contexts. Further research using similar, randomized, and robust methodologies as employed in our study is needed to determine the broader applicability of these findings.

The next analysis compared quiz scores and engagement across the three conditions (matching, unmatched and tutorial) within each of the four learning dimensions. Hypothesis 3 was that tutorials that integrate both teaching styles would yield higher quiz scores and engagement than either matched or nonmatched conditions. Table 3 presents the results of quiz scores.

The results showed that across all dimensions, tutoring consistently outperformed both the matched and unmatched conditions, supporting the hypothesis that combining teaching styles improves students' performance. For example, in the AR dimension, the mean difference between the matched and tutoring conditions was -0.70, indicating that students performed better in tutoring sessions than in classes tailored to their dominant learning styles. Similar trends were observed for the SI (-0.53), VB (-0.51), and SG (-0.40) dimensions.

TABLE 3. Tutorial quiz data summary.

LD	F-Value	p-value	Matching vs. Tutorial	Matching vs. Unmatching	Tutorial vs. Unmatching
AR	137.94	<0.0001	-0.70	-1.13	-1.83
SI	184.85	<0.0001	-0.53	-1.01	-1.54
VB	57.11	<0.0001	-0.51	-0.86	-1.37
SG	79.38	<0.0001	-0.40	-1.05	-1.45

The results show that across all dimensions, tutoring consistently outperformed both the matched and unmatched conditions, supporting Hypothesis 2 that matching teaching styles improves student performance. For example, in the AR dimension, the mean difference between the matched and tutoring conditions was −0.70, indicating that students performed better in tutoring sessions than in classes tailored to their dominant learning styles. Similar trends were observed for the SI (−0.53), VB (−0.51), and SG (−0.40) dimensions.

Tukey's post-hoc HSD tests revealed that the tutorial condition was significantly better than both the matched and unmatched conditions across all the dimensions. The largest differences were observed in the AR and SG dimensions, where the tutorial approach led to significantly improved quiz performance compared with both the matched and unmatched conditions.

Engagement scores followed a similar pattern, as shown in Table 4, where tutorials consistently resulted in higher engagement across all dimensions.

TABLE 4. Tutorial engagement data summary.

LD	F-value	p-value	Matching vs Tutorial	Matching vs Unmatching	Tutorial vs Unmatching
AR	41.76	<0.0001	-5.73	0.98	-4.75
SI	120.57	<0.0001	-2.28	-4.99	-7.27
VB	99.86	<0.0001	-2.49	-4.97	-7.46
SG	78.14	<0.0001	-3.47	-3.61	-7.07

In the AR dimension, for example, the mean difference between the tutorial and pairing conditions was −5.73, showing that students were significantly more engaged during the tutorial sessions. Post-hoc tests also confirmed that tutorials significantly outperformed both pairing and non-pairing conditions for all dimensions, with the largest differences observed in the SG and VB dimensions.

These results are consistent with Felder's [12] argument that effective instruction must balance both sides of a learning dimension. Felder [12] points out that students respond differently to specific forms of instruction, depending on their learning style, and that the goal should not be to exclusively tailor instruction to student preferences but to provide a balance that engages all students. In our study, the tutorial condition, which combined both sides of a learning dimension, supported Hypothesis 2 and Felder's view that integrating diverse teaching methods can lead to better learning outcomes and increased engagement.

C. FACTORS THAT INFLUENCE EXAM PERFORMANCE

The results presented in Table 5 show the relationship between the average quiz and engagement scores in different instructional conditions (matched, mismatched, and tutorial) and midterm and final exam scores. The VIF values for all predictors were below five, indicating that there was no multicollinearity among the independent variables. This suggests that the predictors are not highly correlated, meaning that each predictor contributes unique information to the model.

The R^2 values for the midterm and final exam predictions were negative: −0.3682 for the midterm exam model and −0.0576 for the final exam model. A negative R-squared value indicates that the models perform worse than a simple mean-based model, meaning that the predictors do not explain the variance in exam scores effectively.

In terms of coefficients, the results for the midterm model show that the coefficient for the mismatch questionnaire (1.3024) suggests a slightly positive relationship with midterm exam performance, whereas the coefficient for the tutorial questionnaire (−3.0471) indicates a stronger negative association. Similarly, in the final exam model, the coefficient for the mismatch questionnaire (3.2247) suggests that higher scores under mismatch conditions may be positively associated with final exam performance, whereas the coefficient for the tutorial questionnaire (−3.3986) indicates a negative relationship. These coefficients suggest that questionnaire scores under tutorial conditions do not positively predict exam performance, contrary to expectations.

TABLE 5. Average quiz and engagement scores vs. midterm and exam scores.

Dependent Variable	Predictor Variable	R-Squared	Coefficient	VIF
Midterm	Matching Quiz	-0.3682	-0.8476	1.15
	Mismatching Quiz	-0.3682	1.3024	1.03
	Tutorial Quiz	-0.3682	-3.0471	1.14
	Matching Engagement	-0.5257	0.2604	2.22
	Mismatching Engagement	-0.5257	0.7008	1.20
	Tutorial Engagement	-0.5257	-0.5389	2.47
Final Exam	Matching Quiz	-0.0576	-0.0617	1.55
	Mismatching Quiz	-0.0576	3.2247	1.07
	Tutorial Quiz	-0.0576	-3.3986	1.64
	Matching Engagement	-0.1297	-0.5238	1.84
	Mismatching Engagement	-0.1297	0.2219	1.34
	Tutorial Engagement	-0.1297	0.2849	1.90

The results of the RF model further highlight the inability of the learning-style alignment-based questionnaire data to effectively predict midterm and final exam scores. For the midterm exam, the model produced an R^2 of −0.6414 and an MSE of 173.74, indicating a poor fit. Similarly, for the final examination, R^2 was −0.0335, with an MSE of 151.69. These results suggest that the RF model, which is typically effective at capturing nonlinear relationships, performed worse than expected and was unable to explain the variance in the exam scores. Despite the flexibility of the RF model, it did not improve predictions over the linear regression model.

The negative R^2 values in both models demonstrate that neither the multiple regression model nor the RF model could reliably predict midterm or final exam grades using quiz data alone. High MSE values indicate significant errors between predicted and actual exam grades, suggesting that the quiz data, whether under matched, mismatched, or tutored conditions, did not sufficiently capture the factors driving exam performance.

One possible explanation for the poor performance of both models is that exam scores and learning style alignment may not be strong predictors of long-term academic success, as measured by midterm and final exams. Exams typically test accumulated knowledge, critical thinking, and the ability to apply concepts in broader contexts, which may be more dependent on factors such as study habits, revision practices, and independent learning outside the classroom. Therefore, learning style alignment, while useful for short-term engagement and exam performance, may not directly influence exam outcomes in the same manner.

The results of the multiple regression analysis, shown in Table 6, further support the importance of study habits in influencing exam success. For the midterm exam, the model explained 34.4% of the variance in the scores (R-squared = 0.344, $p < 0.001$). Study quality was a significant predictor ($\beta = 0.537$, $p < 0.001$), as was the frequency of study sessions ($\beta = 1.523$, $p = 0.060$, marginal significance). However, the time spent studying before the midterm exam was not a significant predictor ($\beta = 0.198$, $p = 0.255$). In contrast, the model for the final exam explained 76.6% of the variance in scores (R-squared = 0.766, $p < 0.001$), and the time spent studying after the midterm exam emerged as the strongest predictor ($\beta = 0.660$, $p < 0.001$). Study quality ($\beta = 0.246$, $p = 0.003$) and the frequency of study sessions ($\beta = 1.427$, $p = 0.006$) were also significant predictors of final exam performance.

TABLE 6. Study habits vs. midterm and exam scores.

Dependent Variable	Predictor Variable	R-Squared	Coefficient β	P-value
Midterm	Study Quality Survey	0.344	0.537	< 0.001
	Frequency of Study Sessions	0.344	1.523	0.060
	Time Spent Studying	0.344	0.198	0.255
Final Exam	Study Quality Survey	0.766	0.246	0.003
	Frequency of Study Sessions	0.766	1.427	0.006
	Time Spent Studying	0.766	0.660	< 0.001

In summary, study habits, particularly time spent studying, were significantly more effective in predicting academic success than the scores obtained on quizzes and engagement surveys. The strong correlations and significant regression results highlight the role of consistent study habits, high study quality, and sustained study effort in determining exam performance. These findings underscore the importance of long-term study behaviors in achieving academic success, particularly in the latter part of the semester.

D. PREDICTIVE MODELING OF ACADEMIC PERFORMANCE

Our study evaluated the predictive ability of several machine-learning models for midterm and final exam grades using Moodle logs and SQS data. The models were evaluated using the performance metrics MSE, RMSE, MAE, and R^2, and a feature importance analysis was performed to understand the influence of different study behaviors.

The VE model outperformed other models in predicting midterm exam scores, achieving an R^2 of only 0.260 when broader data such as Moodle logs combined with the total SQS score were used, as shown in Table 7.

TABLE 7. Midterm model predictions from Moodle data and SQS score.

Model	MSE	RMSE	MAE	R^2
Bagging	68.71	8.29	6.83	0.079
SVR	69.73	8.35	6.33	0.066
DT	237.53	15.41	12.47	-2.182
KNN	74.70	8.64	6.57	-0.0001
RF	55.30	7.44	6.03	0.259
VE	55.23	7.43	5.94	0.260

In comparison, when individual SQS question scores were used as inputs, the model achieved the lowest MSE (10.38) and highest R^2 (0.861), as shown in Table 8. This higher R^2 indicates that the model explained a substantial portion of the variability in midterm exam performance. This contrast highlights that the quality of study behaviors, as captured by specific SQS question responses, played a more significant role in predicting midterm exam success than simple study duration or frequency. Using individual SQS item scores, the model explained 86% of the variance, whereas the broader measures explained only 26%.

TABLE 8. Midterm model predictions from SQS data.

Model	MCV	SCV	MSE	RMSE	MAE	R^2
Bagging	0.718	0.0917	13.69	3.70	2.88	0.817
SVR	0.432	0.0938	34.63	5.88	3.99	0.536
DT	0.542	0.2825	25.93	5.09	4.07	0.653
KNN	0.750	0.0839	12.52	3.54	2.89	0.832
RF	0.714	0.117	13.28	3.64	3.11	0.822
VE	0.768	0.0971	10.38	3.22	2.62	0.861

The feature importance analysis, as shown in Figure 3, further supports this observation; the total SQS score emerges as the most critical factor (importance = 0.4921) when using the combined entries from Moodle and SQS logs. The time spent studying before the midterm exams also contributed significantly (importance = 0.3209), while the frequency of study sessions had a minor impact (importance = 0.1870).

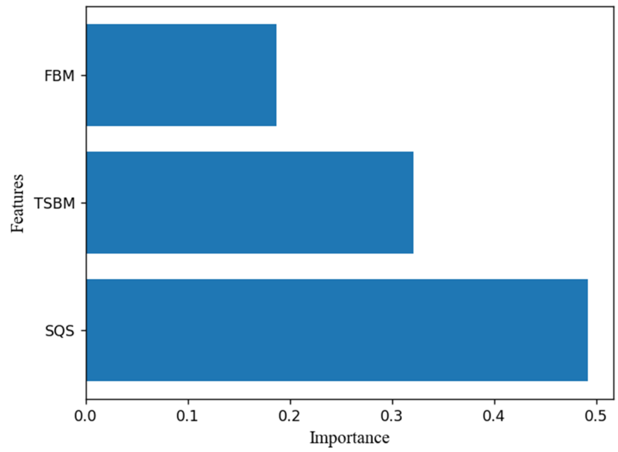

FIGURE 3. Importance of characteristics of study frequency before midterm exam (FBM), study time before midterm exam (TSBM), and study quality survey (SQS) score.

This implies that the effectiveness of study practices, as reflected in the SQS, has a greater influence on midterm performance than the amount of time or consistency in study habits.

When analyzing individual SQS item scores, as shown in Figure 4, the most influential characteristic was reviewing after class (importance = 0.4302), indicating that students who systematically reviewed material shortly after class performed better on the midterm exams. Other behaviors, such as maintaining a distraction-free environment (importance = 0.1076) and utilizing classroom resources (importance = 0.1011) also played a role, highlighting the value of structured and effective study habits before midterm exams.

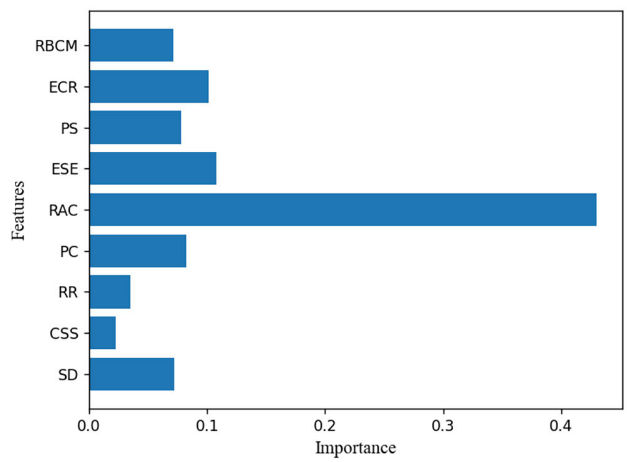

FIGURE 4. Importance of each SQS question in predicting midterm grade. Reading beyond course materials (RBCM), participation in class resources (ECR), study pace (PS), effective study environment (ESE), after-class review (RAC), preparation for class (PC), consistency of study sessions (CSS), and study duration (SD).

In terms of the final exam predictions, the VE model continued to deliver superior results. Using Moodle logs and the SQS total score as input data, the model achieved an MSE of 18.29 and an R^2 of 0.830, as shown in Table 9.

TABLE 9. Final exam model predictions from Moodle and SQS score.

Model	MCV	SCV	MSE	RMSE	MAE	R^2
Bagging	0.481	0.231	19.28	4.39	3.47	0.821
SVR	0.351	0.0461	56.44	7.51	6.13	0.475
DT	0.203	0.214	35.33	5.94	4.67	0.671
KNN	0.609	0.193	18.08	4.25	3.27	0.832
RF	0.511	0.170	19.34	4.40	3.17	0.820
VE	0.609	0.163	18.29	4.28	3.18	0.830

This indicates a strong ability to predict final exam performance, driven primarily by the time spent studying after midterms, as seen by the feature importance of 0.8193 in Figure 5. This highlights that as the semester progressed, the amount of time spent studying became more influential on final exam success, in contrast to midterm predictions, where study quality was more important.

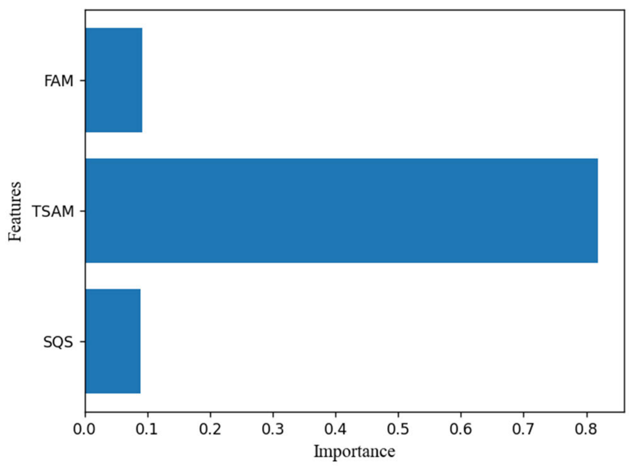

FIGURE 5. Importance of characteristics of frequency of study after midterm (FBM), time of study before midterm (TSAM), and study quality survey (SQS) score.

In comparison, using individual SQS question scores as inputs, the model achieved a slightly lower R^2 of 0.641, with an MSE of 37.78, as shown in Table 10. While this is still a reasonably good fit, it suggests that individual study behaviors, while important, had less predictive power for final exams than the total study time recorded after midterms.

TABLE 10. Final exam model predictions from SQS data.

Model	MCV	SCV	MSE	RMSE	MAE	R^2
Bagging	0.098	0.1520	45.79	6.77	5.56	0.564
SVR	0.225	0.1564	76.87	8.77	6.88	0.269
DT	-0.181	0.1726	39.49	6.28	4.99	0.624
KNN	0.296	0.0789	105.76	10.28	8.78	0.016
RF	0.151	0.2064	44.99	6.71	5.34	0.572
VE	0.158	0.1973	37.78	6.15	4.99	0.641

Consistency of study sessions was the most predictive behavior for final exam performance (importance = 0.2743), followed by study duration (importance = 0.1643), as shown in Figure 6.

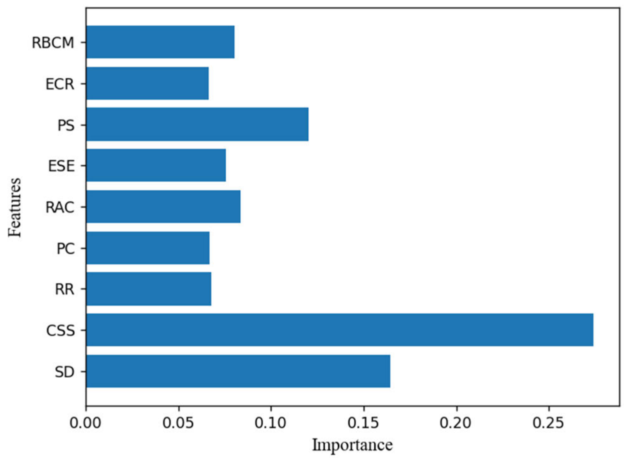

FIGURE 6. Importance of the characteristics of each SQS question in predicting the final exam grade.

The cross-validation results provide details on the performance of the model for different prediction tasks. For predicting midterm grades using SQS questions, the VE model achieved a Mean Cross-Validation (MCV) of 0.768 with a standard deviation of cross-validation (SCV) of 0.0971, demonstrating strong and consistent predictive power. When using Moodle data and SQS total score to predict final exam grades, the model yielded an MCV of 0.609 with an SCV of 0.163, indicating moderate performance with some variability. The model struggled more when using SQS questions to predict final exam grades, with an MCV of 0.158 and an SCV of 0.1973, showing weak predictive power and inconsistency. These data show the strength of the VE model in capturing meaningful academic patterns and suggest that with further refinement, it could be applied to a broader range of educational contexts to improve predictive accuracy.

All data and Python codes used in our study are available at the links provided in the Data Availability section at the end of the paper.

E. STATISTICAL AND PRACTICAL SIGNIFICANCE OF RESULTS (HYPOTHESES 1 TO 3)

The results demonstrated a strong statistical significance across all analyses, confirming the importance of aligning instructional methods with students' learning styles. Paired t-tests revealed significant improvements in the quizzes and engagement scores for matching conditions across all learning dimensions. For instance, in the AR dimension, reflective learners performed significantly better under matching conditions, with $t = 8.94$, $p = 7.92 \times 10^{-10}$ for quiz scores and $t = 5.04$, $p = 2.26 \times 10^{-5}$ for engagement scores. The two-way ANOVA results further supported these findings, identifying significant interaction effects between learning styles and instructional methods, such as $F(1,572) = 115.51$, $p<0.0001$ in the AR dimension. These results support the learning style hypotheses by demonstrating crossover interactions, where students performed best when instructional methods aligned with their preferences. Mixed-effects models added further evidence, showing that quiz scores increased by an average of 1.01 points and engagement scores by 4.57 points under matching conditions, both statistically significant ($p<0.001$).

Beyond the statistical significance, the results have practical significance. The observed differences in quizzes and engagement scores highlight improvements in short-term academic performance and student motivation. These findings are particularly relevant in educational settings such as engineering, where engaging students with complex materials is important. Furthermore, the tutorial condition, which integrated both sides of each learning dimension, consistently outperformed both the matched and non-matched conditions, supporting Hypothesis 3. For example, Tutorials improved quiz performance by an average of 0.70 points in the AR dimension and engagement scores by 5.73 points compared to matched conditions, demonstrating the practical benefits of blending instructional approaches. These results suggest strategies for educators to emphasize the value of personalized and integrated teaching methods to improve both learning outcomes and student engagement.

F. STATISICAL AND PRACTICAL SIGNIFANCE OF RESTULS (HYPOTHESIS 4)

Statistical analysis highlighted the role of study quality and habits in predicting midterm and final exam performance, as evidenced by the regression and machine learning models. Multiple regression results demonstrated that, for midterm exams, the model explained 34.4% of the variance (R^2 =0.344, $p<0.001$), study quality ($\beta = 0.537$, $p < 0.001$), and frequency of study sessions ($\beta = 1.523$, $p = 0.060$) emerged as significant predictors. For the final exams, the model accounted for 76.6% of the variance ($R^2 = 0.766$, $p < 0.001$), where time spent studying after midterm was the strongest predictor ($\beta = 0.660$, $p < 0.001$), along with study quality ($\beta = 0.246$, $p = 0.003$) and session frequency ($\beta = 1.427$, $p = 0.006$).

Machine learning models further highlight the predictive power of study behaviors. For midterm examinations, the VE model achieved an R^2 of 0.861when using individual SQS question scores, capturing 86% of the variance. This performance was significantly higher than using measures such as Moodle logs and total SQS scores ($R^2 = 0.260$). For the final exams, the VE model achieved an $R^2 = 0.830$ using combined Moodle and SQS data, highlighting the increasing importance of total study time as the semester progressed.

Feature importance analysis further emphasized the statistical significance of specific study habits. Reviewing material shortly after class was the most influential predictor of midterm success (importance = 0.4302), while time spent studying after midterm was the dominant predictor of final exam performance (importance = 0.8193). These findings highlight the consistency and reliability of study behaviors as the key drivers of academic success.

While the statistical significance of the findings is robust, their practical implications are equally important. The results highlight the strategies for improving academic performance. For midterms, the quality of study habits, such as reviewing material after class and maintaining a distraction-free environment, was a significant predictor, suggesting that educators should emphasize structured study practices early in the semester. These behaviors provide students with a foundation for understanding and effectively applying course content.

The results of the final exams demonstrated the role of the time spent studying after midterm. This shift suggests that students benefit more from sustained effort and consistent study sessions in a cumulative exam approach. The VE model's ability to predict final exam performance with high accuracy ($R^2 = 0.830$) indicated that tracking and encouraging total study time during the latter half of the semester could lead to meaningful improvements in academic outcomes.

The findings also revealed the limitations of relying solely on quiz scores or learning style alignment to predict long-term success. Despite their value for short-term retention of class material and engagement, these factors did not significantly predict midterm or final exam performance, as indicated by the negative R^2 values in some models. This suggests the need to prioritize study habits and behaviors as long-term predictors of success, shifting the focus from instructional alignment to creating effective student practices.

Educators can use these findings to design interventions that promote effective study strategies, such as guided review sessions or tools for tracking study time. The ability of machine learning models to identify influential predictors, such as study quality and time management, suggests the potential for integrating predictive analytics into academic support systems, enabling tailored feedback and resources to help students succeed.

G. CONTEXT IN ENGINEERING EDUCATION

Our results are similar to those found in engineering education literature, which showed that while learning styles can influence study preferences, effective study habits and time management are key drivers of academic success. Entwistle and Peterson [28] found that strategic study approaches that focus on understanding and applying knowledge have a greater impact on academic outcomes than simply aligning instruction with students' learning styles. As mentioned in the introduction, Heffler [30] concluded that while learning styles can affect how engineering students allocate their study time, this does not necessarily lead to better academic performance.

Kahu and Nelson [42] and Peterson et al. [43] also found that in engineering education, students' engagement and strategic learning are more important than alignment with the learning style. Their research highlighted the importance of cultivating effective study habits that prioritize consistent effort and deeper engagement with the material rather than rigidly adhering to learning style preferences.

Our study also showed that consistent study habits, especially time spent studying, were much more predictive of midterm and final exam performance than quizzes or engagement scores. This is in line with the findings of Rabia et al. [29], who found that structured and regular study routines contributed the most to academic performance regardless of students' learning styles. Regression analysis in our study showed that the time spent studying after the midterm exam was the most significant predictor of final exam success.

Burton and Dowling [44] and Protassov [45] emphasized that high-quality study habits (such as active learning, time management, and regular revision) are more effective in achieving better academic outcomes than simply increasing the time spent studying. Our study aligns with these findings, highlighting the importance of well-managed study times and the need for engineering students to develop consistent and effective study strategies. The role of time management, as identified by Adams and Blair [46], was also supported by our study, which supports the idea that engineering students who manage their time effectively and maintain consistent study efforts are more likely to be academically successful. This observation is further supported by Chitkara et al. [47], who found that higher-performing students consistently follow planned schedules, regularly review lecture materials, and prefer to study in organized, distraction-free environments. These practices can contribute to deeper understanding and better retention of course content, leading to higher academic performance.

Mazumder et al. [48] found a weak correlation between classroom engagement and academic achievement, suggesting that, while engagement is important, it may not be the sole determinant of academic success. Their study indicated that students who performed well academically often adopted effective study habits outside the classroom, such as group studies, independent studies, and thorough review of materials, which may contribute more significantly to their success than class engagement alone.

The results of our study are consistent with broader research on predicting academic performance using machine learning models in engineering education. While the random forest model used in our study performed moderately well in predicting mid-semester exams, explaining 25.9% of the variance ($R^2 = 0.259$), it significantly improved in predicting the final exam, explaining 77.7% of the variance ($R^2 = 0.777$). This change in model performance may indicate that the importance of different study habits changes over time, with study quality being more influential at the beginning of the semester and time spent studying becoming the dominant predictor near the end.

Other studies, such as ours, have shown that academic performance can be predicted when the right variables are used in education. Bithari et al. [49] applied ensemble methods to predict academic performance in engineering students, achieving an accuracy of 82% using DTs, SVMs, and logistic regression. Their results emphasized the importance of various educational and demographic attributes in predicting student outcomes. Raceli and Maaliw 's [50] study on predicting bachelor's exam results in electronic engineering found verbal reasoning to be the most significant predictor with an accuracy of 92.7%. This study further supports the idea that cognitive attributes such as study habits can have a substantial impact on short-term academic performance.

The role of time management in academic success was also demonstrated in DeJong and Karadogan 's [51] research, where grade point averages (GPA) in mathematics and physics were the strongest predictors of success in engineering programs. In their study, random forest regression achieved an R^2 of 0.67 in predicting graduation GPA, demonstrating the effectiveness of time spent in key subject areas on long-term academic success.

Our study's use of feature importance analysis is similar to that of Nachouki et al. [52], where high school grades and grades in key courses such as Discrete Mathematics were identified as primary predictors of GPA in a four-year IT program. Their study also highlighted how different predictors vary in importance depending on the timing and nature of the assessment, with consistent study habits playing an important role in the ultimate performance.

H. CONTEXT IN OTHER ACADEMIC DISCIPLINES

While this study focused on engineering education, the significance of effective study habits and time management extends across various academic disciplines. Research indicates that students in fields such as medicine, business, and the humanities also benefit from strategic learning approaches. For instance, a systematic review by Lone [53] found a positive correlation between structured study habits and academic performance among medical students, emphasizing that consistent study routines enhance learning outcomes regardless of discipline. These findings align with the importance of regular and well-managed studies, as identified in this study.

Furthermore, a study by Calonia et al. [54] on business students demonstrated that time management skills significantly predicted academic success, underscoring the universal applicability of these competencies. While instructional methods may vary across disciplines, foundational elements, such as effective study habits and time management, emerge as strong determinants of academic achievement in diverse educational settings. These parallels suggest that the principles identified in engineering education may be relevant in broader educational contexts, highlighting the importance of transferable strategies for fostering academic success.

Our study provides valuable findings that can be applied to online teaching environments, webinars, and other remote instructional formats. By adjusting teaching methods to align with the diverse learning styles of the participants, educators can create more engaging and effective virtual learning experiences. For instance, integrating multimedia presentations and interactive tools for visual-verbal learners or offering structured discussion forums for active-reflective learners can enhance learners' engagement and comprehension. Furthermore, the predictive models developed in this study, which use data on study habits and engagement metrics, can be adapted to track and support student performance on virtual platforms, such as Moodle. These approaches offer a pathway to improving remote education by using technology and personalized teaching strategies, ultimately encouraging better academic outcomes in a wide range of educational contexts.

Machine learning and predictive analytics can also analyze Moodle data to enhance educational outcomes by predicting performance and identifying at-risk students. Tree-based models, such as random forests and decision trees, can pinpoint key predictors, such as submission actions, while neural networks might deliver high classification accuracy in e-learning contexts. These methods can also address dropout prediction by incorporating activity data, transcripts, and demographic information. Integrating these approaches with learning management systems can enable early intervention and improve the precision of academic performance predictions.

IV. CONCLUSION

Building on the existing literature, our study presented a novel contribution to the field of engineering education by combining an analysis of in-class learning style alignment with an assessment of study behaviors using machine learning models to determine which had a greater influence on academic success. While previous research has explored both areas independently, our work provided a direct comparison, suggesting that while aligning teaching methods with learning styles improved engagement and understanding of the material in the short term, consistency of study habits and time management were the strongest predictors of academic success over the semester.

Aligning teaching methodology with learning styles, specifically using the FSLSM model, led to higher quiz scores and increased engagement, as demonstrated by the paired t-test, Cohen's d effect size, and the plotted crossover interactions from the two-way ANOVA analysis. Furthermore, the repeated measures ANOVA followed by post-hoc comparisons indicated that quiz scores and engagement levels were highest during tutorials where multiple teaching methodologies were combined, suggesting that combining multiple instructional approaches is more effective than adhering to a single learning style. This supports the idea that learning style alignment positively affects short-term comprehension and retention.

However, the comparison of the learning conditions aligned with performance on the midterm and final exams showed no correlation according to the linear regression analysis. This suggests that the teaching methodology used in the class has little or no influence on long-term academic outcomes.

Instead, multiple linear regression indicated that study habits, study frequency, and time spent studying played a much larger role in success on the midterm and final exams. Furthermore, using study behavior data as inputs to several machine learning models allowed us to predict academic performance with high accuracy. For example, the VE model predicted final exam scores with an MAE of 3.18, meaning that the predictions were, on average, within 3.18 points of students' actual scores, and the model explained 83% of the variability.

This supports the argument that, while learning style alignment improves class engagement, which could contribute to higher attendance and participation, it does not directly lead to better academic success. Our results suggest that true academic achievement, particularly in engineering education, occurs outside of the classroom.

Without effective study habits and regular reviews, knowledge is quickly lost after class. Our findings also indicate that engineering is a discipline that requires constant practice and dedication, as supported by our machine-learning feature analysis. Therefore, educators and policymakers should focus on promoting good study practices, teaching students to study effectively, and developing time-management skills to achieve better academic results.

Future research should, therefore, focus on how students learn on their own and what factors influence their ability to learn and apply new materials. Studies could examine how different learning environments (such as online, hybrid, and in-person formats) affect the development and effectiveness of study behaviors. Researchers should also re-evaluate the role of learning styles in education, considering how AI-created personalized learning tools can adapt to individual students' needs without relying on traditional learning style frameworks. Our recent study highlighted the potential of AI-driven learning environments to create adaptive and resource-efficient educational strategies, which could serve as a valuable foundation for further exploration in this area [55]. Future work should focus on integrating study habit tracking tools and AI-powered feedback systems to provide students with personalized recommendations to improve their study techniques and manage their time more effectively.

Furthermore, future studies should assess the long-term impact of these interventions on academic outcomes. The role of real-time data collection through learning management systems could also be explored, offering personalized resources and adaptive strategies as students progress through university. Artificial intelligence and machine learning models should be further refined to develop more accurate predictive models of academic success and to better identify at-risk students earlier in the semester. Finally, future research should investigate the broader applicability of these findings across various educational contexts and disciplines to ensure their relevance and effectiveness in diverse settings.

APPENDIX A
WEEKLY ACTIVITIES, TEACHING METHODOLOGY, TOPICS AND CLASS BREAKDOWN

Tables 11 and 12 outline the weekly structure of the Process Engineering and Electronics Engineering classes, detailing the learning dimension from the FSLSM for each week, topics covered, and corresponding teaching methodologies used in each lecture and tutorial session. Lecture 1 each week focused on the left side of the learning dimension (e.g., Active for AR), while Lecture 2 focused on the right side (e.g., Reflective for AR). Tutorials have incorporated a combination of teaching methodologies, providing a balanced approach. The tables describe the specific class activities and teaching strategies employed to align these learning styles

APPENDIX B
ENGAGEMENT/SATISFACTION SURVEY

The ESS was designed to assess students' perceptions of teaching methods, activities, and overall learning experience each week. It uses a 5-point Likert scale to gauge agreement with statements regarding clarity of instruction, relevance of activities, involvement in class, and satisfaction with the learning process.

A. STUDENT SATISFACTION/ENGAGEMENT SURVEY

*INSTRUCTIONS:*Please indicate your level of agreement with the following statements about the week's activities and teaching methods. Use the scale provided:

1. **Strongly Disagree**
2. **Disagree**
3. **Neutral**
4. **Accept**
5. **Strongly Accept**

SURVEY QUESTIONS:

1. This week's activities helped me better understand the course material.
2. I felt involved during class activities this week.
3. The teaching methods used this week were effective in helping me learn.
4. I enjoyed the class activities and felt motivated to participate.
5. The material presented was clear and easy to understand.
6. The instructor provided adequate support and guidance during the activities.
7. The activities were relevant to the course objectives.
8. I was able to apply what I learned in practical tasks or discussions.
9. The pace of the class was appropriate for my learning.
10. Overall, I am satisfied with my learning experience this week.

APPENDIX C
SQS

The Survey on Quality of Studies evaluates students' study habits and behaviors throughout the course. It consists of ten questions measuring aspects such as study duration, frequency of review, preparation, study environment, and use of additional resources. Responses were collected on a 5-point Likert scale, providing insight into the quality and consistency of students' study practices.

SURVEY ON THE QUALITY OF STUDY

1. Duration of the study On average, how many hours do you spend studying for this course outside of class each week?

1 = Less than 1 hour
2 = 1-2 hours
3 = 3-4 hours
4 = 5-6 hours
5 = More than 6 hours

2. Coherence of study sessions

How often do you study for this course each week?

1 = I usually study only before exams
2 = I study occasionally when I have time
3 = I try to study once or twice a week.
4 = I study several times a week
5 = I study almost every day

3. Review and repeat

How often do you review lecture material or previous assignments?

1 = Just review before exams
2 = I check occasionally, but not regularly
3 = I try to review once or twice a week.
4 = I review the material several times a week
5 = I review the material almost every day

4. Preparing for class

How much time do you usually spend preparing for class (e.g., reviewing notes and reading ahead) before each lecture?

1 = Less than 15 minutes
2 = 15-30 minutes
3 = 30-45 minutes
4 = 45-60 minutes
5 = More than 1 hour

5. Review after class

How long do you review the material covered in the lecture after class?

1 = I don't usually review after class
2 = I review it within a week before the next conference.
3 = I review it within 3-4 days after class.
4 = I review within 1-2 days after class
5 = I review the same day or immediately after class

6. An effective study environment

How often do you study in a distraction-free environment (e.g., a quiet room or library)?

1 = Never
2 = Rarely (only before exams)
3 = Occasionally (once or twice a week)
4 = Regularly (several times a week)
5 = Always

7. Study pace

How often do you spread out your study sessions instead of studying them all at once?

TABLE 11. Weekly activities, topics, and class breakdown: process engineering class.

Week	Learning Dimension	Topic	Lecture 1	Lecture 2	Tutorial
1	AR	Oil production and processing	Teaching methodology: Group discussions, collaborative projects. Activities: Teams engage in immediate problem solving, applying concepts in real time.	Teaching Method: Reflective journal and individual assignments. Activities: Students summarize and reflect on key concepts after class.	Teaching methodology: Combination of active and reflective activities. Activities: Simulations and practical cases that require both real-time application and reflection.
2	SI	Production of soaps and detergents	Teaching Methodology: Practical experiments and step-by-step guides. Activities: Detailed and procedural laboratory tasks to solve practical problems.	Teaching methodology: Conceptual and open discussions. Activities: Explore abstract ideas and potential innovations in production processes.	Teaching Methodology: Practical applications combined with theoretical debates. Activities: Students conduct experiments and then explore conceptual implications.
3	VB	Extraction of oils and fats	Teaching methodology: Visual resources such as diagrams, multimedia presentations. Activities: Analyze processes using flowcharts and visual simulations.	Teaching Methodology: Verbal explanations and group discussions. Activities: Discuss production processes and review reading materials.	Teaching methodology: Visual and verbal combination. Activities: Create visual representations while giving verbal explanations.
4	SG	Mining and metallurgical industries	Teaching methodology: Structured problems, step-by-step guides. Activities: Solve problems using logical sequences.	Teaching methodology: Overview and interdisciplinary connections. Activities: Analyze the mining process within a broader context.	Teaching methodology: Combination of sequential and global approaches. Activities: Apply both step-by-step processes and analysis of the global context.
5	AR **MIDTERM**	Production of ceramics, phosphorus and phosphoric acid	Teaching methodology: Group discussions, collaborative projects. Activities: Teams work on simulations and discuss process improvements.	Teaching Methodology: Reflective essays and post-class summaries. Activities: Students analyze concepts and reflect on what they have learned.	Teaching methodology: Active and reflective integration. Activities: Participate in debates and then write reflective notes.
6	SI	Production of sulfur and sulfuric acid	Teaching methodology: Laboratory practices and case studies. Activities: Practical laboratory work with analysis of real cases.	Teaching methodology: Conceptual and hypothetical discussions. Activities: Generate theoretical ideas to improve sulfur production.	Teaching methodology: Mixed practical and theoretical. Activities: Conduct laboratory experiments and explore conceptual theories afterwards.
7	VB	Production of beer, wine and spirits	Teaching Methodology: Visual aids and flow charts. Activities: Create detailed diagrams of fermentation processes.	Teaching methodology: Readings and group discussions. Activities: Analysis of reading and participation in debates.	Teaching methodology: Visual and verbal synthesis. Activities: Present diagrams and participate in group discussions.
8	SI	Bioethanol Production and Other Industrial Processes	Teaching methodology: Step-by-step instructions and structured guides. Activities: Analyze sequentially each step of bioethanol production.	Teaching methodology: Interdisciplinary analysis and general context. Activities: Understanding the bioethanol process in the environmental and economic framework.	Teaching methodology: Blended approaches. Activities: Conduct structured analysis followed by general discussions.
9	AR	Bioethanol Production	Teaching methodology: Group discussions, interactive exercises. Activities: Real-time problem solving in teams.	Teaching Methodology: Reflective summaries and conceptual analysis. Activities: Students write reflective reports after interacting with the content.	Teaching methodology: Combination of active and reflective activities. Activities: Participate in group work and then reflect on key points.
10	SI	Fermentation processes	Teaching methodology: Laboratory practices and detailed guides. Activities: Follow step-by-step procedures in fermentation laboratories.	Teaching methodology: Conceptual exploration and open design. Activities: Brainstorming innovations in fermentation techniques.	Teaching methodology: Combination of theory and practice. Activities: Apply theoretical knowledge after

TABLE 11. *(Continued.)* Weekly activities, topics, and class breakdown: process engineering class.

					carrying out laboratory exercises.
11	VB	Production of citric and lactic acid	Teaching methodology: Flowcharts and multimedia presentations. Activities: Visualize production processes and analyze diagrams.	Teaching methodology: Reading texts and debates. Activities: Discussing processes based on readings and making verbal presentations.	Teaching methodology: Visual and verbal integration. Activities: Visualize concepts and present findings verbally.
12	SI	Paper and cardboard production	Teaching methodology: Structured problem solving. Activities: Follow the steps sequentially to solve industrial production problems.	Teaching methodology: Global and interdisciplinary analysis. Activities: Linking paper production with environmental and industrial impacts.	Teaching methodology: Step-by-step combined with global. Activities: Sequential tasks combined with broad context analysis.
13	AR	Production of ammonia and nitric acid	Teaching methodology: Interactive laboratories and team discussions. Activities: Simulations and real-time discussions.	Teaching methodology: Reflective essays and conceptual summaries. Activities: Write reflective essays based on the class content.	Teaching methodology: Combination of active and reflective learning. Activities: Combines interactive exercises with reflective analysis.
14	SI	Production of sulfuric acid and nitrogen oxides	Teaching methodology: Practical experiments and procedural tasks. Activities: Conduct laboratory experiments based on the production of sulfuric acid.	Teaching methodology: Conceptual analysis and creative exploration. Activities: Explore creative ways to improve production efficiency.	Teaching methodology: Combination of practice and theory. Activities: Laboratory work followed by conceptual discussions on the design.
15	VB	Analysis of industrial processes	Teaching methodology: Visual representations and flow charts. Activities: Develop detailed visual explanations of industrial processes.	Teaching methodology: Group discussions and presentations. Activities: Present the findings and discuss them verbally in groups.	Teaching methodology: Visual-verbal combination. Activities: Create visual presentations and participate in group discussions.
16	SI **FINAL EXAM**	Production of specialty chemicals	Teaching methodology: Structured problem solving and flowcharts. Activities: Solve problems sequentially using structured methodologies.	Teaching Methodology: Global analysis and interdisciplinary integration. Activities: Explore how the production of specialty chemicals impacts various industries.	Teaching methodology: Mixed sequential-global. Activities: Combination of structured problem solving with global analysis.

1 = I always get soaked at the last minute

2 = I usually study by heart, but sometimes I distribute my study time.

3 = From time to time I distribute my studies

4 = I usually spread my studies over several days.

5 = I always distribute my studies

8. Interaction with classroom resources

How often do you use the class resources (e.g., office hours, discussion forums, study guides) provided by the instructor?

1 = Never

2 = Rarely (only before exams)

3 = Occasionally (once or twice a month)

4 = Regularly (once a week)

5 = Very regularly (several times a week)

9. Read beyond the course materials

How often do you read materials beyond those assigned in the course to deepen your understanding?

1 = Never

2 = Rarely (only if assigned as extra credit)

3 = Occasionally (a few times a semester)

4 = Regularly (a few times a month)

5 = Always (frequently throughout the course)

10. Use of additional resources

How often do you use additional resources, such as case studies and articles, in your study?

1 = Never

2 = Rarely (only if necessary for a project)

3 = Occasionally (once or twice during the semester)

4 = Regularly (a few times a month)

5 = Always (frequently throughout the course)

APPENDIX D

TABLE EXPLANATIONS FOR TABLES 2 TO 10

EXPLANATION FOR TABLE 2: PAIRED T-TEST RESULTS FOR QUIZ AND ENGAGEMENT SCORES

A paired t-test was used to evaluate the differences in quiz and engagement scores between matched and mismatched instructional methods across the ***Felder-Silverman Learning Styles Model (FSLSM)*** dimensions: ***Active/Reflective (AR)***,

TABLE 12. Weekly Activities, Topics and Class Breakdown: Electronic Engineering Class.

Week	Learning Dimension	Topic	Lecture 1	Lecture 2	Tutorial
1	AR	Introduction to electrical machines	Teaching methodology: Group discussions, collaborative projects. Activities: Analyze the magnetic behavior of materials in teams.	Teaching methodology: Reflective journals, individual assignments. Activities: Summarize key points from classes and reflect on concepts.	Teaching methodology: Combination of active and reflective activities. Activities: Interactive simulations and practical cases.
2	SI	Transformer design	Teaching methodology: Practical experiments, step-by-step guides. Activities: Analyze and design single-phase and three-phase transformers.	Teaching methodology: Conceptual discussions, open projects. Activities: Theoretical exploration of transformer design.	Teaching methodology: Mixed practical and theoretical. Activities: Apply theoretical knowledge in design laboratories.
3	VB	Operation of the electric motor	Teaching methodology: Diagrams, multimedia presentations. Activities: Use flowcharts to explain motor operations.	Teaching methodology: Lectures, readings. Activities: Discuss reading materials on motor operations.	Teaching methodology: Visual and verbal combination. Activities: Diagram making and group discussion.
4	SI	Advanced motor control	Teaching methodology: Structured problems, flow charts. Activities: Step-by-step analysis of motor control systems.	Teaching methodology: Overview, interdisciplinary analysis. Activities: Explore motor control in various applications.	Teaching methodology: Mixed sequential and global. Activities: Apply detailed control algorithms to large-scale problems.
5	AR **MIDTERM**	Magnetic circuits and materials	Teaching methodology: Group discussions, collaborative projects. Activities: Simulate magnetic circuits using software.	Teaching methodology: Reflective summaries, individual assignments. Activities: Writing reports on magnetic materials and circuits.	Teaching methodology: Active and reflective integration. Activities: Practical simulations and reflection reports.
6	SI	Power transformers	Teaching methodology: Laboratory experiments, detailed procedure guides. Activities: Testing transformer designs in laboratories.	Teaching methodology: Conceptual design and theoretical scenarios. Activities: Development of theoretical models for transformer applications.	Teaching methodology: Mixed practical and theoretical. Activities: Conduct experiments and explore possible innovations.
7	VB	Dynamics of AC and DC motors	Teaching methodology: Visual resources, flow charts. Activities: Visualize motor dynamics through detailed diagrams.	Teaching methodology: Verbal presentations, readings. Activities: Present findings on motor dynamics and discussion readings.	Teaching methodology: Visual-verbal combination. Activities: Present visual models and participate in group discussions.
8	SI	Industrial applications of electrical machines	Teaching methodology: Sequential problem solving, structured guides. Activities: Step-by-step analysis of machine applications.	Teaching methodology: Overview and interdisciplinary projects. Activities: Analyze the role of machines in various industries.	Teaching Methodology: Sequential-global integration. Activities: Combine structured analysis with big-picture discussions.
9	AR	Maintenance of electrical machines	Teaching methodology: Group projects, interactive simulations. Activities: Develop and simulate team maintenance procedures.	Teaching methodology: Reflective journals, individual problem solving. Activities: Reflect on maintenance and problem-solving strategies.	Teaching methodology: Active-reflective combination. Activities: Fieldwork with reflective analysis.
10	SI	Diagnostic techniques for electrical machines	Teaching methodology: Practical diagnosis and procedural guides. Activities: Conduct diagnostic experiments in laboratories.	Teaching methodology: Conceptual and hypothetical scenarios. Activities: Explore theoretical improvements for diagnostic tools.	Teaching methodology: Mixed diagnostic and theoretical approach. Activities: Apply diagnostics in laboratories and explore theoretical improvements.
11	VB	Electrical Safety and Standards	Teaching methodology: Diagrams, multimedia presentations. Activities: Visualize safety standards and their compliance in diagrams.	Teaching methodology: Verbal explanations and group discussions. Activities: Discuss real electrical safety incidents.	Teaching methodology: Visual-verbal combination. Activities: Present diagrams and discussion compliance with safety regulations.
12	SI	Emerging Technologies in Electrical Engineering	Teaching methodology: Step-by-step analysis, structured diagrams. Activities: Explore the step-by-step process of integrating new technologies.	Teaching methodology: Global analysis and interdisciplinary projects. Activities: Analyze the impact of new technologies on industry.	Teaching methodology: Mixed sequential-global. Activities: Combines step-by-step analysis with discussions of global impact.
13	AR	Electrical machine control systems	Teaching methodology: Interactive problem solving, team projects. Activities: Simulate control systems and analyze them as a team.	Teaching methodology: Reflective journals, conceptual essays. Activities: Reflect on control systems and prepare analysis reports.	Teaching methodology: Mixed active-reflective. Activities: Perform simulations and write reflective reports.

TABLE 12. ***(Continued.)*** **Weekly Activities, Topics and Class Breakdown: Electronic Engineering Class.**

14	SI	Applications of power electronics	Teaching methodology: Laboratory experiments, detailed procedures. Activities: Power electronics tests in practical laboratories.	Teaching methodology: Conceptual discussions and open projects. Activities: Explore new applications for power electronics.	Teaching methodology: Combination of practical and conceptual. Activities: Carry out laboratory practices and explore possible applications of the theory.
15	VB	Control of electric drives	Teaching methodology: Visual resources, multimedia presentations. Activities: Use flowcharts to visualize the control of electrical drives.	Teaching methodology: Verbal presentations, group discussions. Activities: Present control systems and discuss applications.	Teaching methodology: Visual-verbal combination. Activities: Create visual models and present them verbally in groups.
16	SI **FINAL EXAM**	Integration of renewable energy systems	Teaching methodology: Sequential problem solving, structured diagrams. Activities: Analyze integration processes step by step.	Teaching Methodology: Global analysis and interdisciplinary connections. Activities: Examine how renewable energy fits into broader systems.	Teaching methodology: Mixed sequential-global. Activities: Combines step-by-step analysis with broad contextual analysis.

Sensing/Intuitive (SI), ***Visual/Verbal (VB)***, *and* ***Sequential/ Global (SG)***. The t-score measured the size of the difference, and the p-value determined the statistical significance, with values below 0.05 indicating non-random differences. Students performed significantly better in both quizzes and engagement scores when the instructional method matched their learning styles. For instance, in the AR dimension, active learners had a t-score of 4.04 ($p = 0.0002$) for quizzes, while reflective learners achieved a t-score of 8.94 ($p = 7.92 \times 10\ ^{1}\circ$). Engagement scores followed a similar pattern, with active learners scoring 5.79 ($p = 8.56 \times 10.7$) and reflective learners scoring 5.04 ($p = 2.26 \times 10.5$). High t-scores above 5 indicate strong effects, and p-values below 0.01 confirm the reliability of these results.

EXPLANATION FOR TABLE 3: TUTORIAL QUIZ DATA SUMMARY

Table 3 compares the quiz scores across matched, unmatched, and tutorial instructional conditions within the FSLSM dimensions. The F-value was used to measure the variance between conditions, and the p-value confirmed statistical significance. Tutorials consistently outperformed the matched and unmatched conditions. In the AR dimension, the mean difference between the matched and tutorial conditions was −0.70. Similar results were observed for the SI (−0.53), VB (−0.51), and SG (−0.40) dimensions. Tukey's post-hoc test confirmed that tutorials significantly exceeded both the matched and unmatched conditions, demonstrating the value of combining diverse teaching methods to improve student performance.

EXPLANATION FOR TABLE 4: TUTORIAL ENGAGEMENT DATA SUMMARY

Table 4 summarizes engagement scores across matched, unmatched, and tutorial conditions within the FSLSM dimensions. Engagement was measured by student involvement during sessions. Tutorials led to significantly higher engagement across all the dimensions. For example, in the AR dimension, the mean difference in engagement scores between the tutorial and matched conditions was −5.73. The largest improvements were observed in the SG (−7.07) and VB (−7.46) dimensions compared to the unmatched conditions. These results suggest that tutorials enhance both academic performance and engagement, as evidenced by the consistently high F-values and p-values below 0.0001.

EXPLANATION FOR TABLE 5: AVERAGE QUIZ AND ENGAGEMENT SCORES vs. MIDTERM AND EXAM SCORES

Table 5 examines the relationship between quiz scores, engagement levels, and exam performance under the matched, mismatched, and tutorial conditions. Negative ***R-squared (R***^{2}) values (−0.3682 for midterms and −0.0576 for finals) indicate that the models performed worse than a mean-based prediction, suggesting limited predictive power. Coefficients varied in direction, with positive coefficients (e.g., 1.3024 for mismatched quizzes in midterms) indicating a slightly positive relationship and negative coefficients (e.g., −3.3986 for tutorial quizzes in finals) indicating inverse relationships. All ***Variance Inflation Factor (VIF)*** values were below 5, showing no significant multicollinearity among the predictors. The results highlight that quizzes and engagement scores are not reliable predictors of exam outcomes.

EXPLANATION FOR TABLE 6: STUDY HABITS vs. MIDTERM AND EXAM SCORES

Table 6 shows the impact of study habits on midterm and final exam scores. The model explained 34.4% of the variance in the midterm scores ($R^2 = 0.344$) and 76.6% of the variance in the final scores ($R^2 = 0.766$). For midterms, study quality ($\beta = 0.537$, $p < 0.001$) and frequency of study sessions ($\beta = 1.523$, $p = 0.060$) were significant predictors, whereas time spent studying was not ($\beta = 0.198$, $p = 0.255$). For finals, all predictors were significant, with the time spent studying ($\beta = 0.660$, $p < 0.001$) having the strongest influence. These findings emphasize the importance of consistent, high-quality study habits for academic success.

EXPLANATION FOR TABLE 7: MIDTERM MODEL PREDICTIONS FROM MOODLE DATA AND SQS SCORE

Table 7 evaluates the machine learning models predicting midterm scores using combined Moodle log and ***Study Quality Survey (SQS)*** data. Metrics include ***Mean Squared Error (MSE)***, ***Root Mean Squared Error (RMSE)***, ***Mean Absolute Error (MAE)***, and R^2. The ***Voting Ensemble (VE)*** model performed best, with an MSE of 55.23, RMSE of 7.43, and R^2 of 0.260, demonstrating moderate predictive ability. The ***Random Forest (RF)*** model performed similarly (MSE = 55.30, $R^2 = 0.259$). The ***Decision Tree (DT)*** model had the weakest performance, with an MSE of 237.53 and a negative R^2 (-2.182). These results indicate that, while VE and RF moderately captured patterns, the broader dataset had limited predictive power.

EXPLANATION FOR TABLE 8: MIDTERM MODEL PREDICTIONS FROM SQS DATA

Table 8 evaluates the models using the individual SQS question scores as the input. The VE model achieved the best performance, with an MSE of 10.38, RMSE of 3.22, and R^2 of 0.861, explaining 86% of the variance in the midterm scores. ***K-Nearest Neighbors (KNN)*** and RF performed well, with R^2 values of 0.832 and 0.822, respectively. ***Support Vector Regression (SVR)*** was less effective, with an R^2 of 0.536 and MSE of 34.63. These findings show that detailed SQS data provide a stronger predictive power than broader measures.

EXPLANATION FOR TABLE 9: FINAL EXAM MODEL PREDICTIONS FROM MOODLE AND SQS SCORE

Table 9 evaluates the models predicting final exam scores using the combined Moodle logs and SQS data. The VE model achieved the best results with an MSE of 18.29, RMSE of 4.28, and R^2 of 0.830, explaining 83% of the variance in the final scores. KNN also performed well (MSE = 18.08, $R^2 = 0.832$). Models, such as SVR and DT, showed weaker performance, with R^2 values of 0.475 and 0.671, respectively. These results highlight the robustness of the VE model in predicting final exam performance.

EXPLANATION FOR TABLE 10: FINAL EXAM MODEL PREDICTIONS FROM SQS DATA

Table 10 examines the models using individual SQS scores to predict final exam outcomes. The VE model achieved the best results with an MSE of 37.78, RMSE of 6.15, and R^2 of 0.641, which explained 64% of the variance. Other models, such as ***Bagging***, RF, and DT, showed moderate performance, with DT having an MSE of 39.49 and R^2 of 0.624, while KNN performed poorly ($R^2 = 0.016$). These results indicate that SQS responses are less effective than broader data in predicting final-exam outcomes.

APPENDIX I. RECOGNITION

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DATA AVAILABILITY

The data supporting the findings of this study are openly available in the Open Science Framework (OSF) repository at https://osf.io/6edxb/view_only=3a10ccb8f0534503b07af3caf3f88eb4. The repository contains three Excel files: (1) Quiz and Engagement Survey Results, (2) Study Quality Survey question answers, and (3) Study Data containing exam grades, total time studying before and after midterm, frequency of study sessions per week, and SQS scores. All Python codes used for the predictive models and analysis of our data are available on GitHub at the following link:https://github.com/lisaza88/All-codes-used-in-study—A-data-driven-approach-to-engineering-instruction/tree/d1c95804a55cb5baf3da9ed12ab613b70ad95f6a.

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