International Journal for Research in Educational Studies
(ISSN: 2208-2115)
Volume 12, Issue 03, October 2026
DOI: 10.65327/es.v12i3.2551

PREDICTING STUDENT ACADEMIC PERFORMANCE IN VIDEO-CONFERENCING-BASED ONLINE LEARNING ENVIRONMENTS

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Received: 23/03/2026 **Revised:** 28/07/2026 **Acceptance:** 26/08/2026 **Published:** 28/10/2026

ABSTRACT

Online learning, particularly video-conferencing has increased access to higher education, yet it is difficult to detect students at risk of compromised academic performance. In this paper, the relationships between online learning features and self-reported academic performance were examined, and five supervised machine learning classifiers were compared. The dataset of 29 variables and 361 records of a publicly available COVID-19-era questionnaire was analyzed; one of these records was excluded as a duplicate, leaving 360 observations. Three possible outcome-overlapping predictors were eliminated, which reduced the number of categorical predictors to 25. Evaluations of Logistic Regression, Decision tree, random forest, support vector machine and XGBoost have been done with 80: 20 stratified split and five-fold cross-validation. The results were good (72.5%), stable (22.8%), and decreased (4.7) performance. The highest reported relationship with performance was observed with ease of group work (Cramer's V = 0.194). The percentage of cross-validated macro-F1 (0.415) was highest in Random Forest and the test accuracy (73.6%), as well as macro-F1 (0.463) was highest in Support Vector Machine. The chosen Random Forest detected none of the three cases of decreased performance in the test subset, although it was 72.2% overall accurate. The permutation analysis showed significant and uncertain effects of learning ability and perceived efficiency. The results favor a careful exploratory application of prediction models but point to imbalance of classes, self-reported results, and poor minority-class detection. These models require larger externally validated datasets prior to making student support decisions.

Keywords – Academic Performance Prediction; Video-Conferencing-Based Learning; Machine Learning; Online Education; Student Engagement

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1. Introduction

Online education is a significant aspect of higher learning that has revolutionized education by incorporating digital tools and virtual communication. The COVID-19 pandemic furthered this shift as universities looked to utilize online teaching strategies to keep education going. The shift, however, did present a number of problems regarding technology accessibility, student engagement, and effectiveness. Research has shown that there are disparities in academic achievement across online and face-to-face learning environments (Chisadza et al., 2021). In addition, disruptions to learning reiterated the need for good digital education approaches (Clark et al., 2021). Student engagement and instructional support continue to be vital in successful virtual education (Andrew et al., 2021; Chung et al., 2022).

The video-conferencing technology has greatly impacted online education by allowing for live lectures, discussions, collaborative activities, and communication between teachers and students. Technology like Zoom, Microsoft Teams, and Google Meet enables learning to take place beyond the classroom walls. For these technologies to be effective, they must be usable, accessible, and popular with students (Camilleri & Camilleri, 2022). Past studies have shown the relationship between acceptance of video-conferencing and perceived learning outcomes (Bailey et al., 2022). Also, video-conferencing systems affect the educational experiences and instructional communication (Correia et al., 2020). Teaching quality and integration of technology are also factors that affect student satisfaction with video-conferencing instruction (Fatani, 2020).

There are a number of interrelated factors related to technology, pedagogy, and individuals that relate to academic performance in online learning environments. Internet access, student engagement, digital skills, instructional content and participation affect learning experiences. In videoconference-assisted learning environments, research with graduate students has focused on academic outcomes in various educational settings (Bhatti & Miranda, 2024). Likewise, student attributes, learning styles, and institutional resources are found to be essential factors that influence students' academic success in online learning (Chung et al., 2022). Awareness of these relationships is critical to identifying students who need extra academic support, and to making technology-based learning more effective.

Machine learning offers analytical tools that can help detect patterns and forecast success in learning outcomes from education data. Classification algorithms can analyze complex relationships between student characteristics and academic performance categories. There has been previous research that has investigated predictive modelling with relatively small educational datasets (Abu Zohair, 2019). A few hybrid machine learning approaches have also been explored for predicting academic performance in a multiclass setting (Al-Tameemi et al., 2024). Other methods integrate both regression and classification to determine the influential academic factors (Alshanqiti & Namoun, 2020). Systematic reviews give prominence to the increasing use of data mining in Higher Education (Alwarthan et al., 2022). Furthermore,

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machine learning has played a role in early academic risk detection and dropout prediction (Christou et al., 2023; Chui et al., 2020).

Although a growing number of prediction models are applied in education, there are still problems in assessing academic performance in the context of video conferencing-based learning. Previous research often focuses on general online learning outcomes or on more general data sets in education, while predictive assessments involving a combination of video-conferencing experiences, connectivity limitations and learning-related characteristics are still to be explored. Also, prediction reliability may be impacted by model interpretability, limited sample sizes and class imbalance. While previous studies have shown the feasibility of machine learning-based student performance prediction, further comparative analysis is required to establish reliable classification performance with video-conferencing-related educational variables (Al-Tameemi et al., 2024; Alwarthan et al., 2022).

This study aims to build and test machine learning models to predict students' academic performance in a video-conferencing-based online learning environment. In particular, the study aims to analyze the learning traits of students, explore the correlation between the video-conferencing factors and the students' reported learning outcomes, and compare the classification algorithms such as Logistic Regression, Decision Tree, Random Forest, Support Vector Machine and XGBoost. Moreover, this research focuses on determining which are the most influential predictors and also assess the effectiveness of classification based on accuracy, precision, recall, F1 score, and confusion matrices. The results inform evidence-based educational decision-making and the understanding of academic performance trends in online classrooms.

2. Materials and Methods

2.1. Research Design and Analytical Framework

The research in this study was quantitative research with the supervised machine learning approach was used to predict student academic performance in video conferencing online learning. The analytical framework considered dataset pre-processing, descriptive analysis, selection of the predictors, development of the model, and model assessment. It was a correlation study and omitted causal relationships between the characteristics of online learning and the learning outcomes of the students.

2.2. Dataset Description and Data Source

The dataset had 361 student observations and 29 variables consisting of 28 explanatory variables and one outcome variable that measures student academic performance (Miranda et al., 2024b). The variables included video-conferencing experiences, internet connection, learning materials, learning abilities and knowledge of students. On initial assessment, there were no missing values and one duplicate record (360 unique records).

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2.3. Study Variables and Academic Performance Classification

The outcome variable (Academic_Performance) had three options: decreased (0), stable (1), and good (2). Following duplicate removal, these categories included 17 (4.72%), 82 (22.78%), and 261 (72.50%) students, respectively. The explanatory variables were the experiences in video conferencing, internet access, the learning resources, the students' abilities, and the characteristics related to knowledge. To avoid possible overlap with the target variable, three of the variables were not included: Performance, Increase_Value and Positive_effect, leaving 25 predictors for classification.

2.4. Data Preprocessing and Feature Selection

The preprocessing techniques included duplicate removal, completeness check, distribution analysis, and categorical encoding. All recorded variables were coded numerically from 0 to 2. Predictors were not fully documented and were therefore prepared by one-hot encoding as categorical attributes. Feature selection was based on conceptual relevance and potential overlap with the targets. Weighted classification techniques were used to mitigate class imbalance and preprocessing methods were only applied to the training data for model validation, to avoid information leakage.

2.5. Machine Learning Model Development

To select the classification algorithms, five supervised classification algorithms were selected: Logistic Regression, Decision Tree, Random Forest, Support Vector Machine, and XGBoost. Logistic Regression was used to find a linear classification baseline while Decision Tree and Random Forest were used to explore the nonlinear relationships between learning characteristics and academic outcomes. The model used for Support Vector Machine was the RBF kernel and the model used for XGBoost was gradient-boosted decision trees. The classification models were developed into three categories of academic performance to determine the influential learning-related predictors.

2.6. Model Training, Validation, and Performance Evaluation

The modelling protocol called for an 80:20 stratification of training and testing observations which resulted in 288 training observations and 72 testing observations. The training set was used to assess the model using five-fold stratified cross-validation. To assess predictive performance, the accuracy, precision, recall, macro-F1 score, balanced accuracy and confusion matrices were used. The unequal class distribution was a reason that Macro-F1 was given priority. A model with the best performance was determined by the results of the cross-validation and then evaluated using the independent testing subset. Permutation feature importance was chosen as the method of assessing the relative importance of variables.

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3. Results

3.1. Descriptive Statistical Analysis of Student Learning Characteristics

The descriptive analysis included 360 unique student observations after removing one duplicate record. The dataset contained complete responses across all recorded variables. As shown in Table 1, code 2 was the most frequent response for several learning characteristics, including ease of learning (79.7%), adequacy of learning methods (79.2%), and perceived network effects on speed (77.2%).

Table 1. Descriptive Distribution of Selected Student Learning Characteristics (n = 360)

Learning characteristics	Code 0, n (%)	Code 1, n (%)	Code 2, n (%)
Benefit	18 (5.0)	115 (31.9)	227 (63.1)
Efficient	20 (5.6)	122 (33.9)	218 (60.6)
Ease of Learning	12 (3.3)	61 (16.9)	287 (79.7)
Interactive	35 (9.7)	112 (31.1)	213 (59.2)
Adequate Method	10 (2.8)	65 (18.1)	285 (79.2)
Network Affects Speed	15 (4.2)	67 (18.6)	278 (77.2)
Often Disconnected	42 (11.7)	71 (19.7)	247 (68.6)
Knowledge	55 (15.3)	114 (31.7)	191 (53.1)

Figure 1 illustrates the distribution of selected attributes. These findings describe the recorded response codes; their interpretation remains dependent on the original questionnaire coding.

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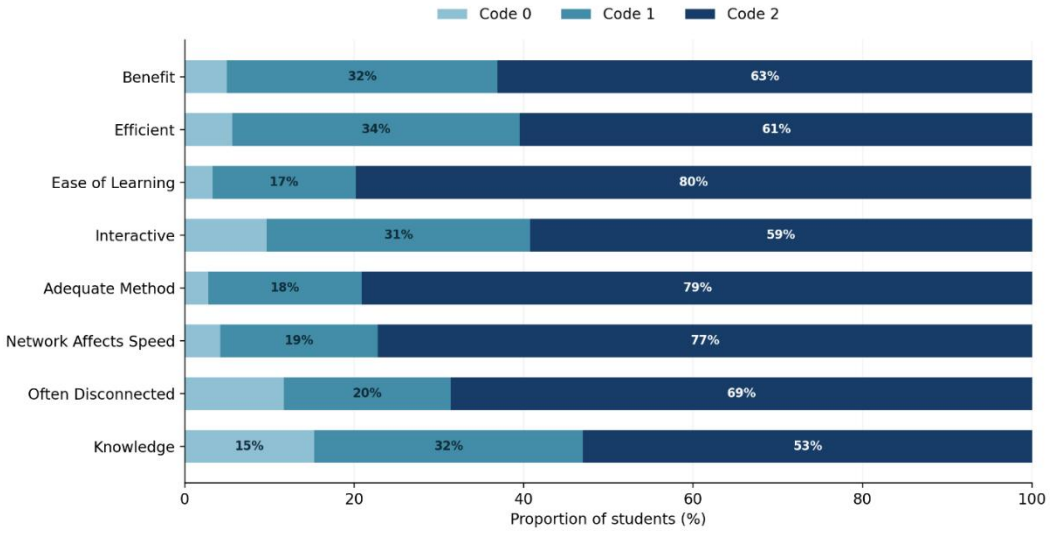

Figure 1. Distribution of coded responses across selected video-conferencing and learning characteristics

3.2. Distribution of Student Academic Performance Categories

The academic performance was categorized as decreased, stable and good. Table 2 shows that good performance was observed the majority of the time (72.5%), followed by stable performance (22.8%) and decreased performance (4.7%).

Table 2. Distribution of Academic Performance Categories and Data Partitioning

Academic performance	**Total, n (%)**	**Training**	**Testing**
Decreased (0)	17 (4.7)	14	3
Stable (1)	82 (22.8)	65	17
Good (2)	261 (72.5)	209	52
Total	360 (100.0)	288	72

Figure 2 demonstrates the considerable imbalance between the categories. Stratified data partitioning preserved their relative representation, although the testing subset contained only three decreased-performance observations.

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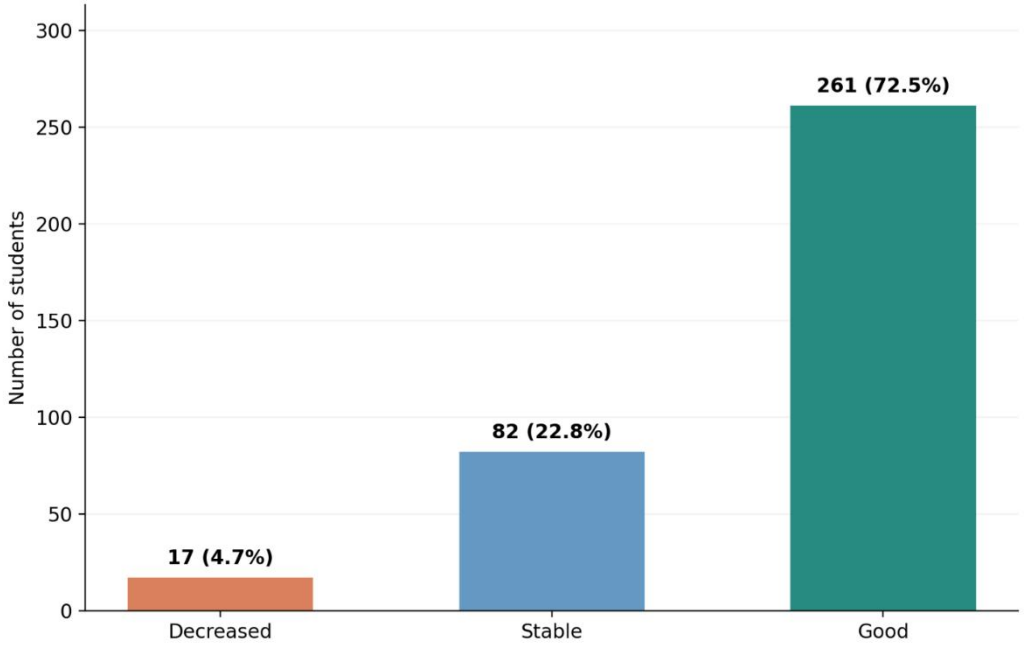

Figure 2. Distribution of students across the three academic performance categories

3.3. Relationship Between Video-Conferencing Factors and Academic Performance

Chi-square statistics and Cramér's V values revealed the exploratory relationships between online learning characteristics and academic performance, and Table 3 reveals that while some relationships are stronger, the ease of group work (V = 0.194), the completion of the project (V = 0.172) and the learning ability (V = 0.172) are among these relationships. There was a weaker relationship with Internet problems (V = 0.088).

Table 3. Associations Between Selected Learning Characteristics and Academic Performance

Learning factor	Cramér's V	p-value
Ease of Group Work	0.194	<0.001
Completing Project	0.172	<0.001
Ability	0.172	<0.001
Knowledge	0.164	<0.001
Interactive	0.155	0.002

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Network Not Affect	0.149	0.003
Network Affects Speed	0.123	0.028
Internet Problems	0.088	0.229

Figure 3 presents the twelve highest association strengths. Although several chi-square tests produced low p-values, sparse expected cell counts require cautious interpretation.

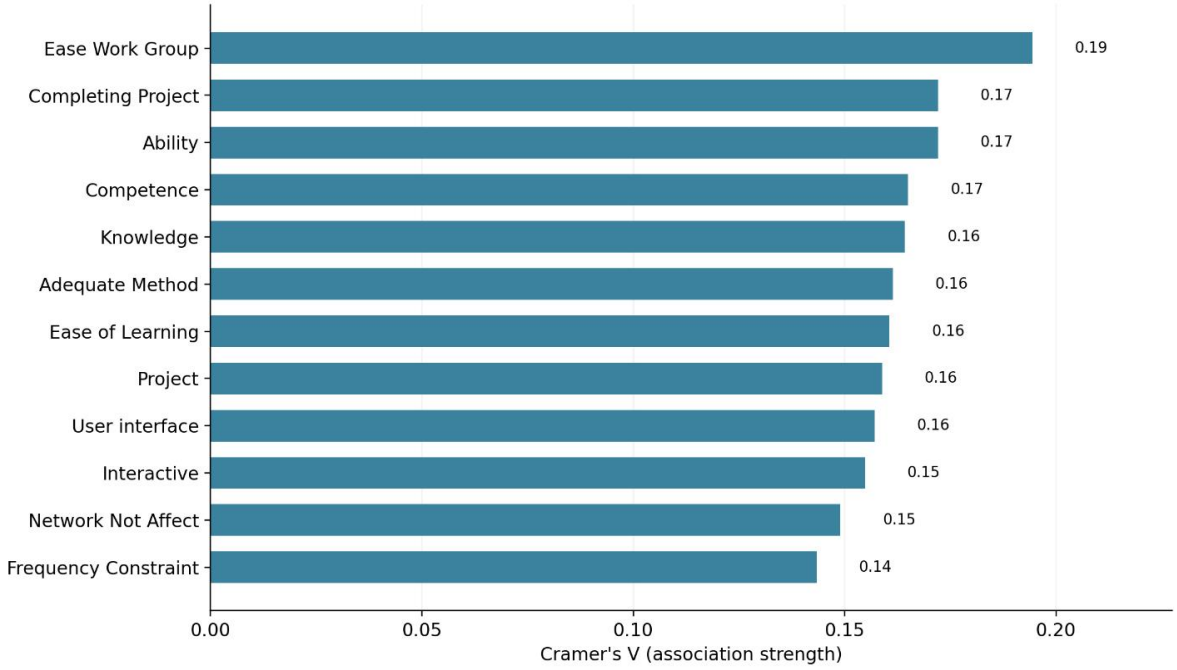

Figure 3. Comparative strength of associations between learning-related predictors and academic performance

3.4. Comparative Performance of Machine Learning Models

Five classification algorithms were tested, using a 5-fold stratified cross-validation and an independent testing subset. The cross-validated macro-F1 score of Random Forest was the highest (0.415 ± 0.065) as shown in Table 4. However, Support Vector Machine obtained the maximum testing accuracy(73.6%) and testing macro-F1(0.463) observed in the experiments. The discrepancies between validation and test results suggest that the predictive performance was not consistent across evaluation partitions. Random Forest was chosen as the model as it gave the best cross-validated score.

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Table 4. Comparative Predictive Performance of Machine Learning Classification Models

Model	CV macro-F1 (mean ± SD)	Accuracy	Macro precision	Macro recall	Macro-F1	Balanced accuracy
Logistic Regression	0.354 ± 0.046	0.542	0.373	0.342	0.352	0.342
Decision Tree	0.322 ± 0.071	0.444	0.387	0.324	0.325	0.324
Random Forest	0.415 ± 0.065	0.722	0.417	0.386	0.383	0.386
Support Vector Machine	0.391 ± 0.030	0.736	0.447	0.485	0.463	0.485
XGBoost	0.380 ± 0.061	0.694	0.441	0.439	0.438	0.439

All metrics other than the CV macro-F1 column were calculated on the independent 72-observation test set. SD denotes standard deviation across the five validation folds.

3.5. Classification Results and Model Evaluation

The cross-validation-selected Random Forest correctly classified 52 out of 72 testing observations, giving an accuracy of 72.2%, macro precision of 0.417, macro recall of 0.386, macro F1 of 0.383, and balanced accuracy of 0.386. With the help of the confusion matrix analysis, it was observed that all three students with lower performance were misclassified as students with good performance. Of 17 students who performed in a stable manner, four were correctly classified, and 48 of 52 students who performed well were correctly classified. The recall scores for decreased performance, stable performance and good performance were 0.000, 0.235 and 0.923, respectively. Interestingly, the accuracy of Random Forest model was close to the accuracy of the majority class-only prediction strategy, which indicates some lack of efficiency in recognizing students with academic problems.

3.6. Identification of Important Predictors of Academic Performance

The selected Random Forest classifier was run 30 times on the held-out test set to test the permutation feature importance. The highest average predictive importance for the variables were learning ability (mean macro-F1 reduction = 0.0254) and perceived efficiency (0.0251) followed by internet problems (0.0165), constraint type (0.0160) and project completion (0.0125) as illustrated in Figure 4. But the importance value for each is relatively low and the differences between the permutations are great, so these rankings are not definite. The results indicate some

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possible predictive factors, but not causal factors of academic performance.

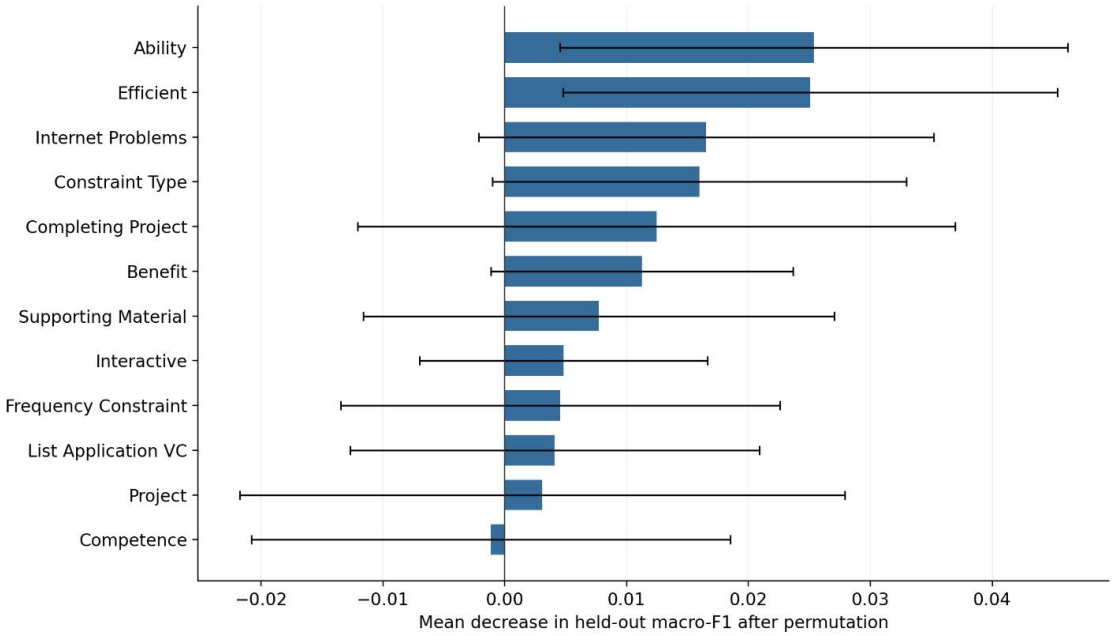

Figure 4. Permutation feature importance of predictors in the selected Random Forest model

4. Discussion

The results illustrate the potential and the current restrictions of the machine learning approach in predicting academic performance in an online learning environment with video conferences. The overall academic achievement was good (72.5%), stable (22.8%) and reduced (4.7%). Random Forest performed the best in cross-validation based on the macro-F1 score, and Support Vector Machine performed best in testing based on the macro-F1 score. But the chosen Random Forest model was not able to detect students with reduced performance, which means it was not very good at predicting that minority. These findings build on previous research on interpretable prediction of academic performance from video-conferencing-related educational data (Miranda et al., 2024a).

The students' academic performance was shown to be measurably related to video-conferencing experiences. Group work ease had the highest observed association (Cramér's V = 0.194) and can thus provide some useful predictive information. This relatively small association, however, suggests that academic outcomes can't be entirely attributed to the video-conferencing experiences. Previous research has emphasized the importance of instructional strategies and technological integration in online education (Iglesias-Pradas et al., 2021; Koh & Daniel, 2022). Further, video-enriched teaching is pedagogically beneficial in higher education (Noetel et al., 2021). The findings demonstrate the significance of an interactive learning environment without

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causal explanations.

The aspects of online learning that were relevant were Internet connectivity and learning engagement. The characteristics of the network showed different relationships with grades, with the internet problems showing a relatively low correlation (Cramér's V = 0.088). Better relationships were found for learning ability and project completion, which may indicate that other predictive information can be obtained from participation-related characteristics. In virtual learning environments, student engagement and satisfaction have emerged as key factors in the research (Maini et al., 2021). Likewise, academic achievement has been reported to be linked with online learning readiness and emotional competence during learning disruptions caused by the pandemic (Wang et al., 2023). The present findings, however, do not indicate a direct link between connectivity/engagement and academic achievement.

The comparison showed that there are differences in the classification performance between Logistic Regression, Decision Tree, Random Forest, Support Vector Machine and XGBoost. Random Forest had the best performance in cross-validation while Support Vector Machine had the best performance in the independent test set. The viability of the application of machine learning in the assessment of online learning experiences and learning outcomes has been shown in previous studies (Ho et al., 2021; Namoun & Alshanqiti, 2020). The selection of algorithms, evaluation processes, and dataset features are also emphasized in systematic reviews (Hellas et al., 2018; Lyu et al., 2025). This current analysis builds on previous studies on the same educational data while highlighting issues of class imbalance and the inability to detect academically vulnerable students (Miranda et al., 2024a).

Results indicated that learning ability, efficiency perceived by the students and the characteristics of the project should be focused when analyzing the evaluation of video-conferencing-oriented education. Educational institutions can gain insights from student engagement, cooperative learning, and learning support used in class and the learning results. Past studies have shown that support during online learning is related to performance (García-Machado et al., 2024). However, only limited minority class recall was observed in this study, making the models used in this study less suitable for making academic intervention decisions on their own. Rather, these predictive outputs can be used in conjunction with evidence from teaching observations and known practices of supporting students.

There are a number of constraints that need to be considered. The data set consisted of 360 distinct observations, significant class imbalance and academic performance categories based on questionnaires. There were only 17 observations in the decreased-performance group, which limits reliable prediction of performance in the minority classes. In addition, the response coding in some cases was not fully documented, and some potentially overlapping predictors were left out of the analyses, affecting their interpretation. Moreover, the context of education in which COVID-19 is experienced is only applicable to current educational settings. Larger and more

balanced datasets, independently verified academic outcomes, external validation, and class-sensitive learning strategies are areas for future research. Further research through longitudinal studies would help elucidate the link between online characteristics and academic outcomes.

5. Conclusion

This study evaluated the potential of supervised machine learning to predict students' self-reported academic performance in video-conferencing-based online learning environments. Across the categories of good performance (72.5%), stable (22.8%) and decreased (4.7%) it was found that there was a clear imbalance. Learning characteristics were generally related to academic outcomes, with comparatively strong relationships found with ease of group work, project completion and learning ability. Random Forest had the best cross-validated macro-F1 (0.415), and Support Vector Machine (SVM) had the best held-out accuracy (73.6%) and macro-F1 score (0.463) out of the five classification algorithms. Even with these results, the cross-validated RF classifier could not classify any students into the decreased performance testing category which shows that good overall accuracy does not necessarily mean good identification of academically vulnerable students. Permutation analysis identified learning ability, perceived efficiency, internet problems and project completion as potentially informative predictors, but with small and uncertain contributions. The results indicate that machine learning is a valuable tool for exploratory evaluation of digital learning experiences, but can not be relied upon as a basis for educational interventions on its own. Limitations for generalizability include the limited sample, uneven class distribution, questionnaire-based outcomes, and pandemic-specific context. Larger independent data sets, verified academic records, minority-class performance and external validation should be prioritized in future research for a greater degree of practical reliability.

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