Uncovering Lifestyle and Mental Well-being Predictors of Academic Performance Change in Online Learning: A Comparative Analysis of Interpretable Machine Learning Models

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ABSTRACT

The transition to online learning has reshaped academic engagement and well-being among students, yet the factors driving changes in performance remain poorly understood. This study investigates how lifestyle and mental health indicators predict self-reported changes in academic performance during online learning using interpretable machine learning models. A dataset of 1,000 students was analyzed through a comparative framework employing Logistic Regression and Random Forest classifiers, complemented by SHAP-based explanations. Descriptive analysis revealed balanced demographic distributions, with most students reporting moderate stress levels and similar proportions across performance categories. Model results showed comparable accuracies of approximately 0.33, reflecting the complexity of predicting academic outcomes. However, both models consistently identified screen time, sleep duration, and physical activity as the most influential predictors, while stress level and exam anxiety exhibited smaller yet coherent effects. Logistic Regression highlighted categorical distinctions such as education level and anxiety, whereas Random Forest captured nonlinear interactions among lifestyle variables. SHAP analyses provided global and local interpretability, confirming that higher screen exposure reduced the likelihood of improvement, while adequate sleep and regular physical activity were positively associated with better outcomes. These findings emphasize the central role of lifestyle balance in sustaining academic performance and mental well-being during remote education. Despite modest predictive power, the interpretable modeling approach offers actionable insights for educators, policymakers, and students to foster healthier and more effective online learning environments.

Keywords Online Learning; Lifestyle Factors; Student Mental Health; Interpretable Machine Learning; Academic Performance

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Introduction

Over the past decade—and sharply accelerated during the COVID-19 pandemic—online learning has become a central modality in higher education, reshaping pedagogy and student experience. Its promise lies in flexibility, access, and autonomy, enabling learners to manage time and place while engaging diverse resources [1], [2]. Yet this same modality places greater demands on self-regulation, digital readiness, and sustained motivation, conditions that vary widely across students and institutions [3], [4].

The dual nature of online learning—high flexibility alongside distinctive

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challenges—has implications for equity and outcomes. Barriers such as limited devices or bandwidth, diminished instructor–student connection, and competing domestic responsibilities can depress engagement, especially among at-risk learners [5], [6]. Quality assurance frameworks and supportive designs that scaffold time management and self-regulated learning are therefore critical to ensure inclusivity and academic success in digital settings [7], [8].

Concurrently, concerns about student mental well-being in virtual environments have intensified. Stress, anxiety, and feelings of isolation have been repeatedly linked to lower satisfaction and poorer academic outcomes during remote learning transitions [9], [10]. Qualitative accounts point to unfamiliar platforms, unclear expectations, and compressed deadlines as proximal stressors, particularly when instructional support is thin or social presence is weak [11], [12].

Lifestyle changes that accompany remote study compound these risks. Increased recreational and academic screen time has been associated with lower performance, sleep disruption, and adverse affect [13], [14]. By contrast, adequate sleep and regular physical activity support memory, attention, and mood regulation—core prerequisites for learning [15], [16]. Emerging “lifestyle psychiatry” evidence further suggests that diet, exercise, and sleep can prevent or alleviate common mental disorders, underscoring the need for holistic approaches to student health [17], [18].

Despite these insights, a clear gap remains: few studies jointly examine how lifestyle behaviors and mental health indicators together relate to changes in self-reported academic performance during online learning, and even fewer do so using interpretable Artificial Intelligence (AI). Prior work often isolates single factors (e.g., screen time or sleep) or privileges prediction over explanation, limiting the translation of findings into targeted, actionable support [19], [20]. In parallel, learning analytics and AI studies demonstrate strong predictive power but not always the transparency needed for stakeholder trust and intervention design [21].

Interpretable Machine Learning (IML) offers a principled path forward. In high-stakes educational contexts, stakeholders value transparency alongside accuracy to ensure fairness, accountability, and trust. Logistic Regression provides intrinsically interpretable coefficients for estimating direction and strength of associations, while tree-based ensembles such as Random Forest capture nonlinearities and interactions that mirror the complexity of student behavior; model-agnostic tools like SHAP yield global and local explanations that connect predictions to features in comprehensible ways. Against this backdrop, the present study investigates which lifestyle factors (screen time, sleep duration, physical activity) and mental health indicators (stress, exam anxiety) are most associated with self-reported changes in academic performance (declinedsameimproved) during online learning.

Literature Review

Online Learning Environments and Student Engagement

The rise of online learning has redefined higher education by emphasizing flexibility, accessibility, and individualized learning pathways. During the COVID-19 pandemic, institutions rapidly adopted virtual modalities that granted learners control over time and place, enabling self-paced study and resource diversity

[22]. However, this flexibility also shifted responsibility toward students, requiring stronger self-regulation and motivation [23]. Studies reveal that students with higher digital readiness and self-discipline tend to engage more effectively in online courses, while those lacking these attributes face difficulties maintaining focus and commitment.

Yet the benefits of online education coexist with persistent inequities and engagement challenges. Learners often encounter technological barriers, inadequate instructional presence, and competing household responsibilities that restrict participation [5]. These conditions are particularly detrimental for at-risk students who may lack supportive learning environments. Research underscores that enhancing quality assurance—through clear course design, prompt feedback, and community building—is crucial to sustain motivation and performance [2]. Moreover, social connectedness plays an essential role in mitigating isolation. As [24] show, peer and instructor support can alleviate depressive symptoms and enhance academic motivation, highlighting that psychological well-being and engagement are mutually reinforcing in virtual classrooms.

Ultimately, research depicts online learning as a dual-edged phenomenon—empowering yet demanding. When coupled with adequate institutional support and technological scaffolds, it can foster autonomy and inclusive participation. Conversely, insufficient engagement mechanisms or inequitable access can erode academic outcomes and mental wellness, motivating deeper inquiry into the psychosocial dimensions of online study.

Student Mental Health and Lifestyle Predictors of Academic Performance

The shift to remote education has amplified mental health challenges such as stress, anxiety, and social isolation among students. Research [9] observed that dissatisfaction with online classes correlates with higher stress, anxiety, and depressive symptoms, while [10] confirmed that elevated stress levels reduce academic satisfaction and performance. This relationship indicates that emotional well-being is a decisive mediator between learning modality and achievement.

Lifestyle disruptions further exacerbate these psychological strains. Increased screen exposure—a hallmark of online education—has been consistently linked to lower academic performance, sleep disruption, and cognitive overload [25]. Prolonged blue-light exposure interferes with circadian rhythms, diminishing sleep quality and, consequently, cognitive efficiency [26]. Sleep deprivation undermines memory consolidation, attention, and mood regulation—factors crucial for academic success.

Simultaneously, reduced physical activity during remote study detracts from mental and cognitive health. Studies demonstrate that active students exhibit lower stress levels, sharper focus, and improved academic outcomes. The “lifestyle psychiatry” perspective integrates these findings, asserting that lifestyle habits—diet, exercise, and sleep—are central to preventing and alleviating mental disorders. Collectively, these studies show that maintaining balanced daily routines and physical engagement is not peripheral but foundational to sustaining both mental wellness and academic productivity.

Despite recognition of these relationships, few investigations have simultaneously modeled multiple lifestyle and psychological variables to predict academic outcomes. Most rely on descriptive or correlational analyses, leaving an interpretive gap regarding how combined behaviors influence self-reported performance change during online learning. Addressing this limitation requires analytical frameworks capable of capturing and explaining complex, multivariate dependencies among mental health, lifestyle, and educational success.

Interpretable Machine Learning in Educational Research

AI and learning analytics now offer powerful means to understand student behavior, yet their adoption in education raises ethical and transparency concerns. In high-stakes domains, interpretability is as valued as accuracy [27]. IML ensures that models are understandable to educators and students, reinforcing fairness and accountability [28].

Among IML techniques, Logistic Regression provides inherent transparency through its coefficient structure, allowing direct interpretation of predictor influence on outcomes [29]. Tree-based ensembles such as Random Forest capture nonlinear interactions and yield feature-importance scores that highlight dominant predictors [30]. Complementarily, SHapley Additive exPlanations (SHAP) offers model-agnostic global and local interpretability, revealing how each feature contributes to a specific prediction. Such tools enable the transformation of “black-box” models into insight-generating systems suitable for educational contexts.

However, while predictive modeling is well explored, comparative research on interpretable methods—especially linking lifestyle factors, mental well-being, and academic performance in online learning—is scarce. This study addresses that gap by juxtaposing Logistic Regression and Random Forest + SHAP to elucidate which predictors most strongly relate to self-reported academic performance changes. Through this comparative IML framework, it seeks to advance both methodological transparency and practical insight for data-driven educational improvement.

Method

Figure 1 illustrates the end-to-end experimental framework, outlining the sequential stages from data ingestion and feature engineering to model training and post-hoc interpretability analysis.

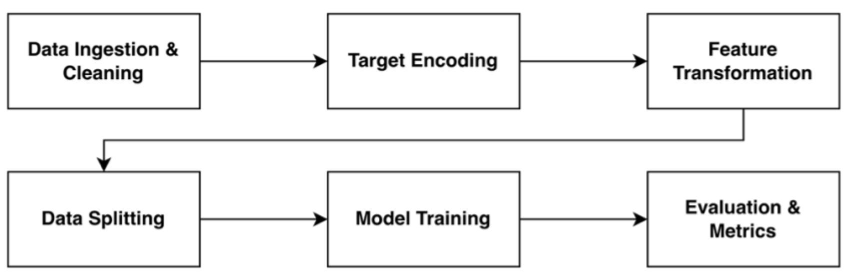

Figure 1 Research Method Flowchart

Data Source, Experiment Setup, and Reproducibility

This study uses the “Student Mental Health Analysis During Online Learning” from Kaggle, stored as a comma-separated values file and referenced in the script as DATA_FILE. All outputs are organized under a root directory research_outputs with subfolders for exploratory plots (eda_plots), serialized models (models), and SHAP figures (shap_plots). The workflow enforces reproducibility by fixing a pseudorandom seed via RANDOM_STATE = 42, which governs the train–test split as well as the initialization of models that accept a seed. Intermediate objects, including the learned preprocessing pipeline and trained estimators, are persisted with joblib.dump to guarantee exact re-use in subsequent sessions.

Exploratory Data Analysis and Initial Cleaning

The raw file is ingested into a pandas DataFrame and inspected for shape, schema, and sample rows to confirm integrity. A working copy (df_eda) is created for exploratory analysis so that the raw frame remains untouched for the formal preprocessing stage. Column names are normalized by trimming whitespace, converting to lowercase, and replacing spaces, slashes, and parentheses with underscores to create stable identifiers. Missingness is enumerated per column and, consistent with prior runs, no gaps are expected; otherwise, imputation would precede modeling. The non-informative identifier name is removed to avoid leakage and reduce dimensionality. Numerical features receive descriptive statistics to summarize central tendency and dispersion, while categorical features are profiled with percentage distributions to reveal imbalance. Visualization comprises histogram–KDE overlays and boxplots for each numeric variable to assess distributional shape and outliers, count plots for categorical variables including the target to examine class frequencies, a Pearson correlation heatmap among numeric features to screen for collinearity, and feature–target relationship plots that present numeric variables by target strata and categorical variables stratified by target labels in a consistent order of Declined, Same, and Improved.

Target Definition and Ordinal Mapping

The outcome variable, academic_performance_change, is treated as an ordered categorical response and encoded using scikit-learn’s OrdinalEncoder with categories specified as ['Declined', 'Same', 'Improved']. This mapping yields deterministic codes of 0 for Declined, 1 for Same, and 2 for Improved, which are printed to the console for traceability. Preserving the ordinal semantics ensures consistent label ordering during evaluation and clearer interpretation of one-vs-rest coefficients and confusion matrices.

Predictors are partitioned by type to enable appropriate transformations through a ColumnTransformer. Numerical variables include age, screen_time_hrs_day, sleep_duration_hrs, and physical_activity_hrs_week, and they are standardized by StandardScaler to zero mean and unit variance so that coefficient magnitudes are comparable and no single scale dominates the optimization.

To ensure that numerical features contribute equally to the model optimization process without being biased by their varying magnitudes, each continuous variable x is standardized to a z-score z. This transformation centers the feature distribution around zero with a unit variance, mathematically defined as:

$$z = \frac{x - \mu}{\sigma}$$

where μ represents the mean of the training samples and σ represents the standard deviation. This scaling is critical for the Logistic Regression baseline to ensure coefficient comparability, while the parameters μ and σ computed from the training set are retained within the pipeline to transform the test set consistently. The ordinal variable stress_level is encoded with OrdinalEncoder using the category order ['Low', 'Medium', 'High'] so that the resulting codes preserve monotonic structure. Nominal variables—gender, education_level, and anxious_before_exams—are transformed with OneHotEncoder(handle_unknown='ignore', sparse_output=False), where the unknown handler prevents inference-time failures when encountering unseen categories and the dense output simplifies downstream integration and SHAP plotting. The column transformer uses remainder='passthrough' to retain any unlisted columns, although none are expected after explicit selection. Following fit_transform on the training set, transformed feature names are reconstructed by concatenating the numeric names, the ordinal name, and the one-hot expanded names obtained via get_feature_names_out, which supports transparent coefficient tables and importance plots.

Train–Test Split and Data Serialization

The dataset is partitioned into training and testing subsets using train_test_split with test_size=0.2, random_state=42, and stratify=y. Stratification preserves the empirical class proportions across folds, thereby stabilizing metric estimates for minority classes. The preprocessing pipeline is fit exclusively on the training subset to avoid information leakage and then applied to both training and testing data. For external inspection and replication, the processed matrices are saved as comma-separated files for features and targets, and the learned preprocessor is serialized to preprocessor.joblib. These artifacts ensure that transformation logic can be reapplied consistently during validation or deployment.

Logistic Regression (Interpretable Linear Baseline)

The first classifier is a multinomial task implemented as a one-vs-rest scheme using Logistic Regression(multi_class='ovr', solver='liblinear', random_ state=42, max_iter=1000). The one-vs-rest configuration fits a separate binary model for each class against the remainder and exposes a coefficient vector per class that can be read as log-odds contributions. The liblinear solver is selected because it is robust for small to medium tabular datasets and supports the one-vs-rest formulation with L2 regularization by default. The max_iter parameter is set to a high ceiling to mitigate non-convergence risks after standardization and one-hot expansion. After training on the processed training set, predictions are generated for the test set and evaluation includes overall accuracy, weighted precision, weighted recall, weighted F1, the full classification report with class-wise metrics, and a confusion matrix. Model interpretability is provided by exporting the coefficient matrix aligned with processed feature names and by plotting the coefficient profile for the "Improved" class, where positive values indicate increases in the log-odds of Improved relative to the other classes and negative values indicate decreases, all on the standardized scale.

Random Forest Classifier (Nonlinear Ensemble)

The second classifier is an ensemble of decision trees trained via RandomForestClassifier(n_estimators=100, random_state=42). The number of trees is set to one hundred to balance variance reduction against computational cost, and the remaining hyperparameters use scikit-learn defaults in classification mode, namely the Gini impurity criterion, unrestricted depth until stopping conditions are met, a minimum split size of two, a minimum leaf size of one, square-root feature sampling per split, and bootstrap sampling enabled. The evaluation protocol mirrors that of the logistic baseline to permit direct comparison, and a confusion matrix is saved to visualize error structure. Global feature importance is first approximated by the model's impurity-based importances, which offer a fast heuristic ranking but may favor variables that split frequently; consequently, SHAP analyses are employed to complement and validate these rankings.

Model Evaluation and Reporting Protocol

Model performance is summarized through accuracy to capture overall correctness and through weighted precision, recall, and F1 to account for support-weighted class contributions under potential imbalance. The scikit-learn classification_report provides per-class metrics and support counts, facilitating an examination of minority-class performance. Confusion matrices are generated as labeled heatmaps with Declined, Same, and Improved on both axes to reveal systematic confusions, such as misclassification between neighboring ordinal categories. A comparative printout consolidates the two models' accuracies and weighted F1 scores, lists the highest magnitude coefficients for the Improved one-vs-rest submodel, and presents the leading features by impurity importance and by mean absolute SHAP value for the Random Forest.

Global and Local Interpretability with SHAP

Model-agnostic interpretability for the Random Forest is obtained using SHAP's TreeExplainer, which leverages tree structure for efficient exact or near-exact attributions. The training data serve as the background distribution to anchor expectation calculations. SHAP values are computed for both training and test partitions, and multiclass outputs are handled robustly by checking whether the library returns a single Explanation object with a three-dimensional values array or a legacy list of per-class arrays. To avoid strict additivity assertions that can fail in some tree settings with post-processing, the explainer is invoked with check_additivity=False, which preserves relative attribution magnitudes used for ranking and visualization. Global explanations are communicated through class-specific SHAP summary plots that rank features by mean absolute contribution and depict how feature values relate to their signed effects. Local and interaction insights are explored through dependence plots for the five most influential features as determined by mean absolute SHAP aggregated across classes, with the interaction index set to automatic selection to surface salient pairwise effects.

Software Stack, Parameters, and Artifacts

All analyses are implemented in Python using pandas and NumPy for data handling, matplotlib and seaborn for visualization, scikit-learn for preprocessing, modeling, and metrics, joblib for persistence, and SHAP for explainability. Critical parameterizations include standardized numerical scaling with StandardScaler, explicit ordinal category orders for the target and for stress_level, robust nominal encoding with OneHotEncoder(handle_unknown='ignore', sparse_output=False), a stratified train–test split with a test proportion of 0.2 and a fixed random seed of 42, logistic regression configured as one-vs-rest with the liblinear solver and an iteration cap of one thousand, and a Random Forest with one hundred trees under default regularization. All figures are exported at 150 dots per inch with tight bounding boxes, and serialized artifacts include preprocessor.joblib, logistic_regression_model.joblib, random_forest_model.joblib, and processed feature and target matrices to ensure complete end-to-end reproducibility.

Result and Discussion

Descriptive Characteristics and Class Balance

The final analytic dataset comprised 1,000 records and 10 variables with no missing values after standardization of column names and removal of the non-informative identifier. Numerical features exhibited reasonable spread: mean age was 20.34 years (SD = 3.46), mean daily screen time was 6.91 hours (SD = 2.91), mean sleep duration was 6.45 hours (SD = 1.47), and mean weekly physical activity was 5.02 hours (SD = 2.93). Categorical distributions were broadly balanced across gender, with 47.5% male, 47.5% female, and 5.0% other, while stress level skewed toward Medium at 49.2%, followed by Low at 32.7% and High at 18.1%. Slightly more than half of the students reported being anxious before exams at 51.3%. The target classes were moderately balanced, with 39.9% reporting the same academic performance, 30.3% reporting improvement, and 29.8% reporting decline. Exploratory plots confirmed unimodal distributions for the main continuous variables, revealed expected correlations among lifestyle measures, and indicated visible but overlapping separations between target groups in feature–target visualizations.

Data Split, Feature Space, and Encodings

Following the predefined ordinal mapping of the outcome to Declined = 0, Same = 1, and Improved = 2, the dataset was partitioned into 800 training and 200 testing instances with stratification to preserve class proportions. The preprocessing pipeline produced 21 modeled features after standard scaling of numeric variables, ordinal encoding of stress level, and one-hot expansion of nominal attributes for gender, education level, and exam anxiety. Feature names were reconstructed from the transformer to enable direct alignment of coefficients, importances, and SHAP attributions to human-readable inputs, ensuring that all subsequent interpretations referred to consistent, well-documented variables.

Predictive Performance of Logistic Regression

The one-vs-rest logistic regression achieved an accuracy of 0.335 on the held-out test set, with weighted precision of 0.3269, weighted recall of 0.3350, and weighted F1 of 0.2981. Class-wise performance indicated that the model best captured the “Same” class with a recall of 0.62 and an F1 of 0.46, while performance for “Declined” and “Improved” was weaker with F1 scores of 0.22 and 0.16, respectively. The confusion matrix showed frequent confusions between neighboring ordinal categories, most notably misclassifying Declined and Improved as Same, which is consistent with the intermediate position of the Same class in the ordinal spectrum. These patterns suggest that linear decision boundaries, even after standardization and categorical expansion, capture some central tendency around the unchanged performance group but struggle to separate students at the tails who reported clear declines or improvements.

Coefficient Patterns from Logistic Regression

Inspection of the one-vs-rest coefficient matrix highlighted several notable associations on the standardized scale. For the Improved versus Rest model, the largest magnitude coefficients were attached to education-related dummies and exam anxiety, with negative signs for education_level_Class 10 (−0.512), education_level_BTech (−0.353), education_level_Class 12 (−0.287), and anxious_before_exams_No (−0.276), and positive coefficients for education_level_BA (0.276), education_level_MTech (0.266), education_level_BSc (0.262), and education_level_MSc (0.250). Gender terms showed a negative coefficient for Female (−0.224) and a smaller positive weight for Male (0.084) relative to the one-hot baseline, while the ordered stress encoding had a negative coefficient (−0.088), aligning higher stress with reduced log-odds of improvement. Continuous lifestyle indicators carried modest weights in the Improved model, with physical activity (−0.074) and sleep duration (−0.021) both negative and screen time near zero, whereas age had a small negative sign (−0.050). These results imply that, within the linear framework, the most discriminative signals for improvement were categorical differentiators—particularly education level and exam anxiety—whereas lifestyle variables exhibited weaker linear separability for improvement once other factors were controlled.

Predictive Performance of Random Forest

The random forest classifier matched the overall accuracy at 0.335 and achieved weighted precision of 0.3271, weighted recall of 0.3350, and weighted F1 of 0.3210. Relative to the logistic baseline, the forest modestly increased the weighted F1 while maintaining similar recall patterns, again with the highest recall for the Same class at 0.51 and lower recall for Declined and Improved at 0.23 and 0.20, respectively. The confusion matrix mirrored the logistic regression’s error structure, showing concentration of predictions in the central class and asymmetrical misclassifications from Declined and Improved toward Same, which is typical when class boundaries are subtle and features overlap around the median performance group.

Global Importance and SHAP-Based Explanations for Random Forest

Gini-based importances positioned physical activity, screen time, and sleep duration as the three most influential features with importance scores of 0.203, 0.196, and 0.186, respectively, followed by age at 0.108 and stress level at 0.061. Exam anxiety, gender, and several education levels formed a secondary tier with notably smaller contributions. SHAP analyses corroborated and refined these rankings by mean absolute attribution, placing screen time, physical activity, sleep duration, and age at the top, with mean absolute SHAP values of 0.025, 0.024, 0.020, and 0.019. Gender, stress level, and exam anxiety contributed smaller yet non-negligible attributions, and education Level Class 10 emerged among the top ten SHAP-ranked variables despite modest Gini importance. Class-specific SHAP summary plots revealed consistent directional patterns: higher screen time tended to increase the log-odds of belonging to less favorable outcomes and reduce the likelihood of improvement, whereas greater physical activity and adequate sleep showed the opposite tendency. Dependence plots further showed that these effects were not strictly linear, with localized regions where changes in lifestyle levels had disproportionate influence and with interactions that varied across classes, particularly between screen time and sleep and between stress level and sleep.

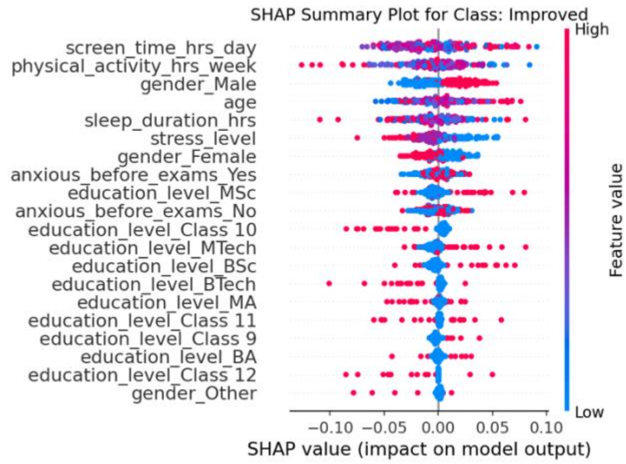

Figure 2 SHAP Summary Plot For The "Improved" Class Generated From The Random Forest Model

As shown in figure 2, the SHAP summary plot identifies screen_time_hrs_day, physical_activity_hrs_week, and gender as the most influential predictors of improved academic performance. Higher screen time (red dots with negative SHAP values) tends to decrease the probability of improvement, indicating that excessive digital exposure adversely affects learning outcomes. Conversely, higher physical activity and adequate sleep duration (red dots with positive SHAP values) positively contribute to improvement, supporting evidence that balanced routines enhance cognitive engagement. Stress level and exam anxiety also exhibit mild negative contributions, reinforcing the psychological dimension of performance variance. Overall, the summary plot captures both the magnitude and direction of each variable's global effect across students, revealing consistent behavioral and wellness trends linked with performance enhancement.

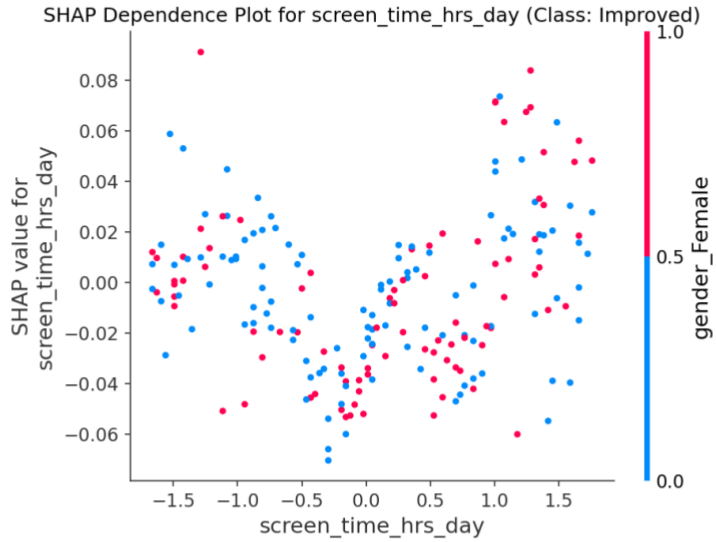

Figure 3 SHAP Dependence Plot for Screen Time (Class: Improved)

Figure 3 illustrates the nuanced effect of screen time on academic improvement probability. The relationship is nonlinear: students with moderate screen use exhibit near-zero or slightly positive SHAP values, suggesting an optimal engagement threshold, whereas excessive or minimal screen exposure tends to reduce improvement likelihood. The color dimension reveals minor gender-based interactions, with female students showing slightly higher SHAP variability at equivalent screen durations. This pattern implies that balanced technology use—neither excessive nor minimal—supports more favorable learning outcomes, especially when accompanied by other healthy behaviors such as sufficient sleep and physical activity.

Comparative Synthesis of Models and Predictors

Taken together, the two models yielded comparable accuracies near one third and highlighted different facets of the predictor–outcome relationship. The logistic regression emphasized categorical separations tied to education level and exam anxiety for the Improved class, while yielding relatively small linear effects for lifestyle variables. The random forest, by contrast, consistently elevated lifestyle measures as global drivers through both impurity and SHAP metrics, indicating that nonlinearity and interactions among screen time, physical activity, sleep, age, and stress better align with the observed class distinctions. Both models struggled to distinctly separate Declined and Improved from the central Same category, suggesting that the three groups share overlapping feature distributions and that additional information, alternative targets, or calibrated decision thresholds may be required to improve tail discrimination.

The results support three primary conclusions. First, lifestyle indicators—screen exposure, weekly physical activity, and nightly sleep—emerge as the most influential global factors in the nonlinear model and display consistent, interpretable directions of effect in SHAP analyses, reinforcing their salience for academic performance change during online learning. Second, stress level and exam anxiety contribute smaller but coherent shifts in class probabilities, with higher stress generally aligning with worse outcomes and exam anxiety differentiating groups in combination with other features. Third, education level and gender exhibit measurable but comparatively weaker roles once lifestyle and stress-related variables are considered, and their explanatory power appears model dependent, being more prominent in the linear coefficient profile than in tree-based importance rankings. Overall performance parity across models, coupled with richer explanations from SHAP, indicates that future gains are likely to come from enriched feature sets, refined target formulations, or class-rebalancing strategies rather than from additional complexity alone.

Discussion

The comparative findings between logistic regression and random forest underscore the multifaceted nature of academic performance change in online learning environments. The relatively low accuracies in both models suggest that student performance outcomes are influenced by complex and interdependent factors that extend beyond the recorded lifestyle and psychological variables. Nevertheless, interpretability analyses revealed consistent evidence that lifestyle behaviors—particularly screen time, sleep duration, and physical activity—are key determinants of students' academic well-being during online education. Higher screen exposure was repeatedly associated with poorer outcomes, while longer sleep and higher physical activity were linked to improvement. These patterns align with the growing literature in lifestyle psychiatry and digital learning, which emphasizes the cognitive and affective benefits of balanced daily habits.

Interestingly, while the linear logistic regression emphasized categorical factors such as education level and exam anxiety, the random forest and SHAP analyses captured nonlinear relationships, highlighting that the combined influence of stress, sleep, and activity may explain subtle variations in student outcomes. The consistent misclassification between "Same" and "Improved" groups further suggests a continuum of adaptation rather than discrete categories, emphasizing that well-being and performance fluctuate dynamically under online learning pressures. Overall, the integration of interpretable machine learning approaches provided a nuanced understanding of both predictive strength and psychological interpretability, bridging quantitative modeling and educational insight.

Limitation

This study has several limitations that constrain the generalization of its results. The dataset is cross-sectional, preventing causal inference between lifestyle factors, mental well-being, and academic outcomes. All variables were self-reported, which introduces potential biases such as inaccurate recall or social desirability effects. The model accuracy remained modest, indicating that unmeasured factors—such as motivation, teaching quality, internet access, or socio-economic background—likely contribute significantly to student performance but were not captured in the current feature set. Moreover, while interpretable models were used, their explanatory scope is inherently limited by the quality and diversity of the available data. Lastly, the class distribution, although moderately balanced, may still have affected the model's ability to distinguish between subtle differences in "Improved" and "Same" performance groups.

Future Research Suggestions

Future work should expand on this analysis by incorporating longitudinal data to capture temporal variations in lifestyle, stress, and academic performance over time. Integrating objective behavioral metrics from digital learning platforms, wearable devices, or sleep trackers could reduce bias and enhance model accuracy. Further exploration using hybrid deep learning combined with explainable techniques, such as Gradient Boosted Trees with SHAP or LIME extensions, could capture latent nonlinearities while maintaining interpretability. Additionally, multi-level modeling across demographic or institutional strata would clarify how contextual factors—like discipline type or regional education policy—modulate lifestyle–performance relationships. Finally, qualitative studies or mixed-method designs could complement machine learning outcomes with richer insights into students' lived experiences, thereby supporting more personalized well-being interventions in digital education.

Conclusion

This study demonstrates that interpretable machine learning can effectively reveal how lifestyle and mental health indicators relate to academic performance change in online learning environments. Both logistic regression and random forest models identified screen time, physical activity, and sleep duration as primary predictors, while stress and anxiety contributed additional, smaller effects. Despite modest predictive accuracy, the combined use of global (Gini, SHAP) and local interpretability analyses clarified how these factors interact to shape learning outcomes. The findings reinforce the importance of balanced digital engagement, adequate rest, and physical activity as critical components of academic resilience in remote learning contexts. By providing interpretable, data-driven insights, this research bridges predictive analytics and educational psychology, offering a foundation for future studies and policy efforts aimed at improving student well-being and academic success in online education.

Declarations

Author Contributions

Conceptualization: D.F.; Methodology: C.J.H.; Software: C.J.H.; Validation: C.J.H.; Formal Analysis: D.F.; Investigation: C.J.H.; Resources: D.F.; Data Curation: C.J.H.; Writing Original Draft Preparation: D.F.; Writing Review and Editing: D.F.; Visualization: C.J.H.; The author have read and agreed to the published version of the manuscript.

Data Availability Statement

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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