Online-Journals.org

iJOE International Journal of Online and Biomedical Engineering

iJOE | eISSN: 2626-8493 | Vol. 22 No. 7 (2026) | OPEN ACCESS

https://doi.org/10.3991/ijoe.v22i07.61225

PAPER

Decoding Online Student Behavior and Procrastination Using Clustering and Predictive Analytics

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ABSTRACT

In the age of online education, it is crucial to comprehend the behavioral elements that influence student performance in order to improve learning outcomes and facilitate personalized approaches. This study proposes a data-driven framework to model and predict student behavioral patterns associated with procrastination in online learning environments. Rather than directly predicting procrastination as a binary construct, we operationalize it as a latent behavioral spectrum using indicators derived from submission timing and engagement patterns. K-Means clustering is first applied to identify six distinct latent behavioral profiles. These clusters, interpreted as procrastination-related patterns (ranging from strategic delay to dysfunctional procrastination), are subsequently predicted using supervised learning models including random forest, XGBoost (XGB), support vector machines (SVM), and logistic regression. To ensure interpretability and algorithmic fairness, we integrate explainable artificial intelligence (AI) techniques using SHapley Additive exPlanations (SHAP) and Local Interpretable Model-agnostic Explanations (LIME). Experimental results demonstrate that the proposed framework effectively captures meaningful behavioral patterns with a peak predictive accuracy of 98.36% (SVM). Furthermore, the Explainable AI (xAI) analysis provides actionable, behaviorally-grounded insights, thus offering a robust foundation for early, equitable intervention in online learning environments and Smart Campuses.

KEYWORDS

artificial intelligence (AI), explainable AI (xAI), procrastination, student performance, education, clustering, prediction

1 INTRODUCTION

In the modern era, the optimization of educational frameworks is a fundamental driver of regional innovation and economic sustainability; indeed, recent empirical evidence (2014–2024) demonstrates that strategic financial investment in engineering education significantly promotes regional growth, provided it is supported by robust digital transformation [1]. Within the rapidly evolving landscape of higher

Izourane, F.-Z., Bella, B., Ardchir, S., Ounacer, S., Azzouazi, M. (2026). Decoding Online Student Behavior and Procrastination Using Clustering and Predictive Analytics. *International Journal of Online and Biomedical Engineering (iJOE)*, 22(7), pp. 67–85. https://doi.org/10.3991/ijoe.v22i07.61225

Article submitted 2026-03-09. Revision uploaded 2026-04-26. Final acceptance 2026-05-06.

education, understanding and predicting student performance has become increasingly vital for institutions aiming to enhance learning outcomes and support student success. While traditional predictive models have primarily focused on academic indicators such as grades and attendance, they often overlook critical behavioral factors. Among these, procrastination stands out as a pervasive behavior characterized by the voluntary postponement of intended actions despite anticipating negative consequences that adversely affects retention and the overall educational experience.

Recent advancements in machine learning and explainable artificial intelligence (xAI) have emerged within a research domain experiencing exponential growth; indeed, a 2025 systematic review spanning a decade of literature (2015–2025) reports a 32.75% annual increase in AI-driven educational research output [2]. This surge has paved the way for new methods of analyzing extensive educational data. Techniques such as SHapley Additive exPlanations (SHAP) and Local Interpretable Model-agnostic Explanations (LIME) offer capacity to clarify the decision-making processes of intricate models, empowering educators to make informed, data-driven decisions. Furthermore, recent research emphasizes that xAI is not only a tool for transparency but also a means to ensure the stability of prediction models across different cohorts, bridging the gap between purely predictive and explanatory learning analytics [3]. However, a significant gap remains: the majority of current research tends to treat procrastination as a secondary metric or a simple binary outcome, often overlooking the subtle, multifaceted behaviors that define it.

Unlike prior work that attempts to directly classify procrastination as a binary label, this study adopts a behavioral perspective, where procrastination is inferred from observable engagement patterns. This allows for a more robust and data-driven representation of student behavior, reducing reliance on subjective or self-reported measures. By leveraging the Open University Learning Analytics Dataset (OULAD), we utilize an unsupervised clustering approach (K-Means) to let these behavioral archetypes emerge naturally before applying supervised classification, This approach allows us to differentiate between nuanced behaviors, such as 'strategic delay' and 'dysfunctional procrastination.'

This study seeks to address the existing literature gap by creating an xAI-based methodology that places these behavioral patterns at the forefront of predicting student trajectories. By incorporating SHAP and LIME, our methodology not only improves predictive accuracy, reaching up to 98.36%, but also ensures that the underlying factors are transparent and ethically grounded, answering the following research questions:

RQ1: What are the key behavioral features driving model predictions of student procrastination profiles, and how do these dynamic indicators outweigh static demographic variables in the decision logic?

RQ2: How can xAI techniques like SHAP and LIME provide actionable, instance-specific insights for educators and administrators to address dysfunctional procrastination and improve student outcomes with modern digital learning environments?

2 RELATED WORK

2.1 xAI

Several studies have explored the application of xAI in the realm of forecasting student performance. In a key paper, Adnan et al. present an xAI model that delivers comprehensive and specific interpretations of student performance at multiple intervals during the course timeline [4]. The researchers highlight the limitations of traditional machine learning and deep learning methodologies in delivering comprehensible data analysis outcomes for educational purposes and emphasize the importance of xAI in helping instructors interpret individual student strengths and weaknesses. The integration of xAI techniques with traditional machine learning and deep learning models has the potential to provide valuable insights into the factors influencing students' performances [5]. This lack of interpretability can be a significant limitation, as it prevents educators and administrators from fully understanding the factors that contribute to student performance and making informed decisions based on the predictions [6].

In this context, the qualitative assessment of explainability is crucial for educational stakeholders. Current research on xAI techniques in education emphasizes that tools such as SHAP and LIME do not merely provide technical transparency but also offer qualitative insights that educators can translate into early interventions [7]. The model developed by Nnadi et al. utilizes ensemble algorithms trained on demographic, clickstream, and assessment data to optimize performance predictions, with the algorithm that demonstrated the highest performance ultimately chosen as input for the xAI framework [8]. While Pawar et al. present a systematic literature review on the use of data mining and AI techniques for predicting student performance, highlighting the importance of explainability in AI models to facilitate informed decision-making in educational settings, the authors propose a combinatorial model that integrates multiple AI techniques to enhance the accuracy of predictions [9]. In their study on student dropout prediction, Ardchir et al. utilize feature engineering and ensemble learning, specifically XGBoost (XGB) and Random Forest, to determine the critical features driving student attrition in high-stakes classification settings [10] [11]. Similarly, Padmasiri et al. focus on predicting student dropout rates using a combination of Machine Learning algorithms and xAI techniques, including the use of LIME for local interpretability and SHAP for global interpretation [12]. Moreover, Johora et al. validated the efficacy of stacking ensemble classifiers combined with the duality of SHAP and LIME to ensure fairness and reliability in academic achievement predictions, establishing a benchmark for interpretable data-driven interventions [13]. Furthermore, Raji et al. focus on the academic performance of Deaf and Hard of Hearing students by employing a novel machine learning system that integrates xAI techniques to predict risk factors affecting their academic success. The study utilizes LIME and SHAP to elucidate the factors influencing performance, showcasing the potential of xAI in catering to diverse educational needs [14].

2.2 Academic procrastination

Procrastination in education poses a considerable challenge, affecting both student performance and retention rates. Recent research has utilized machine learning methods to forecast procrastination tendencies. To understand the evolution of this phenomenon, a recent comprehensive bibliometric analysis spanning from 1960 to 2024 reveals that research in this field has accelerated rapidly over the last decade, peaking in 2023. This study identifies academic achievement, time management, and motivation as the strongest thematic clusters, providing a critical shift toward a more psychological and contextual perspective on how students delay their intended actions [15]. Building on this historical evolution, recent research has transitioned toward utilizing machine learning methods to forecast specific procrastination tendencies. Hooshyar et al. introduced an innovative algorithm (PPP) designed to examine students' assignment submission habits in order to forecast procrastination tendencies, achieving an impressive accuracy rate of 96%, it highlights the importance of comprehending behavioral patterns prior to assignment deadlines, thereby offering valuable insights into online education and performance forecasting [16]. Similarly, Akram et al. presented an algorithm named SAPE, which leverages homework submission data to categorize students into procrastinators and non-procrastinators, by utilizing a range of classification techniques, it examines behavioral trends, thereby assisting educators in comprehending and tackling academic procrastination within blended learning settings [17]. In another study, Imhof et al. examines the prediction of procrastination-related behaviors in online assignments, it utilizes statistical analysis techniques to investigate behavioral trends, with the goal of improving comprehension and intervention approaches for procrastination within online educational environments [18]. Following this data-driven approach, Yang et al. proposed a method to predict students' procrastination tendencies based on their submission behavioral patterns in online learning, achieving 97% accuracy using a linear support vector machine, highlighting the importance of feature selection for effective clustering and classification [19]. Finally, research by Raj et al. focuses on forecasting academic procrastination in e-learning environments through the application of ensemble classification models, with a particular emphasis on the random forest model, which demonstrates an accuracy rate of 85%. Nonetheless, it does not investigate the cognitive or emotional conditions of students, which restricts a comprehensive understanding of their behavioral patterns [20].

3 METHODOLOGY

This study adopts a rigorous data-driven pipeline (see Figure 1) that integrates multi-source data fusion, unsupervised learning for student segmentation, supervised learning for performance prediction, and advanced interpretability. The approach enables the identification of at-risk student profiles and the understanding of key factors driving success or dropout, with an innovative focus on model explainability, including LIME and SHAP, utilizing behavioral data obtained from the OULAD.

3.1 Dataset

The Open University Learning Analytics Dataset encompasses comprehensive data regarding courses, students, and their engagement with the virtual learning environment (VLE) across seven designated modules [9]. This dataset consists of seven interconnected tables; each linked through unique identifiers and formatted in CSV. It includes information pertaining to 22 courses and 32,593 students, detailing their assessment outcomes and logs of their interactions with the VLE, which are represented by daily summaries of student clicks, totaling 10,655,280 entries. The dataset is accessible for free at https://analyse.kmi.open.ac.uk/open_dataset under a CC-BY 4.0 license [9].

3.2 Data preprocessing

The dataset used in this study is sourced from the OULAD, comprising multiple relational tables including studentInfo, studentVle, studentAssessment, studentRegistration, courses, assessments, and vle. These tables were merged on the keys id_student, code_module, and code_presentation to form a unified dataset. Categorical variables such as gender, disability, age_band, and activity_type were encoded using appropriate transformation techniques (e.g., one-hot or label encoding). Behavioral features were engineered to capture meaningful patterns in student interaction with the VLE, including total number of clicks, most frequent activity type (preferred activity), average assessment scores, and submission rate for assignments. Missing values were handled through imputation based on the nature of the variable (mean, mode, or domain-specific default). Finally, all numerical features were normalized to ensure compatibility with distance-based algorithms and to improve model convergence. This preprocessing step ensures data consistency and enhances the quality of feature representation for both clustering and classification tasks.

3.3 Procrastination operationalization

Procrastination is a complex behavioral construct that is not directly observable in log-based educational datasets. Therefore, in this study, it is treated as a latent construct inferred from observable student behaviors. Instead of relying on self-reported measures, which are unavailable in the OULAD dataset, we adopt a behavioral analytics perspective by analyzing patterns such as interaction frequency, submission behavior, and temporal activity distribution. Specific features including submission rate, timing of interactions, and overall engagement intensity are used to characterize these behaviors. These variables capture variations in learning strategies, such as the delayed engagement and last-minute activity commonly associated with procrastination. To model these dynamics, K-Means clustering is applied to group students into homogeneous behavioral profiles. These resulting clusters are interpreted as representing different levels of engagement and procrastination tendencies. While this operationalization is indirect, it aligns with prior work in learning analytics where behavioral traces serve as proxies for psychological states. Ultimately, this approach offers a scalable and data-driven approximation suitable for large-scale online learning environments, providing a robust alternative to traditional psychological surveys.

3.4 Clustering model (K-Means)

Integrating K-Means for student performance prediction helps in clustering students based on learning styles, engagement metrics, and performance levels, and it allows for better understanding of students' learning characteristics and guiding teaching more effectively [21], and for academic evaluation it can produce accurate clustering results, adapt to different indicators, and make full use of big data [22].

This article investigates the performance of a Clustering algorithm for partitioning students based on behavioral patterns. The K-Means algorithm was applied to the numerical features of the preprocessed dataset, excluding identifiers and outcome variables. The optimal number of clusters was determined using both the Elbow method and the Silhouette score, ensuring a balance between intra-cluster cohesion and inter-cluster separation. The resulting clusters are interpreted as distinct behavioral profiles associated with varying levels of engagement and potential procrastination tendencies.

3.5 Classification models

The identified clusters were used as target labels to train multiple classification models to assess predictability of student groups. Our selection of support vector machines (SVM), random forests (RF), and logistic regression (LR) is grounded in their proven capacity to model intricate behavioral dynamics. As noted by Meftah et al., these algorithms excel in capturing the subtle nuances of user engagement within loyalty-driven environments, providing the high-fidelity predictive precision required to inform personalized intervention strategies [23]. Furthermore, we prioritized ensemble learning architectures, specifically XGB and RF, to manage the complexity and non-linearity inherent in digital learning logs. This methodological choice aligns with the integrated frameworks established by Ardchir et al., which demonstrate that ensemble methods achieve superior accuracy in high-stakes classification scenarios by effectively handling complex, non-linear datasets [11].

Specifically, the models were configured to maximize both stability and interpretability: we implemented RF with an ensemble of 200 trees to ensure robustness against outliers, XGB for its advanced gradient boosting capabilities, and SVM utilizing a Radial Basis Function (RBF) kernel to map non-linear decision boundaries. LR was included as a transparent baseline to ensure results remained grounded in traditional statistical theory. Model performance was rigorously assessed via precision, recall, macro F1-score, and overall accuracy.

3.6 Explainability methods (SHAP and LIME)

This step integrates xAI techniques to provide both global and local insights into the classification models. SHAP is employed to provide a global understanding of feature importance, highlighting the variables that most influence cluster assignments, while LIME offers local explanations for individual predictions. Together, these methods enable a deeper interpretation of model behavior and offer actionable insights into the factors driving student groupings.

The primary explainability analysis is conducted on the SVM model due to its strong predictive performance and ability to capture non-linear relationships. SHAP values for SVM are computed using KernelExplainer (calibrated with a 100-sample background distribution) with a representative background dataset obtained via k-means sampling. To strengthen the robustness of the explainability framework, a supplementary SHAP analysis is conducted on the XGB model using TreeSHAP. This allows validation of feature importance consistency across different model architectures. Both global and local LIME explanations are analyzed to ensure interpretability and reliability of the model outputs.

3.7 Evaluation metrics

Our evaluation focuses on ensuring both the global stability of the models and their predictive sensitivity toward specific student profiles. While we report accuracy to establish a baseline of overall correctness, we prioritize the Macro F1-score as our primary performance benchmark. Given that educational datasets often exhibit class imbalance, where high-risk student groups may be numerically smaller but pedagogically more significant, the Macro F1-score ensures that each cluster is weighted equally, preventing the results from being skewed by more dominant populations. To achieve a finer granularity of analysis, we supplement these global figures with Cluster-wise Precision, Recall, and F1-scores. This tri-metric approach allows us to evaluate the "correctness" of our assignments against the model's ability to "recover" all members of a specific cohort, a critical requirement for early-warning systems where missing a student at risk can have severe academic consequences. These results are contextualized by the Support count, providing transparency regarding the distribution of data across clusters. To ensure that our findings are robust and represent generalizable patterns rather than localized noise, we utilize a 70/30 stratified train-test split. All reported metrics are derived exclusively from the unseen test set, offering a rigorous validation of the framework's ability to generalize across diverse student engagement landscapes. This evaluation framework ensures a detailed and balanced analysis of model performance, capturing both global accuracy and cluster-specific behavior in predicting structured student engagement patterns.

4 RESULTS

4.1 Optimal number of clusters

After cleaning and preparing the student assessment data and before applying K-Means clustering, we aim to validate the optimal number of clusters using the elbow method combined with silhouette analysis:

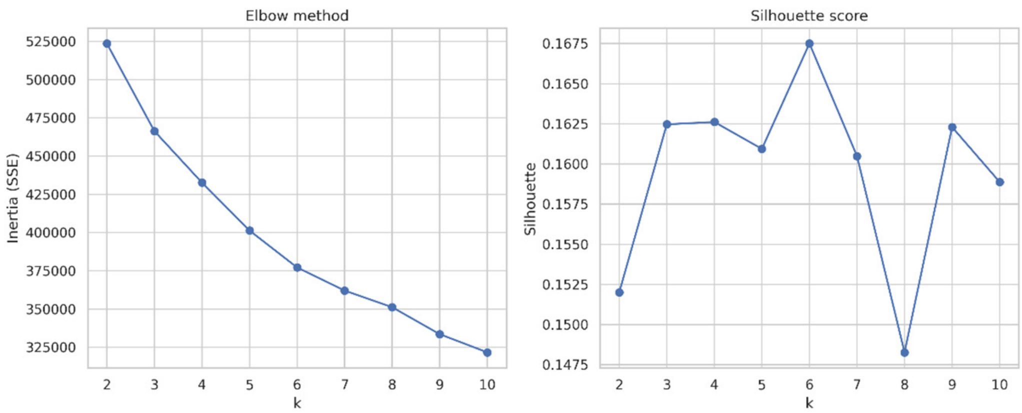

Fig. 1. Elbow and silhouette method for optimal number of clusters

The elbow method and silhouette score were jointly applied as illustrated in Figure 1 to determine the optimal number of clusters for grouping students based on their behavioral and academic features. The elbow curve revealed a steep decline in inertia from k = 2 to k = 4, after which the slope began to flatten, indicating diminishing returns in variance reduction beyond this range. The most notable inflection point occurred between k = 4 and k = 6, suggesting these as potential candidates for optimal k.

In parallel, the silhouette analysis provided complementary insights into the structural quality of the clusters. The silhouette score peaked at k = 6 (~0.1675), slightly outperforming k = 3 (~0.1625), indicating better cluster cohesion and separation at k = 6. Lower scores observed for higher k values, such as k = 8, indicated poorer separability, likely due to over-fragmentation of the data.

By combining both approaches, k = 6 emerges as a strong candidate for the optimal number of clusters, offering a balance between compact, well-separated clusters and minimal complexity. This choice not only captures distinct patterns in the dataset but also allows for meaningful interpretation of the student profiles associated with each cluster.

4.2 Data clustering

K-Means clustering was applied with k = 6, informed by the Elbow and Silhouette methods, to identify latent groups within the student population based on their engagement and performance indicators. To enable interpretability, the high-dimensional feature space was reduced to two principal components using Principal Component Analysis (PCA). This dimensionality reduction preserved the majority of the variance and facilitated the visualization of cluster structure in a two-dimensional space (see Figure 2).

The different colors represent the identified clusters (k = 6). We can see some separation between the clusters, suggesting that the clustering captured distinct groups of students based on the features used.

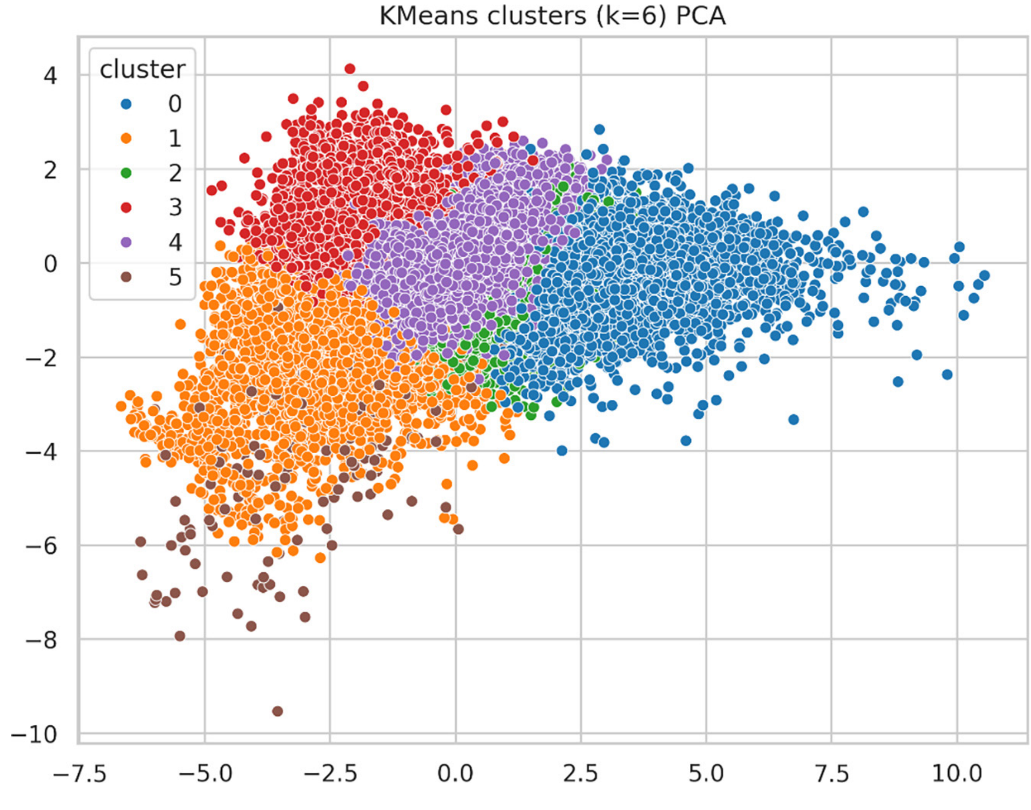

Fig. 2. PCA visualization of K-means clustering results with k = 6

As illustrated in Figure 2, the resulting clusters exhibit clear structure and varying degrees of overlap, reflecting distinct behavioral profiles among students. For example, Cluster 0 (blue) spans a broad area, indicating heterogeneous engagement, whereas Cluster 1 (orange) and Cluster 3 (red) appear denser and more cohesive. Cluster 5 (brown), positioned in the lower left corner, is sparsely populated and may correspond to a subgroup of disengaged or at-risk students. The central positioning of Cluster 4 (purple) suggests it may act as a transitional group between more and less active learners.

To gain deeper insight into the characteristics of each cluster, Figure 3 presents a heatmap of the mean values for each feature across clusters. Several important patterns emerge.

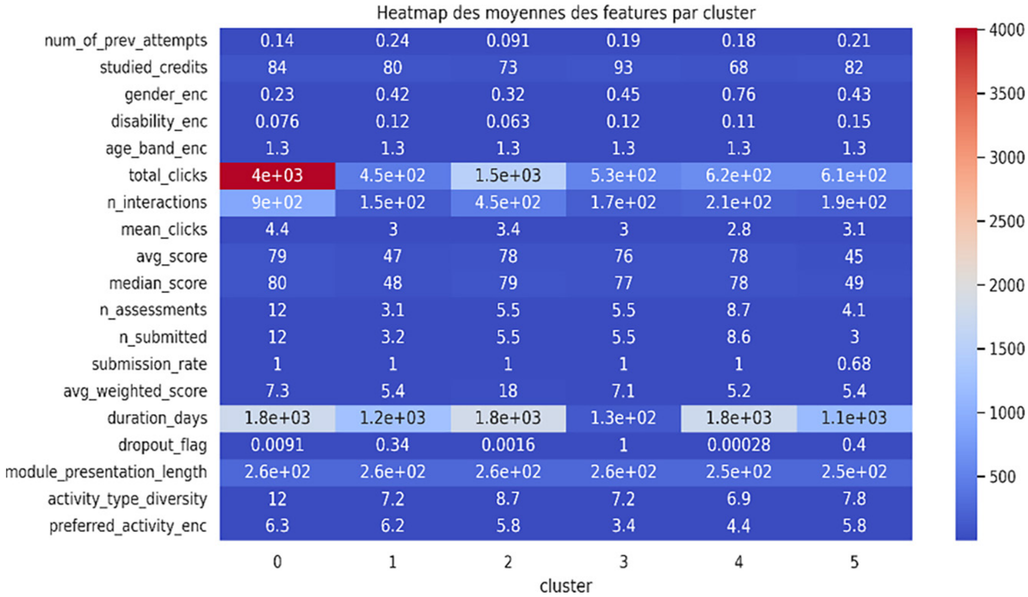

Fig. 3. Heatmap of mean feature values across student clusters (k = 6)

Cluster 0 is defined by the highest levels of engagement and performance, with the greatest number of total clicks, interactions, assessment submissions, and the highest academic scores. These students also demonstrated the lowest dropout rate and the longest study durations, indicating a stable and high-achieving learner profile. By contrast, Cluster 1 exhibited relatively low academic performance despite moderate engagement, with an average score of 47 and a dropout rate of 0.34. Cluster 2 represents efficient learners who, with moderate engagement levels, achieved high academic scores and the highest weighted average scores, accompanied by an extremely low dropout rate. Cluster 3 stands out with minimal engagement and the shortest study durations yet maintains moderate scores, although all students in this cluster dropped out, possibly early in the course. Cluster 4 includes students who are less interactive but maintain high submission rates and stable performance, suggesting independent or low-maintenance learning styles. Finally, Cluster 5 includes learners with low performance and a high dropout rate, despite engagement metrics comparable to those in other groups, pointing to potential motivational or comprehension challenges. Overall, the clustering output provides interpretable behavioral segmentation, offering insights into different learning strategies and risk levels across the student body, potentially enabling targeted pedagogical interventions.

In summary, the clustering results reveal distinct student profiles based on behavioral and academic indicators. These profiles range from highly engaged and successful learners to disengaged and at-risk students. The differentiation between clusters supported by both PCA visualization and feature-level analysis offers a foundation for targeted pedagogical interventions aimed at improving retention and performance among specific student subgroups.

4.3 Data training and testing

To assess the discriminative power of these clusters and predict student outcomes, several classification models, including Random Forest, XGB, SVM, and Logistic Regression, were trained on a 70/30 train-test split of the data (stratified to maintain class proportions). The identified clusters were used as target labels to train multiple classification models to assess predictability of student groups. Models included random forest (RF, 200 trees) for robustness to outliers, XGB for gradient boosting performance, SVM with RBF kernel for non-linear boundaries, and LR as an interpretable baseline. Performance was evaluated using precision, recall, macro F1-score, and overall accuracy.

The results, summarized in Table 1, demonstrate that all four models achieved high predictive performance, with accuracy scores exceeding 97%. The SVM slightly outperformed the other methods, achieving an accuracy of 98.36% and an F1-macro score of 0.9798, indicating balanced performance across all clusters. XGB followed closely with an accuracy of 98.14% and an F1-macro of 0.9806, while RF and LR achieved slightly lower but still robust performance (97.13% and 97.32% accuracy, respectively).

Table 1. Comparison of classification models on cluster labels

Model	Accuracy	F1-Macro	Cluster-Wise Precision/Recall/F1 (Support)
Random Forest	0.9713	0.9667	C0: 0.98/0.97/0.97 (1454), C1: 0.96/0.94/0.95 (1269), C2: 0.95/0.98/0.97 (2313), C3: 0.99/0.99/0.99 (2547), C4: 0.97/0.96/0.97 (2136), C5: 1.00/0.92/0.96 (59)
XGB	**0.9814**	**0.9806**	C0: 0.98/0.98/0.98 (1454), C1: 0.98/0.97/0.97 (1269), C2: 0.97/0.99/0.98 (2313), C3: 0.99/0.99/0.99 (2547), C4: 0.98/0.97/0.98 (2136), C5: 0.97/1.00/0.98 (59)
SVM (RBF)	**0.9836**	**0.9798**	C0: 0.98/0.98/0.98 (1454), C1: 0.98/0.97/0.98 (1269), C2: 0.98/0.99/0.98 (2313), C3: 0.99/1.00/0.99 (2547), C4: 0.99/0.97/0.98 (2136), C5: 0.95/0.98/0.97 (59)
Logistic Regression	0.9732	0.9674	C0: 0.98/0.97/0.98 (1454), C1: 0.97/0.93/0.95 (1269), C2: 0.95/0.99/0.97 (2313), C3: 0.99/1.00/0.99 (2547), C4: 0.98/0.96/0.97 (2136), C5: 0.93/0.97/0.95 (59)

These findings suggest that the features derived from prior preprocessing and clustering steps were highly informative and linearly/separably structured in the transformed feature space. This step in the pipeline is therefore essential for enabling early identification of student profiles, which supports proactive interventions and personalized learning strategies in subsequent stages of the educational analytics framework.

The evaluation of these models revealed high predictive performance across the board, with SVM and XGB demonstrating marginally superior accuracy and macro F1-scores in predicting cluster membership. Considering the goal of applying explainable AI, these results support the selection of all four models for interpretability analysis, but we will prioritize SVM and XGB. Their high predictive performance ensures that subsequent explanations via SHAP and LIME will be meaningful and reliable.

4.4 xAI (SHAP and LIME)

To enhance the interpretability of the machine learning models used in this study, a comparative explainability analysis was conducted across the SVM and

XGB models. Firstly, SHAP (SHapley Additive exPlanations) interaction values were computed for the SVM to analyze model interpretability, using KernelExplainer (calibrated with a 100-sample background distribution). These values allow for the decomposition of predictions into main effects and pairwise interactions between features, providing a more nuanced understanding of how input variables jointly influence model outputs.

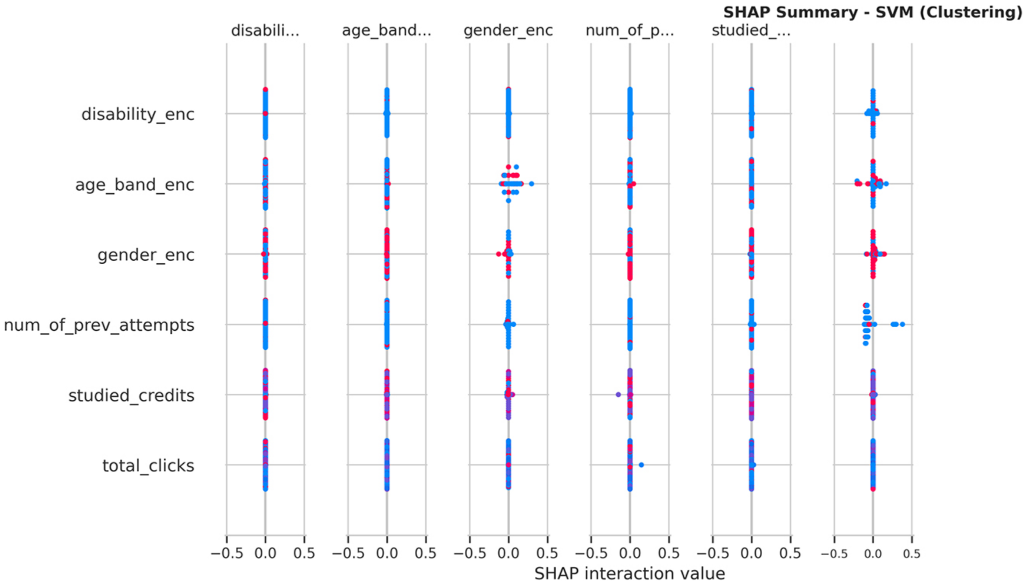

Fig. 4. SHAP plot for SVM

Figure 4 displays the SHAP interaction summary plots for the SVM model. Each plot illustrates the magnitude of interaction effects between feature pairs. The diagonal elements capture the main effects (individual feature contributions), while the off-diagonal elements represent interaction effects between pairs of features.

A key observation is the non-linear interaction between behavioral engagement, represented by total_clicks, and a student's academic context, such as studied_credits and num_of_prev_attempts. The variance in interaction values suggests that the SVM model effectively contextualizes student effort, allowing it to distinguish between 'strategic delay,' where high-performing students optimize their interactions, and 'dysfunctional procrastination,' where low engagement is compounded by high academic pressure or a history of previous failures. Furthermore, the interaction analysis serves as a rigorous validation of the model's ethical integrity. The near-zero interaction values for demographic variables including gender_enc, age_band_enc, and disability_enc confirm that these attributes do not modulate the predictive weight of learning behaviors. This lack of interaction ensures that the proposed detection system is behaviorally grounded and equitable, triggering interventions based on dynamic student actions rather than static personal characteristics, thereby providing a robust foundation for personalized pedagogical support.

The SHAP plot (Bar) analysis in Figure 5 reveals that the SVM model prioritizes a decision-making hierarchy where academic performance and longitudinal engagement act as the primary indicators of procrastination behavior within the OULAD dataset. The dropout_flag emerges as the most influential feature, particularly for Cluster 3 (100% dropout rate) and Cluster 4 (near-zero dropout), signifying that a student's final persistence status is the most powerful differentiator of their behavioral profile.

Following this, academic metrics such as avg_weighted_score and median_score form a second critical pillar of importance; these features are especially predictive for Cluster 1 (High-risk Procrastinators) and Cluster 2. This suggests that the model identifies early assessment failures as reliable proxies for disengagement caused by procrastination-led delays.

Beyond performance, the model distinguishes between "strategic" and "dysfunctional" procrastination by valuing the quality and consistency of engagement over raw interaction volume. Features such as activity_type_diversity and duration_days rank higher in importance than the total number of clicks, indicating that a varied and persistent interaction with learning resources is a stronger signal of success than erratic, high-frequency activity. For instance, while Cluster 2 (Strategic Procrastinators) maintain high scores despite lower activity, students in Cluster 5 (Dysfunctional Procrastinators) are identified by their low submission rate (0.68), which serves as the most direct metric of procrastination delay. Ultimately, the minimal impact of demographic variables confirms that the model is behaviorally grounded and equitable, focusing on dynamic learning actions to provide a robust foundation for an early warning system.

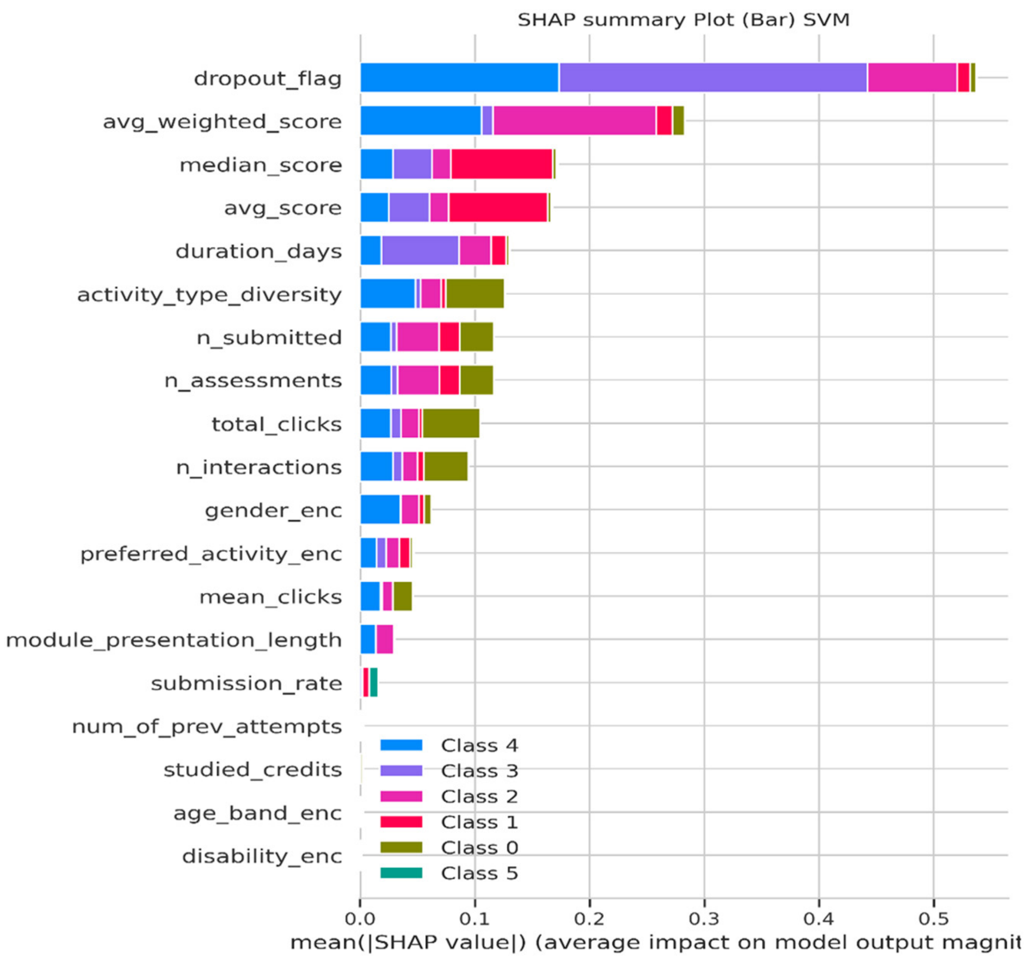

Fig. 5. SHAP plot (Bar) for SVM

To complement the SVM analysis, we utilized TreeSHAP to deconstruct the "black box" of the XGB model. As shown in Figure 6, which displays the global summary plot ranking features by their mean absolute SHAP value, the feature importance hierarchy is largely consistent with that of the SVM model.

The data reveals that dropout_flag is the most significant predictor, particularly for Classes 3 and 4. However, once we look past this binary indicator, the model's logic is dominated by granular behavioral metrics rather than static demographics. Metrics such as avg_weighted_score and total_clicks emerge as the primary drivers of the prediction, underscoring the weight the model places on consistent engagement and academic milestones.

What is particularly striking is the high ranking of duration_days and submission_rate, which serve as vital proxies for student self-regulation and procrastination. Their influence on the model's output significantly outweighs traditional structural variables like num_of_prev_attempts or studied_credits. Notably, demographic features including gender_enc, age_band_enc, and disability_enc reside at the bottom of the hierarchy, corroborating the SVM findings and suggesting that what students do within the learning environment is far more predictive of their success than who they are or their background.

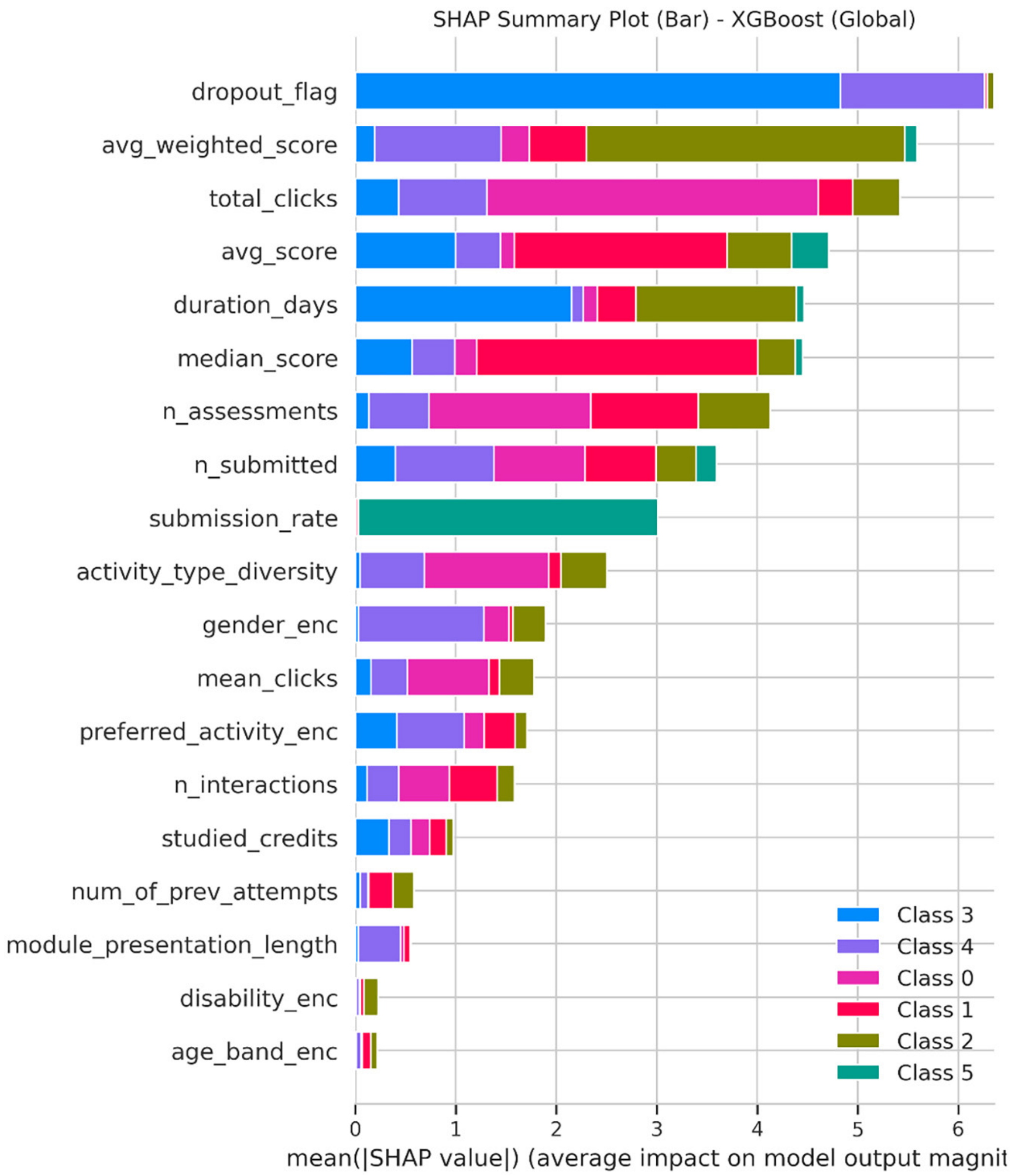

Fig. 6. SHAP plot (Bar) for XGB

To complement the global feature importance insights derived from SHAP analysis, we utilized the LIME method to gain fine-grained, instance-specific interpretations of model predictions.

Figure 7 presents LIME explanations for six representative student instances (one for each cluster). These plots show the contribution of individual features to the prediction for each student, offering a personalized view of the decision logic.

Across all six instances, academic performance indicators, specifically median_score and avg_score, consistently emerged as highly influential factors in the local decision logic. These features were also among the top-ranked globally in the SHAP summary plots, reinforcing the model's strong reliance on student performance when predicting procrastination or academic outcome. For each at-risk instance, lower scores in these metrics substantially increased the likelihood of an unfavorable prediction, aligning with the global SHAP results that highlighted these as dominant predictors.

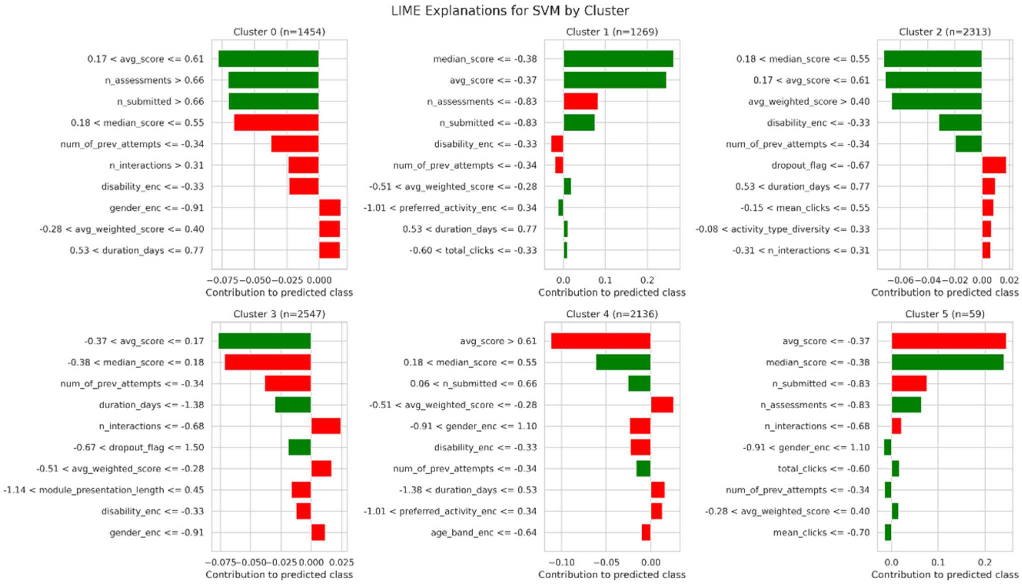

Fig. 7. LIME explanation plot for 6 instances

The local explanations across the six identified student archetypes demonstrate high fidelity to the global importance hierarchy, with academic performance metrics acting as the primary catalysts for cluster assignment. For high-engagement and successful groups, such as Cluster 0 and Cluster 2, positive contributions from avg_score, n_assessments, and n_submitted reinforce the model's identification of proactive learning patterns. Specifically, in Cluster 2 (the "strategic" learners), the model relies on high weighted scores and the absence of a dropout flag to solidify its prediction, corroborating the earlier findings where this group maintained high academic efficiency despite moderate activity volume.

Conversely, the LIME explanations for at-risk profiles, particularly Clusters 3 and 5, pinpoint the specific behavioral thresholds that trigger failure or procrastination-related predictions. In Cluster 3, which is globally characterized by a 100% dropout rate, the local model fidelity is driven by low behavioral and performance metrics (e.g., duration_days <= –1.38 and avg_score <= –0.17), marking the terminal impact of chronic disengagement. For the critical Cluster 5, LIME reveals that extreme negative deviations in avg_score (<= –0.37) and median_score (<= –0.38) are the decisive factors for its classification. These local insights confirm that the SVM model effectively navigates specific, actionable student metrics such as submission counts and granular score thresholds to distinguish between strategic delay and dysfunctional procrastination.

5 DISCUSSION

A central contribution of this study is the reconceptualization of procrastination in online learning environments. Rather than treating it as a binary state to be directly classified, we operationalize procrastination as a latent behavioral construct emerging from observed engagement patterns. The challenge of operating with limited or weakly labeled data is a persistent hurdle in deep learning applications. As highlighted by Ouassit et al., when precise ground-truth labels are scarce, weakly supervised methodologies become essential to extract meaningful patterns from complex datasets. Our study echoes this requirement by utilizing an unsupervised clustering approach (K-Means) to derive behavioral archetypes, thereby mitigating the reliance on subjective or binary labels in procrastination research [24]. By leveraging K-Means clustering as a preliminary step, we move beyond reductive "at-risk" labels to identify a spectrum of six distinct clusters (profiles). This methodology reveals that procrastination is not a monolithic phenomenon. The comparison between Cluster 0 (Hyper-active) and Cluster 4 (Efficient) demonstrates that lower interaction volume is not systematically synonymous with academic failure; instead, it often reflects high self-regulation and learning efficiency. This distinction between strategic delay and dysfunctional procrastination provides a more nuanced theoretical foundation for understanding how students navigate digital learning spaces who make the novelty regarding [4] and [12].

The high classification performance observed, reaching 98.36% accuracy for SVM and 98.14% for XGB, indicates that student behavioral patterns are highly structured and separable in the transformed feature space. These results significantly exceed recent benchmarks, such as the 97% accuracy achieved by Yang et al. [19] and the 96% reported by Hooshyar et al. [16], respectively. Our framework's ability to achieve such high accuracy underscores the robustness of modern predictive architectures. These results align with contemporary research in diverse high-stakes domains, such as the generalized risk prediction models developed by Aitelbour et al., which demonstrate that structured data preparation and ensemble learning can effectively map complex, non-linear patterns, whether in crime prevention or student behavior analysis [25].

The success of our framework stems from the hybrid use of unsupervised and supervised learning. By first isolating unique profiles, such as Cluster 3 (students with high performance but sudden behavioral disengagement), we effectively removed statistical noise that typically hampers predictive models relying solely on grades. This ensures that the final classification is grounded in a refined behavioral taxonomy, providing a highly reliable basis for early intervention. To establish a robust interpretability baseline, we conducted a comparative xAI analysis using model-specific methodologies. We utilized SHAP KernelExplainer for the SVM and TreeSHAP for the XGB model. The remarkable convergence in feature importance across these different architectures where dropout_flag, submission_rate, and duration_days consistently dominate the decision logic validates that these markers are inherent signatures of student engagement rather than algorithmic artifacts.

Furthermore, the near-zero impacts of demographic variables (gender, age, and disability) across both SHAP and LIME analyses serve as empirical proof of algorithmic fairness. In the context of modern educational digitalization, this ensures that pedagogical support is triggered by dynamic learning actions (what students do) rather than static personal characteristics (who they are), aligning our framework with ethical AI standards for talent concentration and regional growth. As noted by Cai et al. (2024), the effectiveness of engineering education in driving regional growth depends heavily on the quality of the learning environment and talent concentration [1].

Beyond achieving high predictive accuracy, the integration of xAI through LIME provides the "fine-grained" diagnostic capability essential for university administration. By pinpointing specific behavioral thresholds such as an average score drop below –0.37 or a critical reduction in activity_type_diversity, our framework bridges the theoretical gap between data analytics and pedagogical intervention.

In a Smart Campus ecosystem [26], these insights facilitate a shift from reactive to proactive management through a multi-layered intervention strategy: (i) Targeted Feedback: Automated reminders can be tailored to the specific behavioral triggers identified in Cluster 5 (Dysfunctional Procrastinators), addressing the root causes of their delay rather than just the symptoms. (ii) Proactive Mentoring: By identifying the subtle "procrastination-led disengagement" characteristic of Cluster 1, instructors can intervene before these behaviors impact final grades. (iii) Strategic Resource Allocation: This approach advances an Adaptive Feedback Regulation Framework [2], allowing institutions to prioritize high-risk profiles with transparent, data-driven justifications.

Ultimately, this hybrid methodology combining unsupervised clustering with supervised explainability ensures that when our models interpret a student's risk, they are not relying on isolated indicators but on a rich behavioral taxonomy that reflects the measurable dynamics of student effort.

Despite the framework's robust performance, several limitations warrant acknowledgment. First, our reliance on the OULAD dataset may constrain the generalizability of these results across diverse cultural and institutional contexts where VLE engagement patterns might differ. Second, while behavioral proxies are highly effective for predictive modeling, they do not fully capture the complex psychological and motivational dimensions of procrastination. Furthermore, our current analysis represents a snapshot of student behavior. Procrastination is a dynamic process that unfolds over time; our models are currently limited in their ability to account for the temporal evolution of these archetypes during a semester.

Future research, in line with recent bibliometric trends [2], should focus on longitudinal tracking to observe how students transition between behavioral clusters in real-time. Developing the next generation of proactive and adaptive learning analytics will require moving toward temporal xAI, which can provide even deeper insights into the catalysts of student success and disengagement. By continuing to refine the operationalization of procrastination as a latent behavioral construct, we can better support personalized and equitable learning experiences in the digital age.

6 CONCLUSION

This study establishes a robust, explainable framework for identifying and analyzing procrastination patterns in online learning environments. By integrating unsupervised clustering with high-performance supervised models and model-agnostic xAI techniques, we have transitioned from a binary view of student success to a nuanced understanding of procrastination as a latent behavioral construct.

Our findings demonstrate that student engagement in Virtual Learning Environments (VLE) is highly structured, allowing our hybrid methodology to achieve a peak predictive accuracy of 98.36% with SVM and 98.14% with XGB. Beyond these metrics, the deployment of SHAP and LIME has provided a critical layer of transparency. The convergence of feature hierarchies across different architectures validates those behaviors such as submission regularity and engagement intensity are stable indicators of academic risk. Furthermore, the near-zero influence of demographic variables serves as a mathematical guarantee of algorithmic fairness, ensuring that early-warning systems remain grounded in dynamic student actions rather than static personal traits.

From a practical standpoint, the identification of six distinct behavioral archetypes ranging from "Strategic" to "Dysfunctional" procrastinators offers a clear roadmap for personalized pedagogical intervention. By pinpointing specific thresholds (e.g., critical drops in avg_weighted_score), our framework enables university administrators to move beyond generic alerts toward tailored support strategies that address the unique disengagement triggers of each student group.

While this study provides a powerful baseline using the OULAD dataset, future work should focus on the temporal dynamics of these behavioral clusters to capture the real-time migration of students between archetypes. Additionally, we emphasize the need to transition toward the longitudinal and ethical assessment of xAI systems in diverse STEM contexts for the next generation of proactive, adaptive learning analytics. Ultimately, this work bridges the gap between complex data science and actionable educational insights, fostering a human-centered approach to data-driven learning analytics and paving the way for more equitable and effective Smart Campus ecosystems.

7 DECLARATION

AI-assisted technologies were used solely to support paraphrasing and improve the clarity, readability, and language of the manuscript. The use of these tools did not affect the scientific content, data analysis, methodology, or interpretation of results.

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