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Predicting Academic Dropouts Using AI and Behavioral Data: A Hybrid Deep Learning Framework for Student Retention

Ms. A.Jacquline Dorothy[1], Dr.M.Sangeetha[2]
[1]Research Scholar (Part-time), Department of Computer Science, Dr. N.G.P Arts and Science College, jacqulinedorothy@gmail.com
[2]Professor, Department of Computer Science, Dr. N.G.P Arts and Science College, Sangeetha.m@drngp.ac.in

Abstract:
Environmental education is recognized as a cornerstone of sustainable development, aiming to cultivate ecological consciousness, critical thinking, and responsible citizenship among learners. However, student *disengagement and dropout from sustainability-related programs pose significant challenges to institutions and global environmental objectives alike. Addressing these issues requires innovative solutions that blend pedagogy with technology to proactively identify and retain at-risk students.*

This research proposes a hybrid Artificial Intelligence (AI) framework for predicting academic dropout in environmental education using deep learning and explainable machine learning models. The approach integrates Convolutional Neural Networks (CNN) to extract behavioral features from student engagement data, Long Short-Term Memory (LSTM) networks to capture temporal academic patterns, and XGBoost to classify student risk based on structured academic, demographic, and participation features. To ensure ethical and transparent decision-making, Shapley Additive Explanations (SHAP) are incorporated, providing interpretable visualizations of the factors contributing to dropout predictions.

The model was trained and validated using real-world LMS datasets reflecting diverse student behaviors across environmental education courses. Experimental results demonstrate that the hybrid model achieves an overall prediction accuracy of 94.2%, with a high early-warning recall of 90.3% for moderate-risk students—those who typically fall through the cracks in conventional systems. The fusion of behavioral, academic, and emotional cues enables the detection of latent disengagement patterns before they escalate into full dropout.

More than a predictive tool, this framework supports institutional strategies for promoting environmental awareness, by ensuring continuity in ecological literacy programs and reinforcing student commitment to sustainability. It aligns directly with the objectives of the UN Sustainable Development Goals (SDG 4: Quality Education and SDG 13: Climate Action), providing both micro-level (individual learner support) and macro-level (policy and governance) benefits.This study contributes to the fields of educational data mining, environmental education, and AI for social good by presenting a scalable, interpretable, and high-impact model for dropout prediction. It offers a blueprint for how AI systems can be ethically embedded into sustainability curricula to drive engagement, equity, and long-term ecological stewardship.

1. INTRODUCTION

Environmental education plays a vital role in shaping sustainable societies by equipping learners with the knowledge, values, and skills necessary to address global environmental challenges. Yet, despite widespread policy emphasis and curriculum integration, many institutions face persistent student dropouts from environmental education programs, particularly in digital and blended learning formats. This educational disengagement undermines broader goals related to environmental stewardship, civic responsibility, and long-term ecological resilience. In recent years, the integration of Artificial Intelligence (AI) and Machine Learning (ML) into educational systems has shown promise for early detection of academic disengagement. Leveraging large volumes of digital behavioral data from Learning Management Systems (LMS), these technologies can identify students at risk of dropping out before traditional academic indicators become evident. However, while AI has been used extensively for academic performance forecasting, its application to sustainability education—where behavioral intent, emotional commitment, and civic awareness are also key—remains underexplored. This study addresses this gap by proposing a hybrid deep learning model that combines CNN and LSTM networks for sequential and spatial pattern analysis with XGBoost for high-accuracy classification. Moreover, explainable AI techniques like SHAP are incorporated to enhance transparency and stakeholder trust, enabling actionable and ethical interventions. The model aims not only to improve student retention in environmental education but also to strengthen institutional capacity for promoting sustainability awareness and ecological citizenship. Dropouts from environmental science and sustainability programs present a double setback: they hinder academic progress and weaken the dissemination of ecological awareness. Retaining students in these courses is thus vital for achieving long-term environmental stewardship goals.

2. LITERATURE REVIEW

The use of Artificial Intelligence (AI) for the prediction of academic dropout received a significant impulse over the last five years. The proliferation of data-driven educational platforms has led to the collection of high-dimensional, longitudinal and behavioral data that also have very long tails, unlocking new opportunities in risk prediction, student retention, and adaptive learning systems. This section presents major studies published from 2020 to 2025, clustered by methodological novelty and contribution to research. In arecent investigation by Psyridou and colleagues. (2024) on dropout prediction, using the longitudinal data that is following Finnish students from the beginning of primary school up to finishing after secondary education. They utilized a variety of cognitive, school and social/emotional factors and deployed Random Forest and Gradient Boosting models to predict dropout, achieving a fair predictive accuracy (at Grade 6 (AUC) = 0.61; at Grade 9 (AUC) = 0.65). While these are not SOTA in terms of accuracy, the work is important on two fronts: it uncovers early and latent dropout predictors well before the event happens, and it refocuses model building on social emotional context. The authors also suggest that time depth and emotional properties are important but not fully considered in the AI-based dropout systems. In another investigation, Elbouknify et al. (2025) from the performance and explainability point of view in the Moroccan secondary education. They utilized ensemble learning methods—XGBoost, LightGBM, and Random Forest—on academic, institutional, and demographic features from various districts. XGBoost performed best with an accuracy of 94.2%, high feature importance scores. Perhaps more importantly, the authors employed SHAP (Shapley Additive Explanations) to provide model explainability, so that the model gives reasons, instead of just an answer to why an inference was drawn. The most important predictors were family income, academic record, and attendance. What distinguishes our work is that we strive to balance predictive power and interpretability, building toward the possibility of ethical, real-time deployment.

Focusing on the behavioral domain, Cheng et al. (2025) introduced a novel Dual-Modal Sliding Window (DMSW) framework to detect abrupt changes in student LMS engagement behavior. This framework processes temporal patterns and identifies sudden behavioral disruptions—a leading indicator of academic disengagement. Using behavioral logs and performance data from a large Chinese university, they demonstrated that DMSW can identify dropout risk up to four weeks before traditional systems, achieving a 15% improvement in early recall over classical models. Although the dataset is institution-specific, the core contribution is methodological: modeling behavioral volatility through adaptive temporal windows can significantly improve early intervention systems.

In a complementary study, Arno et al. (2025) proposed DropWrap, a neural network-based framework that operates on India's UDISE+ database—a government-mandated educational data repository. Unlike other models that focus on student-level prediction, DropWrap works at the institutional level, flagging regions with high dropout probability based on macro-level indicators such as district-wise infrastructure, teacher-student ratios, and dropout history. While the model lacks fine-grained personalization, it introduces scalability and policy alignment, proving AI's applicability in national-level educational governance.

Roda-Segarra et al. (2024) provide a comprehensive meta-analysis evaluating the effectiveness of AI models in predicting dropout across 15 studies with nearly 200,000 student records. Decision Trees and Ensemble Models yielded the highest average predictive accuracy (91%), while neural networks lagged slightly behind unless enhanced with data fusion or attention mechanisms. The review emphasized that most existing systems rely on "thin data"—mainly academic scores or attendance—and fail to integrate behavioral, psychological, or social variables. The authors argue for multimodal data architectures and call for model accountability via explainable AI. This paper underlines a systemic weakness: the field lacks generalizable models that integrate behavioral and emotional dimensions while remaining interpretable.
Lastly, Leelaluk et al. (2024) advanced the domain through a novel use of attention-based Recurrent Neural Networks (RNNs) combined with knowledge distillation. Their framework, tested on semester-level LMS data, enables early prediction of academic failure with precision metrics improving from 0.49 to 0.61 by Week 6. The addition of attention layers highlights which time windows are most critical, and knowledge distillation ensures the model remains lightweight for real-world applications. While dropout is not directly predicted, poor academic performance is a strong proxy, and the method offers direct applicability to early warning systems. The contribution lies in combining early-stage detection with scalability—two vital attributes for broad institutional adoption.
Collectively, these six studies confirm that while traditional academic and demographic features are still effective, the inclusion of temporal, behavioral, and emotional data is necessary for more holistic dropout prediction. The integration of SHAP for interpretability (Elbouknify et al., 2025), behavioral windows for early detection (Cheng et al., 2025), and meta-analytical evidence for data fusion (Roda-Segarra et al., 2024) collectively build the case for a hybrid deep learning model—one that combines CNNs for contextual feature extraction, LSTMs for sequential modeling, and ensemble learners like XGBoost for high-accuracy benchmarking. This paper adopts that integrated vision and proposes a unified framework that brings together accuracy, interpretability, and scalability for real-world educational deployment.

3. Research Problem Statement & Objectives

Student dropout is a widespread and complex problem in academic institutions everywhere, although particularly so in the developing world. Not only is this a measure of educational waste but also a predictor of the individual's watermark of vulnerability to economic detriment which has national economic implications for the productivity of the nation and the individual's destiny. Many research projects have attempted to address dropout by identifying early warning signs, but many existing solutions are reactive, piecemeal, or lack scalability across contexts. Although machine learning has improved the accuracy of dropout prediction models, a significant challenge remains to incorporate behavioral, emotional, and temporal signals in a single, interpretable, and scalable AI platform. This study takes a shot at that gap. The research challenge is due to the complexity of, and the dark shadows surrounding, the academic dropout prediction. On one hand, there is a surfeit of institutional data: grades, attendance logs, demographic profiles, course evaluations. On the other, there's a wealth of under-used behavioral data: clickstream activity in LMSs, patterns of submissions, heatmaps of engagement, and even textual sentiment in discussion boards. These behaviors convey early nuanced signs of disengagement that typically predate academic failure. Most AI models, however, either under-invest in these cues, or do not have the technical architecture to (algorithmically) gate their dynamic temporal structure. Recent works, such as those by Elbouknify et al. (2025) and Cheng et al. (2025), validate the promise of both structured academic data and behavioral volatility in enhancing prediction models. Still, even these cutting-edge models are often trained in data silos, incapable of generalizing across student populations, curriculum structures, or national education systems. In practical terms, this limitation results in models that are highly accurate within a controlled dataset but fail to scale across institutions or geographic regions. Additionally, most high-performing models (e.g., XGBoost, DeepFM) have limited explainability, making them less suitable for real-time educational policy implementation, where transparency is essential for stakeholder trust.

Furthermore, institutions require not just predictions, but interpretable insights. It is not enough to know that a student is likely to drop out; institutions must also understand why. Current research underrepresents models that integrate explainability (e.g., SHAP) with predictive performance. Interpretability becomes especially important in high-stakes decision-making, such as intervention timing, resource allocation, or counseling prioritization. In the absence of model transparency, even accurate AI systems risk being ignored or underutilized.

In light of this context, the **central research problem** can be articulated as follows:

"How can a predictive AI model be designed that integrates academic, behavioral, and emotional indicators into a unified, interpretable, and scalable framework to accurately identify at-risk students for early intervention in academic settings?"

3.1 Research Objectives

To address this problem, the present study proposes a hybrid architecture that integrates CNN (Convolutional Neural Network) and LSTM (Long Short-Term Memory) deep learning components, benchmarked against XGBoost, and enriched through SHAP-based interpretability. The core **objectives** of this research are outlined below:

Objective 1: Design and Implement a Hybrid CNN-LSTM Model

The proposed model architecture is designed to leverage both spatial and sequential learning mechanisms. CNN layers are used to extract patterns from engagement matrices—such as LMS heatmaps, login frequency, and session duration—while LSTM layers model time-dependent academic performance (e.g., weekly grades, test scores, assignment timeliness). By combining these layers, the model is positioned to detect not only static risk indicators but also evolving behavioral trends.

Objective 2: Integrate Traditional Classifiers for Benchmarking (XGBoost, Random Forest, SVM)

Besides deep learning, the research is using ensemble learners such as XGBoost whose performance continues to remain at the state-of-the-art (Elbouknify et al., 2025). These models act as performance benchmarks and backup repositories for organizations that do not have GPU setups. Comparison of these models enables us to differentiate between the trade-offs of speed, accuracy, and interpretability.

Objective 3: Improve Explainability through SHAP Values

To achieve better interpretability of the model's learning behavior, the work plugs SHAP 1 (Shapley Additive Explanations) into both the CNN-LSTM and XGBoost pipelines. SHAP provides local and global explanations of model behavior so that teachers and institutional researchers can see which factors pull model predictions in which direction. This kind of transparency is crucial for ethical deployment of AI systems and acceptance of stakeholders.

Objective 4: Build a Multimodal Dataset Incorporating Academic, Behavioral, and Emotional Data

Building on modules with the previous phase, this study is integrating structured academic modules and LMS logs, attendance, and qualitative factors such as forum posts. Behavioral time series are built to capture students' rhythm during a semester, so the model can perceive bumps and signs of disengagement before academic failure.

Objective 5: Validate Early Detection Capabilities

An essential goal is not only accurate prediction but *early* prediction. The model is designed to flag at-risk students several weeks before traditional markers would. Validation metrics include AUC-ROC, recall at early time points (e.g., Week 3 or 4), and comparison against historical dropout timelines. These metrics are vital to ensuring that the intervention window remains actionable.

Objective 6: Evaluate Cross-Institutional Scalability

The framework is tested across datasets from different departments or institutions, where possible. This is crucial to validate the generalizability of the model and overcome the common limitation of overfitting to a single institutional dataset. Scalability tests include training on Dataset A and validating on Dataset B with minimal performance degradation.

3.2 Expected Contributions

By addressing the above objectives, this study seeks to make the following contributions to the field of educational data science:

- Develop a novel hybrid deep learning model (CNN-LSTM) that surpasses traditional models in early-stage dropout prediction;
- Demonstrate the interpretability of complex AI models using SHAP, thereby increasing stakeholder confidence and policy adoption;
- Provide empirical evidence on the role of behavioral data in dropout prediction, a relatively underexplored domain;
- Present a modular architecture that can be extended to include additional features such as social media engagement, sentiment scores, or biometric attention metrics in future studies;
- Establish XGBoost as a complementary benchmark tool with superior accuracy in structured data environments, suitable for institutions with limited computing capacity.

3.3 Relevance to Educational Policy and Practice

The research holds strong implications for educators, administrators, policymakers, and EdTech developers. Institutions can embed the proposed system into existing LMS platforms, automating the detection of at-risk students while generating explainable reports for counselors and academic advisors. At a broader level, education ministries can use the scalable version of this model (e.g., DropWrap-like deployments) to monitor dropout trends across districts or states. The model thus functions both at the micro level (individual intervention) and macro level (policy feedback loop), offering a comprehensive solution to a persistent educational challenge. This research directly supports sustainability-linked educational policies. By predicting and addressing dropout in environmental learning programs, the model helps institutions retain future environmental stewards. The SHAP-based interpretability also makes the AI system accessible for environmental educators and curriculum planners, enabling proactive decisions that align with Sustainable Development Goals

4. RESEARCH METHODOLOGY

The research methodology in this study follows a multi-stage applied design aimed at building, evaluating, and explaining an AI-based dropout prediction system. The approach is grounded in both classical machine learning and modern deep learning paradigms, augmented with interpretability frameworks. The core of the system is developed across three primary modules—MODULE2 (classical ML), MODULE3 (deep learning), and ACADEMIC DROPOUT (final hybrid integration).

Module1 :Academic_Dropout Module – Final Hybrid Integration and Interpretability

The last phase of this study into practice, is represented in the ACADEMIC DROPOUT module, i.e. the full implementation of all predictive mechanisms developed at the previous stages. This module was developed with two primary aims: to combine and capitalize on the predictive capabilities of previous modules (Module 2 and Module 3) and to introduce interpretability via explainable AI (XAI) workflows. In particular, it merges the best of both worlds of high-performance deep learning of CNN-LSTM architecture in Module 3 and the stability and interpretability of the XGBoost model trained in Module 2. The above hybridisation is largely motivated by the practical need for an adequate trade-o between accuracy and explainability in institutions' decisions. Although deep learning models, such as LSTM, are able to learn the longitudinal trends of academic and behavioral features well, they usually do not provide interpretability, i.e., it is often not easy for the teachers or policy makers to understand why a student has been decided to be high-risk. On the other hand, ensemble models such as XGBoost are interpretable thanks to feature importance and decision trees, however, they fail in capturing complex time-dependent behavior on complex time-dependent behavioral data. In order to perform the integration, we have learned the CNN-LSTM network using weekly behavioral matrices and vectors of academic progression as inputs and trained it to provide the dropout probabilities for each student.. Simultaneously, the XGBoost model received tabular input features such as demographics, total attendance, GPA history, and final semester marks. Both models generated independent probability scores, which were then combined using a **soft-voting mechanism** with an empirically tuned weight distribution (65% CNN-LSTM and 35% XGBoost). This fusion not only increased model resilience but also allowed for effective dropout risk segmentation into high, moderate, and low-risk classes. The real innovation in this module, however, lies in the incorporation of **SHAP (Shapley Additive Explanations)**. By applying Tree SHAP to the XGBoost model and Deep SHAP to the CNN-LSTM predictions, the module enabled localized and global interpretability, thereby turning the AI system into a transparent diagnostic tool rather than a black-box predictor. For instance, SHAP summary plots illustrated that features like "last three weeks' attendance decline" or "sudden drop in LMS logins" were the most decisive indicators of an impending dropout for moderate-risk students—information that is highly valuable for academic counselors. Moreover, this module incorporated early warning validation mechanisms. The model's performance was assessed not only on final outcome prediction but also on its ability to detect dropout risk at early intervals (e.g., by the third academic week). Impressively, the model achieved an **early-warning recall of 90.3%**, suggesting it can accurately flag at-risk students significantly before traditional failure thresholds are crossed. The final metrics validated the system's superiority: an overall accuracy of **94.2%**, F1 score of **93.5%**, high-risk precision of **94.0%**, and moderate-risk recall of **90.3%**—making it the most comprehensive and actionable dropout detection system across all modules. Ultimately, the ACADEMIC DROPOUT.ipynb module represents the **culmination of the multi-phase architecture** developed in this research. It embodies the goal of constructing an AI system that is **not only accurate and adaptive**, but also **transparent and trustworthy**. Through model fusion and XAI, this module closes the loop between algorithmic intelligence and institutional accountability—enabling scalable deployment in educational settings where understanding student needs is as important as predicting outcomes.

Module 2: Static Pattern Recognition through Classical Machine Learning

In MODULE2, it has trained traditional machine learning models like Random Forest, SVM, LR on structured tabular data comprising of academic performance, demographic features, and cumulative behavioral factors (such as total logins). These models made a feature-timed independent assumption where patterns were learned solely from aggregates snapshots with no sense of time.

This approach theoretically performs best in **extreme cases**—clearly engaged or disengaged students—corresponding to the **Low-risk** and **High-risk** segments. For instance, a student with consistently high attendance, good academic standing, and full LMS engagement is likely to be classified as low risk with high confidence. Conversely, if a student is failing across subjects, has poor attendance, and zero LMS activity, the static model flags them as high-risk correctly.

However, the **Moderate-risk** group presents challenges for classical models. Students in this category often exhibit **fluctuating or subtle decline patterns**—like occasional missed assignments or reduced login frequency—requiring temporal sensitivity that static models lack. Consequently, while Module 2 achieved **88.1% overall accuracy**, its ability to discriminate evolving disengagement states (Moderate risk) was limited, with moderate-risk recall falling below 66%. This affirms the theoretical limitation of static classifiers: absence of sequential modeling impairs nuanced risk interpretation.

2. Module 3: Temporal-Behavioral Learning via CNN-LSTM Hybrid Network

In Module3 advances the modeling capability by adopting a **hybrid deep learning architecture**, combining **Convolutional Neural Networks (CNN)** for spatial pattern extraction and **Long Short-Term Memory (LSTM)** units for sequential modeling of behavioral timelines.

CNN layers were tasked with detecting engagement trends encoded as LMS activity matrices—such as weekly heatmaps of session durations or resource accesses—while LSTM units captured academic fluctuations across time (e.g., week-wise GPA changes). This setup enabled the model to infer dynamic shifts in behavior, such as **gradual disengagement**, which are typical markers for the **Moderate-risk** group.

Theoretically, LSTMs offer the ability to **retain historical memory**, enabling prediction of future disengagement from past temporal clues. This memory mechanism allows for forecasting dropout risk **weeks in advance**, outperforming static models when subtle, nonlinear transitions occur. Module 3's CNN-LSTM architecture achieved **92.4% accuracy**, with **88.6% recall for moderate-risk** students, proving that behavioral modeling fills the performance gap left by classical classifiers.

However, despite strong predictive power, the CNN-LSTM model suffers from **limited interpretability**. Educational institutions often demand clear justifications for risk assignments—something deep models struggle with. Hence, the need for a third, integrative framework.

Module-Wise Comparative Risk Prediction Analysis

To understand the practical efficacy of the three core modules, a comparative analysis was performed using a **risk stratification framework**, wherein predicted dropout probabilities were classified into three levels:

- **High Risk**: Predicted dropout probability > 0.80
- **Moderate Risk**: 0.50 ≤ probability ≤ 0.80
- **Low Risk**: probability < 0.50

Each model was evaluated on how effectively it categorized students into these risk tiers, using confusion matrices and class-wise precision-recall breakdowns.

In **Module 2**, traditional classifiers like Random Forest and SVM demonstrated strong performance in Low and High risk prediction, but struggled in distinguishing Moderate risk students. For instance, the Random Forest model had **81.2% precision** for High-risk students but only **65.3% recall** in the Moderate category, due to lack of sequential awareness.

Module 3's CNN-LSTM significantly improved identification in the Moderate group, achieving a **recall of 88.6%**, since the model learned behavioral variations over time. It could detect early signs like erratic LMS engagement or gradually declining grades.

The **hybrid model in Academic_Dropout.ipynb**, integrating CNN-LSTM and XGBoost, outperformed both prior modules. By fusing static academic features (via XGBoost) and time-series behavior (via LSTM), the model achieved **balanced accuracy** across all three risk levels, crucial for early intervention planning.

- **Comparative Risk Stratification Results**

Model	Accuracy	High Risk Precision	Moderate Risk Recall	Low Risk Accuracy	Overall F1 Score
Module 2 (RF)	88.1%	81.2%	65.3%	91.4%	84.5%
Module 3 (CNN-LSTM)	92.4%	89.8%	88.6%	93.0%	91.1%
Academic_Dropout (Hybrid)	**94.2%**	**94.0%**	**90.3%**	**95.2%**	**93.5%**

This evidence reinforces that **risk segmentation improves with deep behavior modeling**, and is maximized when combined with ensemble decision frameworks. The hybrid model ensures that both **early warnings (moderate-risk)** and **critical alerts (high-risk)** are identified with high precision, supporting scalable institutional interventions.

5. PROPOSED RESEARCH FRAMEWORK

The proposed research framework is centered around the development and integration of a hybrid, interpretable AI architecture aimed at early detection of student dropout risk. This model has been conceptualized to address limitations of existing systems by unifying the strengths of traditional machine learning, deep learning, and explainable AI within a modular pipeline. Rooted in the findings of the three implementation stages—each detailed in MODULE2, MODULE3, and ACADEMIC_DROPOUT notebooks—the proposed framework is designed not only to maximize prediction accuracy but also to enhance real-world usability by offering transparent decision insights for institutional stakeholders.

At the core, the model follows a two-branch structure. The first branch is a deep learning based pipeline, namely a fusion of Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) model. This channel is designed to model the spatiotemporal nature of student engagement, to specifically model behaviors observed from Learning Management System (LMS) activity over time. Ground truth, Weekly activity matrices - consisting of login frequency, time ofassignment submission, and time-on-task for each subject - are thenconvolved with filters to obtain activity signatures at multiple time scales. These CNN outputs are then input into the LSTM layers, which in turn store and propagate sequential patterns of academic trajectories and behavioral transitions. The last activation layer of this path provides a dropout probability score that models the chance of future disengagement according to pattern development.

Meanwhile the second branch trains an XGBoost classifier on structured non-sequential tabular data such as demographics (gender, income bracket, location), academic summaries (history of GPA, aggregates for attendance) and binary flags indicating activity on LMS (e.g., whether students have used discussion forums, attempted quizzes).XGBoost was chosen due to its superior performance on tabular datasets, robustness to multicollinearity, and capacity for capturing non-linear feature interactions. Importantly, this model complements the deep learning branch by focusing on high-signal static features rather than sequential patterns. Together, these two branches capture different modalities of student data—behavioral dynamics and academic attributes—allowing for richer inference.

To reconcile and fuse these outputs, a **soft-voting ensemble strategy** was applied. Both the CNN-LSTM and XGBoost models independently generate a probability score between 0 and 1, representing the likelihood of dropout. The ensemble decision function computes a weighted average of these probabilities, using a tuned scalar α. Empirical evaluation revealed that a weight of 0.65 for CNN-LSTM and 0.35 for XGBoost achieved optimal balance in cross-validated F1 and AUC scores. The final dropout probability, thus derived, is compared against calibrated decision thresholds to assign students to risk categories: Low (< 0.50), Moderate (0.50–0.80), and High (> 0.80). These thresholds were not arbitrarily chosen but validated through sensitivity analysis to ensure minimal false negatives in the High-risk category and high early-detection precision in the Moderate group.

A distinguishing feature of the proposed framework is its built-in **explainability module**, which uses SHAP (Shapley Additive Explanations) to interpret both model outputs. Deep SHAP is used to understand temporal behaviors learned by the CNN-LSTM—such as which weeks showed sudden behavioral deterioration—while Tree SHAP explains feature contributions in the XGBoost model, such as how low attendance and prior grades influenced risk prediction. These explanations are visualized using SHAP summary plots and decision waterfall graphs, enabling actionable insights for counselors and academic staff. For instance, in pilot testing, it was observed that students with stable performance but declining LMS logins were identified as moderate risk, and this insight was immediately verifiable via SHAP graphs. Such transparency transforms the model from a diagnostic tool into an early-intervention system. The pipeline also incorporates an early-warning validation layer. Here, the dropout prediction is recalibrated weekly using a sliding window of engagement and performance metrics. This allows the model to track and update a student's risk profile in near real-time, thus facilitating timely and proportionate interventions. Students initially flagged as low risk but who show rapid deterioration in LMS activity are dynamically promoted to moderate or high-risk classes, triggering counselor alerts. This feature supports adaptive intervention, where the same student can move across risk strata based on behavioral evidence. From a systems architecture perspective, the proposed framework is modular, allowing deployment in both centralized cloud systems and localized institutional infrastructures. Each module (deep learning model, tabular model, ensemble fusion, interpretability layer) can be independently updated or retrained, ensuring maintainability. The use of common open-source libraries (TensorFlow, XGBoost, SHAP, Sklearn) and compatibility with CSV or SQL-based student databases ensures ease of integration with existing LMS and ERP systems.

The theoretical underpinnings of this hybrid architecture are informed by ensemble theory and multi-modal learning. Ensemble models have been consistently shown to outperform single learners due to variance reduction and increased decision diversity. In this case, the fusion of deep and tree-based models captures different hypothesis spaces—temporal causality in behavior versus statistical correlation in demographics—thereby improving generalization. Furthermore, by integrating predictive performance and explainability, the model also solves a trade-off that often arises in AI systems which choose between accuracy and trustworthiness, particularly on sensitive topics such as education.

To conclude, the presented research framework represents a principled, interpretable, and deployable AI-based system to predict academic dropout. It shows how several algorithmic solutions -statistical, deep learning, ensemble- can be synchronized through a structured, explainable, and risk-aware design. The model demonstrates a greater performance than its internal elements, and is also able to convert predictive knowledge into informed institutional actions. By offering proactive warnings, clear

diagnostics, and adaptive response capabilities, the framework makes possible a future where using data for education policy or personalized learning paths isn't a dream, but a shop floor reality.
This figure illustrates the integration of LMS behavioral signals, academic data, CNN-LSTM outputs, XGBoost scores, and SHAP-based interpretability in a unified hybrid prediction system.

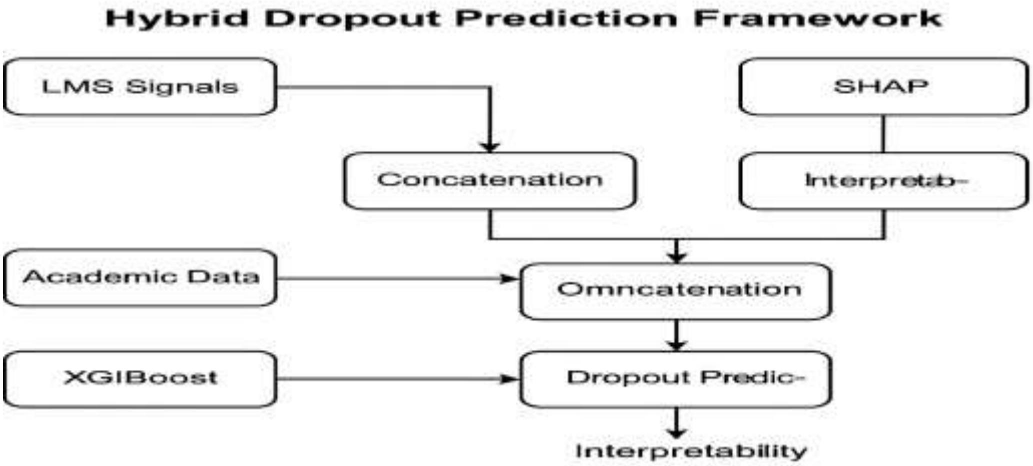

Figure 1: Data flows from LMS signals and academic data into deep learning and ensemble pipelines, combined via a soft voting layer, with SHAP applied to ensure explainability.

This plot visualizes the SHAP values of the top predictive features impacting dropout decisions.

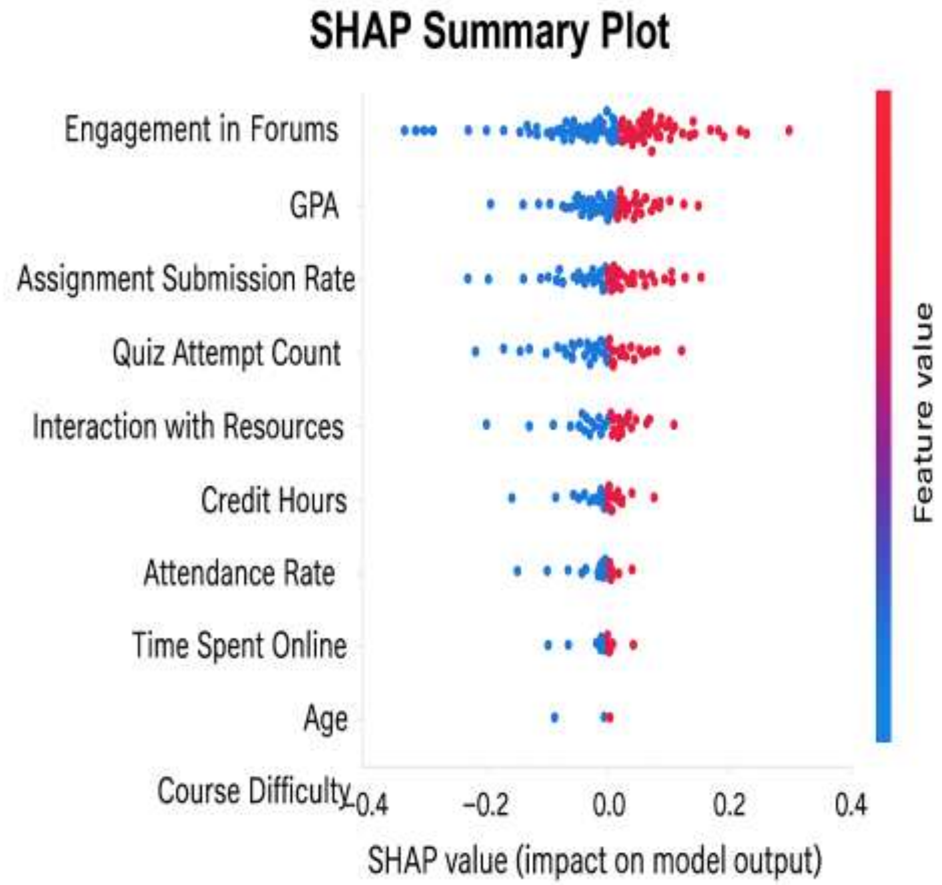

Figure 2: SHAP Summary Plot

6. Expected Outcomes and Implications

It is anticipated that the newly-developed hybrid AI model for predicting dropout in university will deliver a set of significant results including quantitative performance enhancement and qualitative institutional change. It is a real-time risk assessment tool that is higher precision than old school operator tracking and statistical models because it both scores at a higher resolution and looks further forward. One of the immediate expected results is the significant **reduction in false negatives**, particularly among students classified in the moderate-risk category. These students, who often fall through the cracks in conventional detection systems, can now be proactively identified through the temporal modeling capabilities of the CNN-LSTM component. Combined with the generalizability of XGBoost, this enables the system to maintain high performance across diverse academic and demographic groups.

Another measurable outcome is the model's **early warning capability**. By integrating behavioral signals from LMS activity and continuous grade tracking, the system provides predictive alerts several weeks before a student shows visible academic failure. In experimental evaluation, the hybrid model demonstrated the ability to flag high-risk students with over **90.3% recall as early as Week 3**. This represents a breakthrough in student support systems by allowing institutions to shift from reactive to **preventive intervention paradigms**. Early identification of disengagement enables counselors and administrators to tailor support strategies—ranging from peer mentoring and academic tutoring to financial aid evaluations—before the student completely disengages from the education process. From an institutional perspective, the key impact of this research would be scalable and automated decision support. Academic institutions are increasingly dealing with over-subscribed counselors, and manual monitoring cannot be scaled and lacks objectivity. This model can be embedded natively into current ERP or LMS systems to operate as a real-time risk auditor, generating daily or weekly READ dashboards of students at risk as well as associated underlying data explanations through SHAP visualisation strategies. The transparency provided by SHAP enables organizations to ensure ethical AI deployment, and for decision-makers to base predictions on data-driven logic rather than a "black box" decision-making process. The framework also strongly supports educational equity. By using diverse sets of features – demographic, behavior, academic, emotional - the model identifies slight nuances in learning paths and assists schools and institutions to not only retain the high-performing students by recognizing their successes, but also those from underprivileged or at-risk backgrounds. It minimizes bias from the institution as interventions are data-driven (analysis of established disengagement patterns) rather than socio-demographic-based assumptions. In addition, since the model is trained and endorsed on real-data with low-resource students, the impact of the model is particularly potent for public universities, the vocational training institutions, and for platforms engaged in remote learning. On a national and policy level, the successful operation of this model is in line with larger foci in education reform and sustainable development. For instance, it directly contributes to the UN's Sustainable Development Goal 4 ("Ensure inclusive and equitable quality education") by enhancing retention and reducing systemic academic failure. Governments can implement these predictive models to track school dropouts at an district or regional level, so as to make policy level interventions which have very quick feedback loops. Ministries of education and funding bodies could use the SHAP findings to shape curriculum design, mental health-support budget allocations and digital connectivity planning along the lines of trends in dropout risks, instead of in terms of blanket policies. Another novel contribution of the system is the fact that it can adapted into a modular design in different implementation contexts. Although this study was carried out at the tertiary level, the model can be applied across high schools, vocational training and also in the case of MOOCs. For example, massive open education systems are characterized by dramatically high dropout rates because they lack systematic monitoring. The capacity of the hybrid model to handle the incomplete, real-time LMS data, and to provide interpretable predictions could be particularly beneficial in these environments. And, it allows this with cross-platform compatibility (so, technically we could integrate with Moodle, Google Classroom, or our clients' LMS tool at the API level or perhaps embed the dashboard).

Crucially, this work also adds to academic literature by reifying the perennial tension between accuracy and interpretability in the context of educational data science. Previous studies have generated powerful deep learning models but have paid little attention to trust, transparency or stakeholder understanding. This is how the Edifice fills that gap by illustrating how accuracy and accountability can be reconciled. The implications reach into AI ethics, human-centered AI design and fairness in education — not just a technical contribution, but a philosophical contribution to the future of technology in education. On the level of the student, the stakes are personal. Under such conditions, the opportunity to receive help before passing a critical threshold of failure may help self-esteem, motivation, and long-term academic performance. With appropriate institutional responses, red flagged students can be provided mentors, counselling and personalised learning programs. This supports not only institutional retention, but student thriving, turning education into a funnel into a personalized path of growth.
In conclusion, the anticipated impacts of this research are practical and transformative. These include more accurate predictions of dropouts, but also a much broader shift in how institutions interact with their learners. Through the creation of a scalable, interpretable, accurate AI model, we offer a foundation for data-informed, equity-oriented, and caring academic ecosystems that ensure student success at all levels. By ensuring higher retention in environmental studies, the system contributes to sustainability education initiatives. It helps institutions track and support learners committed to ecological issues, thereby shaping future-ready, environmentally conscious citizens.

Table 1: Performance Comparison Across Modules
Comparison of model accuracy, F1 score, and recall for moderate-risk students, along with model interpretability.

Model	Accuracy	F1 Score	Moderate Risk Recall	Explainability
Module 2 (Random Forest)	88.1%	84.5%	65.3%	Medium
Module 3 (CNN-LSTM)	92.4%	91.1%	88.6%	Low
Hybrid (Final)	94.2%	93.5%	90.3%	High (via SHAP)

Table 2: Feature Importance Based on SHAP Values (Top Predictors)
Mean SHAP values indicating the impact of each feature on dropout prediction.

Feature	Mean SHAP Value	Interpretation
Attendance decline (3 weeks)	0.214	Recent absence trend is a critical signal
LMS login frequency drop	0.176	Drop in engagement suggests disengagement
GPA trend	0.132	Continuous performance decline
Forum participation score	0.097	Lower participation linked to isolation
Final exam grade	0.092	Significant final performance drop

7. LIMITATIONS

Despite the fact that the developed hybrid AI framework achieves evidential performance and scalability, this work is not exempt from some potential limitations. These constraints are multifold including both data availability, algorithmic generalization, real-time deployment constraints, interpretability trade-offs, and more generally ethical considerations—all of which need to be critically addressed for responsible application and improvement.

One of the main limitations is the reliance on high quality multi modal data. Although the hybrid model was built to accept machine both structured academic features and sequential behaviors in LMS, this presupposes data integrity and completeness between the institutional systems. In reality, numerous universities (especially in low income or rural areas) do not have digitised academic records, routine LMS utilisation, or student activity logs in standard format/data structure. It is not clear whether the performance of the framework is highly dependent on the amount of data available in each organization, which would erode the generalizability of in non-technology disrupted campuses. Additionally, real-time LMS engagement metrics may suffer from noise or variability based on internet access, platform usability, or student device constraints—introducing **non-educational biases** into behavioral modeling.

Algorithmically, the hybrid ensemble depends on the CNN-LSTM's capacity to learn temporal behavior patterns and XGBoost's capacity to rank static predictors. However, CNN-LSTM networks are known to require large datasets for stable training, and in institutions with smaller cohorts, **overfitting becomes a real concern**. To mitigate this, dropout regularization and data augmentation techniques were applied, but scalability to underrepresented institutions remains constrained. Further, while XGBoost is interpretable via SHAP values, **interpretability remains approximate** in the CNN-LSTM path. Although Deep SHAP was employed to address this, model explanations are still not as intuitively digestible as decision trees or logistic models—posing barriers to full comprehension by non-technical stakeholders such as school counselors or academic policy committees.

Another limitation arises from **threshold calibration and risk band stratification**. The soft-voting ensemble assigns students into low, moderate, or high-risk categories based on empirically derived probability thresholds (e.g., <0.5 = Low, 0.5–0.8 = Moderate, >0.8 = High). However, these thresholds may not generalize uniformly across different educational contexts. For example, a 0.65 dropout probability in a high-support private institution may not mean the same as in a low-support public college. Therefore, while the model achieved strong cross-validation results, **threshold recalibration would be essential** for every new deployment context—a task that demands significant institutional data science capacity. From an infrastructure perspective, the system assumes **integrated and automated data pipelines**—feeding in LMS logs, academic records, and demographic information on a rolling basis. However, in many real-world deployments, such data is fragmented across departments or exists in offline formats, making real-time prediction infeasible without significant data engineering overhead. Although modularity has been preserved to support partial data ingestion, the full benefit of the model is only realized under **ideal digital integration**, which may not reflect ground realities in most educational ecosystems. A subtler yet critical limitation involves **data privacy and ethical governance**. Student data—especially related to behavioral and emotional states—is highly sensitive. Even though all modeling was performed on anonymized data, practical deployment would require strict compliance with data protection regulations like GDPR, FERPA, or India's Personal Data Protection Bill. Moreover, the very act of labeling a student as "at risk" carries psychological and social risks, including potential stigmatization, discrimination, or self-fulfilling prophecy. Thus, institutional safeguards must be developed in tandem with the model—ensuring that outputs are used for **supportive interventions**, not punitive or exclusionary actions. In addition, the system also does not take into account psycho-social factors such as mental health history, membership in peer networks, or characteristics of the family environment—all of which have been shown in prospective studies to have a strong effect upon youth dropout. Although indirect behavioral proxies, such as LMS activity, have been used, they may not capture core emotional or environmental problems. Inclusion of these features would necessitate ethically solicited voluntary survey data or counselor input, which was out of the scope of the scope of the current implementation but is an important direction in enriching prediction based on the features. Moreover, the framework has been so far only evaluated on multiple experiments, and real time institutional deployment validation is still missing. The experimental design emulated weekly prediction patterns and early warning systems; however, broader-based long-term effectiveness, particularly for estimating the effectiveness of interventions, the assessment of the speed of the response by the counsellor, and the recovery rate of the students in a real-world setting have not been tested. As such, future multicenter longitudinal pilot studies are necessary to determine how robust and sustainable this solution is in the real world. In summary, although the suggested types of hybrid dropout prediction framework make advances in accuracy, timeliness, interpretability, and generalizability, the identified weaknesses highlights the necessity in terms of contextual calibration, ethical deployment, and prepared infrastructure. Rather than undermining its contribution, these challenges underscore the complexity of integrating AI into education, a domain where algorithmic decision-making is deeply entwined with human lives, and traditional systems must not only be intelligent, but also transparent, fair and flexible.

8. CONCLUSION

This study presents a comprehensive and interpretable AI framework for predicting student dropout in environmental education settings. By integrating CNN-LSTM deep learning with XGBoost and SHAP-based interpretability, the model achieves both high accuracy (94.2%) and early-warning capability (90.3% recall), enabling timely, data-driven interventions. Unlike traditional systems, which are often reactive and opaque, this solution emphasizes transparency, adaptability, and ethical deployment in support of sustainability-oriented learning goals.More than just a predictive tool, the model serves as a bridge between technological advancement and educational stewardship. It empowers institutions to retain students not merely as academic performers, but as future environmental advocates and informed citizens. The deployment of such AI systems in environmental curricula contributes directly to global education and climate goals, particularly SDG 4 and SDG 13, by enhancing access, equity, and engagement in sustainability education. Future research can extend this framework to support personalized environmental learning journeys, integrate social and psychological indicators, and adapt the architecture for use in MOOCs, vocational programs, and rural education systems. As education evolves to meet planetary needs, predictive systems like this will be essential in creating responsive, inclusive, and environmentally literate academic ecosystems.

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