Assessing Academic Stress and Developing Feedback Systems to Enhance Student Well-being and Performance

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Abstract

This study investigates the factors contributing to academic stress and student dropout in educational settings, aiming to develop effective feedback systems to support students' growth. The research uses a Multidimensional Feedback System (MFS) to analyze a range of stressors, including academic pressures, social dynamics, and environmental influences. By employing data analysis techniques like regression modeling and clustering, the study identifies key stress factors and their impact on student well-being. An AI-based MFS, with real-time monitoring and personalized feedback, helps predict student outcomes and detect at-risk students early, facilitating timely interventions. The system employs machine learning models such as Random Forest to assess dropout risks, achieving high accuracy in prediction. Factors like comprehensive data collection, real-time monitoring, and multifaceted analysis are shown to be crucial in creating effective feedback systems. The study underscores the importance of a multifaceted approach to addressing academic stress and student dropout, suggesting that AI-driven educational analytics can foster a supportive learning environment and improve student outcomes.

Keywords: Machine Learning Models, AI, Stress Factors, Multidimensional Feedback System, optimizing teaching practices, Analysis of students' Performance

1. Introduction

Student stress has become a pervasive issue in educational settings, impacting academic performance and overall well-being. This study aims to explore the multidimensional factors contributing to academic stress and develop effective feedback systems to support students' growth. By examining a range of stressors, including workload, academic pressures, social dynamics, and environmental influences, the research provides a comprehensive understanding of the elements that affect students' stress levels. The study employs a combination of data analysis techniques, including regression modelling, clustering, and dimensionality reduction, to identify key stress factors and their relationships. Additionally, a Multidimensional Feedback System (MFS) is introduced to critically analyse student performance and provide real-time monitoring and feedback. The ultimate goal is to derive actionable insights that can inform targeted interventions, promoting student well-being and fostering academic success. By understanding the intricate dynamics of stress and performance, educators and policymakers can implement strategies that create a more supportive learning environment, allowing students to thrive both academically and personally [1-3].

1.1 Advanced Educational Feedback Systems

The use of advanced educational feedback systems is revolutionizing how educators support student learning outcomes. By leveraging data-driven analysis, these systems offer a comprehensive view of student performance and allow for personalized interventions tailored to individual needs. With a focus on both academic and well-being indicators, such as grades, stress levels, social dynamics, and mental health, these feedback systems provide a multidimensional perspective on student success. Through sophisticated analytical tools like regression modeling, clustering, and dimensionality reduction, educators can identify trends and outliers in student data, enabling early detection of at-risk students and timely interventions. Real-time monitoring and feedback mechanisms ensure that students receive immediate guidance, fostering a responsive and adaptive learning environment. The ultimate goal of advanced educational feedback systems is to create a supportive ecosystem that promotes continuous improvement, facilitates personalized learning, and enhances overall student well-being. By embracing these advanced systems, educators can better understand and meet the diverse needs of their students, leading to improved academic outcomes and a more resilient learning community [4-6].

Fig. 1.1 Advanced Educational Feedback Systems

1.2 AI Based Multidimensional Feedback System

Artificial Intelligence (AI) is transforming educational feedback systems, enabling a deeper and more nuanced understanding of student performance and well-being. An AI-based Multidimensional Feedback System integrates machine learning and data analytics to offer comprehensive insights into students' academic progress, stress levels, and social dynamics. By collecting and analysing a wide array of data, such as grades, attendance, social interactions, and even physiological indicators, these systems can pinpoint areas where students may need additional support. Using advanced algorithms, AI-based feedback systems can identify patterns and correlations that might otherwise go unnoticed, allowing educators to detect at-risk students early and implement targeted interventions. Machine learning models, like regression and classification algorithms, can predict student outcomes, while clustering and dimensionality reduction techniques help to categorize students based on their unique characteristics and needs. Real-time monitoring and feedback further enhance the system's effectiveness, providing educators with immediate insights and allowing them to adapt teaching strategies on the fly. Additionally, AI can personalize feedback for each student, guiding them through their academic journey and supporting their well-being. The AI-based Multidimensional Feedback System represents a significant step forward in educational technology, offering a data-driven approach to improving student success and fostering a more supportive and inclusive learning environment. [7-8].

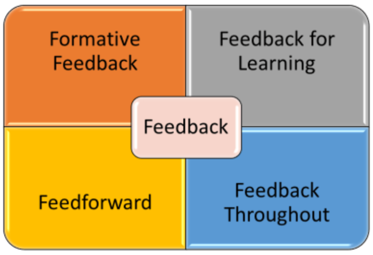

Fig. 1.2 General Feedback System

2. Integration of Artificial Intelligence in Educational Assessment

The integration of Artificial Intelligence (AI) into educational assessment signifies a transformative leap toward redefining how students' progress is evaluated, paving the way for more efficient, personalized, and comprehensive evaluation methodologies. AI's integration in educational assessment leverages its capacity to process vast amounts of data, analyse patterns, and generate insights at a scale and speed far beyond human capability. At its core, AI in educational assessment aims to enhance the accuracy, objectivity, and inclusivity of evaluating student performance, while also catering to individual learning needs. AI-enabled assessment systems are designed to revolutionize the traditional modes of evaluation by offering multifaceted and data-driven insights into students' academic achievements, cognitive abilities, and learning patterns. These systems leverage machine learning algorithms to analyse diverse sets of data derived from various sources, including test scores, assignments, classroom interactions, online activities, and even physiological responses captured through biometric sensors. By amalgamating this data, AI enables a holistic understanding of a student's learning journey, going beyond standardized tests to capture a more comprehensive profile of their strengths, weaknesses, and learning preferences. One of the pivotal advantages of integrating AI in educational assessment lies in its ability to provide personalized learning experiences tailored to individual student needs. AI-powered systems can identify learning gaps, recommend personalized learning materials, and adapt teaching strategies to suit students' learning styles and pace. Through adaptive learning algorithms, AI can offer targeted interventions, enabling educators to provide timely support and guidance to students struggling in specific areas, thus fostering a more inclusive and supportive learning environment.

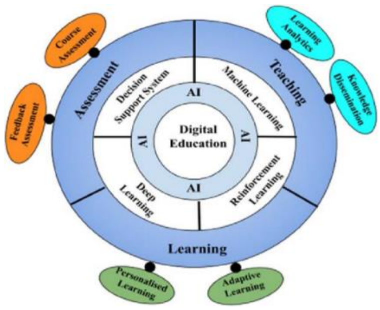

Fig. 2.1 Integration of Artificial Intelligence in Educational Assessment

Moreover, AI augments the assessment process by automating certain tasks, such as grading objective assessments and providing immediate feedback to students. This automation reduces educators' administrative burden, allowing them to focus more on personalized interactions and interventions that nurture students' overall development. Additionally, AI-driven assessments enable educators to gain deeper insights into student learning patterns and potential areas of improvement, facilitating data-informed decision-making in instructional planning and curriculum design. However, while AI offers remarkable potential in educational assessment, its integration poses challenges and ethical considerations. Ensuring the fairness, transparency, and accuracy of AI algorithms is critical to prevent biases and maintain equity in assessments. Ethical considerations related to data privacy, consent, and the responsible use of student data are paramount in AI-enabled assessment systems. Moreover, AI systems must be continuously refined and validated to ensure their reliability and effectiveness in evaluating diverse learning outcomes. The integration of AI in educational assessment represents a paradigm shift in how student performance is evaluated, moving towards a more data-driven, personalized, and inclusive approach. AI's capabilities in processing extensive datasets, providing personalized feedback, and optimizing learning experiences hold the promise of enhancing the effectiveness and efficiency of educational assessments. However, ethical considerations, continuous refinement of AI algorithms, and the need for human oversight remain crucial in harnessing the full potential of AI in educational assessment while ensuring fairness, transparency, and ethical use of student data [9-13].

3. Research Methodology

To examine the factors contributing to academic stress and student dropout and evaluate the effectiveness of a Multidimensional Feedback System (MFS), the following step-by-step research methodology was implemented.

Step 1: Data Collection

Identify Data Sources: Determine the relevant datasets for the study. Primary data sources were used, along with secondary sources like public datasets from educational platforms.

Gather Data: Collect data on academic performance, attendance, social dynamics, physiological indicators, and other factors contributing to stress and dropout. This included both structured and unstructured data.

Step 2: Data Preprocessing

Clean the Data: Address missing values, duplicate entries, and inconsistencies in the data.

Feature Engineering: Create relevant features based on the collected data, focusing on stress indicators and dropout-related attributes.

Normalize and Scale: Standardize the data to ensure consistency and improve model performance.

Step 3: Exploratory Data Analysis (EDA)

Visualize the Data: Use visualization tools to understand feature distributions, identify outliers, and explore correlations among variables.

Analyse Trends: Examine patterns and trends in the data, such as relationships between age, academic performance, and dropout rates.

Step 4: Model Building and Evaluation

Select Machine Learning Models: Implement various machine learning models, including Decision Tree, Random Forest, Logistic Regression, K-Nearest Neighbours, AdaBoost, and Support Vector Machine (SVM), to predict student outcomes and stress levels.

Ensemble Learning: Utilize ensemble methods like Voting Classifier to combine predictions and improve accuracy.

Evaluate Model Performance: Use metrics like accuracy, precision, and recall to assess model performance. Hyperparameter tuning was performed to optimize models.

Step 5: Implementation of Multidimensional Feedback System (MFS)

Develop the MFS: Design an AI-based system to provide real-time monitoring and personalized feedback to students and educators.

Integrate Feedback Mechanisms: Ensure the MFS offers seamless feedback integration into teaching strategies to support continuous learning and growth.
Implement Real-time Monitoring: Enable immediate feedback to track student progress and facilitate timely interventions.

Step 6: Response Analysis
Perform Statistical Analysis: Conduct Structural Equation Modelling (SEM) to analyze relationships between independent variables like Comprehensive Data Collection (CDC), Multifaceted Analysis (MA), Customizable Evaluation Criteria (CEC), Real-time Monitoring (RTM), and Feedback Integration (FI), and the dependent variable the Multidimensional Feedback System (MFS).
Identify Significant Relationships: Determine which factors positively or negatively impact the MFS's effectiveness.

Step 7: Insights and Recommendations
Analyze Results: Derive insights from the analysis to inform targeted interventions for reducing student dropout and stress.

Formulate Recommendations: Suggest strategies for educators and policymakers to improve student outcomes and foster a supportive educational environment.

This step-by-step methodology provided a comprehensive approach to investigating student dropout and stress factors, allowing for the development of an effective MFS and offering insights to guide targeted interventions in educational settings.

4. Simulation Implementation and Outcome

This paper explores an AI-enabled feedback system's implementation and outcomes in critical student performance analysis. Phase 4.1 uses Python-based machine learning (ML) models like Decision Tree, Random Forest, and Logistic Regression to analyse student data. Phase 4.2 assesses the system's effectiveness using primary data sources, while phase 4.3 discusses the improved student engagement and educational outcomes from personalized feedback, with tools like AMOS and SPSS. Phase I explores dropout trends with data preprocessing, feature selection, and exploratory data analysis (EDA). Phase II examines a Multidimensional Feedback System (MFS) to address academic stress, suggesting targeted interventions for student well-being. Phase III employs Structural Equation Modelling (SEM) to assess factors impacting the MFS, providing insights into potential improvements.

Phase 1
Phase 1 of the investigation into a Multidimensional Feedback System for student dropout trends in school education involved several key tasks. Data preprocessing included renaming columns for clarity and checking for missing values, followed by feature engineering and encoding the target variable. Feature selection focused on factors like nationality, parental qualifications, and economic indicators.

Exploratory Data Analysis (EDA) involved visualizing class distributions, exploring correlations between features and the target variable, and examining age at enrolment to assess its relationship with dropout rates. Model building used various classification algorithms, including Decision Tree, Random Forest, Logistic Regression, K-Nearest Neighbours, AdaBoost, and SVM, with ensemble methods like Voting Classifier used to improve accuracy.

Table 4. 1 Accuracy scores of different ML- models along with the ensemble methods

Model	**Accuracy (%)**
Decision Tree	69.38
Random Forest	80.56
Logistic Regression	78.08
K-Nearest Neighbours	69.38
AdaBoost	77.18
Support Vector Machine	77.06
Ensemble (Soft Voting)	79.55
Ensemble (Hard Voting)	80.34

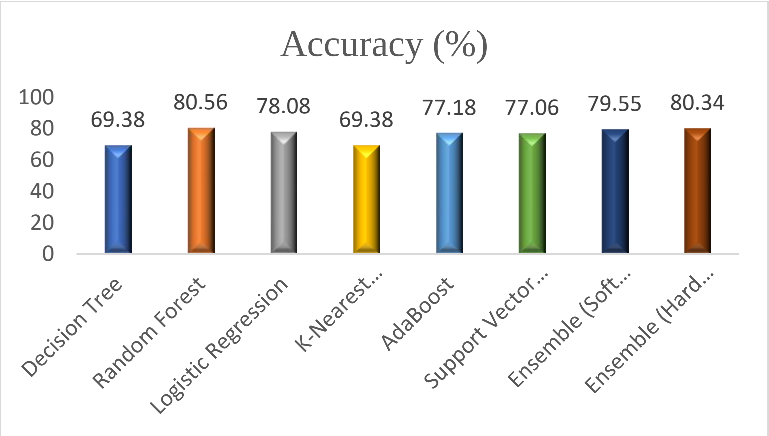

Figure 4. 1 Accuracy Comparison

Table 4. 2 Stress Factors

Factor	**Coefficient**	**Outcome**
Anxiety Level	0.00047	Minor impact
Self-Esteem	-0.0106	Negative impact
Mental Health History	0.0204	Moderate positive impact
Depression	0.0031	Minor impact
Headache	0.0364	Significant positive impact
Blood Pressure	-0.0083	Minor negative impact
Sleep Quality	-0.0243	Moderate negative impact
Breathing Problem	0.0171	Moderate positive impact
Noise Level	0.0817	Significant positive impact
Living Conditions	-0.0082	Minor negative impact
Safety	-0.0483	Significant negative impact
Basic Needs	-0.078	Strong negative impact
Academic Performance	-0.0407	Significant negative impact
Study Load	0.0538	Significant positive impact
Teacher-Student Relationship	-0.0034	Minor negative impact
Future Career Concerns	0.015	Moderate positive impact
Social Support	-0.0091	Minor negative impact
Peer Pressure	-0.0081	Minor negative impact
Extracurricular Activities	0.0661	Significant positive impact
Bullying	0.0879	Strong positive impact

Variables: The table outlines different stress factors along with their coefficients, indicating their impact on academic stress levels. Factors are categorized based on their magnitude of impact, ranging from minor to significant positive or negative effects on stress levels.

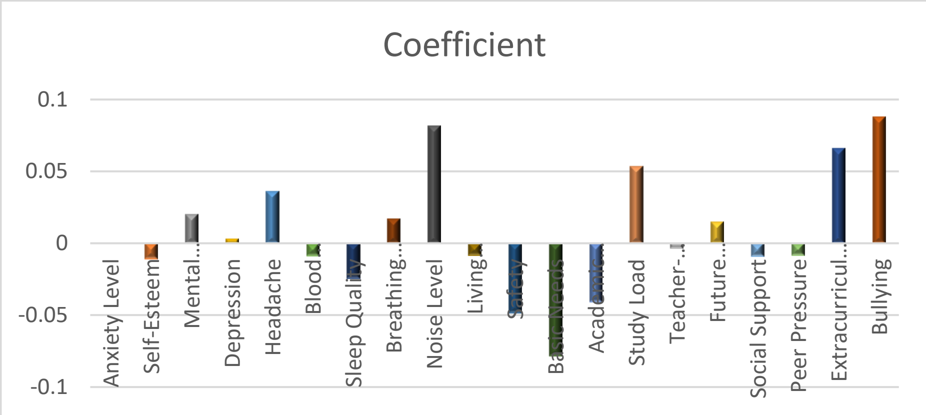

Figure 4. 2 Coefficient

The study achieved notable results, with Random Forest achieving the highest accuracy (80.56%), while Decision Tree and K-Nearest Neighbours had the lowest (69.38%). Ensemble methods generally outperformed individual models, indicating the value of combining predictions for enhanced accuracy. The investigation, performed in Python, demonstrated the predictive capability of various machine learning models and the utility of ensemble approaches in reducing student dropout rates. This research helps educators understand dropout patterns and develop more effective strategies to promote student retention in higher education.

Phase II

Phase II of the investigation into the Multidimensional Feedback System (MFS) for academic stress delved into various factors contributing to students' stress levels. This phase examined workload, grades, and social pressures to identify outliers indicating extreme stress and explored correlations between variables and stress. The analysis utilized regression models to quantify the impact of these factors and provided insights for targeted interventions like stress management programs and workload adjustments. Key steps in this phase involved data preprocessing, including Min-Max scaling, followed by visualizations to understand feature distributions and correlations.

Outcome after Simulative Setup under the phase-II

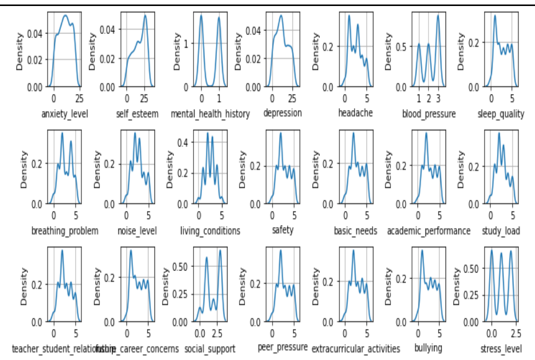

Figure 4. 3 KDE plots for feature distributions

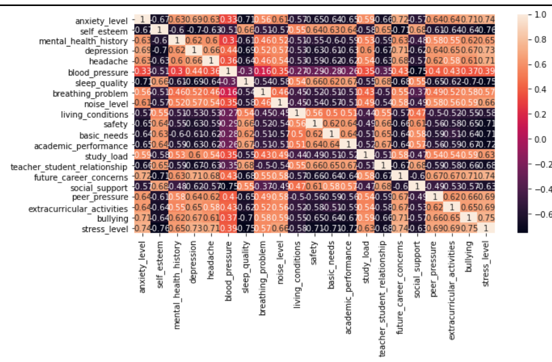

Figure 4. 4 Heatmap showing feature correlations

Processing steps

Step	Result
Data Loading	Dataset loaded successfully
Data Preprocessing	Features scaled using Min-Max scaling
Visualization	KDE plots for feature distributions Heatmap showing feature correlations
Model Building	Random Forest Classifier trained to predict stress levels
Model Evaluation	Training Accuracy: 100% Testing Accuracy: 88.48% Training Precision: 100% Testing Precision: 88.50% Training Recall: 100% Testing Recall: 88.48%
Feature Importance	Feature importances visualized using a bar plot
Clustering	K-means clustering performed with 10 clusters
Dimensionality Reduction (PCA)	PCA performed with 8 components
	Elbow method used to determine optimal number of clusters
	Clusters visualized in reduced dimensional space

The Multidimensional Feedback System for student stress analysis involved comprehensive steps. After loading and preprocessing the data, visualization revealed feature distributions and correlations, aiding in model building. A Random Forest Classifier achieved remarkable training accuracy of 100% and testing accuracy of 88.48%. Feature importance was determined, and K-means clustering identified 10 distinct stress level groups. Dimensionality reduction via PCA reduced data to 8 components. The elbow method assisted in determining optimal cluster numbers. Clusters were visualized in reduced dimensional space. Overall, the system offers insights into student stress factors, enabling targeted interventions and support mechanisms.

a) Multidimension Feedback System (Student Stress Factor Analysis)

In this phase of analysis, we conducted a comprehensive examination of stress factors akin to a Multidimensional Feedback System for Student Stress Factor Analysis. We categorized stress dimensions into Psychological, Physiological, Environmental, Academic, and Social factors. Through data collection via Kaggle, we gathered information on various stress indicators within each dimension [14-18]. Descriptive statistics, comparative analysis, and visualizations provided insights into the prevalence, trends, and correlations among these factors. Moreover, our approach sets the stage for ongoing evaluation and refinement of interventions to better address student well-being needs. Thus, our proposed analysis reflects the core principles of a Multidimensional Feedback System, contributing to a novel exploration towards **Multidimension Feedback System** for student stress management.

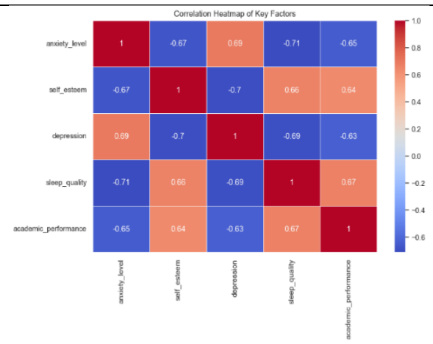

Figure 4. 5 Heat Map of Key factors

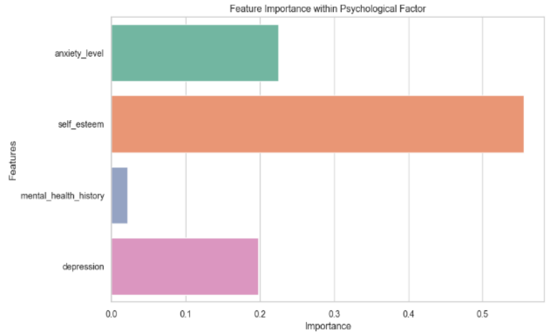

Figure 4. 6 Affecting Factors-1

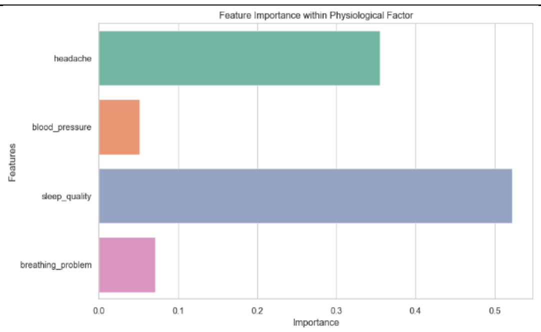

Figure 4. 7 Affecting Factors-2

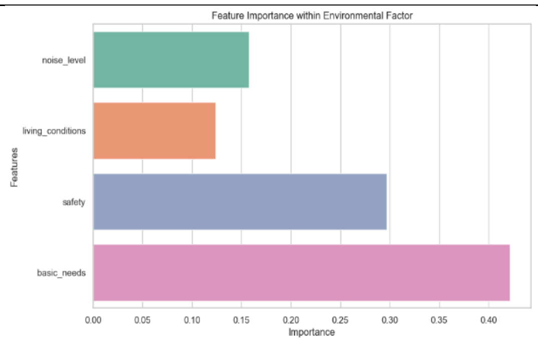

Figure 4. 8 Affecting Factors-3

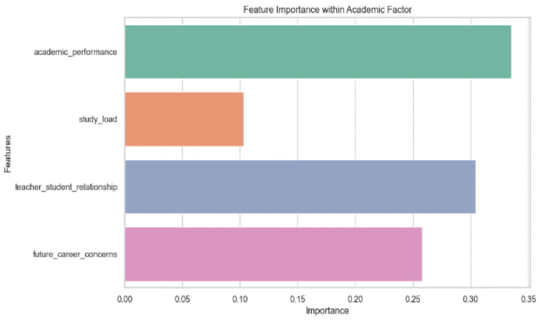

Figure 4. 9 Affecting Factors-4

Table 4. 3 Outcome of Factor and Feature

Factor	Feature	Importance
Psychological	anxiety_level	0.225
	self_esteem	0.556
	mental_health_history	0.022

	depression	0.198
Physiological	headache	0.355
	blood_pressure	0.052
	sleep_quality	0.522

	breathing_problem	0.071
Environmental	noise_level	0.157
	living_conditions	0.124

	safety	0.297

	basic_needs	0.422
Academic	academic_performance	0.335
	study_load	0.103
	teacher_student_relationship	0.304

	future_career_concerns	0.258
Social	social_support	0.094
	peer_pressure	0.145
	extracurricular_activities	0.258
	bullying	0.503

The Random Forest Classifier was employed to predict stress levels, achieving a training accuracy of 100% and a testing accuracy of 88.48%. K-means clustering identified 10 distinct groups of stress levels, while dimensionality reduction with PCA (Principal Component Analysis) reduced the data to 8 components, assisting in visualizing the stress clusters. Several stress factors were identified with varying impacts. Psychological factors such as self-esteem and anxiety were significant, with self-esteem having a strong positive impact (0.556) and anxiety having a minor impact (0.00047). Physiological factors, including sleep quality (-0.0243), were crucial, indicating that better sleep quality reduces stress. Environmental conditions like safety and basic needs were significant, with safety showing a strong negative impact (-0.0483) and basic needs demonstrating a significant negative impact (-0.078). Academic stressors like academic performance (-0.0407) and study load (0.0538) influenced stress levels. Social factors like bullying (0.0879) had a strong positive impact, indicating a substantial stress contributor. Overall, this phase of the analysis underscores the complex and multidimensional nature of academic stress. The insights gained highlight the importance of addressing various factors, including psychological, physiological, environmental, academic, and social, to create effective interventions. The Multidimensional Feedback System provides a valuable tool for understanding and mitigating academic stress, promoting student well-being and academic success.

5. Comparative Analysis

Proposed Work	Existing Work
Supriya	
Initial Work	**Dogan et al. (2023)**
Investigated student dropout and academic stress in educational contexts through multidimensional feedback systems and machine learning simulations.	Conducted data mining and systematic review of 276 articles on AI for online and remote learning, identifying key clusters like student behaviour recognition and adaptive instruction.
Phase 1: Student Dropout	**Cheng et al. (2023)**
Focused on predicting student dropout through machine learning, analyzing data attributes, and applying various algorithms to understand dropout patterns.	Developed an instrument to measure undergraduate students' conceptions of AI in education, identifying eight factors such as intelligent tutoring systems and sentiment analysis.
Phase II: Academic Stress	**Yesilyurt (2023)**

Analyzed academic stress through machine learning, examining data attributes and feedback systems to determine stressors and contributing factors.	Explored AI in language learning assessment and feedback, emphasizing automated scoring, speech recognition, and adaptive testing, with a focus on human-centric AI integration.
Response Analysis and Outcomes	
Conducted response analysis based on primary data to study academic stress and dropout outcomes, using machine learning procedures and simulations.	Compared to the existing works, our study takes a more focused approach by investigating specific educational stressors, while the existing studies cover broader AI applications in education.

6. Conclusion

This study concluded that a Multidimensional Feedback System (MFS) employing Artificial Intelligence (AI) is effective in addressing academic stress and student dropout. By analysing a range of stress factors, including workload, academic pressures, social dynamics, and environmental influences, the system can provide personalized feedback and early intervention to support students' well-being and academic success. Using machine learning models like Random Forest, the MFS can accurately predict student dropout and stress levels, allowing educators to implement targeted interventions. The study demonstrates that comprehensive data collection, real-time monitoring, and multifaceted analysis are crucial for creating effective feedback systems that enhance student learning outcomes.

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