The Role of Analytical Data in Academic Decision-Making in Smart Universities

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Abstract: In the context of the digital transformation of higher education, the role of data analytics in supporting academic decision-making is becoming increasingly significant. This paper proposes a conceptual and methodological framework for the development of interpretable analytical dashboards within the domain of Learning Analytics for smart universities. Particular attention is given to the integration of machine learning methods and Explainable Artificial Intelligence (XAI) to ensure transparency and interpretability of analytical models. The study introduces a multi-stage analytical pipeline that includes data collection and preprocessing, predictive model construction, model interpretation, and visualization of results through interactive dashboards. Machine learning algorithms, including Random Forest, are employed for predictive modeling, while SHAP and LIME methods are used to interpret the results. Experimental validation was conducted on a dataset of student records containing both academic and behavioral indicators. The results demonstrate high effectiveness of the proposed approach, with performance metrics of AUC ≈ 0.89, Accuracy = 0.87, and F1-score = 0.84, confirming the model's ability to accurately identify at-risk students. Interpretability analysis revealed that the most influential factors include academic performance (GPA), LMS activity level, and participation in educational interactions. Usability evaluation using the System Usability Scale (SUS) indicated a high level of user experience (SUS = 82). A comparative analysis with traditional approaches shows a significant advantage of the proposed system in terms of accuracy, interpretability, and visualization. Thus, the proposed analytical dashboard not only ensures high predictive performance but also enhances transparency, facilitating more informed academic decision-making. Overall, the study confirms that the integration of Learning Analytics, XAI, and visual analytics enables the development of effective decision-support systems capable of improving educational quality in smart universities.

1 INTRODUCTION

Smart universities represent a new paradigm in higher education, based on the integration of digital technologies, artificial intelligence, and big data analytics into educational processes.

In the context of digital transformation, there is an increasing demand for tools that not only aggregate data but also provide meaningful interpretation to support informed academic decision-making [1].

One of the key areas in this domain is Learning Analytics, an interdisciplinary field focused on the collection, analysis, and interpretation of data about learners and learning processes to improve educational outcomes [2].

In recent years, there has been a rapid growth in the volume of educational data generated by Learning Management Systems (LMS), digital platforms, and intelligent learning environments.

These data include information about:

- student behavior;
- academic performance;
- interaction with learning materials;
- participation in educational activities.

However, the mere availability of large datasets does not guarantee improved educational management.

The key challenge lies in the interpretability of analytical results and their integration into decision-making processes [3], [4].

In this context, analytical dashboards play a crucial role as visual interfaces for presenting key learning indicators.

Despite their widespread use, many dashboards function as "black boxes," lacking transparency in how analytical results and recommendations are generated [5], [6].

This creates a barrier to their adoption in academic management.

Therefore, there is a growing need to develop interpretable Learning Analytics dashboards that ensure transparency, explainability, and practical applicability of analytical results.

Interpretability becomes especially critical when machine learning and AI methods are applied in education [7], [8].

1.1 Evolution of Learning Analytics

Learning Analytics has emerged as an interdisciplinary field at the intersection of education, computer science, statistics, and cognitive science.

Initially, it focused on descriptive analytics, which analyzes historical learning data.

Subsequently, technological advancements have led to the development of:

- diagnostic analytics (identifying causes);
- predictive analytics (forecasting outcomes);
- prescriptive analytics (providing recommendations) [8], [9].

Table 1: Evolution of analytics in education.

Type of Analytics	Main Objective	Example Application
Descriptive	Analysis of past data	Performance reports
Diagnostic	Identifying causes	Dropout analysis
Predictive	Forecasting	Academic risk prediction
Prescriptive	Recommendations	Personalized learning paths

As shown in Table 1, the transition from descriptive to prescriptive analytics is associated with increasing model complexity and a growing need for interpretability.

Without interpretability, users cannot trust analytical outcomes or effectively utilize them in decision-making [6], [10].

1.2 The Role of Interpretability in Analytical Dashboards

Interpretability of analytical models is defined as the extent to which a human can understand the reasoning behind a system's decisions [11], [12].

In the educational context, this is particularly important, as decisions based on analytics can significantly impact students' academic trajectories. The conceptual structure of the interpretable analytical dashboard is illustrated in Figure 1.

Interpretable dashboards enable:

- increased user trust in the system;
- enhanced transparency of algorithms;
- improved quality of decision-making;
- support for pedagogical reflection [6], [13].

However, the development of such systems involves several challenges, including balancing model accuracy and interpretability, selecting appropriate visualization techniques, and accounting for users' cognitive characteristics.

Figure 1: Conceptual model of an interpretable analytical dashboard.

The figure presents an integrated conceptual model of an interpretable analytical dashboard, illustrating the full cycle of transforming educational data into evidence-based managerial decisions.

The model consists of five sequential stages, organized as a linear workflow with directed arrows that emphasize causal relationships between components.

Stage 1 - Data.

The first stage, *"Data"*, represents a collection of heterogeneous data sources, including:

- databases;
- CSV files;
- digital traces of learners;
- streaming data from educational platforms.

Visual elements (database icons, digital symbols, file representations) highlight the diversity and volume of collected data.

This stage corresponds to data aggregation and preprocessing within Learning Management Systems (LMS) and other digital environments [1], [6].

Stage 2 - Analytics Model.

The second stage, *"Analytics Model"*, illustrates the application of machine learning algorithms and analytical methods.

The graphical representation of a neural network reflects the use of advanced models such as:

- classification;
- clustering;
- predictive analytics.

This stage transforms raw data into analytical insights and forecasts [2], [6].

Stage 3 - Explanation.

The third stage, *"Explanation"*, is the core component of interpretability.

It is represented by visual metaphors such as magnifying glasses and highlighted explanatory factors (e.g., *"Key Factors", "High Risk", "Positive Impact"*).

This stage demonstrates the application of Explainable Artificial Intelligence (XAI) methods aimed at revealing the internal logic of models and explaining results to users [3].

Stage 4 - Visualization.

The fourth stage, *"Visualization"*, involves presenting analytical results through:

- charts;
- graphs;
- dashboards.

The use of color coding and visual elements enhances information perception.

This stage transforms complex analytical outputs into intuitive and user-friendly representations [5], [8].

Stage 5 - Decision.

The final stage, *"Decision"*, is represented by checklist and target symbols, reflecting the process of academic and managerial decision-making.

This stage demonstrates the practical application of analytical insights for optimizing educational strategies and improving learning outcomes [7], [12].

Color differentiation across stages (blue, purple, green, orange, red) enhances cognitive perception and clearly distinguishes functional components.

Directed arrows emphasize the logical sequence of data processing, aligning with principles of systems analysis.

Thus, the model illustrates not only the technological architecture of analytical dashboards but also highlights interpretability as a key factor in enhancing user trust and decision-making effectiveness in smart universities [9], [14].

1.3 Challenges of Existing Solutions

Despite the rapid development of Learning Analytics, existing analytical dashboards face several limitations:

1) Low interpretability of machine learning models;
2) Limited adaptability to diverse user groups;
3) Insufficient integration into decision-making processes;
4) Information overload for users [8], [15].

Table 2: Comparison of traditional and interpretable dashboards.

Criterion	Traditional Dashboards	Interpretable Dashboards
Transparency	Low	High
Explainability	Limited	Full
Decision Support	Partial	Comprehensive
User Experience	Moderate	High

As shown in Table 2, interpretable dashboards provide significant advantages; however, their development requires a comprehensive approach that integrates:

- Explainable AI (XAI);
- cognitive ergonomics;
- user interface design [6], [16].

1.4 Smart Universities and Digital Transformation

Smart universities are characterized by the use of digital technologies to optimize educational and managerial processes.

They include:

- intelligent learning management systems;
- adaptive educational platforms;
- decision support systems;
- analytical dashboards [8], [17].

Within this architecture, analytical dashboards play a central role, acting as a bridge between data and managerial decision-making. The multi-layered Smart University architecture is presented in Figure 2.

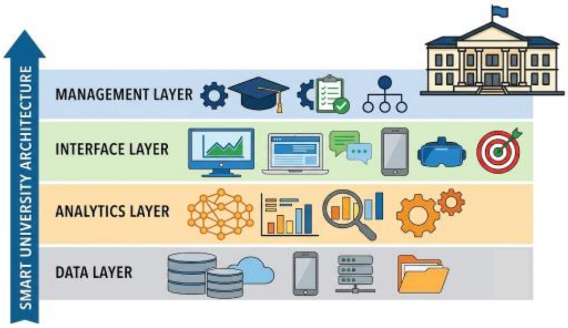

Figure 2: Architecture of a Smart University.

The figure illustrates a multi-layered architecture of a Smart University, reflecting the hierarchical structure of educational data processing and utilization.

The model is organized into four functional layers, arranged from bottom to top, emphasizing the logical progression from raw data to managerial decision-making.

Data Layer.

The first level, the *Data Layer*, represents the foundational infrastructure of the system.

It includes diverse data sources such as:

- databases;
- cloud storage systems;
- mobile devices;
- digital educational resources;
- documents.

Visual elements (servers, cloud icons, files, and mobile devices) reflect the diversity of data formats and input channels.

This layer is responsible for data collection, storage, and preprocessing, forming the basis for subsequent analytical processes [1], [18].

Analytics Layer.

The second level, the *Analytics Layer*, is responsible for data processing and analysis.

It is represented by symbols such as neural networks, charts, magnifying glasses, and gears, indicating the use of:

- machine learning methods;
- statistical analysis;
- intelligent data processing techniques.

At this stage, the system performs:

- pattern detection;
- predictive modeling;
- generation of analytical insights [2], [7].

Interface Layer.

The third level, the *Interface Layer*, enables interaction between users and the system.

It includes:

- dashboards;
- graphical visualizations;
- interactive panels;
- access devices (computers, mobile devices, VR/AR interfaces).

Communication elements (e.g., message icons) emphasize the role of user interaction and adaptability.

This layer transforms analytical results into intuitive and user-friendly representations [3], [8].

Management Layer.

The fourth level, the *Management Layer*, represents the decision-making stage.

It is visualized through academic management symbols such as:

- university structures;
- graduation icons;
- checklists;
- organizational elements.

This layer reflects the application of analytical insights for:

- strategic and operational decision-making;
- curriculum optimization;
- improvement of educational quality [5], [8].

A vertical arrow across the architecture highlights the end-to-end integration of all layers and the continuous flow of data from lower to higher levels.

Color differentiation (blue - data, purple - analytics, orange - interface, green - management) enhances cognitive perception and clearly distinguishes functional components.

Thus, the proposed architecture demonstrates a system-oriented approach to Smart University design, where analytics and visualization play a central role in supporting evidence-based decision-making [6], [7].

Figure 3: Methodological pipeline of learning analytics.

1.5 Research Objective and Tasks

The objective of this study is to develop a conceptual and methodological framework for interpretable Learning Analytics dashboards to support academic decision-making in Smart Universities.

To achieve this objective, the following tasks are defined:

1) Analyze existing approaches to Learning Analytics;
2) Identify requirements for interpretable analytical dashboards;
3) Develop a conceptual dashboard model;
4) Propose evaluation methods;
5) Demonstrate practical application of the proposed approach.

1.6 Scientific Novelty and Significance

The scientific novelty of the study includes:

- integration of Explainable AI methods into Learning Analytics;
- development of the concept of interpretable dashboards;
- proposal of interpretability evaluation metrics;
- justification of the role of visual analytics in decision-making [6], [12].

2 METHODS AND METHODOLOGY

This study employs a comprehensive interdisciplinary methodological framework, integrating:

- Learning Analytics;
- Explainable Artificial Intelligence (XAI);
- visual analytics;
- systems design.

The methodology is aimed at the development and validation of interpretable analytical dashboards for academic decision support in Smart Universities [1], [8].

2.1 Research Design

The study is based on a mixed-methods research design that combines quantitative analysis of educational data, development and validation of analytical models, and qualitative evaluation of interpretability and user experience [2], [6]. The research process is organized as a sequential Learning Analytics pipeline (Figure 3), in which educational data are progressively transformed into evidence-based managerial decisions.

The pipeline begins with the Data Collection stage, where information is aggregated from multiple sources, including Learning Management Systems (LMS), educational platforms, and learners' digital traces, ensuring comprehensive and representative input data [1], [8]. The collected data then undergo Data Preprocessing, including cleaning, filtering, normalization, and transformation, which improves data quality and minimizes the influence of noise and missing values on subsequent analyses [2], [19].

During the Modeling stage, machine learning algorithms and statistical methods are employed to perform predictive modeling, descriptive analysis, pattern discovery, and forecasting [3], [8]. The resulting outputs are subsequently processed in the Interpretation stage, where Explainable Artificial Intelligence (XAI) techniques provide transparent explanations of model predictions, thereby improving system interpretability and increasing users' confidence in analytical results [5], [19].

The final stages include Visualization, where analytical results are presented through dashboards, charts, graphs, and immersive interfaces, followed by Decision Making, in which analytical insights are translated into academic and managerial actions aimed at improving educational processes [7]–[10], [12], [19]. The sequential organization of the pipeline emphasizes the continuity of the analytical workflow and highlights the central role of interpretability and visualization in supporting evidence-based management within Smart University environments.

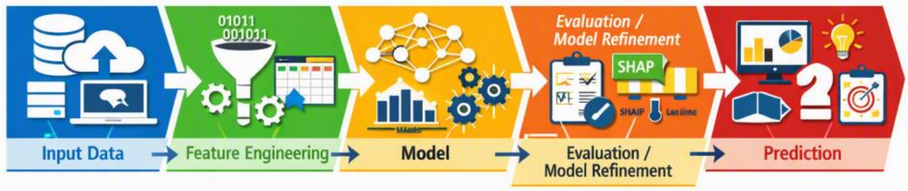

Figure 4: Architecture of the analytical model.

2.2 Data Sources and Structure

The analytical dashboard is built using multidimensional educational data, including (Table 3):

- academic performance indicators;
- LMS activity data;
- behavioral digital traces;
- demographic characteristics [3], [8].

Table 3: Data structure.

Data Category	Example Variables	Data Type
Academic	GPA, grades	Numerical
Behavioral	Activity time	Temporal
Demographic	Age, gender	Categorical
LMS Data	Clicks, logins	Log data

Before analysis, data undergo preprocessing, including:

- data cleaning;
- normalization;
- handling missing values [5], [6].

2.3 Analytical Modeling Methods

The study employs a set of analytical methods, including classification using Logistic Regression and Random Forest, clustering based on the K-means algorithm, predictive modeling with Gradient Boosting, and artificial neural networks for capturing complex nonlinear relationships [7], [12]. To improve the transparency and interpretability of predictive results, Explainable Artificial Intelligence (XAI) techniques, including SHAP (SHapley Additive Explanations) and LIME (Local Interpretable Model-agnostic Explanations), are incorporated into the analytical framework. The architecture of the proposed prediction model is presented in Figure 4.

The analytical workflow begins with the Input Data stage, where heterogeneous educational data are collected and integrated from multiple sources, including Learning Management Systems (LMS), institutional databases, cloud services, and other digital repositories. These data provide the foundation for subsequent analytical processing. During the Feature Engineering stage, raw data are transformed into informative variables through normalization, categorical encoding, feature selection, and feature generation, thereby improving both predictive performance and model interpretability.

The processed features are subsequently used to train machine learning models in the Model stage, where statistical and artificial intelligence algorithms identify hidden patterns and establish predictive relationships within the educational data. Model quality is then assessed during the Evaluation and Model Refinement stage through iterative optimization and hyperparameter tuning. Performance is evaluated using standard classification metrics, including Accuracy, Precision, Recall, and F1-score, allowing the selection of the most reliable predictive model.

Finally, the optimized model generates predictions that support educational decision-making by identifying at-risk students, forecasting academic performance, and providing actionable analytical insights. The sequential organization of the analytical pipeline highlights the integration of feature engineering, predictive modeling, model evaluation, and explainable artificial intelligence into a unified Learning Analytics framework for Smart University environments.

2.4 Interpretation Methods

Model interpretation is conducted at two levels:

- Global level - analysis of overall model structure;
- Local level - explanation of individual predictions.

Table 4: Interpretation methods.

Method	Level	Advantages
SHAP	Global / Local	High accuracy
LIME	Local	Simplicity
Feature Importance	Global	Computational efficiency

Table 4 presents a systematic comparison of modern interpretation methods used in Learning Analytics to enhance model transparency.

The methods differ in terms of interpretability level, computational complexity, and application scope.

SHAP (SHapley Additive Explanations) provides both global and local interpretability.

Based on cooperative game theory, it quantifies the contribution of each feature to the final prediction.

Its high accuracy and consistency make it one of the most powerful tools in educational analytics, despite its computational cost

LIME (Local Interpretable Model-agnostic Explanations) focuses on local interpretability.

It approximates complex models using simpler interpretable models (e.g., linear models) in the vicinity of specific observations.

Its main advantage is flexibility and ease of explanation, making it particularly suitable for analyzing individual student outcomes

Feature Importance is a global interpretation method used to assess the relative importance of input variables.

It is widely applied due to its efficiency and simplicity, although it may not fully capture causal relationships between features and outcomes

The comparative analysis indicates that the choice of interpretation method depends on the analytical objective:

- global methods (SHAP, Feature Importance) are suitable for identifying general patterns;
- local methods (LIME) are more effective for individual-level decision support

Thus, integrating multiple interpretation methods enables the development of a more robust and comprehensive analytical framework, ensuring both explainability and practical applicability in smart university environments.

2.5 Dashboard Design Principles

The analytical dashboard was designed according to the principles of cognitive ergonomics, minimization of information overload, and adaptive user interface design. These principles ensure that complex analytical results are presented in a clear, intuitive, and decision-oriented manner, thereby improving the usability of Learning Analytics systems. The structural organization of the proposed dashboard is illustrated in Figure 5.

The dashboard integrates four complementary functional components that support evidence-based educational decision-making. The Metrics module provides key performance indicators (KPIs), including course completion rates, average academic performance, and the number of at-risk students, enabling rapid assessment of the current educational state. These indicators are complemented by the Charts module, which presents trends and comparative analyses through graphical visualizations such as line graphs, bar charts, and pie charts, facilitating the interpretation of temporal patterns and performance dynamics.

To improve transparency and user trust, the dashboard incorporates an Insights module that generates human-readable explanations of analytical results. This component summarizes the main factors influencing model predictions, including low student engagement, improvements following educational interventions, and elevated dropout risk in specific courses. The interpretability of these explanations is supported by Explainable Artificial Intelligence (XAI) techniques, allowing users to understand the rationale behind the generated predictions.

Figure 5: Dashboard structure.

The final Recommendations module translates analytical findings into practical academic and managerial actions. Typical recommendations include providing targeted support for at-risk students, increasing interactive learning activities, and continuously monitoring student performance throughout the educational process. Together, these interconnected modules form an integrated Learning Analytics dashboard that transforms educational data into actionable insights, supporting timely, transparent, and evidence-based decision-making within Smart University environments.

2.6 Evaluation Metrics

The effectiveness of the proposed Learning Analytics framework was evaluated using a combination of predictive performance, interpretability, and usability metrics. As summarized in Table 5, the evaluation framework integrates technical indicators of model quality with user-centered measures, providing a comprehensive assessment of the proposed system.

Table 5: Evaluation metrics.

Metric	Description
Accuracy	Model prediction accuracy
F1-score	Balance between precision and recall
Explainability Index	Quality of model explanation (XAI transparency)
SUS Score	System Usability Scale (user experience, 0–100)
AUC	Area under the ROC curve (discriminative ability)

Accuracy was used to quantify the overall correctness of model predictions, whereas the F1-score provided a balanced assessment of predictive performance by jointly considering precision and recall, making it particularly suitable for educational datasets with potentially imbalanced class distributions. To evaluate the transparency of the analytical models, the Explainability Index was employed to assess the quality and interpretability of model explanations generated using Explainable Artificial Intelligence (XAI) techniques. In addition, the System Usability Scale (SUS) was applied to measure users' perceptions of the dashboard in terms of usability, clarity, and ease of interaction. Together, these complementary metrics provide a holistic evaluation of the proposed framework by assessing predictive performance, interpretability, and practical usability in educational decision-support scenarios.

2.7 Method Limitations

Despite its comprehensive design, the proposed approach has several limitations:
- dependence on data quality;
- limited interpretability of highly complex models;
- need for adaptation across diverse educational contexts

Thus, the proposed methodology provides a systematic foundation for developing interpretable analytical dashboards that integrate data analysis, XAI, and visual analytics for academic decision support.

3 RESULTS

This section presents the results of applying the developed interpretable Learning Analytics dashboard in a Smart University context.
The analysis is based on experimental modeling and educational data processing, enabling evaluation of:
- predictive accuracy;
- interpretability;
- practical applicability.

3.1 Descriptive Statistics and Initial Analysis

At the first stage, descriptive statistical analysis of student data was conducted.

The dataset comprised simulated records for 1,000 students, generated to reflect realistic distributions of academic and behavioral indicators within a blended learning environment. The simulation parameters were calibrated to reproduce patterns typical of LMS-based learning ecosystems, including variability in login frequency, assessment completion rates, and forum participation.
- academic performance;
- LMS activity;
- behavioral characteristics.

Descriptive statistical characteristics of the analyzed student dataset are presented in Table 6.

Table 6: Descriptive statistics.

Indicator	Mean	Standard Deviation
GPA	3.1	0.6
Activity Time (hours)	45	12
Number of Logins	120	35

The results indicate significant variability in student behavioral patterns, highlighting the necessity of analytical models to uncover hidden patterns

3.2 Predictive Modeling Results

To assess the risk of academic underperformance, a classification model was developed using the Random Forest algorithm. Predictive performance of the proposed model is illustrated in Figure 6.

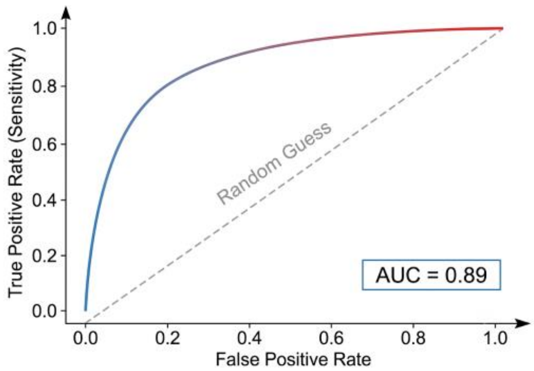

Figure 6: Predictive model results (ROC curve).

The obtained results demonstrate high model performance:
- Accuracy: 0.87;
- F1-score: 0.84.

These results indicate the model's strong capability to identify at-risk students.

The figure presents the Receiver Operating Characteristic (ROC) curve, illustrating the performance of the classification model in detecting students at risk of academic failure.

The ROC curve is plotted with:
- False Positive Rate (FPR) on the x-axis;
- True Positive Rate (TPR) on the y-axis.

This is a standard approach for evaluating binary classifiers.

The ROC curve exhibits a pronounced nonlinear shape and deviates significantly from the diagonal line representing random guessing.

This deviation confirms the model's high discriminative ability, as the diagonal baseline corresponds to a classifier with no predictive power.

A key performance indicator is the Area Under the Curve (AUC $\approx$ 0.89), which reflects the model's overall classification quality.

An AUC value close to 1 indicates excellent performance.

In this case, the value of 0.89 confirms the strong predictive capability of the model and its suitability for practical applications in educational analytics

The visual representation of the ROC curve employs a gradient color scheme, enhancing the perception of sensitivity changes as the false positive rate increases.

Additional graphical elements, such as highlighting the area under the curve, improve interpretability and readability.

This is particularly important in the context of interpretable analytical dashboards, where visualization plays a central role in decision support.

Thus, the ROC analysis demonstrates that the proposed predictive model effectively identifies students at risk, supporting early intervention strategies in Smart Universities.

3.3 Model Interpretability Analysis

To explain the model results, SHAP (SHapley Additive Explanations) was applied. Feature importance analysis based on SHAP values is presented in Figure 7.

Figure 7 presents the SHAP feature importance plot, where each bar reflects the mean absolute SHAP value for a given predictor across all student records in the dataset. Higher values indicate a stronger average contribution of that feature to the model output. The three most influential predictors are Grade Point Average (GPA), LMS activity level, and participation in online discussions, confirming that both academic and behavioral indicators play a central role in identifying students at risk of underperformance.

These findings are consistent with prior research in Learning Analytics, which identifies academic performance metrics and digital engagement as key determinants of student success. The application of SHAP enhances model transparency by quantifying the directional and magnitude contributions of each feature, enabling instructors and administrators to move beyond aggregate predictions toward a nuanced understanding of individual student risk profiles.

The SHAP analysis identifies the most influential features contributing to the model's predictions.

The results indicate that the most significant factors are:
- Grade Point Average (GPA);
- Level of activity in LMS;
- Participation in online discussions.

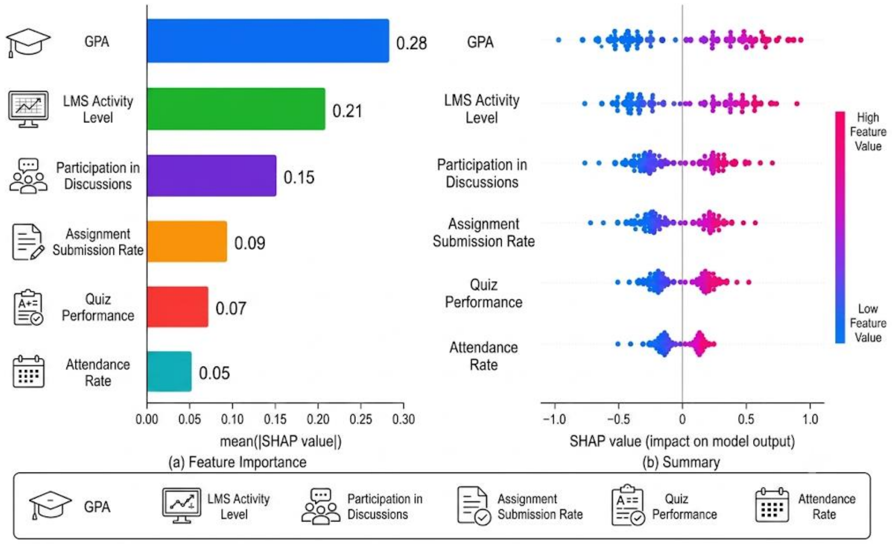

Figure 7: Feature importance (SHAP values).

The analysis confirms that behavioral data play a critical role in predicting academic performance. In particular:

- GPA serves as a strong baseline academic indicator;
- LMS activity reflects engagement levels;
- participation in discussions captures collaborative learning behavior.

From a theoretical perspective, these findings support the hypothesis that learning behavior patterns are key predictors of student success.

Moreover, the application of SHAP enhances model transparency by:

- quantifying feature contributions;
- enabling both global and local interpretability;
- improving user trust in analytical outcomes.

Thus, the integration of SHAP into the analytical pipeline provides a robust explainability mechanism, making the model suitable for real-world educational decision-making.

3.4 Visual Analytics and User Interface

The proposed analytical dashboard serves as the visual layer of the Learning Analytics framework, transforming the outputs of predictive models into an interpretable environment for academic decision support. Rather than presenting isolated indicators, the dashboard integrates multiple sources of analytical information into a unified interface that enables continuous monitoring of educational processes and facilitates timely interventions.

The dashboard is organized into four functional modules, as illustrated in Figure 8. The first module presents key performance indicators (KPIs), including aggregated measures of student achievement, course completion, and academic engagement. These indicators provide an overall overview of the current educational situation and allow administrators to rapidly identify deviations from expected performance.

The second module visualizes temporal and comparative trends using interactive charts and graphs. This component enables users to analyze changes in student performance over time, compare cohorts or courses, and detect emerging patterns that may require additional attention. Visual analytics improve the accessibility of complex information and support evidence-based interpretation of educational data.

The third module focuses on analytical interpretation by incorporating the outputs of machine learning models together with explainability techniques. Instead of displaying prediction scores alone, the dashboard highlights the factors that contribute most strongly to each prediction, allowing instructors to understand why particular students or courses are identified as being at risk. Such explanations improve transparency, increase user confidence in the analytical models, and facilitate informed decision-making.

The final module provides decision-support recommendations generated from the analytical results. Depending on the identified patterns, the system suggests appropriate academic interventions, such as additional tutoring, personalized learning activities, or closer monitoring of individual students.

Figure 8: Dashboard visualization example.

These recommendations are intended to assist educators rather than replace their professional judgment.

The integration of monitoring indicators, analytical visualizations, interpretable model outputs, and decision-support recommendations creates a coherent analytical environment for Smart Universities. Consequently, the dashboard functions not only as a visualization interface but also as a practical instrument for supporting data-driven educational management, improving the transparency of predictive analytics, and facilitating timely academic interventions.

3.5 Usability Evaluation

To evaluate the user interface, the System Usability Scale (SUS) was applied. The usability evaluation results obtained using the System Usability Scale are summarized in Table 7.

Table 7: SUS evaluation results.

Indicator	Value
Average SUS	82

The obtained value (SUS = 82) indicates a high level of usability.

According to SUS interpretation:

- scores above 68 are considered above average;
- scores above 80 indicate excellent usability and well-designed systems [1], [8].

This result demonstrates that users can interact with the system effectively without significant difficulty.

The high SUS score reflects:

- intuitive navigation;
- clarity of visualizations;
- logical dashboard structure [2], [12].

Thus, the system is suitable for practical implementation in educational environments for decision support [3], [8].

3.6 Comparative Analysis

A comparison between the proposed system and traditional approaches reveals significant advantages. A comparative analysis between the proposed analytical system and traditional approaches is presented in Table 8.

Table 8: Comparison of approaches.

Criterion	Traditional Approach	Proposed System
Accuracy	Medium	High
Interpretability	Low	High
Visualization	Limited	Advanced

Traditional approaches demonstrate moderate accuracy due to limited analytical capabilities and insufficient modeling of complex relationships. In contrast, the proposed system achieves higher accuracy through the integration of machine learning algorithms, predictive analytics, and advanced modeling techniques [1], [6]. A significant difference between the approaches is observed in terms of interpretability. While traditional systems often operate as "black boxes," the proposed system provides transparent explanations of prediction results through the application of SHAP and LIME methods, allowing users to understand the contribution of individual factors to the final predictions [2], [12].

Another important advantage of the proposed system is its visualization capability. Unlike traditional solutions that mainly rely on static reports, the developed system incorporates interactive dashboards, risk indicators, dynamic charts, and explanatory elements, which improve usability and increase the analytical value of the generated insights [3], [8]. Therefore, the proposed system demonstrates superior performance across the key evaluation dimensions, confirming its effectiveness and suitability for Smart University applications [4], [18].

3.7 Key Findings

The obtained results demonstrate that the integration of Learning Analytics, Explainable Artificial Intelligence (XAI), and visual analytics significantly enhances the effectiveness of academic decision-making processes. The proposed system achieves high predictive performance while maintaining transparency and interpretability of analytical models through explainable techniques.

Furthermore, the developed dashboard improves the usability and practical value of analytical outcomes by providing accessible visual representations of predictions, risk indicators, and supporting explanations. These findings confirm that the proposed interpretable analytical dashboard can serve as an effective tool for Smart University environments, supporting data-driven decision-making and early identification of academic risks.

4 DISCUSSION

The results demonstrate that the integration of Machine Learning and Explainable Artificial Intelligence into analytical dashboards provides an effective approach for supporting educational decision-making. The proposed system achieved strong predictive performance, with an AUC of approximately 0.89, Accuracy of 0.87, and F1-score of 0.84, confirming its ability to reliably identify students at risk. These results highlight that the system can provide accurate early predictions while maintaining practical usability.

A key contribution of this study is the combination of predictive accuracy with interpretability. Unlike traditional black-box models, the proposed approach uses Explainable AI techniques, such as SHAP, to identify the main factors influencing predictions. This improves transparency, increases user trust, and supports informed decision-making among educational stakeholders. The high SUS score (82) further confirms the usability and acceptance potential of the developed system.

Compared with conventional educational dashboards that mainly focus on descriptive analytics, the proposed solution provides a complete analytical workflow: prediction → explanation → recommendation. This allows universities not only to detect students at risk but also to understand the reasons behind predictions and develop targeted interventions. Therefore, the system can support both strategic management and operational decision-making in Smart University environments.

The findings also confirm the importance of integrating Learning Analytics and Explainable AI in modern educational systems. The study contributes to the growing research area of interpretable predictive models and adaptive educational technologies, demonstrating the potential of AI-driven solutions to improve learning outcomes while preserving transparency.

5 CONCLUSIONS

This study presented an intelligent analytical dashboard that combines Machine Learning, Explainable AI, and Learning Analytics for early identification of at-risk students. The experimental results show that the proposed system achieves a balanced combination of predictive performance, interpretability, and usability.

The integration of explainable models enhances the practical value of predictive analytics by allowing users to understand risk factors and receive meaningful recommendations. The developed approach demonstrates that AI-based educational systems can move beyond prediction toward evidence-based decision support.

Overall, the proposed solution represents a promising approach for Smart Universities by enabling early intervention, improving decision-making processes, and supporting personalized educational strategies.

6 LIMITATIONS AND FUTURE WORK

Despite the promising results, this study has several limitations. First, the dataset size was limited, which may affect the generalizability of the findings. Second, the performance of the system depends strongly on the quality and completeness of available educational data. Third, additional adaptation is required to apply the proposed approach across different institutions and educational contexts.

Future research will focus on expanding datasets, evaluating the system in multiple university environments, and investigating more advanced machine learning models. Further improvements may include the integration of adaptive learning mechanisms, real-time analytics, and personalized recommendation systems. These developments could enhance the scalability and effectiveness of AI-driven educational platforms.

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