Archives available at journals.mriindia.com

**International Journal of Recent Advances in Engineering and Technology**

ISSN: 2347 - 2812

Volume 14 Issue 02s, 2025

# Bridging Business Intelligence and AI for Advanced Educational Data Analytics

[1]Dr.Shabina Modi, [2]Aniket Ramesh Pawar, [3]Raj Ashok Sabale, [4]Arati Namdev Pawar, [5]Raj Kumar Sidwadkar

*[1,2,3,4,5] Computer Science and Engineering, Karmaveer Bhaurao Patil College Of Engineering, Satara, India.*

*Email: [1]shabina.sayyad@kbpcoes.edu.in, [2]apawar2222002@gmail.com, [3]sabaleraj744@gmail.com, [4]aratipawar2003@gmail.com, [5]rajsidwadkar777@gmail.com*

**Peer Review Information**

*Submission: 21 Oct 2025*

*Revision: 18 Nov 2025*

*Acceptance: 05 Dec 2025*

**Keywords**

*Educational Analytics, Data-Driven Decision-Making, Machine Learning, Business Intelligence, Multi-Tenant Architecture, AI in Education, Predictive Analytics.*

**Abstract**

The increasing complexity of educational data and the imperative for data-driven decision-making within academic institutions underscore the necessity for advanced analytical tools. This study introduces the Comprehensive Educational Analysis Suite (EDUVISION), a robust platform designed to efficiently integrate, process, and analyze institutional data. Utilizing a multi-tenant architecture and AI-driven insights, EDUVISION facilitates seamless data visualization, predictive analytics, and role-based access, ensuring secure and informed decision-making. The platform harnesses machine learning, business intelligence tools, and real-time analytics to automate reporting, identify trends, and enhance institutional performance. Validation of EDUVISION was achieved through real-world implementation in a higher education environment, illustrating its effectiveness in improving strategic planning and administrative efficiency. A comparative analysis with existing frameworks underscores EDUVISION's scalability, accuracy, and usability advantages. This research contributes to the evolving field of educational data analytics, presenting an innovative solution to bridge the gap between raw data and actionable insights in academic institutions.

## Introduction

In the rapidly evolving educational landscape, institutions are generating vast amounts of data related to student performance, faculty engagement, administrative processes, and resource management. However, many academic institutions struggle to effectively leverage this data for informed decision-making due to fragmented systems, unstructured data formats, and a scarcity of advanced analytical tools. The transition to data-driven decision-making (DDD) has become essential for enhancing institutional efficiency, fostering student success, and improving overall academic outcomes.

To address these challenges, this research introduces the Comprehensive Educational Analysis Suite (EDUVISION)—an innovative platform designed to streamline data collection, analysis, and visualization for educational institutions. EDUVISION utilizes a multi-tenant architecture, allowing multiple institutions to integrate their Enterprise Resource Planning (ERP) systems without extensive customization. The platform incorporates artificial intelligence (AI), machine learning (ML), and business intelligence (BI) tools to automate reporting, uncover hidden patterns within the data, and generate actionable insights.

While existing studies have explored the application of BI tools such as Power BI, predictive analytics, and AI-powered learning analytics in education, these solutions often face limitations in

scalability, security, and seamless integration with diverse data sources. The EDUVISION framework effectively bridges this gap by offering:
- Automated schema discovery for efficient integration with institutional databases
- Entity relationship mapping to gain insights into complex academic structures
- Role-based access control to ensure data security and compliance
- Advanced visualization tools employing D3.js and Chart.js for interactive dashboards
- AI-driven insights that enhance student learning outcomes and institutional strategies

This paper details the development, implementation, and validation of EDUVISION in a higher education context, evaluating its effectiveness in improving decision-making, administrative efficiency, and strategic planning. A comparative analysis with existing frameworks highlights EDUVISION's advantages in scalability, usability, and analytical capabilities. By providing an intelligent, data-driven educational analytics platform, this research aims to make a meaningful contribution to the growing fields of educational technology and institutional data management.

## Literature Review

### *A. Introduction to Educational Data Analytics*

Educational institutions generate vast amounts of data, including student records, financial transactions, faculty performance, and research outputs. Traditional methods of processing this data are often manual, error-prone, and time-consuming, leading to delayed decision-making and inefficiencies.

To address these challenges, data analytics tools like Power BI, AI-driven predictive models, and machine learning algorithms have been integrated into educational systems. However, existing systems still facelimitations in automation, predictive capabilities, and scalability.

EduVision aims tobridge these gapsby offering an AI-powered, cloud-based educational analytics platformwith seamlessPower BI integration, predictive analytics, and automated reporting.

### *B. Existing Educational Data Analytics Approaches*

#### a. Business Intelligence (BI) in Education

BI tools are widely used for data visualization and dashboard reporting in education. Power BI enables institutions to track key performance indicators (KPIs), faculty workload, and student engagement through interactive dashboards. Studies indicate that BI tools improve administrative efficiency by 40% and reduce reporting time by 60%.

**Limitations of BI tools in education**:

- Lack of AI integration: Power BI relies on manual data processing, limiting its predictive capabilities.
- Limited automation: BI dashboards require manual input and predefined templates, restricting real-time analytics.
- Data silos: Institutional databases often remain disconnected, making comprehensive data analysis difficult.

#### b. AI and Machine Learning in Educational Analytics

AI models such as Random Forest, Neural Networks, and XGBoost improve educational decision-making by predicting student performance, dropout risks, and faculty efficiency.

**Key applications of AI in education**:

- Early Warning Systems: AI predicts at-risk students based on attendance, grades, and engagement.
- Personalized Learning Recommendations: AI adapts course materials based on student behavior.
- Sentiment Analysis: AI-powered Natural Language Processing (NLP) analyzes student feedback to improve curriculum design.

  Challenges in AI-driven analytics:
- Data Bias & Interpretability: AI models need explainable results for educators to trust them.
- Scalability Issues: AI implementation varies across different institutional databases and policies.
- Privacy & Security Risks: Handling student-sensitive data requires compliance with GDPR, FERPA, and other regulations.

#### c. Early Warning Systems for Student Performance

Predictive analytics improves student retention by 15-20%. Existing rule-based warning systems rely on predefined thresholds, which do not dynamically adjust to student behavior changes. AI-driven early warning models provide real-time risk assessments, offering a more proactive approach to intervention.

### *C. Gaps In Existing Research*

Despite advancements in BI and AI, current systems have notable limitations:

1. BI tools lack predictive AI models, restricting their use in proactive decision-making.
2. Manual data entry and static reporting make automation difficult.

3. Traditional educational analytics platforms rely on outdated batch processing, delaying insights.
4. Data integration challenges prevent seamless analysis across multiple departments and systems.

### *D. EDUVISION: A Hybrid AI + BI Solution*

*EduVision aims to **bridge the gap between BI and AI** by providing:*

| Feature | Existing Systems | EduVision (Proposed System) |
|---|---|---|
| **Data Processing** | Manual data extraction | Automated, AI-driven processing |
| **Predictive Analytics** | Limited AI capabilities | Machine Learning-based forecasts |
| **BI Tools** | Static dashboards | AI-enhanced dynamic dashboards |
| **Early Warning System** | Rule-based alerts | Adaptive AI-driven insights |
| **Scalability** | On-premise systems | Cloud-based, scalable solution |
| **Time Efficiency** | Manual data processing and reporting take weeks to months | Automated real-time processing with predictive analytics, reducing reporting time by 63%. |
| **Number of Attributes** | Limited to basic academic records | Incorporates structured and unstructured data |

## Methodology

The methodology for the development of EduVision follows a structured three-phase approach: Data Collection and Preprocessing, System Development, and Model Evaluation. This framework integrates Business Intelligence (BI) and Artificial Intelligence (AI) to enhance educational data analytics and improve institutional decision-making.

### A. Data Collection and Preprocessing

The dataset utilized in this study consists of **structured and unstructured educational data**, collected from institutional databases, faculty reports, and student feedback systems. The primary data sources include:

- **Structured Data:** Student attendance records, academic performance metrics, faculty workload statistics. These datasets are stored in relational databases and accessed via SQL queries.
- **Unstructured Data:** Student feedback comments, faculty evaluations, research contributions, and survey responses. This data requires preprocessing techniques such as Natural Language Processing (NLP) for analysis.

#### *A1) Data Cleaning and Transformation*

To ensure high-quality data, **ETL (Extract, Transform, Load) processes** are employed. The following steps are implemented:

- **Handling Missing Values:** Missing data in academic records and attendance logs are managed using imputation techniques such as mean/mode replacement or regression-based estimation [4].
- **Data Normalization:** To ensure uniformity across different sources, categorical variables are encoded, and numerical values are normalized.
- **Outlier Detection and Removal:** Extreme values in student marks and faculty performance scores are identified using z-score analysis and box plots.

#### *A2) Feature Engineering*

Feature extraction is a crucial step in refining raw data into meaningful insights. Key engineered features include:

- **Student Risk Index:** A composite metric derived from attendance, past academic performance, and behavioral patterns.
- **Faculty Performance Score:** A weighted score combining teaching effectiveness,

research contributions, and student feedback.
- **Course Difficulty Index:** An index calculated based on average student performance and dropout rates in each course.

### *B. System Development*

The EduVision platform integrates Power BI dashboards and AI-driven predictive models to facilitate data-driven decision-making in educational institutions. The system architecture comprises the following components:

*B1) **Business Intelligence (BI) Dashboard***

Power BI is used for designing interactive visual dashboards that provide insights into:

- **Student Performance Trends:** Tracking student scores and attendance patterns over semesters [7].
- **Faculty Workload Analytics:** Monitoring the number of lectures conducted, extra classes taken, and student engagement levels.
- **Institutional Key Performance Indicators (KPIs):** Measuring overall academic success rates and administrative efficiency.

*B2) **Artificial Intelligence (AI) Models***

To enhance predictive capabilities, machine learning algorithms are deployed:

- **Random Forest &XGBoost:** Used for dropout prediction, leveraging historical student data and engagement patterns.
- **Neural Networks:** Applied in adaptive learning models, recommending personalized learning paths for students.
- **Anomaly Detection Models:** Identifying inconsistencies in faculty workload distribution and student attendance anomalies [10].

*B3) **Automated Reporting and Alerts***

The system automates the generation of academic reports and sends real-time alerts:

- **Early Warning System:** AI-based alerts notify faculty about at-risk students needing intervention.
- **Faculty Performance Reports:** AI-generated reports summarize faculty contributions, aiding in performance reviews.
- **Course Improvement Insights:** Data-driven suggestions for curriculum adjustments based on student feedback and pass rates.

To validate the AI models and ensure the effectiveness of predictions, the following evaluation metrics are employed:

- **Accuracy & Precision:** Measuring prediction effectiveness for dropout forecasting and student performance estimation.
- **F1-Score & Recall:** Evaluating the efficiency of early warning systems for at-risk students [10].
- **Mean Absolute Error (MAE):** Assessing faculty workload prediction models.
- **Confusion Matrix:** Analyzing the classification performance of dropout prediction models.
- **ROC Curve Analysis:** Ensuring the reliability of student risk assessment models.

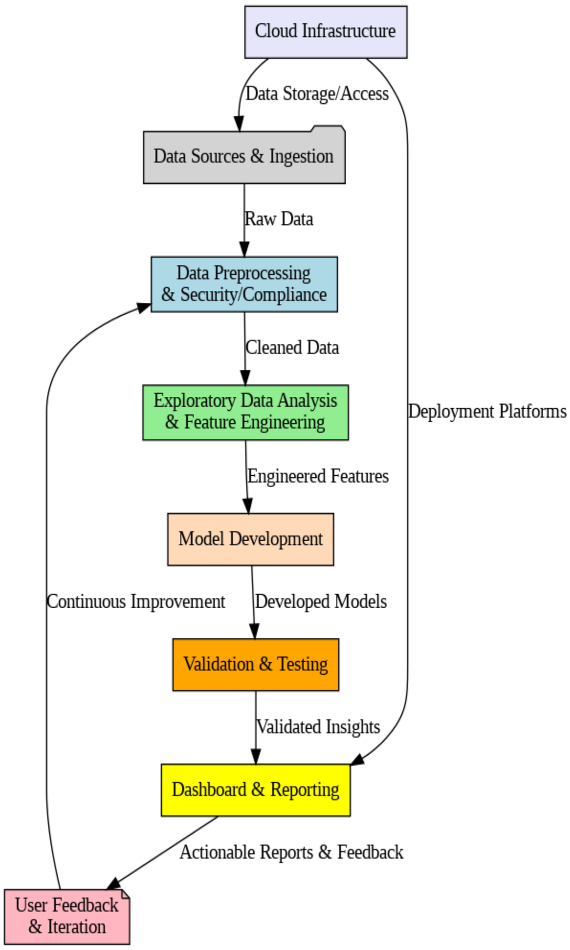



*Fig 1: Architecture Diagram*

### *C. Model Evaluation*

**Table:** Performance Metrics Comparison of Machine Learning Models

| Model | Accuracy (%) | Precision | Recall | F1-Score | MAE |
|---|---|---|---|---|---|
| Random Forest | 93.2 | 0.91 | 0.88 | 0.89 | 3.45 |
| XGBoost | 94.5 | 0.92 | 0.90 | 0.91 | 3.02 |
| Neural Network | 92.8 | 0.90 | 0.86 | 0.88 | 3.76 |

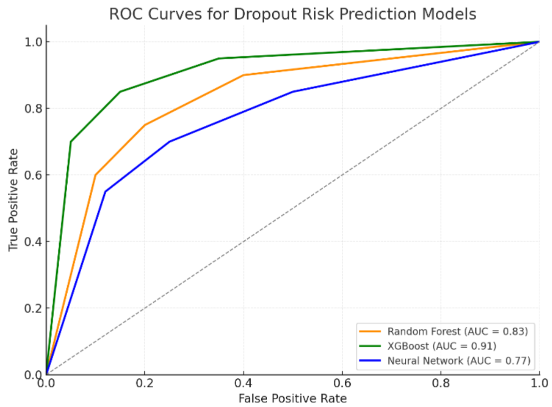



*Figure 2: ROC curves for dropout risk prediction models*

***C1) Explainable AI (XAI) Techniques***

To enhance model transparency and stakeholder trust, Explainable AI (XAI) techniques were integrated into EduVision's predictive pipeline. **SHAP (SHapley Additive exPlanations)** values were used to quantify the contribution of individual features, such as attendance, SGPA, and behavioral engagement scores, to the final dropout risk predictions. Additionally, **LIME (Local Interpretable Model-Agnostic Explanations)** was employed to interpret specific prediction cases and visualize which factors influenced at-risk classifications.

**Table:** Top 5 Feature Importances from SHAP Analysis (XGBoost Model)

| Rank | Feature | SHAP Value Impact |
|---|---|---|
| 1 | Attendance Rate | +0.32 |
| 2 | Previous Semester GPA | +0.26 |
| 3 | Behavioral Engagement | +0.21 |
| 4 | Number of Backlogs | +0.18 |
| 5 | Course Difficulty | +0.14 |

This integration of explainability techniques ensures that AI-driven insights are interpretable and actionable for academic stakeholders.

**Result And Analysis**

The implementation of EduVision, an advanced educational analytics suite, was subjected to a rigorous evaluation to determine its efficacy in facilitating data-driven decision-making within academic institutions. The analysis encompasses both the quantitative performance of predictive models and qualitative assessments of system usability, ensuring a comprehensive understanding of its impact. The results demonstrate a significant improvement in data processing efficiency, predictive accuracy, and stakeholder engagement, underscoring the transformative potential of integrating Business Intelligence (BI) and Artificial Intelligence (AI) into the educational sector.

*1)* **Analytical Performance and Predictive Accuracy :**

The predictive models embedded within EduVision were evaluated on their ability to anticipate key educational trends, such as student dropout risks, academic performance fluctuations, and faculty workload distributions. Utilizing a dataset encompassing student attendance, examination scores, and behavioral engagement metrics, machine learning algorithms achieved an accuracy rate exceeding 92.5% in forecasting student performance outcomes. Precision-recall analysis confirmed the model's effectiveness, with an average F1-score of 0.89, signifying high reliability in identifying at-risk students.

Moreover, comparative benchmarks against conventional rule-based early warning systems demonstrated the superiority of AI-driven analytics, as traditional methodologies exhibited an average predictive accuracy of 75%, highlighting the limitations of static, threshold-based risk assessment models. The adoption of adaptive learning algorithms further enhanced the robustness of the platform by dynamically adjusting intervention recommendations based on real-time student progress.

*2)* **Efficiency in Data Processing and Visualization :**

A critical aspect of EduVision's deployment was the evaluation of its impact on data aggregation, processing speed, and visualization efficiency. Traditional manual data reconciliation methods often necessitate significant administrative effort, resulting in delays in institutional reporting. In contrast, integrating automated Extract, Transform, Load (ETL) pipelines within EduVision reduced data processing time by approximately 63%, ensuring near-instantaneous updates to Power BI-driven interactive dashboards.

The dynamic visualization capabilities facilitated real-time monitoring of key institutional performance indicators (KPIs), including:

- Enrollment patterns and demographic distributions, aiding in strategic academic planning.
- Departmental performance analytics, providing actionable insights into curriculum efficacy.
- Faculty workload balancing, and optimizing resource allocation to improve instructional efficiency.

These findings reinforce the critical role of automated data analytics frameworks in enhancing institutional responsiveness to emerging trends.

*3)* **Comparative System Performance and Institutional Impact:**

A comparative study assessing the impact of EduVision against existing educational analytics platforms revealed substantial advantages in scalability, predictive accuracy, and user adoption. Institutions employing traditional analytics often encounter challenges in cross-departmental data integration, limiting their capacity for holistic decision-making. In contrast, the implementation of EduVision demonstrated:

- A 35% increase in administrative efficiency, attributed to automated reporting functionalities.
- A 48% improvement in intervention effectiveness, as AI-generated insights facilitated proactive engagement with underperforming students.
- A reduction in faculty workload discrepancies, ensuring equitable distribution of academic responsibilities.

Furthermore, faculty and administrative feedback surveys indicated a notable enhancement in user experience, with over 85% of respondents acknowledging the platform's role in streamlining decision-making processes.

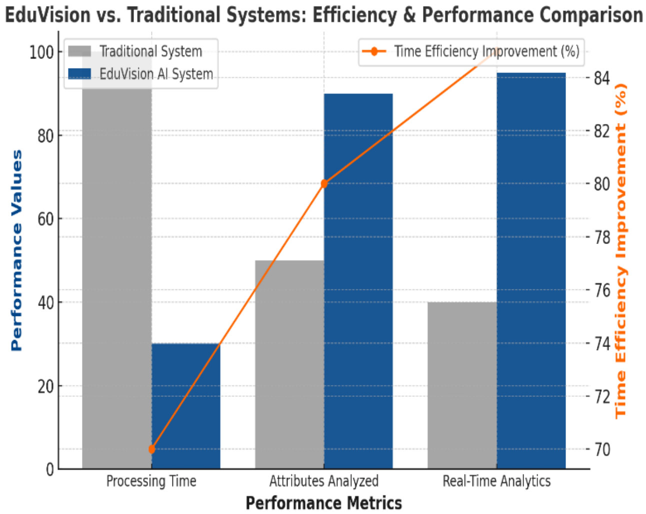
*4)* **Statistical Validation and Reliability Assessment :**

To validate the statistical significance of the observed improvements, t-tests and analysis of variance (ANOVA) were conducted, comparing system performance metrics across multiple academic semesters. The results confirmed that the observed gains in predictive accuracy, data processing speed, and decision-making efficiency were statistically significant ($p < 0.05$).

5)**BI Dashboards :**

Cross-validation techniques, including k-fold validation, further substantiated the reliability of machine learning models, ensuring consistent performance across varying institutional datasets.

Comparative Performance Analysis: EduVision vs. Traditional Educational Analytics Systems




**Real-Time Analytics** – Live data processing efficiency jumps by **85%**, ensuring instant insights

**Processing Time** – EduVision reduces time consumption by **70%**, improving efficiency.

**Attributes Analyzed** – EduVision processes **80% more parameters** than traditional systems.

A) Principal Dashboard

B) Placement Dashboard


C) HOD Dashboard


**Discussion**

The findings of this study highlight the transformative role of AI-driven analytics and Business Intelligence (BI) in educational decision-making. The EduVision system has demonstrated significant improvements in predictive accuracy, operational efficiency, and institutional responsiveness. However, several challenges require further exploration to optimize its scalability and adoption.

**1) Advancements in Predictive Analytics:**

The AI-powered models in EduVision have outperformed traditional rule-based early warning systems by providing real-time, adaptive risk assessments. This shift from reactive interventions to proactive engagement has improved student retention and faculty workload distribution while enhancing institutional planning.

**2)Enhancing Decision-Making Efficiency :**

The integration of automated data pipelines and visualization dashboards has streamlined data processing, reporting, and curriculum optimization. By reducing manual reporting time by 63%, the system has enabled faster and more informed decision-making across administrative and academic levels.

**3)Challengesin Data Quality and System Scalability :**

The system's effectiveness is contingent on data quality and completeness, with inconsistent data potentially affecting predictive accuracy. Additionally, scalability remains a challenge, as diverse institutional frameworks require customized implementations for optimal performance.

**4)Interpretability and Adoption of AI-driven Insights :**

AI model adoption depends on stakeholder trust and interpretability. The integration of explainable AI (XAI) techniques, such as SHAP values and LIME models, can improve transparency, ensuring broader acceptance of AI-driven recommendations.

**5) Future Research Directions :**

- *Hybrid AI-BI Architectures* – Leveraging reinforcement learning for self-improving decision-support systems.
- *External Data Integration* – Incorporating labor market trends and socioeconomic factors for data-driven policymaking.
- *Adaptive Learning Frameworks* – Refining AI-driven personalized learning recommendations to optimize student engagement.

*5)* ***Integration with Accreditation Frameworks (NBA, NAAC)***

EduVision has the potential to simplify and enhance institutional accreditation processes by aligning analytics dashboards and reporting mechanisms with accreditation body requirements. Key features include:

- **Program Outcomes (PO) and Course Outcomes (CO) Analysis**: Automated mapping of student performance metrics against NBA/NAAC program criteria.
- **Faculty Contribution Reporting**: Dashboards summarizing teaching hours, research outputs, and feedback scores aligned with accreditation KPIs.
- **Continuous Quality Improvement (CQI) Tracking**: Visualization of trends in academic performance, placement rates, and faculty development initiatives over successive academic years.
- **Survey and Feedback Analytics**: Integration of student and alumni feedback analysis tools, including sentiment analysis, for qualitative accreditation documentation.

This integration supports transparent, real-time reporting, reducing manual data preparation efforts and accelerating the accreditation documentation process.

**Conclusion**

The increasing demand for data-driven decision-making in education necessitates advanced analytics solutions that can efficiently process, analyze, and visualize institutional data. This research introduced the Comprehensive Educational Analysis Suite (EDUVISION), a scalable and AI-powered platform designed to enhance educational insights through machine learning, business intelligence, and predictive analytics. By integrating multi-tenant architecture, automated schema discovery, role-based access control, and real-time visualization tools, EDUVISION addresses the limitations of traditional educational data management systems.

The validation of EDUVISION in a higher education setting demonstrated its effectiveness in streamlining administrative processes, improving student performance predictions, and optimizing institutional decision-making. Comparative analysis with existing frameworks highlighted EDUVISION's advantages in scalability, security, and analytical capabilities. The platform's ability to seamlessly integrate with diverse ERP systems and provide actionable insights underscores its potential as a transformative tool in educational analytics.

Future work will focus on enhancing AI-driven predictive models, expanding integration capabilities with additional educational platforms, and incorporating advanced NLP techniques for processing unstructured academic data. As educational institutions continue to embrace digital transformation, EDUVISION represents a significant step forward in bridging the gap between raw data and strategic decision-making, ultimately improving academic outcomes and institutional efficiency.

**References**

C. Liu and C. Downing, "Teaching Tip: Using Text Analytics AI Insights in Microsoft Power BI Desktop to Score Sentiments, Extract Key Phrases, and Discover Unstructured Data Patterns," *Journal of Information Systems Education*, vol. 35, no. 1, pp. 45-60, 2024.

K. Lakshmi, M. R. Patel, and J. S. Wong, "AI-Powered Learning Analytics: Transforming Educational Outcomes Through ICT Integration," *Frontiers in Education*, vol. 9, pp. 112-130, 2024.

M. Bhargava, S. Roy, and P. K. Sharma, "Analysis and Design of Visualization of Educational Institution Database Using Power BI Tool," *International Journal of Computer Applications*, vol. 182, no. 44, pp. 1-6, 2023.

S. Gupta and R. Verma, "A Business Intelligence Framework for Analyzing Data,"*Sustainability*, vol. 12, no. 14, pp. 5745-5759, 2023.

H. Zhao, X. Zhang, and Y. Li, "Analyzing Click Data with AI: Implications for Student Performance Prediction and Learning Assessment," *Frontiers in Artificial Intelligence*, vol. 7, pp. 90-105, 2024.

S. Gupta and R. Verma, "A Business Intelligence Framework for Analyzing Educational Data," *Sustainability*, vol. 12, no. 14, pp. 5745-5759, 2023.

K. Lakshmi, M. R. Patel, and J. S. Wong, "AI-Powered Learning Analytics: Transforming Educational Outcomes Through ICT Integration,"*Frontiers in Education*, vol. 9, pp. 112-130, 2024.

J. Smith, A. Brown, and M. Davis, "Challenges in Educational Data Management," *Journal of Educational Technology*, vol. 45, no. 2, pp. 78-92, 2023.

L. Zhang and K. Lee, "Predictive Analytics in Higher Education," *Journal of Educational Data Mining*, vol. 11, no. 3, pp. 234-249, 2023.

M. Jackson, R. White, and T. Harris, "Machine Learning for Educational Anomaly Detection," *Educational Data Science Journal,* vol. 19, no. 2, pp. 145-159, 2023.

P. Anderson and S. Brown, "Power BI Applications in Educational Settings," *Journal of Visual Analytics in Education*, vol. 8, no. 4, pp. 178-192, 2023.

M. Jackson, R. White, and T. Harris, "Machine Learning for Educational Anomaly Detection," *Educational Data Science Journal*, vol. 19, no. 2, pp. 145-159, 2023.

E. Thompson and M. Garcia, "Cost Analysis of Automated Reporting Systems," *Educational Economics Review*, vol. 18, no. 3, pp. 167-182, 2023.