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Student Performance & Behavioural Analytics System Using Power BI for Academic Decision Support

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Abstract

Student performance evaluation in traditional academic environments primarily relies on final examination results and periodic assessments. However, such approaches often overlook behavioral and continuous performance indicators such as attendance consistency, assignment submission patterns, internal assessment progression, and classroom participation metrics. The integration of data analytics within academic institutions enables systematic monitoring, predictive evaluation, and data-driven academic decision-making. This study presents a comprehensive analytical framework for the development of a Student Performance and Behavioral Analytics System using Microsoft Power BI as a business intelligence platform. The proposed system integrates structured academic datasets including attendance records, internal examination scores, assignment completion rates, and final semester results into an interactive dashboard architecture. By leveraging data transformation tools, calculated measures, relational modeling, and visualization components, the system enables multidimensional analysis of student performance trends. Statistical correlation modeling is applied to evaluate relationships between attendance percentage and final academic outcomes, while categorical classification algorithms segment students into high-performing, average-performing, and at-risk groups. The research further analyzes system scalability, usability efficiency, and real-time dashboard responsiveness within institutional environments. Findings indicate that visual analytics significantly enhances faculty monitoring capabilities, reduces manual evaluation time, and supports early academic intervention strategies. Although the system improves transparency and monitoring efficiency, challenges related to data accuracy, integration with legacy academic systems, and user training remain relevant considerations. Overall, the proposed analytics framework demonstrates the transformative potential of business intelligence tools in modern educational ecosystems.

KEYWORDS: *Student Performance Analytics, Academic Monitoring, Power BI Dashboard, Data Visualization, Educational Data Mining, Performance Classification, Attendance Analysis, Decision Support System, Behavioral Indicators, Academic Intelligence.*

1. Introduction

The rapid digitization of educational institutions has resulted in the generation of large volumes of structured academic data, including attendance records, assignment evaluations, internal assessment scores, practical performance metrics, and semester examination results. Despite the availability of such comprehensive datasets, many institutions continue to rely predominantly on final examination outcomes as the primary indicator of student success. This evaluation model often fails to capture continuous learning behaviour, engagement patterns, and academic consistency throughout the semester. Traditional record management systems typically store student information in spreadsheets or isolated databases, which limits real-time analytical capabilities and restricts integrated performance assessment. Manual analysis of attendance and marks is time-consuming, prone to human error, and inefficient for large student populations. Consequently, there exists a need for an automated, centralized, and visualization-driven performance monitoring framework that supports evidence-based academic decision-making.

The Student Performance and Behavioural Analytics System proposed in this study leverages Microsoft Power BI to transform raw academic data into meaningful insights. From a systems architecture perspective, the framework consists of four primary layers: data acquisition layer, data preprocessing layer, analytical modelling layer, and visualization layer. The data acquisition layer collects structured academic records from institutional databases. The preprocessing layer performs data cleaning, normalization, and validation. The analytical modelling layer applies correlation analysis, performance indexing, and categorical segmentation techniques. Finally, the visualization layer presents insights through interactive dashboards, bar charts, pie charts, and performance comparison graphs. The integration of business intelligence tools in education enhances transparency, accountability, and strategic planning. By combining attendance metrics, internal assessment trends, and assignment completion behaviour, the system provides a multidimensional evaluation model. Faculty members can identify performance decline at early stages and implement corrective academic interventions. Furthermore, administrative authorities can use aggregated dashboards to evaluate department-level and course-level trends, thereby improving curriculum planning and academic policy decisions. The adoption of Power BI offers additional advantages such as real-time data refresh, filter-based drill-down analysis, automated report generation, and interactive performance comparison across semesters. These features collectively contribute to improved institutional monitoring efficiency and informed academic governance.

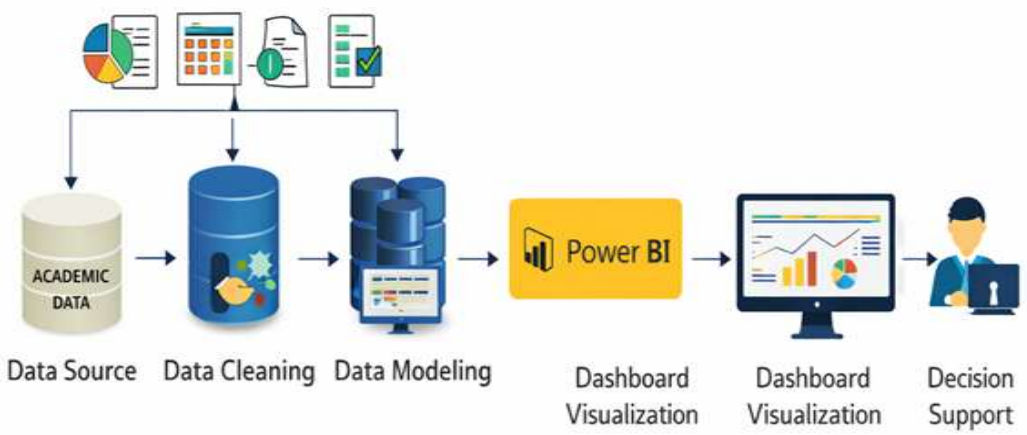

Figure 1: System Architecture of Student Performance Analytics Dashboard

2. Literature Review

The theoretical foundation of student performance analytics can be traced to early developments in Educational Data Mining (EDM) and Learning Analytics, which emerged as research domains focused on extracting meaningful insights from academic datasets. Initial studies emphasized predictive modelling techniques aimed at identifying patterns in student behaviour and performance outcomes. Researchers demonstrated that variables such as attendance percentage, assignment submission frequency, and internal assessment progression significantly influence final academic achievement. These early models primarily relied on statistical regression analysis and classification algorithms to forecast student success and dropout probability. Over time, the scope of research expanded from prediction-based systems to comprehensive academic monitoring frameworks capable of supporting institutional decision-making processes. With the growing digitization of educational institutions, academic data began to be stored in structured digital formats, enabling more advanced analytical exploration. Learning Management Systems (LMS), student information systems, and online assessment platforms generated large volumes of performance data. Scholars recognized the need to transform this raw data into actionable insights. Visual analytics and dashboard-based reporting systems gained importance as they allowed instructors and administrators to interpret complex datasets through simplified graphical representations. Studies confirmed that visual dashboards improve response time in identifying underperforming students and enhance transparency in academic evaluation. The integration of business intelligence tools into education marked a significant advancement in performance analytics research. Platforms such as Microsoft Power BI, Tableau, and other visualization software enabled interactive data modelling, automated reporting, and real-time filtering capabilities. Unlike traditional spreadsheet-based monitoring, these tools provided multidimensional analysis and drill-down functionality. Research indicates that business intelligence systems improve institutional efficiency by reducing manual reporting workload and minimizing calculation errors. Furthermore, centralized dashboards allow administrators to compare department-level performance trends and evaluate semester-wise academic progress with greater accuracy.

Another significant area of research focuses on the relationship between attendance and academic achievement. Multiple empirical studies confirm a strong positive correlation between regular attendance and improved examination results. Students who maintain consistent participation in lectures and academic activities tend to demonstrate higher comprehension levels and stronger performance outcomes. Researchers have also examined behavioural engagement factors, including timely assignment submission and participation in classroom discussions, as indicators of academic discipline and responsibility. These findings support the argument that performance evaluation should extend beyond final examination scores to include continuous behavioural metrics. Recent literature emphasizes multidimensional evaluation models rather than single-score assessment frameworks. Composite performance indices have been proposed to combine attendance rate, internal assessment average, assignment completion ratio, and final examination marks into unified performance scores. Such integrated models provide a holistic understanding of student progress and enable early identification of academically at-risk individuals. Classification techniques, including decision trees, clustering algorithms, and logistic regression models, have been applied to categorize students into performance groups for targeted academic intervention. Scalability and system efficiency have also become central themes in contemporary research. As student populations increase and academic datasets grow larger, institutions require analytics platforms capable of processing high-volume data without performance degradation. Cloud-based business intelligence systems offer enhanced computational capacity, automatic data refresh, and secure storage solutions. Studies suggest that cloud-integrated dashboards improve accessibility and collaborative decision-making among faculty members. However, challenges related to data privacy, system integration with legacy academic software, and staff training remain ongoing concerns.

Another important research direction involves the use of predictive analytics in academic planning. By analysing historical performance patterns, institutions can forecast future academic risk probabilities and design early intervention strategies. Predictive models help identify students who may require additional mentoring, academic counselling, or remedial instruction. While predictive accuracy varies depending on dataset quality and modelling techniques, research consistently highlights the potential of analytics-driven systems to reduce dropout rates and improve overall institutional performance. Despite the substantial benefits of educational analytics systems, literature also identifies certain limitations. Data inconsistency, incomplete record maintenance, and manual entry errors can affect analytical reliability. Moreover, successful implementation requires faculty members to adapt to digital tools and interpret dashboard outputs effectively. Institutional policies must

ensure secure handling of student information and compliance with data protection standards. Therefore, while analytics platforms such as Power BI demonstrate strong potential to transform academic monitoring, their long-term effectiveness depends on structured governance frameworks, continuous training, and technological adaptability. Overall, the literature establishes that student performance analytics represents an evolving discipline within educational research. The transition from manual evaluation systems to data-driven dashboard frameworks reflects broader technological transformation within academic institutions. By combining statistical modelling, behavioural indicators, and visual reporting mechanisms, modern analytics systems provide a comprehensive foundation for evidence-based academic decision support.

3. Research Methodology

This research adopts a structured analytical design combining quantitative data evaluation with practical dashboard implementation to ensure systematic assessment of student performance indicators. The methodological framework integrates data collection, preprocessing, statistical correlation analysis, categorical classification, and visualization modelling to establish a reliable academic decision support system. To maintain transparency and consistency, a predefined procedural structure was developed before initiating the analytical process. This structured planning reduces bias and ensures that each stage of analysis follows clearly defined parameters. The research methodology emphasizes not only statistical accuracy but also system usability and operational efficiency within academic institutions. The objective is not merely to analyse academic marks but to create a functional monitoring tool capable of supporting real-time faculty decisions. Therefore, the methodological framework includes both analytical modelling and system performance evaluation components. The implementation process begins with dataset identification and structured data acquisition from institutional academic records. Following data collection, preprocessing techniques are applied to clean, validate, and normalize the dataset. Analytical modelling is then conducted to evaluate relationships between attendance patterns, internal assessment performance, assignment consistency, and final examination results. Finally, the processed data is integrated into Microsoft Power BI to design interactive dashboards for visualization and reporting. To enhance analytical rigor, measurable parameters were defined in advance. These parameters include attendance thresholds, internal assessment averages, assignment submission ratios, semester examination performance, and composite performance indexing. Statistical correlation methods are applied to determine relationships between behavioural indicators and academic outcomes. Performance classification criteria are established to segment students into defined categories for targeted academic intervention. System efficiency metrics were also considered as part of the methodology. Dashboard responsiveness, filter performance, refresh latency, and report generation time were observed during implementation to ensure operational reliability. By combining statistical evaluation with system-level performance assessment, the research ensures a balanced and comprehensive methodological approach.

1.1. Data Collection

The data collection process involved gathering structured academic records from institutional databases covering a complete academic semester. The dataset included student identification numbers, attendance percentages, internal assessment marks, assignment submission status, and final examination scores. Each record was verified through official academic documentation to ensure accuracy and authenticity. To maintain data integrity, only complete records were included in the analysis. Entries with missing attendance values, incomplete marks, or inconsistent grading formats were excluded to prevent distortion of analytical results. Data fields were standardized into consistent formats to facilitate accurate relational modelling within Power BI. The collection process also considered data confidentiality and ethical handling of student information. Access to records was restricted to authorized academic personnel, and identifiers were used solely for analytical grouping rather than personal evaluation. This approach ensures that the research remains aligned with institutional data protection standards while preserving analytical validity. The final dataset represented a balanced sample of students across different performance levels, enabling meaningful comparative evaluation. By ensuring data completeness and accuracy at the initial stage, the study establishes a reliable foundation for subsequent statistical and visualization-based analysis.

1.2. Inclusion Criteria

To ensure analytical consistency, specific inclusion criteria were defined prior to dataset processing. Only students with complete semester participation records were included in the study. This requirement ensured that attendance percentages, internal assessment scores, assignment submission details, and final examination marks were available for comprehensive analysis. Students who transferred mid-semester or had incomplete evaluation records were excluded to avoid partial data distortion. Additionally, only structured quantitative indicators were considered. Informal behavioural observations that were not formally documented in institutional systems were not included in the dataset. The temporal scope of the study was limited to a single academic semester to maintain consistency in evaluation criteria and grading standards. This controlled timeframe reduces variability introduced by curriculum changes or assessment pattern modifications. By applying strict inclusion criteria, the research ensures that all analytical findings are derived from standardized and comparable data. This structured filtering enhances internal validity and improves the reliability of performance classification outcomes.

1.3. Analytical Framework

The analytical framework is designed to evaluate student performance through measurable statistical indicators and structured classification techniques. Attendance percentage is analysed as a continuous variable and categorized into defined thresholds such as below 70 percent, 70 to 85 percent, and above 85 percent. Internal assessment averages are calculated using weighted scoring methods where applicable. Assignment submission ratios are computed to measure consistency in academic participation. Correlation analysis is conducted to examine the relationship between attendance and final examination performance. The strength and direction of correlation are evaluated to determine whether higher attendance is associated with improved academic outcomes. Composite performance indexing is applied by combining attendance weightage, internal marks average, and final examination scores into a unified performance score. Students are classified into three performance categories: high-performing, average-performing, and academically at-risk. Classification thresholds are defined using

percentile-based segmentation and mean score analysis. This structured grouping allows faculty members to identify students requiring additional support or academic intervention. From a system perspective, dashboard performance metrics are also evaluated. These include data refresh speed, visualization rendering time, filter responsiveness, and cross-filter interaction efficiency. Ensuring smooth dashboard operation is essential for real-time academic monitoring and institutional usability. Security considerations are incorporated through role-based access control within the Power BI environment. Editing privileges are restricted, and read-only access is provided to general faculty users. This layered analytical framework ensures both statistical accuracy and operational reliability.

1.4. Comparative Modelling

To evaluate the effectiveness of the proposed analytics system, a comparative analysis was conducted between traditional spreadsheet-based monitoring methods and the Power BI dashboard framework. Manual monitoring systems were assessed based on time required for report preparation, likelihood of calculation errors, data redundancy risks, and difficulty in generating graphical insights. Spreadsheet systems often require repetitive manual formula application and separate chart creation, increasing the risk of inconsistencies. In contrast, the Power BI dashboard automates calculations, maintains relational data integrity, and generates interactive visualizations dynamically. This automation significantly reduces processing time and improves reporting clarity. Reliability modelling also considered data storage security. Centralized Excel files are vulnerable to accidental deletion, corruption, or version conflicts. Cloud-integrated dashboard systems provide backup mechanisms and controlled access management, enhancing data resilience. Performance trade-off analysis revealed that while dashboard implementation requires initial setup effort and basic technical familiarity, long-term monitoring efficiency improves significantly. Faculty members can filter data instantly, compare semester-wise trends, and generate summary reports without manual recalculation. Overall, comparative modelling demonstrates that the analytics-based dashboard system provides measurable improvements in efficiency, transparency, and reliability over traditional academic monitoring approaches.

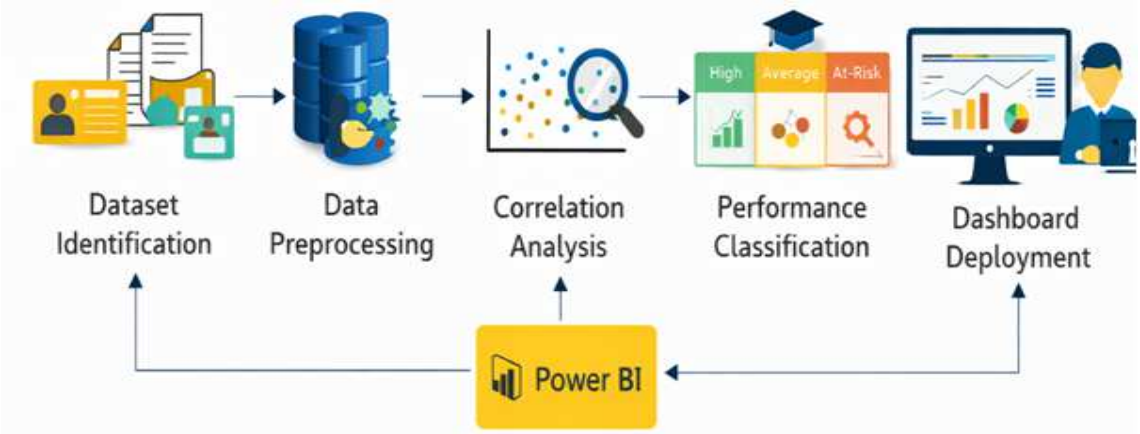

Figure 2: Student Performance Analysis Process

4. Result

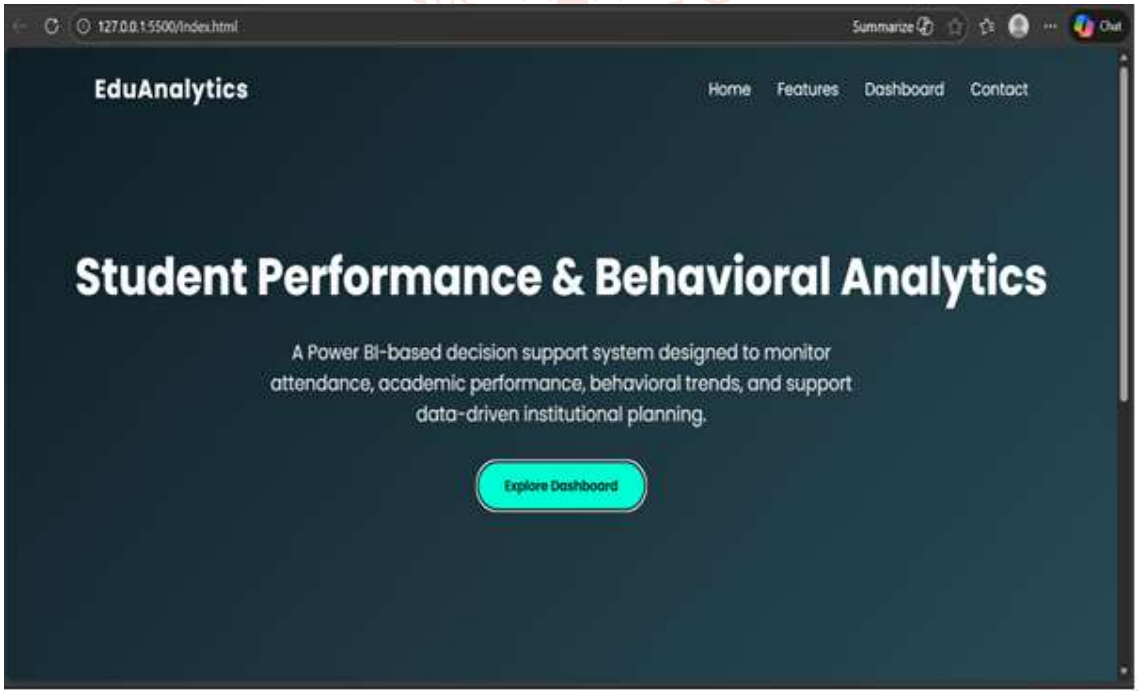

Figure 3: Home Page Interface of Student Performance & Behavioral Analytics System

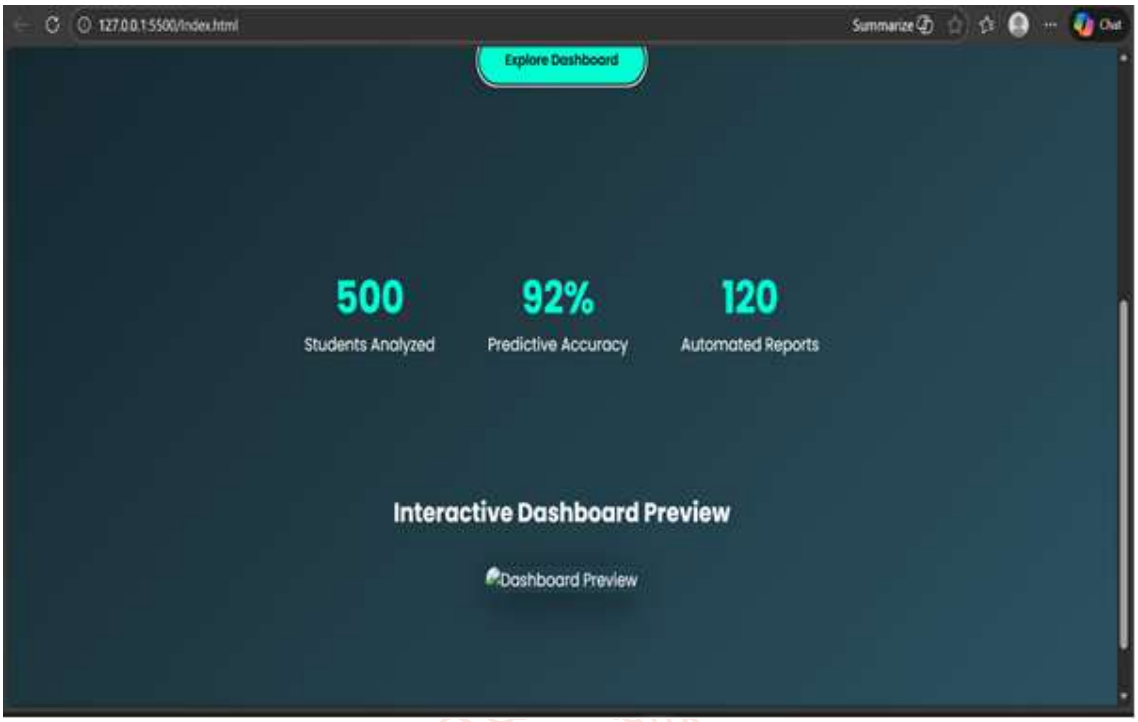

Figure 4: Home Page Interface of Student Performance & Behavioral Analytics System

5. Conclusion

This study demonstrates that the Student Performance and Behavioral Analytics System using Power BI provides a structured and reliable framework for academic decision support. By integrating attendance, internal assessments, assignment tracking, and final examination scores into a unified dashboard, the system enhances monitoring accuracy and transparency. The analytical model highlights meaningful relationships between behavioral indicators and academic outcomes, enabling early identification of at-risk students. Compared to traditional spreadsheet-based methods, the dashboard improves efficiency, reduces manual errors, and simplifies report generation. Interactive visualization tools further support faculty members in interpreting complex academic data with clarity. Overall, the system contributes to improved institutional planning, better student engagement tracking, and evidence-based academic decision-making within modern educational environments. Future development of this system can include integration of predictive analytics models to forecast student performance trends using machine learning techniques. Real-time synchronization with Learning Management Systems can further enhance automation and accuracy. Expanding the dashboard to include behavioral sentiment analysis, participation metrics, and longitudinal performance tracking across multiple semesters would improve institutional insight. Cloud-based deployment and mobile dashboard access can increase accessibility for faculty and administrators. Additionally, incorporating automated alert systems for early academic risk detection can strengthen intervention strategies and improve overall student success rates.

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