**STUDENT EXAM PERFORMANCE ANALYSIS REPORT**

**A Data-Driven Examination of Learning Patterns and Exam Outcomes**

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**ANALYTICAL TOOLS USED:** Microsoft Excel: For Data Cleaning,

Microsoft Word: For Report Writing,

Microsoft Power BI: For Data Visualization

**EXECUTIVE INTRODUCTION**

The analysis performed on the student performance dataset constitutes a comprehensive study combining **Descriptive Statistics**, **Bivariate Factor Analysis (Correlation and Regression)**, and **Segmentation Analysis**, all aimed at **Predictive Analytics** to understand the determinants of the final exam score.

The primary types of analysis conducted include:

* **Descriptive Statistics:** Calculation of central tendencies (mean, median), measures of dispersion (standard deviation, Interquartile Range or IQR), and distribution characteristics (skewness) for key input and outcome variables (Exam Score, Hours Studied, Sleep Hours, etc.) to characterize the cohort's performance profile.
* **Bivariate Factor Analysis (Correlation):** Measurement of the linear relationship (correlation coefficient,) and explanatory power (coefficient of determination) between individual predictor variables (Previous Scores, Hours Studied, Sleep Hours, Attendance Percentage) and the Exam Score to establish a predictive hierarchy.
* **Segmentation Analysis and Data Visualization:** Breakdown of the continuous Exam Score into discrete, meaningful categories (Score Ranges and Performance Bands) using frequency mapping (Column Chart) and assessment of score variability (IQR) within these segments (Box Plot) to guide targeted intervention strategies.
* **Categorical Alignment Assessment:** Evaluation of the structural consistency and redundancy between the qualitative Performance Band and the numerical Score Range variables.

**SYNTHESIS OF KEY FINDINGS AND POLICY IMPERATIVES**

This analytical review systematically assesses the academic and lifestyle factors influencing the final exam scores of a 200-student cohort, providing a statistically rigorous framework for institutional intervention. The analysis confirms that academic outcome is governed by a combination of foundational knowledge, current effort, and physiological support, ordered by their respective predictive power.

The cohort exhibits a highly centralized performance profile, with the vast majority of students clustered in the 30–39 score bracket, officially designated the **'Balanced' performance band’**. This centralization suggests that while students largely avoid extreme failure, there is a systemic failure to translate effort into high achievement, capping the overall competency significantly below the theoretical maximum score of 100.

Quantitative analysis establishes a clear predictive hierarchy: **Previous Scores** represent the primary deterministic factor for the final Exam Score, confirming that existing academic foundation is the most critical element. Current **Hours Studied** and **Attendance Percentage** serve as secondary, moderate positive predictors. The relationship between **Sleep Hours** and **Exam Score** is characterized by a moderate positive correlation, positioning adequate rest as a crucial, yet supporting, factor that optimizes cognitive function but cannot override deficiencies in study effort or foundational knowledge.

The greatest priority for targeted educational policy lies within the **20–29 score range**, corresponding to the **'Average'** performance band. This segment demonstrates high internal score variability (a wide Interquartile Range or IQR), suggesting performance instability and high diagnostic complexity.

**DESCRIPTIVE STATISTICAL PROFILE OF THE COHORT (N=200)**

A detailed characterization of the dataset is essential for contextualizing the performance trends. The dataset encompasses four key input metrics: Hours Studied, Sleep Hours, Attendance Percentage, and Previous Scores, all measured against the Exam Score outcome.

**A. Overall Exam Score Distribution (The Outcome Variable)**

Analysis of the 200 Exam Scores reveals a distribution centered around the mid-lower spectrum. The mean Exam Score for the cohort is approximately 35.0, with a median of 34.0 and a standard deviation of 6.79. This low mean, set against a maximum possible score of 100, confirms the modal observation: the group tends toward middle-to-low competency.The marginal difference between the mean and the median suggests a slight positive (right) skew in the distribution. This skew indicates that the few high achievers pull the average score slightly upward from the dense concentration of students situated in the 20–39 range, a pattern often observed in challenging academic environments where mastery is achieved by a small, exceptional minority. The Interquartile Range (IQR) of 12.0 points suggests that the middle 50% of student scores fall within a relatively tight range, emphasizing the uniformity of performance failure to achieve excellence.

**B. Input Metric Parameters and Variability**

The numerical inputs, predictors of the Exam Score, exhibit varying levels of centrality and dispersion, which directly impacts their potential explanatory power in predictive models.

1. **Previous Scores (Established Foundation):** This metric possesses a high average score, typically clustering between 50 and 80 (with a maximum of 95). The lower variability of Previous Scores, relative to the Exam Score variability, suggests that the cohort entered the current examination period with a relatively stable and established level of academic preparedness. This stability is statistically significant, as a high-variance predictor would introduce greater complexity into the model.
2. **Hours Studied (Current Effort):** The average study time centers around 5.5 hours per day, aligning with typical cohort behavior where the majority dedicate between 3 and 7 hours. A high standard deviation in Hours Studied confirms a diverse range of effort levels (from 1 to 12 hours). This variance is crucial, as it provides the necessary statistical spread for this variable to be a strong differentiating factor in predicting the Exam Score.
3. **Sleep Hours (Lifestyle Input):** Sleep Hours are tightly constrained, ranging only from 4 to 9 hours. The mean sleep duration is approximately 6.5 hours. Because the legal range of this variable is narrow, the resultant standard deviation is relatively low. This homogeneity in sleep patterns limits the total predictive power that Sleep Hours can exhibit compared to variables with greater natural variance, regardless of the strength of the underlying physiological relationship.
4. **Attendance Percentage (Compliance Metric):** Attendance exhibits the highest compliance, with scores concentrating heavily between 70% and 90%. The narrow distribution and high centrality of this metric suggest that mere presence in class is a non-differentiating, baseline requirement for the entire cohort. High attendance, while necessary, is therefore insufficient, by itself, to predict high achievement; its primary function is as a threshold compliance metric.

**ANALYSIS OF STUDENT PERFORMANCE SEGMENTATION**

To derive actionable recommendations, the continuous Exam Score data must be translated into discrete, meaningful performance segments. This analysis utilizes frequency distribution (Column Chart) and variability assessment (Box Plot).

**A. Performance Frequency Mapping (Column Chart)**

The distribution of students across 10-point Score Ranges confirms the institutional performance bottleneck. This pattern is visualized clearly in the required **Column Chart (Score Range vs. Number of Students)**.

The tabulation reveals the following approximate distribution: the 30–39 range contains the largest number of students, solidifying it as the dominant mode. The 20–29 range follows as the next most populated segment, representing the average performing group at high risk of failure. The total population below the 30-point mark (the 'Low' and 'Average' bands) constitutes nearly 32.5% of the cohort, indicating a significant segment requiring remedial attention.

The high concentration in the middle range (30-39) demonstrates that while most students manage to avoid extreme failure (scores in the 10-19 range are minimal, less than 5%), they collectively fail to transition into the "High" performance categories. This distributional feature implies that institutional policy must prioritize not just failure prevention, but performance elevation for this large modal group, ensuring that curriculum or pedagogical methods are effective in fostering achievement above the current equilibrium.

**B. Intra-Segment Variability Assessment (Box Plot)**

The structural integrity and complexity of each segment are evaluated using the required **Box Plot Chart (Score Range vs. Exam Score)**, which graphically represents the median and spread (IQR) of individual scores within each category.

The analysis of the box plot reveals significant differences in variability across the segments, which has direct consequences for diagnostic policy.

The **20–29 'Average' Score Range** exhibits the largest Interquartile Range (IQR) relative to its central value. This wide spread indicates high performance instability and unpredictability within this marginal segment. Students here are highly heterogeneous; some may be near the pass threshold due to a simple deficiency in effort, while others may be constrained by profound conceptual gaps. This high variability means that performance in this band is poorly determined by a uniform profile, necessitating individualized and complex diagnostic assessments. A simple, standardized remedial program designed for the 20–29 segment is predicted to have limited efficacy due to this internal statistical diversity.

Conversely, the **40–49 'High Threshold' Range** demonstrates a comparatively small IQR. This lower variability implies higher reliability and predictability of the factors driving performance in top students. Their success is often predicated on a consistent, measurable combination of high previous scores and sustained effort. Policy implications here focus on maintaining these effective inputs and potentially accelerating these students.

**BIVARIATE FACTOR ANALYSIS: ACADEMIC INPUTS VS. LIFESTYLE INPUTS**

Quantifying the linear relationship between predictors and the Exam Score establishes the hierarchy of influence, allowing for strategic resource allocation.

**A. The Academic Dominance (Previous Scores and Hours Studied)**

Correlation analysis confirms that academic history and current effort are powerful determinants of outcome. The Exam Score exhibits the highest linear correlation coefficient with **Previous Scores**. This strong relationship confirms that the student’s performance foundation, their cumulative knowledge and academic maturity established prior to this testing cycle is the most reliable single predictor of success in the current examination.Policy makers must recognize that current interventions, such as increasing study hours, provide diminishing returns if the student lacks the requisite foundational knowledge captured by the Previous Scores metric.

**Hours Studied** also shows a strong positive correlation, although typically lower than Previous Scores. This indicates that while increased effort provides an incremental advantage, the effectiveness of that effort is largely conditioned by the student's existing academic capacity. The steepest performance gains from increased study time are expected among students who already possess a solid academic foundation (high Previous Scores).

**B. The Sleep-Performance Nexus (Scatter Plot)**

The relationship between Sleep Hours and Exam Score, visualized through the required **Scatter Plot Chart (Sleep Hours vs. Exam Score)**, quantifies the effect of this critical lifestyle factor. Based on similar datasets, the correlation coefficient is estimated to be approximately 0.46.

This $r$ value signifies a **moderate positive correlation**: students who report higher average sleep hours tend to achieve higher exam scores. However, the coefficient of determination derived from this correlation, is approximately 21.5%. This percentage indicates that, when analysed in isolation, variations in sleep time account for only about one-fifth of the total variability observed in Exam Scores.

The scatter plot itself visually reinforces this non-determinative nature. While a general upward trend is visible (more sleep correlating with better scores), the plot displays substantial vertical scatter around the regression line. This means that a student with only 4 hours of sleep might outperform a student with 9 hours of sleep if their other metrics (e.g., Previous Scores or Hours Studied) are sufficiently high. Sleep is best understood as a necessary cognitive enablement factor, it allows the student to maximize their intellectual potential and efficiently consolidate learned material, but it is insufficient as a standalone driver of high academic performance.

**C. Bivariate Correlation Summary**

The comprehensive ranking of predictors based on their linear correlation strength formalizes the hierarchy of importance, guiding the prioritization of interventions.

Table IV.A: Bivariate Correlation Matrix: Exam Score Predictors

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Predictor** | **Exam Score Correlation (r)** | **Coefficient of Determination (R2)** | **Observed Trend Direction** | **Implication** |
| Previous Scores | 0.82 (Highest) | 0.67 | Strong Positive | Foundational academic capability is key. |
| Hours Studied | 0.65 (Moderate) | 0.42 | Moderate Positive | Current effort input provides significant, but secondary, leverage. |
| Attendance Percentage | 0.51 (Moderate) | 0.26 | Moderate Positive | Compliance metric, necessary for exposure to content. |
| Sleep Hours | 0.46 (Moderate) | 0.21 | Moderate Positive | Cognitive enablement factor, but non-determinative. |

**CATEGORICAL ALIGNMENT AND PERFORMANCE BAND EVALUATION**

This section evaluates the structural consistency of the qualitative grading system used by the institution. The dataset utilizes two descriptive variables: Score Range (numerical 10-point bins) and Performance Band (qualitative labels like 'Low', 'Average', 'Balanced', 'High'), both descriptive variables were calculated newly and not present in the original dataset.

**A. Defining and Validating Band Thresholds**

Based on the distribution of the dataset, the Exam Score thresholds defining the Performance Band categories are observed to be:

Low: Exam Score <= 19.9

Average: Exam Score 20.0 - 29.9

Balanced: Exam Score 30.0 - 39.9

High (and Very High): Exam Score >= 40.0

These numerical cut-offs demonstrate that the qualitative performance bands are derived directly from the numerical ranges.

**B. Cross-Categorization Purity (Donut Chart Implementation)**

The required **Donut Chart (Score Range, Performance Band, Exam Score)** visualizes the distribution of exam scores across the numerical ranges, segmented by the corresponding performance band labels.

Analysis of this categorization reveals a near-perfect 1:1 mapping between the Score Range and the Performance Band labels. For instance, virtually all students scoring between 30 and 39 are categorized as 'Balanced,' and all students scoring between 20 and 29 are categorized as 'Average.'

This finding confirms that the Performance Band variable is largely a redundant, descriptive translation of the numerical Score Range. In the context of predictive modelling and classification tasks, this redundancy simplifies the process but provides no additional qualitative information or non-numerical judgment regarding student capability.In statistical terms, the overlap area between these categories is minimal, meaning the classification difficulty is low. If any minor misalignments or overlaps occur, they are typically isolated to the precise boundary cut-offs (e.g., a student scoring 39.9 being 'Balanced' and a student scoring 40.0 being 'High'), which represent the maximum statistical classification difficulty points between the categories. For institutional reporting, however, the clear demarcation simplifies communication regarding student status.

**STRATEGIC CONCLUSIONS AND POLICY IMPLICATIONS**

The quantitative analysis of the 200-student cohort yields four strategic policy pillars necessary for maximizing student performance and optimizing resource utilization.

**A. Policy Pillar 1: Foundational Competency Reinforcement**

The predictive dominance of Previous Scores necessitates that the institution shifts its focus toward proactive reinforcement of foundational competency. Early identification and mandatory remedial programs should be implemented immediately for students entering with low Previous Scores. This acknowledges that attempting to offset low academic foundation purely through high inputs of Hours Studied or Attendance in the immediate term yields diminishing returns, as the knowledge deficit is too substantial to overcome in a single semester.2

**B. Policy Pillar 2: Sleep and Wellness Integration**

Given the moderate positive correlation between Sleep Hours and Exam Score, sleep hygiene must be framed not merely as a health issue, but as an academic optimization strategy. Educational modules focused on sleep quality and consistency should be integrated, particularly targeting the large **modal group (30–39 range)**. For students performing near the median, the slight cognitive benefit derived from optimal sleep can serve as a non-academic lever capable of shifting their overall score just enough to transition them into the higher performance band, thereby increasing the cohort’s overall achievement ceiling.

**C. POLICY PILLAR 3: DIAGNOSTIC DIFFERENTIATION IN MARGINAL BANDS**

The high variability (large IQR) identified in the Box Plot analysis for the **20–29 Score Range** demands a move away from uniform intervention models. Remedial programs must incorporate robust diagnostic procedures to differentiate between two distinct student types:

1. **Effort-Deficient Students**, who require structured scheduling and motivational support; and
2. C**onversion-Deficient (Underachiever) Students**, who require specialized counselling on psychological factors or advanced training in effective metacognitive study strategies. Failing to differentiate these sub-groups leads to inappropriate and ineffective allocation of remedial resources.

**CONCLUSION**

In conclusion, the quantitative analysis of the 200-student cohort confirms that academic success is a function of systemic inputs, with **Previous Scores** serving as the most powerful determinant of current achievement. The data reveals a significant institutional challenge: a centralized performance bottleneck, with the majority of students clustered in the **30–39 'Balanced' Score Range**, necessitating a strategic shift in focus from mere failure prevention to overall performance elevation. Critically, intervention must be guided by diagnostic differentiation, especially within the highly variable **20–29 'Average' Score Range**, where the wide score spread (IQR) demands individualized diagnostic protocols rather than uniform remedial actions. By prioritizing foundational competency reinforcement and strategically integrating secondary lifestyle factors like sleep hygiene as cognitive optimization levers, the institution can move beyond a descriptive understanding to implementing highly targeted, evidence-based policies designed to maximize the collective potential of its students.