A Study of Daily Routines and Their Effects on Student Achievement

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Abstract—In this project, we consider how daily habits of students, including the number of hours spent studying, number of sleeping hours, and number of social media hours, affect their performance at school. We used data from Kaggle covering these habits along with other facts like their gender, the quality of the internet, whether they have a job, and whether they participate in extracurricular activities. We followed a precise process to clean and sanitize the data to make it accurate and reliable. We developed an interactive Power BI dashboard to present important trends and associations, such as average study time, sleep duration, and examination scores. The students were classified in terms of their performance to study how different habits influence their results. The dashboard enables one to see how various behaviors are linked to learning success in various types of students. The research shows the importance of the balance between day-to-day activities and presents a good resource for students, instructors, and school administrators to find habits that support learning. Finally, the research seeks to assist in making more informed decisions using information that can pave way for healthier study habits and improved school outcomes.

Keywords—Academic habits, student performance, data analytics, sleep, study hours, Power BI, education dashboard.

I. INTRODUCTION

A. Background and Problem Statement

In today's fast-changing education environment, student success isn't just about being smart or having great teachers. Increasingly, individuals are becoming aware that a student's daily life—such as the way they spend their time, utilize their energy, and attend to their obligations—affects their performance at school significantly. This encompasses the number of hours they devote to studying, the amount of sleep they get every night, and the amount of time they spend on social media or other screen time.

These habits as a set influence how children attend, remain motivated, remember, and do well in school. Though increasingly people grasp this, there is a great gap between correctly calculating these relations and condensing them into a form amenable to understanding based on actual data. Earlier studies studied a single habit in isolation, and though they have failed to connect data on behavior, personal circumstances, and environment to monitor how lifestyle aspects influence and impact one another and learning and other factors and work and affect, studies based on actual data become imperative to answer involved queries like these: would a student by putting in three hours of studies and sleeping only for four hours perform better or worse than a student putting in fewer hours and sleeping longer? Does a student using social media websites a great deal behave differently for different batches, like girls compared to boys, or part-jobbers? These advanced queries necessitate studies based on actual data going beyond speculation and giving firm replies based on actual data.

This work is attempting to answer a few questions by using a dataset on Kaggle that informs us on how kids spend their time and how their grades are. It covers things like how much kids report studying per day, sleep time, and time on social media. It covers their test scores and other information like gender, quality of internet, if they work, and if they do extracurricular activities. These multiple variables not only let us observe how habits on a single day have impacts on work in academe, but also these sorts of things like what type of student and lifestyle a person runs on can alter these impacts. Considering all these variables, we can observe things from a plurality of different perceptive, like when sleep has different impacts on grades based on if a student's internet is good or bad or studying longer makes studying ineffectual if you work. This sort of research can be incredibly revealing in determining the risk factors for academic underperformance.

As these results are truly significant, the project is also one offering an easy and enjoyable way of presenting data. A Power BI dashboard was built to make day-to-day data interactive, so individuals can see quickly and easily whether or not there are patterns, trends, or correlations. This dashboard shows useful details such as how many students sleep and study, test results, and how many are placed into different performance ranks such as high, average, or poor. It also contains filters where users can explore their individual group based on gender, quality of internet, work status, and whether they do other activities or not.

The dashboard allows users to see how different habits and characteristics can impact academic performance. It is a tool for data analysis and decision-making. Teachers have useful information to assist their learners, learners can reflect and modify their habits, and policymakers are able to utilize their knowledge on behavior to support academic programs improvement. This work makes a contribution to data science in education by demonstrating how analysis of behavior can function within learning contexts.

B. Project Objectives

The ultimate objective of this work is to observe how day-by-day student habits—how many hours per day on studying, how many hours per day on sleeping, and how much time on social media—get converted into their test results. This work attempts to demonstrate these results clearly and comprehensively so that all individuals can easily grasp them. Focusing on working on observing how various habits translate into test outcomes, work attempts to find facts and actual trends out of actual data, not hypotheses. These results can aid learners, teachers, and education consultants in making better choices. In attempts to achieve this objective, work is divided into five broad portions that span all work stages on data, from obtaining information and arranging it, to making it easily comprehensible by using charts and graphs via a Power BI dashboard.

Data Cleaning and Preparation: Priority on the list was ensuring that the dataset was cleaned and uniform. Though data was a public dataset on Kaggle, it was quite a bit of work before going into analysis. This involved eliminating missing or corrupted data and altering some fields to the proper type of data. It was also enriched by infusing performance labels like high, average, or low, based on outcomes of exams, so data could be binned and trend comparisons could be made by comparing.

Exploratory Data Analysis (EDA): We made a thorough exploratory data analysis before creating any visualization models in such a way that we could understand key things about data and identify early patterns. We created basic summaries for time studied, time slept, time on social media, and test results and identified flagged stray data values and non-evenly divided data. These results allowed us to make decisions on variables to emphasize the dashboard and on which relationship would yield us the most revealing results.

Dashboard Design and Development: One of the main aspects of the work involves designing a basic and user-friendly Power BI Dashboard. It is used to view key measures of progress as well as scatter charts, pie charts, and special filters referred to as slicers. These enable users to view how various behavioral propensities relate to measures of progress in academic institutions. It enables users to view data in a stupendous number of various ways and enables comparing trends between various cohorts and behavioral cohorts.

Interactive Filtering and Segmentation: The dashboard includes tools that let users sort data by things like gender, internet quality, whether they have a part-time job, and if they participate in extra activities. This makes the solution more personalized, enabling more precise and relevant analysis based on each student's unique circumstances.

Insight Generation and Practical Application: The project also aims to develop valuable insights that assist both students and teachers in making informed decisions based on data. It identifies habits that are strongly linked to good academic performance, which can help improve students' study. These results also provide practical, research-backed ideas for enhancing academic support systems and creating more effective policies.

II. REPORT STRUCTURE

This report is organized in a manner that will lead the reader through every section of the data analytics project, which deals with students' habits and their performance in academics.

Section II gives a full description of the dataset, covering its origin, why it was chosen, and how the data was cleaned and prepared to make it precise and reliable.

Section III presents the findings of Exploratory Data Analysis (EDA). It contains basic statistics and easy-to-read charts illustrating how school performance is related to factors such as study time, hours of sleep, and social media usage.

Section IV discusses how the Power BI dashboard was developed. It includes the types of charts employed, how the data can be filtered by users, and the key figures (KPIs) that allow individuals to more easily comprehend the data and discover meaningful insights.

Section V covers the key findings from the dashboard. It examines trends between various groups, their levels of performance, and how their tendencies are interconnected. It also discusses how useful the dashboard is and any constraints in what it can display.

Section VI summarizes the major findings, provides evidence-based recommendations for students and educators, and suggests future directions for expanding the analysis or integrating additional behavioral and academic variables.

III. DATA DESCRIPTION AND PREPARATION

A. Data Source and Collection

The primary data for the project was obtained from Kaggle, a well-known data science and analytics website. The particular dataset that was utilized was titled "Student Habits vs Academic Performance." This dataset contains data that students provided about themselves, based on more than 1000 individuals. It addresses various aspects of their lives and how they perform in school. The data contains information such as the amount of studying they do, their sleeping habits, their online activities, and their exam performance. It also contains data on their gender, internet quality, if they have a part-time job, and whether they engage in school activities or not. All these factors make the dataset a suitable option for analyzing how the habits and decisions of students influence their school performance in a realistic and contemporary manner.

Data arrived in CSV format and was directly imported to data analysis and interactive dashboard tool Microsoft Power BI. Power BI is capable of reshaping data, creating new calculations, and building easily understandable charts. No additional data files were required since the first file contained complete data on student academic and behavioral outcomes. It made everything easier and ensured analysis was consistent by having a single clear-cut data set. Additionally, since data was stand-alone, it made it easy for us to observe how student personal habits—recorded by themselves alone and not by any assistance from schools—aligned with their academic progress. This was done by making it easy to have a goal of converting raw behavioral data into meaningful knowledge regarding education using a multipurpose and easy-to-understand dashboard.

B. Data Overview

Each student displayed through each entry before the beginning of any analysis into the dataset that was neatly stored on a table. Each entry, in which behavior and academic aspects, such as daily study hours, time spent sleeping, time spent on social media, and their final examination score, comprised vital points that underscored the analysis on how lifestyles contribute to academic performance. Also included in the data set were all other background and personal information such as sex, quality of internet connection, whether working part-time, and being part of clubs or activities.

These extras brought about the students' classification into groups and comparisons between their performance. The dataset contained both numerals and categories which furthermore justified the data as usable for all forms of visual and statistical analysis without extra data or complex models.

C. Data Quality and Preprocessing

The original dataset was mostly clean; however, it did have some missing values in the areas of how many hours students studied, their hours of sleep, social media use, and their test scores. Since those values were important for our analysis, we removed any records that had no information to keep the data reliable. This helped to ensure that the charts and results that we made were accurate as well as comprehensive. We also changed how the data were organized.

For example, some categories like student club membership had mixed capitalization, which we rectified for consistency. We also converted some numbers to the correct format to work optimally in Power BI for sorting and filtering. By adding another column that critically grouped students into high, average, or low achievers based on their test scores, the performance levels were easily illustrated in the dashboard. All this was done very carefully so that the main structure of the data has not changed. The final cleaned dataset

IV. Exploratory Data Analysis

The Exploratory Data Analysis (EDA) phase in this project gave a complete comprehension of the dataset's format and the actions impacting student grades. The EDA intended to uncover relationships among daily habits, for example, study hours and sleep duration. It also looked at student performance metrics as exam scores plus categorized achievement levels. This phase employed a dual approach:

A. Descriptive Statistics

A preliminary quantitative examination of the student_habits_cleaned dataset provided foundational insights into the behavioral and academic characteristics of the student population. Key descriptive statistics for several continuous variables in our dataset included study hours per day, sleep duration, social media usage, attendance percentage, and exam score.

These statistics offer a comprehensive summary of the central tendency (mean and median), dispersion (standard deviation), and range (minimum, maximum, and interquartile values) of these crucial academic and lifestyle metrics. The average study duration was **3.55** hours, while students reported an average sleep duration of **6.47** hours. The mean exam score was **69.60**, with a standard deviation of **12.64**, indicating moderate variability in academic performance. This quantitative snapshot establishes typical student profiles and provides a baseline for interpreting the subsequent visual analyses and behavioral correlations explored in the next section.

B. Data Visualization

Visualizations helped us to highlight correlations, trends, and anomalies through interpretable charts and distribution plots. Through this exploration, the study revealed:

How habits such as optimal sleep and regular study routines are linked positively with academic success.
Reduced exam performance correlates to how excessive engagement happens through passive digital activities like Netflix and social media.
We distributed students into defined performance categories (High, Medium, and Low). Trends in scoring did also vary based on gender.
For inter-variable relationships, use of a correlation heatmap is done so that they can support or challenge initial assumptions.

Visual analysis played a crucial role in identifying behavioral patterns and their correlations with academic success. This histogram in Figure 1 shows that most students study between 2 to 5 hours per day, with a peak of around 3.5 hours. The distribution appears slightly skewed, indicating fewer students with exceptionally high study duration. This visualization supports the statistical average of 3.55 study hours observed in the descriptive analysis.

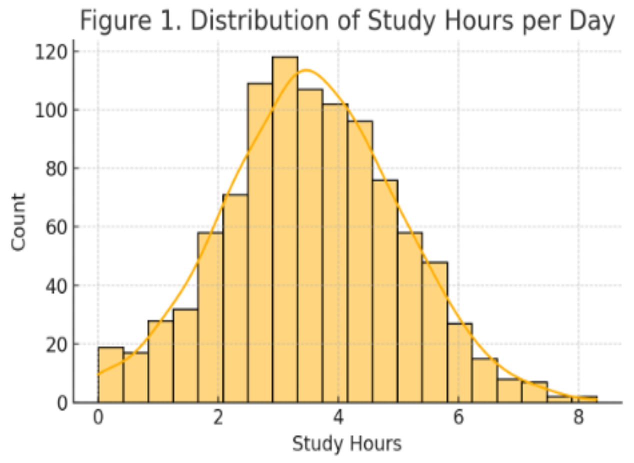

Figure 1. Distribution of Study Hours per Day

Social media vs. Exam Score: Figure 2, the scatter plot reveals a weak negative trend between social media usage and exam scores. Students who spent less time on social media generally performed better. This suggests that time spent on digital distractions may detract from academic focus, although causation cannot be inferred directly.

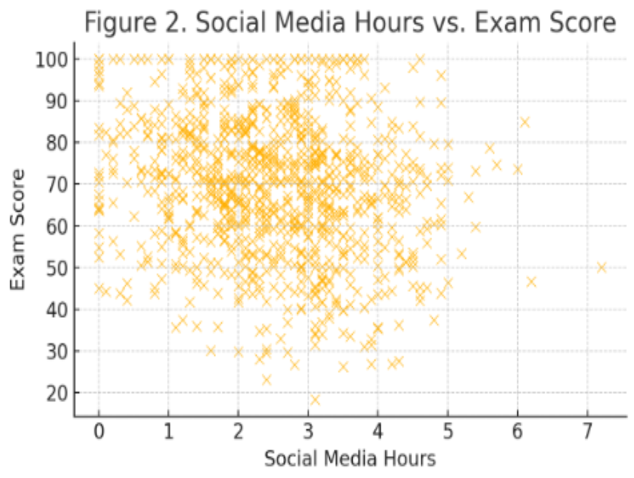

Figure 2. Social Media Hours vs. Exam Score

Sleep Hours by Performance Category: Figure 3. This boxplot presents the distribution of reported sleep hours across three academic performance categories: High Performer, Average Performer, and Low Performer. The most consistent and centered range of sleep hours approximately 6 to 8 hours is observed among high-performing students, with a narrower interquartile range and minimal outliers. This suggests that a structured and adequate sleep routine is common among academically successful individuals. In contrast, the low-performing group displays greater variability, including both under-sleeping (<5 hours) and over-sleeping (>9 hours) patterns. This irregularity may reflect underlying lifestyle imbalances such as stress, poor time management, or lack of routine, all of which could impair academic performance. The average performers show a distribution pattern that lies between the two extremes, reinforcing a gradient relationship between sleep consistency and academic success.

These insights affirm that sleep quality and regularity are crucial behavioral predictors of student achievement, highlighting the importance of rest as part of a healthy academic lifestyle.

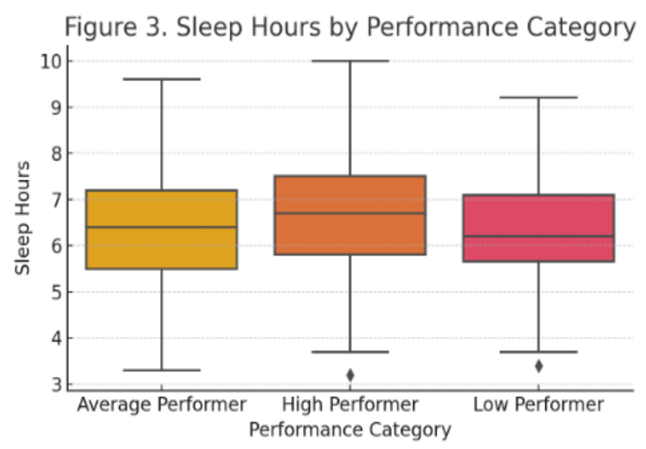

Figure 3. Sleep Hours by Performance Category

Distribution of Student Performance Categories: Figure 4, this count plot shows that 49.1% of students fall in the average performance category, while 37.8% are high performers and 13.1% are low performers. This relatively balanced distribution provides a stable base for comparative behavior analysis.

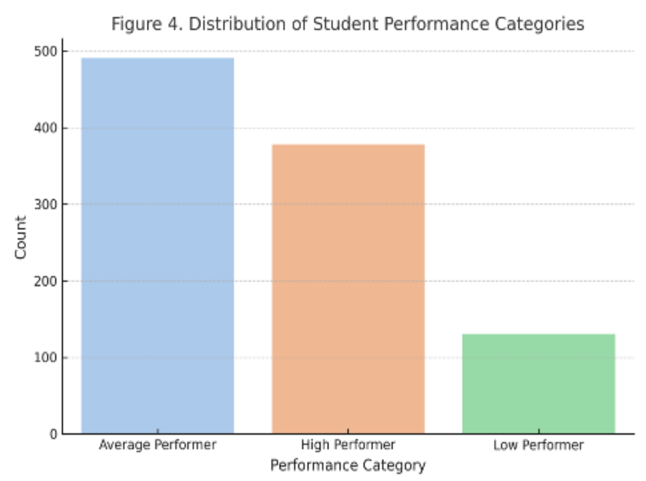

Figure 4. Distribution of Student Performance Categories

Average Exam Score by Gender: Figure 5, the bar plot illustrates the comparison of average exam scores between male and female students. The visual analysis indicates that both genders perform almost equally, with only marginal differences in mean scores. This suggests that gender is not a significant factor influencing academic performance within this dataset. The near-identical outcomes imply that external and behavioral factors—such as study habits, attendance, and mental health—play a more critical role in determining exam results than gender-based attributes.

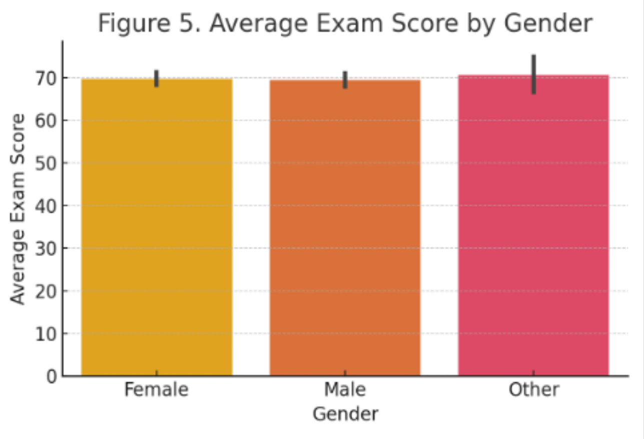

Figure 5. Average Exam Score by Gender

Correlation Heatmap of Numeric Variables: Figure 6, the correlation heatmap provides a visual representation of the Pearson correlation coefficients between continuous numeric variables in the dataset. It reveals that exam scores are most positively correlated with study hours and attendance percentage, indicating that increased academic engagement and consistent class participation enhance performance. In contrast, variables such as social media hours and Netflix hours show a mild negative correlation with exam scores, suggesting these leisure activities may interfere with productive study time. This analysis highlights which behavioral metrics are most predictive of academic success and informs future feature selection.

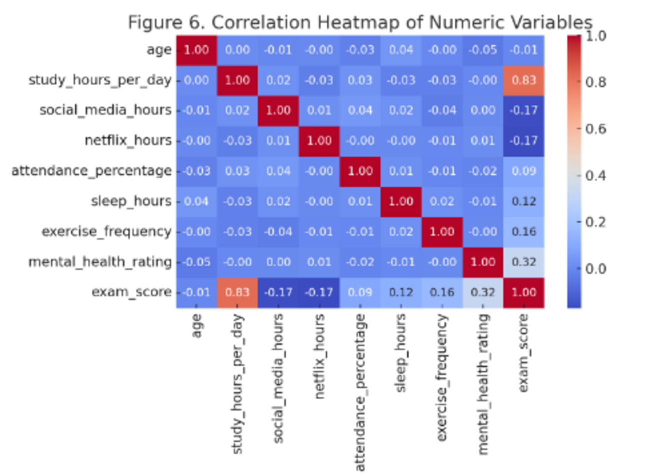

Figure 6. Correlation Heatmap of Numeric Variables

Density across the Exam Score: Figure 7, this chart plots exam scores of students against the education level of their parents. The analysis covers three distinct groups:

• Parents with a Master's degree
• Parents with a High School diploma
• Parents with a Bachelor's degree

Students whose parents completed high school typically score within a narrow band, clustering between 65 and 70 points. This group demonstrates remarkable consistency in performance. Children of Bachelor's degree holders achieve somewhat higher results, with most scores falling between 70 and 75 points. However, their performance shows greater variability compared to the high school group.

Students with Master's degree-holding parents display the most scattered performance pattern. Their scores range widely across the spectrum, with some students performing below average while others reach exceptionally high levels. This group lacks the consistency seen in the other categories but includes students who achieve the highest possible scores. The data reveals an interesting pattern: children of more educated parents don't automatically score higher across the board. Instead, they show greater variation in performance, with some individuals reaching peak achievement levels that exceed what other groups typically attain.

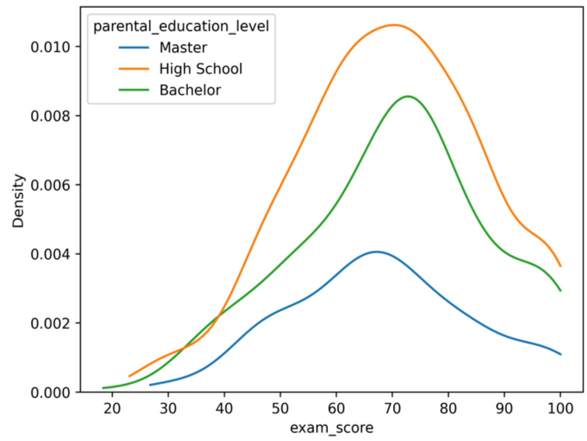

Figure 7. Exam Score against parents' education level

Study Hours vs Exam Score: Figure 8, each dot in the chart for Scatter Plot Summary represents a student. The horizontal axis shows how many hours a student studies per day. The vertical axis shows their exam score (out of 100).
The colors of the dots indicate the parental education level.
Strong Positive Relationship - This relationship goes beyond a slight trend. The correlation is strong, with the correlation heatmap showing a value of 0.825 with exam scores. Parental Education Doesn't Change the Pattern Much Across all parental education levels (Master's, Bachelor's, High School, Unknown), the more a student studies, the better they perform. Students whose parents didn't attend college can still achieve success through increased study time.

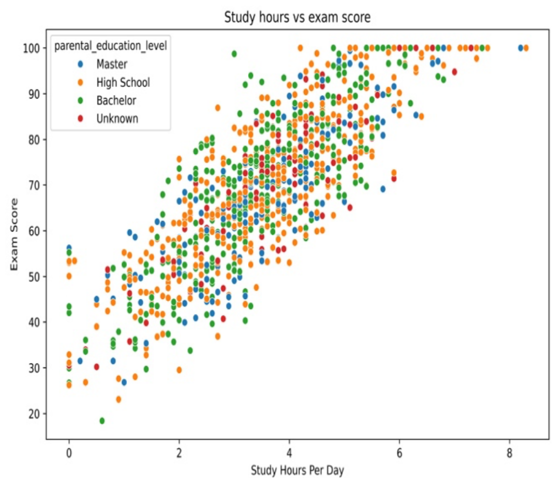

Figure 8. Study hours vs Exam Score

V. METHODOLOGY

A. Analytical Approach

This assignment makes use of a descriptive and comparative analytical method to discover how students' workouts affect educational performance. The goal is to identify and recognize correlations between behavioral habits along with examine hours, sleep period, food plan, and display time and labeled academic overall performance levels (high, Medium, Low). as opposed to predicting man or woman scores, this study emphasizes sample popularity and segmentation. students were grouped based on their examination ratings, allowing contrast of lifestyle characteristics throughout those categories. This method supports proof-based insights into which everyday behaviors tend to align better or decrease educational consequences. The analysis is grounded in a real-international dataset containing demographic and behavioral functions. Through exploratory strategies and performance grouping, they have a look at actionable observations applicable to educators, counselors, and college students.

B. Performance Categorization and Feature Analysis

Instructional overall performance becomes categorized into 3 instructions high, Medium, and low based on exam score thresholds. These classes served as the premise for comparative evaluation of lifestyle features.

Key variables analyzed included:

- Study time Per Day
- Sleep hours
- Nutrition Quality
- Social Media Usage
- Parent Education Level
- Exercising Frequency
- Mental Health awareness
- Internet Access

Preliminary exploratory facts evaluation （EDA） revealed high-quality and poor associations between those factors and academic performance. As an instance, better observe hours and better sleep patterns were typically observed among college students inside the excessive-performance class, while excessive display screen time and poor mental health correlated with decrease overall performance.

Specific variables had been standardized into constant codecs for evaluation. for example, weight loss plans satisfactory and intellectual fitness had been encoded into truly defined stages (e.g., bad, average, true), allowing significant go-group comparisons.

VI. TOOLS AND TECHNOLOGIES

The present study employed a data analytical technique, making use of modern tools and technologies to investigate the connection between students' daily behavior and academic performance. The dataset was sourced from Kaggle, comprising information on students' life-style attributes together with sleep period, screen time, and GPA. Facts processing and analytical duties have been conducted through the usage of a combination of Python, Microsoft Excel, and Power BI, decided on for his or her performance, versatility, and suitability for statistical and visual evaluation.

All information preprocessing and modifications had been carried out in Python, with the Google Collaborator (Collab) platform. The Jupyter notebook interface allows for collaborative coding of Python scripts with platform to scalable compute sources. The processing section protected statistics of loading, lacking price imputation, express encoding, numerical normalization, and column renaming for readability.

Following data cleaning, the study moved into statistical speculation testing and descriptive analysis. This section integrates Python-based statistical libraries—considerably SciPy, Stats models, and Matplotlib—and Microsoft Excel for cross-verification. Paired sample t-assessments have been used to evaluate behavioral styles throughout unique performance categories, whilst impartial t-tests assessed the importance of variations among excessive- and low-acting corporations.

For the facts presentation and built-in built integrated, Power BI was employed to develop integrated built-interactive dashboards. The processed dataset was imported integrated to power BI laptop, built-in integrated modeled and visualized the usage of integrated various equipment. Key metrics, built-in common sleep length built-in integrated GPA class and display screen time distribution across instructional performers, have been visualized in the usage of integrated bar charts, pie charts, and integrated graphs. Slicers and filters enable dynamic exploration, giving stakeholders the opportunity to pay attention to specific demographics or performance bands. Power BI's drag-and-drop capability and DAX expressions facilitated complicated aggregations without the need for additional cointegration, built integrated, and built-in delivery.

VII. RESULTS AND DISCUSSION

The analysis of scholar life-style behavior and educational performance discovered numerous noteworthy styles derived via descriptive statistics, speculation trying out, and visible exploration. The cleaned dataset, processed using Python and Excel, turned into examined throughout key variables inclusive of sleep length, display time, take a look at hours, and academic performance categories (e.g., high, common, low GPA). The statistical distribution of every variable becomes visualized and summarized using Python libraries and Excel charts to establish foundational understanding before deeper comparative try out.

Students with better instructional rankings continually suggested longer common sleep durations and decreased display screen time, helping broadly held instructional theories about sleep's wonderful correlation with cognitive performance. The results were in addition illustrated through dynamic dashboards constructed in power BI, enabling intuitive and interactive visualization of developments. Key findings covered the clustering of better GPAs amongst students who maintained regular examine hours, restricted their recreational screen time, and prioritized sleep. The dashboards enabled actual time filtering primarily based on demographic or behavioral elements, inclusive of gender or weekday/weekend display screen time, making it less complicated to discover subgroup developments. For instance, power BI visuals highlighted that student spending more than five hours in line with day on display screen activities had a visibly skewed GPA distribution in the direction of decrease classes.

Moreover, correlation matrices and scatterplots advanced in Python showed weak-to-moderate bad correlations among screen time and academic overall performance ($r \approx -0.4$) and moderate wonderful correlations among sleep length and GPA ($r \approx +0.5$). those visible styles complemented the speculation testing effects and furnished clear, records-sponsored justification for claims. Moreover, precise information computed in Excel, consisting of imply, median, and preferred deviation throughout classes, bolstered the robustness of the findings and supported interpretability in tabular format.

A. Interactive Visualization and Result Dissemination

The very last segment of this analytical venture focused on turning in the insights in an interactive, one-hand, and user-pleasant format. Instead of deploying a machine mastering version, the center goal becomes to make the outcomes of the statistical analysis and behavioral insights to be seen to a much broader audience via dynamic dashboards and interpretable statistics visualizations. This was carried out by the use of Microsoft Power BI, supported by preprocessing and statistical computation in Python, and precise validations in Excel.

Initialization and information Integration: The wiped clean and statistically processed dataset, at the beginning handled in Python (using Pandas and NumPy), became exported in .csv format for integration into power BI. Prior to import, crucial capabilities consisting of sleep length, display time, observe hours, and educational overall performance classes had been pre-aggregated and labeled for better visible readability. Excel played a critical position in formatting the facts, computing summary facts, and validating class groupings, making sure that the input to power BI turned steady and accurate.

Dashboard layout and format: The interactive dashboard titled "people behavior and performance Explorer" changed into designed in power BI to provide customers an intuitive, multi-layered visible revel in. It featured multiple pages, every committed to precise dimensions of student conduct, including sleep patterns, display screen utilization, and academic status. Dropdown slicers have been introduced for filters which include gender, age institution, and GPA class, permitting users to segment the records and explore targeted subgroups. Graphical elements together with clustered bar charts, pie charts, heatmaps, and scatter plots were used to form relationships between variables.

Interactive evaluation experience: Upon selecting diverse filters, students could take a look at real-time updates in visuals reflecting how behavioral traits modified across instructional performance stages. For instance, adjusting the slicer to view most effective students with GPAs above 3.5 dynamically altered all charts to spotlight longer average sleep durations and reduced display screen usage. Similarly, comparing weekdays to weekends illustrated how observing time consistency correlated with higher educational outcomes. These talents transformed a static dataset into interactive analytical surroundings wherein educators and stakeholders ought to discover hypotheses visually.

End result communique: Key statistical findings, inclusive of the outcomes from t-tests and correlation analyses carried out in Python, have been embedded as annotated playing cards or KPI visuals inside power BI. For example, cards displayed p-values and impact sizes, presenting context for found trends. Descriptive metrics consisting of common GPA, suggest screen time, and sleep trendy deviation were also supplied prominently. This allowed non-technical customers to interpret complex results while not having to study raw tables or statistical outputs.

Deployment and Accessibility: The very last dashboard became published to the power BI cloud provider and shared with relevant stakeholders via a public or company-precise hyperlink. This ensured the analysis became no longer restrained to researchers or analysts with coding competencies; however, it became reachable to instructors, counselors, and educational directors. Unlike a system studying version that predicts future effects, this deployment method emphasized exploration, pattern recognition, and statistics-pushed choice-making, fostering an obvious and attractive interpretation of scholar habits and their instructional impact.

B. Challenges and Limitations

Despite of successful improvement and deployment of the student overall performance analytics dashboard, numerous challenges and inherent limitations have been encountered while the study

Self-reported data Accuracy: The dataset broadly speaking depends on self-mentioned inputs for behavioral factors including study hours, sleep period, and social media usage. Such data can be subjective and prone to recollect bias or social desirability bias. For instance, students might also by accident misreport their sleep styles or study intervals, resulting in discrepancies among actual behaviors and recorded facts. This will distort the power and course of the relationships discovered inside the evaluation.

Constrained Scope of functions: Even as the dashboard captures certain behavioral dimensions, it lacks broader educational and private context. Crucial variables inclusive of instructor great, gaining knowledge of disabilities, socio-monetary status, or peer have an effect on are not represented within the dataset. Those unmeasured factors might also play an essential role in shaping academic results and could beautify predictive accuracy if incorporated.

Static and non-temporal information: The analysis makes use of cross-sectional facts from an unmarried time point, stopping the exploration of tendencies and long-time period behavioral impacts. Because student behavior and educational performance evolve over the years, the absence of longitudinal monitoring restricts the potential to evaluate motive-effect relationships or dependency development. As a result, the findings stay correlational instead of predictive through the years.

Rating-primarily based Categorization: The classification of student overall performance into “excessive,” “average,” and “low” is based on constant numerical cutoffs. These thresholds may not align with institutional grading structures or curriculum rigor in academic settings, thereby restricting the generalizability of the findings past the pattern used.

Loss of interplay and multivariate evaluation: Even though the dashboard consists of filters for gender, net first-class, part-time work, and extracurricular participation, it does not discover the interplay effects among these variables. As an example, the educational impact of bad net connectivity may additionally fluctuate with the aid of gender or activity popularity. Incorporating multivariate models or interaction terms would permit a deeper, more nuanced understanding of ways these elements combine to influence performance.

Correlation vs. Causation: The relationships provided within the dashboard replicate statistical institutions, not direct causation. for example, college students who spend extra time studying tend to reap better grades, but this may additionally correlate with higher motivation, prior coaching, or more potent guide systems. Further, the discovered link between excessive social media utilization and poor performance might be inspired by way of underlying variables like stress or distraction-inclined conduct.

Generalizability and pattern range: If the dataset is skewed towards a particular age organization, instructional level, or geographic place, the version results will not be representative of the broader student population. An extra numerous and balanced dataset could decorate outside validity and boost the relevance of insights for different institutions.

Dashboard Interpretability: While the visualizations offer accessible insights, they require a baseline stage of data literacy to interpret correctly. Customers unfamiliar with records evaluation might also misinterpret styles, and the dashboard currently lacks features to simulate conduct adjustments or visualize longitudinal results.

Broader Behavioral Complexity: The dataset relies on self-suggested records, which may additionally introduce bias or inaccuracies. Moreover, the analysis is go-sectional, limiting the ability to set up causal relationships over the years. Past observation hours, sleep, and social media use, variables inclusive of mental health, eating regimen excellent, internet, and parental education additionally showed moderate institutions with overall performance. Those should be further explored to understand their holistic impact. Habits like reduced sleep or high display time can be symptomatic of deeper demanding situations which include educational stress, part-time employment, or inadequate to have a look at aid—elements that warrant deeper investigation. Those insights can aid college students, parents, educators, and school directors in designing supportive environments. Tailored interventions may be crafted based on diagnosed behavioral patterns. Longitudinal research should provide more potent proof of causal outcomes and dependency modifications over the years. Integrating psychological well-being and motivation metrics may add additional information. Schools and educators would possibly not forget to impose techniques such as time control workshops, intellectual fitness resources, virtual literacy applications, and guidelines that sell more healthy exercises and a balanced life.

VI. Conclusion

Primarily based on the analytical insights derived from the dashboard, it is glaring that students’ academic performance is notably inspired by the aid of their everyday conduct. A robust positive correlation discovered among hours and exam ratings indicates that multiplied instructional engagement contributes to better performance. Conversely, social media usage verified a bad correlation with exam ratings, suggesting that excessive time spent on digital distractions can avoid academic results. Sleep length additionally showed a mild impact, where students retaining balanced sleep hours (about 6–8 hours) tended to be carried out higher academically. The dataset revealed common sleep hours of 6.47, and a mean examination score of 69.60. Significantly, 37.8% of students are labeled as high performers, while 49.1% fell into the common overall performance segment. These findings highlight the importance of promoting healthy workouts, good sleep, and controlled social media use amongst college students to foster advanced academic performance. Future academic interventions and coverage choices should not forget those behavioral elements to enhance student fulfillment.

REFERENCES

[1] E. N. Li, "Effects of daily exercise time on the academic performance of students: An empirical analysis based on CEPS data," *arXiv*, Nov. 30, 2023.

[2] N. A. Girardini, S. Centellegher, A. Passerini, I. Bison, F. Giunchiglia, and B. Lepri, "Adaptation of student behavioural routines during COVID-19: A multimodal approach," *arXiv*, Jun. 14, 2023.

[3] S. Spotts, "How schedules impact student well-being," *Challenge Success Team Blog*, Jan. 30, 2025.

[4] D. E. Merz, "Daily routine and a bedtime story can boost children’s brains," *Brain and Behaviour*, as reported by *The Times*, Mar. 18, 2025.

[5] International Journal of Indian Psychology, "Sleep patterns and alertness in class," *International Journal of Indian Psychology*, Dec. 2024.

[6] G. O. Galaviz, L. A. Zazueta, C. Y. Quiroz Campas, C. García Lirios, and G. Bermúdez Ruiz, "Impact of time management on academic performance," *Journal of Information Systems Engineering and Management*, vol. 10, no. 21s, Feb. 2025.

[7] B. Johnson Mary, "A quantitative study of the impact of daily study hours on academic performance among high school students," *New York University Research Report*, Dec. 2024.

[8] S. García, S. Ramírez-Gallego, J. Luengo, J. M. Benítez, and F. Herrera, "The interplay between positive lifestyle habits and academic success in undergraduates: LSTM-based lifestyle modeling," *Humanities and Social Sciences Communications*, 2025.
[9] M. Aljafer, A. Almadani, A. AlDughaither, A. Basfar, S. AlGhadir, Y. AlGhamdi, B. AlHubaish, O. AlMayouf, S. AlGhamdi, T. Ahmad, and H. Abdulghani, "The impact of study habits and personal factors on academic achievement of medical students," *BMC Medical Education*, vol. 24, article 888, 2024.
[10] R. Da Silva, "The power of routines in a classroom," *Western University Teaching Report*, Apr. 2023.
[11] P. Fernandes and J. Rodrigues, "The impact of self-regulated learning and academic time management planning on primary school performance," *Education Sciences (MDPI)*, vol. 4, no. 2, article 16, 2024.
[12] M. Spott, "Study longer or study effectively? Better study strategies," *British Journal of Educational Psychology*, 2024.
[13] A. BMC Team, "To what extent do study habits relate to performance? A PMC analysis," *PLOS Medical Education*, 2024.
[14] Parents Staff, "Day and night: The back-to-school routine," *Parents Magazine*, Jul. 31, 2023.