TECHNOLOGICAL INSTITUTE OF THE PHILIPPINES

938 Aurora Blvd. Cubao, Quezon City

COLLEGE OF COMPUTER STUDIES

Information Technology Department

StudyPulse: An Analytical Dashboard for Student Well-being and Performance

A Data Analytics Article

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Submitted by:

Baluyut, Jerome J.

Mejia, Igel D.

Novenario, Jose Miguel R.

Pascual, John Paul L.

Vasquez, Christian Lloyd G.

Submitted to:

Ms. Nila D. Santiago

Instructor

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Jerome J. Baluyut
qjbaluyut@tip.edu.ph

Igel D. Mejia
qidmejia@tip.edu.ph

Jose Miguel R. Novenario
qjmnovenario@tip.edu.ph

John Paul L. Pascual
qjplpascual@tip.edu.ph

Christian Lloyd G. Vasquez
qclgvasquez@tip.edu.ph

ABSTRACT

In support of the United Nations Sustainable Development Goal 4 (Quality Education), this project explores the impact of student behavioral patterns such as study hours, screen time, and sleep duration on academic performance. Using a synthesized dataset of 1,000 records developed through an interactive R Shiny dashboard titled *StudyPulse*, the project applies exploratory data analysis (EDA), classification models, and data visualization techniques. The findings suggest that study time and screen consumption are significant predictors of academic success. The dashboard enables educators and administrators to gain actionable insights and proactively support students at risk of underperforming.

1. INTRODUCTION

In modern education, academic performance is often viewed through the lens of scores and grades. However, cognitive factors alone do not fully capture a student's ability to succeed. Behavioral patterns—such as how long a student studies, how much time they spend on screens, and how much sleep they get—play a substantial role in shaping academic outcomes. With this in mind, the *StudyPulse* dashboard was developed to investigate how these daily habits affect performance. This project aims to empower schools with data tools that go beyond grades and uncover hidden behavioral patterns for timely and targeted intervention.

2. BACKGROUND OF THE STUDY

While the education system has long focused on grades and attendance, studies now suggest that non-academic behaviors strongly influence academic success. Excessive screen time, inadequate study routines, and inconsistent sleep have all been linked to poor academic outcomes (Hale & Guan, 2015). In contrast, students with structured study habits often perform better academically.

The goal of this study is to transform raw student habit data into meaningful insights using interactive analytics. The dataset, though synthetic, mimics real-world behaviors and is ideal for building and testing educational dashboards. *StudyPulse* serves as a visual analytics tool for school counselors, teachers, and education researchers to analyze trends, predict risks, and personalize academic support.

3. PROBLEM STATEMENT AND RESEARCH QUESTIONS

Problem Statement

Educational institutions struggle to identify struggling students early due to a lack of tools that track behavioral metrics. There is a need for data-driven solutions that connect daily habits to academic performance.

Research Questions

Exploratory Data Analysis:

1. Which behavioural factors, the amount of time spent on the screen, the amount of study hours, the quality of sleep, and the exercise rate, have the most significant relationship to the performance of the students?
2. What are some of the frequent problems or behaviors that have become common among students who are most likely not to excel in school?
3. Which of these habits and behaviors have the most significant effects on the performance of students?
4. What is the balance between the amount of screen time and the length of sleep, and how does it affect the performance of students?
5. What role do demographic and lifestyle factors, including age, gender, quality of diet, and internet access, play in the variations in academic performance of students?

Classification and Prediction:

1. Can study hours and screen time predict a student's performance level?
2. Can study hours and screen time predict a student's mental health status?
3. How accurately can decision trees classify students into performance bands?

Demographics:

1. How do gender and age influence performance in the presence of behavioral data?
2. How could internet quality and internet access influence performance in the presence of habitual data?

4. OBJECTIVES OF THE STUDY

4.1 General Objective

To analyze the behavioral factors affecting student academic performance and develop an interactive Shiny dashboard for identifying performance trends and risk factors.

4.2 Specific Objectives

- To identify which habits (study time, screen time, sleep) have the strongest correlation with exam scores.
- To categorize students into performance levels based on behavioral data.
- To build a decision tree model that can predict academic performance using study hours and screen time.
- To visualize behavioral trends and enable dynamic filtering using a Shiny dashboard.

5. RELATED LITERATURE

The increasing interest in data-driven education has led to a growing body of research exploring how non-academic behaviors influence student performance. While traditional metrics such as grades and attendance offer a snapshot of achievement, they often fail to capture underlying behavioral patterns that contribute to learning outcomes.

Behavioral Predictors of Academic Success

According to Anwar et al. (2024), behavioral factors like study routines, screen time, and sleep patterns significantly improve the accuracy of academic performance models when included alongside traditional metrics. Their study, which employed machine learning techniques, demonstrated that models incorporating behavioral data outperformed those relying solely on demographic or academic history. Similarly, Ouatik et al. (2022) emphasized the importance of daily study hours as a core predictor of academic performance. Using a decision tree and logistic regression, their research showed that students who studied consistently (at least 4 hours daily) were far more likely to achieve higher grades, regardless of socioeconomic background.

Screen Time and Its Cognitive Implications

A recurring theme in the literature is the negative impact of excessive screen time. Hale and Guan (2015) conducted a systematic review of over 67 studies and concluded that prolonged exposure to screens, especially during evening hours, adversely affects sleep quality and attention span. This, in turn, leads to reduced academic performance. Their findings support the inclusion of screen time as a key variable in educational analytics, particularly in the context of post-pandemic remote learning, where digital consumption has increased drastically. Perez-Chada et al. (2023) further explored this by analyzing the simultaneous effect of screen time and sleep deprivation. Their study found that while sleep remains important, screen time has a more immediate and measurable correlation with poor academic outcomes, especially when usage exceeds six hours per day.

Role of Demographics and Lifestyle Variables

West et al. (2019) examined how demographic and lifestyle variables such as age, gender, internet access, and diet relate to academic performance. While they acknowledged minor effects, their findings suggest that these variables have weaker predictive power compared to behavioral indicators. This reinforces the idea that actionable insights in educational analytics are better drawn from dynamic, modifiable behaviors rather than static personal traits.

6. METHODOLOGY

6.1 Business Understanding

Educational stakeholders need tools to identify at-risk students early based on lifestyle and study habits, not just grades.

6.2 Data Understanding

The dataset includes 1,000 students with attributes such as:

- study_hours_per_day, sleep_hours_per_day, netflix_hours, social_media_hours, attendance, exam_score, diet_quality, internet_quality, exercise_frequency, and age.

A new feature, screen_time, was created by summing netflix_hours and social_media_hours. performance_level was computed by binning exam scores into six categories from Low to Excellent.

6.3 Data Preparation

- Missing values were minimal and removed.

- String columns were converted to factors.

- Age groups were binned.

- Data was saved as a cleaned CSV for use in the dashboard.

6.4 Dashboard Implementation (Shiny App)

The dashboard was built using:

- **R packages**: shiny, shinydashboard, plotly, ggplot2, rpart, shinyjs, dplyr, and tidyverse.

- **UI components**: sidebar filters for gender, age range, and performance levels.

- **Output components**: correlation matrix, summary statistics, scatter plots, decision trees, boxplots, and heatmaps.

- **Dark mode toggle** was added using shinyjs.

7. RESULTS AND FINDINGS

Insight 1: Study Hours Correlate Most Strongly with Performance

Students who study more than 5.5 hours/day are most likely to fall into "High" and "Excellent" performance levels. A correlation coefficient of 0.62 was observed between study_hours_per_day and exam_score.

Insight 2: Low Performers Show High Screen Time and Poor Attendance

The bottom 25% of students consistently had higher screen time (avg. 7.2 hrs/day), lower attendance (<60%), and minimal study hours (<2 hrs/day).

Insight 3: Decision Tree Predicts Performance Accurately

A decision tree using only study_hours_per_day and screen_time showed clear splits:

- If study hours < 1.7 and screen time > 6.5 → "Low"

- If study hours > 5.6 and screen time < 4 → "Excellent"

Insight 4: Screen Time is More Predictive than Sleep

Heatmaps showed screen time decreased linearly with performance level, whereas sleep duration stayed constant at 6.5–7.5 hours across all groups.

Insight 5: Demographics Have Weak Predictive Value

Analysis by gender and age showed no significant differences in average scores or behavioral trends. Predictive models relying only on demographic variables underperformed.

8. CONCLUSION

This project highlights the importance of tracking behavioral metrics—especially study hours and screen time—in predicting and improving student academic performance. The *StudyPulse* dashboard transforms these insights into an interactive platform for proactive intervention. By focusing on behaviors rather than static demographics, schools can personalize support strategies and drive better academic outcomes.

9. RECOMMENDATIONS

- Encourage students to adopt structured study routines exceeding 4 hours per day.
- Introduce digital wellness programs to reduce excessive screen time.
- Use dashboards like *StudyPulse* in guidance counseling to detect risk patterns early.
- Collect real behavioral data from LMS or surveys for continuous monitoring.

10. FUTURE DIRECTION

- Integrate real institutional datasets and perform longitudinal analysis.
- Add predictive risk scoring and alerts to the dashboard.
- Apply clustering and collaborative filtering to group students and personalize learning plans.
- Expand the tool for use across different educational levels (e.g., high school, tertiary).

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Honor Pledge:

“I accept responsibility for my role in ensuring the integrity of the work submitted by the group in which I participated.”