Screen Time and Its Impact on Sleep Quality and Academic Productivity: A Personal Data Science Study

Joyce Anne Colocado
College of Computing and Information Technologies
National University Philippines
Manila, Philippines
colocadojd@students.national-u.edu.ph

Abstract — **This study examines how daily screen time behavior affects sleep quality and academic productivity using 69 days of daily tracked data from a college student participant. The data covers total screen time, social media use, gaming hours, entertainment consumption, productive screen time, sleep duration, sleep quality, mood, stress, and caffeine intake, all collected between December 4, 2025 and February 10, 2026. Four statistical tests were used: an independent samples t-test, Pearson correlation, one-way ANOVA, and chi-square test of independence. A multiple linear regression model was also built to predict daily productivity from screen time variables. Results show that weekday and weekend screen time differ significantly ($p < .001$), with weekends averaging 1.96 hours more. Gaming level was found to significantly reduce productivity ($F = 37.08$, $p < .001$). The regression model explained 86.2% of the variance in daily productivity on test data ($R^2 = 0.86$), with social media hours and entertainment hours being the strongest negative predictors. These findings suggest that managing non-productive screen time, especially social media and gaming, could meaningfully improve a student's daily academic output.**

Index Terms — **screen time, sleep quality, academic productivity, self-tracking, data science, linear regression, college student behavior, exploratory data analysis**

I. INTRODUCTION

College students spend a large portion of their waking hours on screens, split between productive activities (online classes, studying, research) and leisure activities (social media, gaming, streaming). While some screen use supports academics, excessive non-productive screen time has been linked to disrupted sleep patterns [1] and declining academic focus [2]. More than 60% of college students report poor sleep quality, and excessive digital screen time is frequently cited as a contributing factor [1].

Prior research supports these concerns. Systematic reviews have found that electronic media use is associated with shorter sleep and poorer sleep quality [3], and that higher screen time in young people is linked to lower psychological well-being [4]. Social media use has also been shown to negatively affect academic performance [5]. However, most of these studies rely on cross-sectional survey data rather than daily tracking, and they tend to group all screen time together rather than separating productive and non-productive use. Few studies examine the weekday-versus-weekend dynamic, which is important because student behavior shifts dramatically between school days and days off.

This study addresses these gaps by analyzing 69 consecutive days of screen time data from a college student, tracking total screen time and its components (gaming, social media, productive use, entertainment) alongside sleep, mood, stress, caffeine intake, and self-rated productivity. The research questions are:

RQ1: Is there a significant difference in total screen time between weekdays and weekends?

RQ2: What is the relationship between screen time before bed and sleep quality?

RQ3: Does gaming time significantly affect productivity levels?

RQ4: What screen time factors best predict a student's daily productivity score?

RQ5: How do screen time patterns and trends change over the 69-day observation period?

II. LITERATURE REVIEW

A. Screen Time and Sleep

Electronic media use is consistently associated with delayed bedtimes, shorter sleep duration, and poorer sleep quality across age groups [3]. The proposed mechanisms include the stimulating effect of screen content, displacement of sleep time, and blue light suppression of melatonin [6]. Höhn, Hahn, Gruber, and Pletzer [7] showed that evening smartphone use specifically delays sleep onset and impairs next-morning memory performance in young adults. Brautsch, Lund, Andersen, Jennum, and Gottlieb [8] further found that different types of digital media may have different effects on sleep, supporting the need to examine screen time by category rather than as a single total.

B. Screen Time and Academic Performance

Social media use has been shown to negatively affect academic performance among college students, mediated by social comparison and reduced self-esteem [5]. Smartphone use more broadly is negatively associated with academic outcomes, even after controlling for demographics and usage patterns [9]. For gaming specifically, Alzahrani and Griffiths [10] found a dose-response relationship: moderate gaming showed weaker effects, while excessive gaming was linked to significantly worse academic outcomes. Balasubramanian [11] reported that voluntary digital detox periods improved academic focus and engagement, reinforcing the idea that reducing non-productive screen time benefits academic output.

C. Self-Tracking and Behavioral Data Science

Self-tracking research has grown alongside wearable devices and digital health apps. Vaid and Harari [12] demonstrated that consistent smartphone-based tracking over time yields meaningful behavioral insights. Toebosch, Berger, and Lallemand [13] proposed a framework for how individuals engage with self-tracking data through collection, exploration, and reflection. Chopra, Juarez, Fogarty, and Munson [14] found that even individual-level self-tracking projects produce actionable insights when data is collected systematically, supporting the longitudinal single-participant design used in this study.

D. Gaps Addressed

Most existing studies use cross-sectional survey data, group all screen time together, rarely analyze weekday-versus-weekend dynamics, and seldom apply predictive modeling at the individual level. This study addresses these gaps by collecting daily data across 69 days, separating screen time into four categories, comparing weekday and weekend patterns, and building a regression model to predict productivity.

II. METHODOLOGY

A. Participants

The participant in this study is a college student in their undergraduate years who follows a typical academic schedule with weekday classes and free weekends. No private identifying information (full name, school, or exact age) is disclosed. This single-participant longitudinal design is appropriate for behavioral data science studies where the goal is to analyze individual behavioral patterns over time [14].

B. Data Collection Methods

Data was collected daily for 69 consecutive days, from December 4, 2025 to February 10, 2026. This period covers parts of the academic semester, a holiday break (approximately December 22, 2025 to January 4, 2026), and the start of a new semester.

The following 15 variables were recorded each day:

VARIABLE	TYPE	UNIT	METHOD
Date	Date	YYYY-MM-DD	Calendar
Day_of_Week	Categorical	N/A	Derived from date
Day_Type	Categorical	N/A	Manual label (Weekday/Weekend/Holiday)
Total_Screen_Time_hrs	Numeric	Hours	Phone/device screen time reports
Social_Media_hrs	Numeric	Hours	App usage tracker
Gaming_hrs	Numeric	Hours	Manual log
Productive_Screen_Time_hrs	Numeric	Hours	App usage tracker
Entertainment_hrs	Numeric	Hours	App usage tracker
Mood	Ordinal	1–5 scale	Self-rating at end of day
Stress_Level	Ordinal	1–5 scale	Self-rating at end of day
Productivity_Score	Ordinal	1–5 scale	Self-rating at end of day
Study_Hours	Numeric	Hours	Manual log
Sleep_Duration_hrs	Numeric	Hours	Manual log
Sleep_Quality	Ordinal	1–5 scale	Self-rating upon waking
Screen_Before_Bed_min	Numeric	Minutes	Manual estimate
Bedtime	Time	HH:MM	Manual log
Caffeine_Drinks	Numeric	Count	Manual count

Data was logged at the end of each day using a spreadsheet (Google Sheets/Excel) and exported as a CSV file for analysis. Screen time data was sourced from built-in device screen time reports available on the student's phone and computer.

C. Operational Definitions

Each variable was defined precisely to ensure consistency throughout the 69-day collection period:

Total_Screen_Time_hrs: The total number of hours the participant spent looking at any screen (phone, laptop, tablet, gaming console) during the day.

Social_Media_hrs: Time spent on social media platforms such as Facebook, Instagram, Twitter/X, and TikTok.

Gaming_hrs: Time spent playing video games on any device.

Productive_Screen_Time_hrs: Time spent on work or study-related screen activities, including online classes, coding, writing papers, and research.

Entertainment_hrs: Time spent on streaming services, YouTube, and other non-social, non-gaming entertainment.

Mood: A self-rated score from 1 (very bad) to 5 (very good), recorded at the end of each day.

Stress_Level: A self-rated score from 1 (very low) to 5 (very high), recorded at the end of each day.

Productivity_Score: A self-rated score from 1 (very low) to 5 (very high), reflecting how productive the participant felt that day.

Study_Hours: Total hours spent studying or doing academic work, including both on-screen and off-screen activities.

Sleep_Duration_hrs: Total hours of sleep from bedtime to wake-up time.

Sleep_Quality: A self-rated score from 1 (very poor) to 5 (very good), recorded upon waking.

Screen_Before_Bed_min: Estimated minutes of screen use within the one hour before falling asleep.

Bedtime: The time (in 24-hour format) the participant went to bed.

Caffeine_Drinks: The number of caffeinated beverages (coffee, energy drinks, tea) consumed during the day.

D. Data Cleaning

The raw dataset contained 69 rows and 17 columns. The following cleaning steps were applied:

1. **Missing values:** Three missing values were identified: one each in Mood, Sleep_Quality, and Caffeine_Drinks. These were filled using median imputation. The median was chosen over the mean because these variables are ordinal (1–5 scale), and the median better preserves the central tendency of ordinal data. After imputation, Mood was filled with 3.5, Sleep_Quality with 3.0, and Caffeine_Drinks with 1.0.
2. **Outlier detection and treatment:** Boxplots and the interquartile range (IQR) method were used to detect outliers. One outlier was found in Screen_Before_Bed_min, a value of 200 minutes, which exceeded the upper bound of 117.5 minutes (Q3 + 1.5 × IQR). This value was capped (winsorized) at 117.5 minutes to reduce its influence without removing the observation entirely. Fig. 1 shows the boxplots used for outlier detection.

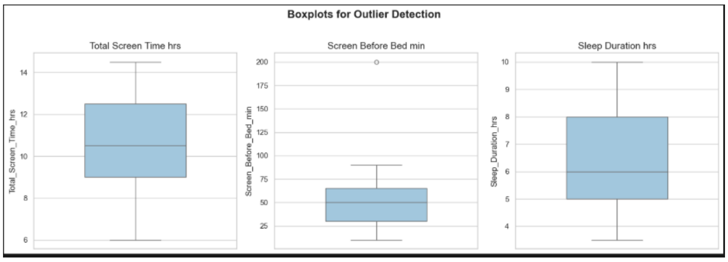


Fig. 1: Boxplots for Outlier Detection

3. Feature engineering: Four new variables were created to support analysis:
   - Bedtime_Hours: The Bedtime string (e.g., "02:30") was converted to a numeric value (e.g., 2.5) representing hours past midnight.
   - Is_Weekday: A binary variable (1 = Weekday, 0 = Weekend/Holiday) derived from the Day_Type column.
   - Non_Productive_hrs: Calculated as Total_Screen_Time minus Productive_Screen_Time, capturing all leisure-related screen use.
   - Day_Number: A sequential count from 1 to 69 used for trend analysis over time.
4. Verification: After cleaning, the dataset had 69 rows and 21 columns, zero missing values, and zero duplicate entries.

E. Statistical Analysis

All analysis was performed in Python using pandas, NumPy, SciPy, scikit-learn, Matplotlib, and Seaborn. The significance level for all tests was set at $\alpha = 0.05$. An independent samples t-test was used to compare mean total screen time between weekdays and weekends (RQ1). Pearson correlation was used to measure the linear relationship between screen time before bed and sleep quality (RQ2). A one-way ANOVA compared mean productivity scores across three gaming level groups (RQ3), with gaming hours grouped into No Gaming (0 hours), Low Gaming (0.5–2.5 hours), and High Gaming (3+ hours). A chi-square test of independence examined the association between gaming level and day type as a supplementary analysis. A multiple linear regression model was built to predict daily productivity from screen time and lifestyle features (RQ4), using an 80/20 train-test split (55 training samples, 14 testing samples) and evaluated with R^2, mean absolute error (MAE), and root mean squared error (RMSE). Exploratory data analysis, including histograms, time-series plots, boxplots, scatter plots, and correlation heatmaps, was used to identify patterns, trends, and distributions across the dataset (RQ5).

Potential sources of bias were considered. Because all data is self-reported, there is a risk of recall bias and social desirability bias. The single-participant design limits the ability to generalize results to other students. The 69-day window, while substantial for an individual-level study, is short compared to longitudinal research in the field.

IV. RESULTS

A. Descriptive Statistics

Table I presents the overall summary statistics for the key numeric variables in the dataset.

TABLE I: DESCRIPTIVE STATISTICS FOR KEY VARIABLES (N = 69)

VARIABLE	MEAN	MEDIAN	SD	MIN	MAX
Total_Screen_Time_hrs	10.76	10.50	2.04	6.00	14.50
Social_Media_hrs	1.83	1.50	0.93	0.50	4.00
Gaming_hrs	2.40	2.00	2.04	0.00	6.00
Productive_Screen_Time_hrs	3.94	4.00	2.06	0.00	8.00
Entertainment_hrs	2.59	2.50	1.07	1.00	5.50
Mood	3.46	3.50	0.97	1.00	5.00
Stress_Level	2.49	2.00	1.43	1.00	5.00
Productivity_Score	2.64	3.00	1.21	1.00	5.00
Study_Hours	2.91	3.00	2.09	0.00	7.00
Sleep_Duration_hrs	6.45	5.50	1.80	3.50	10.00
Sleep_Quality	3.22	3.00	1.08	1.00	5.00
Screen_Before_Bed_min	46.38	45.00	23.83	10.00	117.50
Caffeine_Drinks	1.30	1.00	1.01	0.00	3.00

The participant averaged 10.76 hours of total screen time per day (SD = 2.04), with a range from 6.0 to 14.5 hours. Gaming accounted for an average of 2.40 hours per day, while productive screen time averaged 3.94 hours. The average productivity score was 2.64 out of 5 (SD = 1.21), and average sleep duration was 6.45 hours (SD = 1.80). Figures below shows the distributions of six key variables.

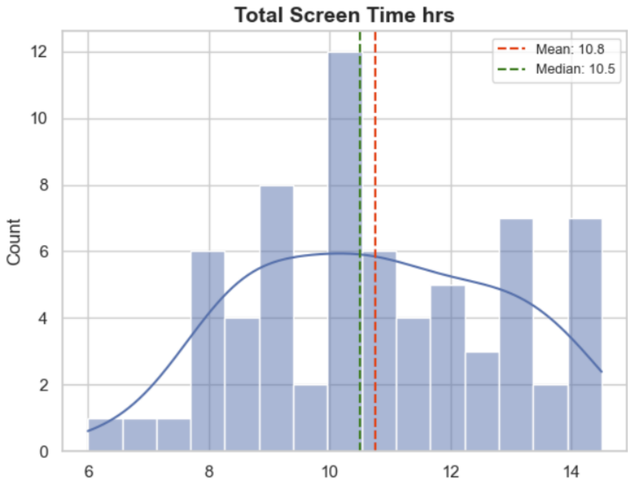


Figure 2a. Distribution of Total Screen Time (hours)

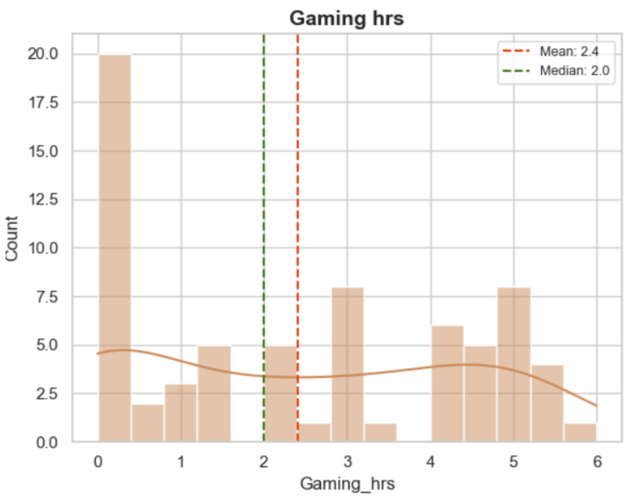


Figure 2b. Distribution of Gaming Hours

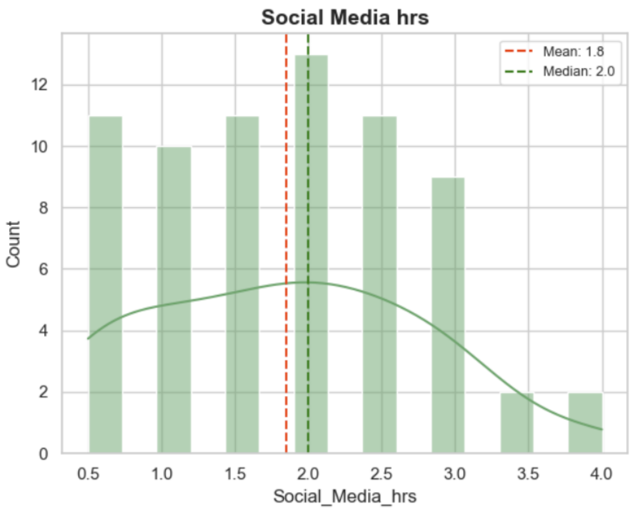


Figure 2c. Distribution of Social Media Hours

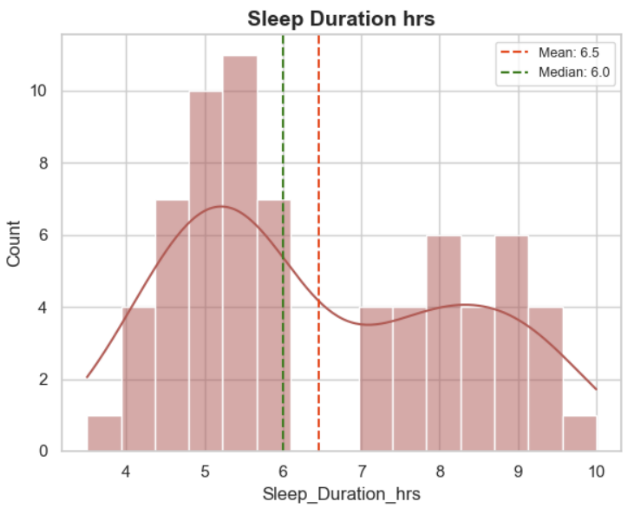


Figure 2d. Distribution of Sleep Duration (hours)

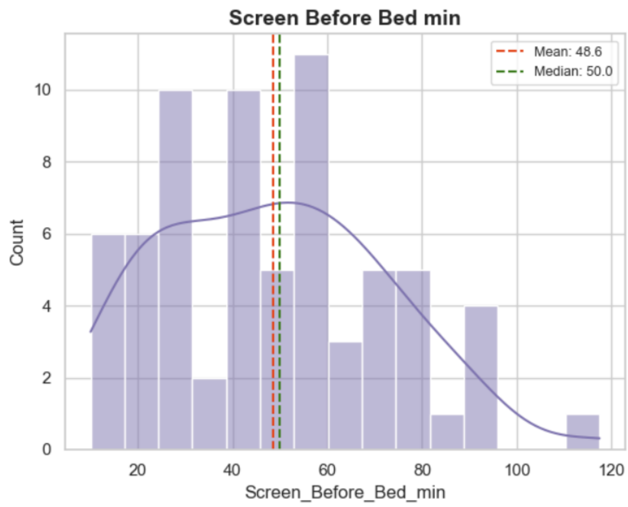


Figure 2e. Distribution of Screen Before Bed (minutes)

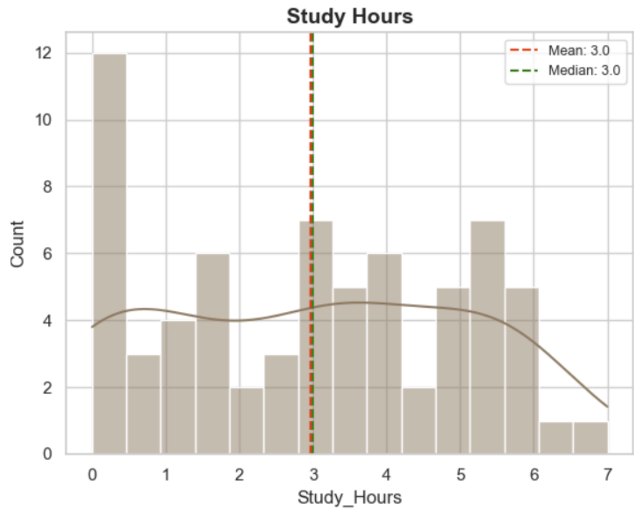


Figure 2f. Distribution of Study Hours

B. Weekday vs. Weekend Patterns

Table II compares key variables between weekdays and weekends.

TABLE II: MEAN VALUES BY DAY TYPE

VARIABLE	WEEKDAY (N=39)	WEEKEND (N=30)
Total_Screen_Time_hrs	9.91	11.87
Gaming_hrs	1.50	3.58
Productive_Screen_Time_hrs	5.28	2.20
Productivity_Score	3.33	1.73
Sleep_Duration_hrs	5.06	8.27
Study_Hours	4.08	1.38
Caffeine_Drinks	1.92	0.50

Weekends showed higher total screen time (+1.96 hrs), higher gaming (+2.08 hrs), and longer sleep (+3.21 hrs), but much lower productivity scores (−1.60 points) and fewer study hours (−2.70 hrs). Caffeine consumption was nearly four times higher on weekdays (1.92

vs. 0.50 drinks/day), suggesting that caffeine was used to support studying on school days. Figures below visualizes these differences.

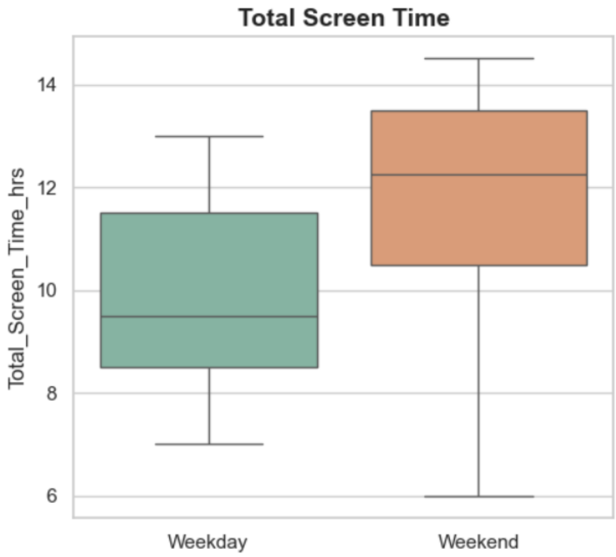


Figure 3a**.** Weekday vs Weekend: Total Screen Time (hours)

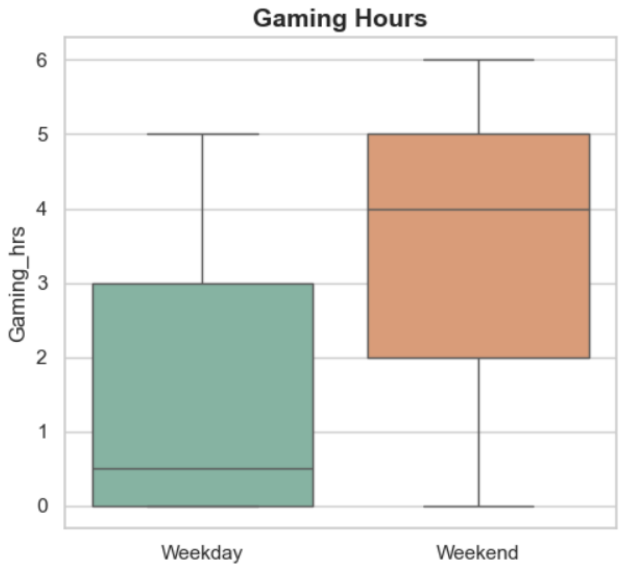


Figure 3b. Weekday vs Weekend: Gaming Hours

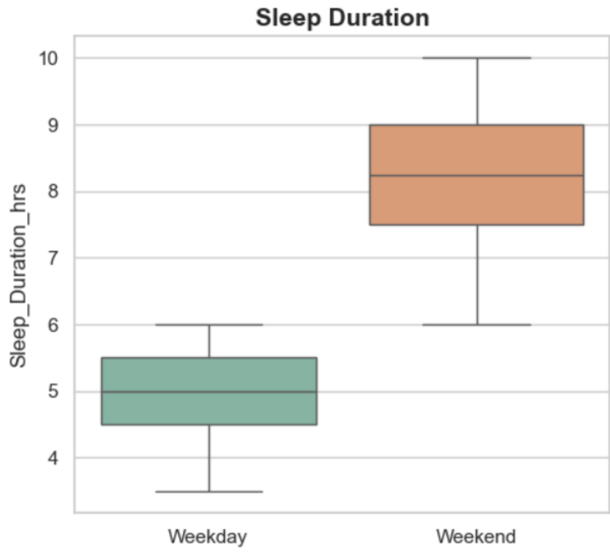


Figure 3c. Weekday vs Weekend: Sleep Duration (hours)

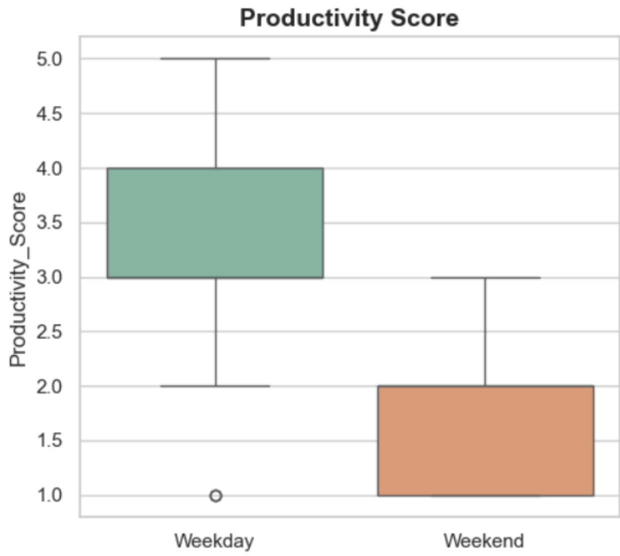


Figure 3d. Weekday vs Weekend: Productivity Score

C. Correlation Analysis

The Pearson correlation matrix revealed several strong relationships with Productivity_Score:

TABLE III: CORRELATIONS WITH PRODUCTIVITY SCORE

VARIABLE	PEARSON R	STRENGTH
Study_Hours	+0.971	Strong positive
Productive_Screen_Time_hrs	+0.962	Strong positive
Stress_Level	+0.913	Strong positive
Caffeine_Drinks	+0.869	Strong positive
Social_Media_hrs	−0.921	Strong negative
Entertainment_hrs	−0.890	Strong negative
Mood	−0.860	Strong negative
Sleep_Quality	−0.814	Strong negative
Sleep_Duration_hrs	−0.779	Strong negative
Gaming_hrs	−0.776	Strong negative
Screen_Before_Bed_min	−0.747	Strong negative
Total_Screen_Time_hrs	−0.687	Strong negative
Bedtime_Hours	+0.253	Weak positive

The strongest positive correlations with productivity were Study_Hours (r = +0.971) and Productive_Screen_Time (r = +0.962). The strongest negative correlations were Social_Media_hrs (r = −0.921) and Entertainment_hrs (r = −0.890). These results indicate that days with more non-productive screen time were consistently associated with lower productivity. Fig. 4 displays the full correlation heatmap, and Fig. 5 shows scatter plots for four key variable pairs.

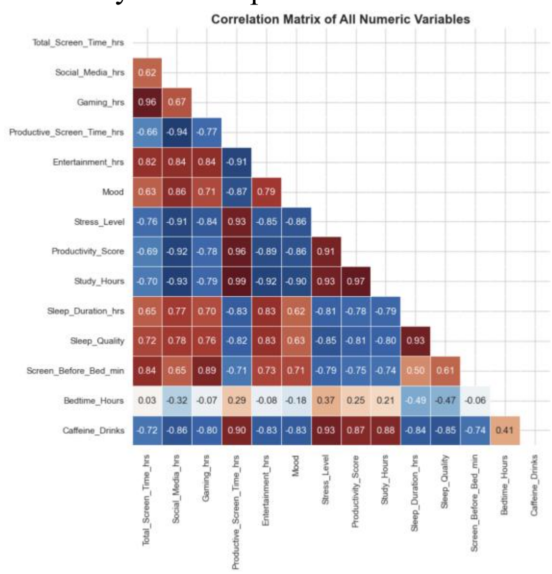


Fig. 4: Correlation Matrix of All Numeric Variables

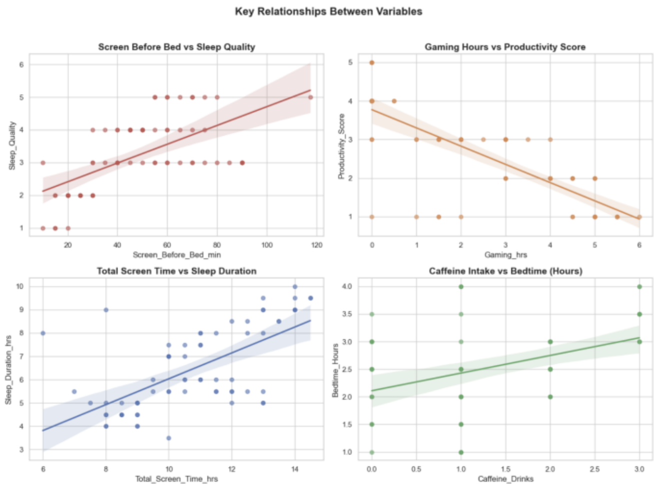


Fig. 5: Key Relationships Between Variables

The strong positive correlation between Stress_Level and Productivity_Score (r = +0.913) suggests that productive days were also high-stress days, likely because they involved heavy academic workloads. The negative correlation between Mood and Productivity (r = −0.860) seems counterintuitive but reflects the pattern that the participant felt happier and more relaxed on low-productivity weekend days.

D. Statistical Test Results

Test 1: Independent Samples t-test (RQ1)

This test compared mean total screen time between weekdays and weekends.

- **Hypotheses:** H_0: No difference in mean screen time. H_1: A significant difference exists.
- **Assumption check:** Levene's test for equal variances was not significant (F = 0.77, p = .382), so equal variances were assumed.
- **Result:** $t(67) = -4.34$, $p < .001$.
- **Decision:** Reject H_0. There is a statistically significant difference in total screen time between weekdays (M = 9.91, SD = 1.71) and weekends (M = 11.87, SD = 2.03).

Weekend screen time was significantly higher, driven primarily by increased gaming and entertainment hours.

Test 2: Pearson Correlation (RQ2)

This test measured the linear relationship between screen time before bed (in minutes) and sleep quality (1–5 scale).

- **Hypotheses:** H_0: No linear relationship. H_1: A significant linear relationship exists.
- **Result:** $r = 0.614$, $p < .001$.
- **Decision:** Reject H_0. There is a significant moderate positive correlation.

This positive direction was unexpected. More screen time before bed was associated with *higher* sleep quality. However, this result is likely confounded by day type: weekends feature both more screen time before bed and longer, higher-quality sleep. The relationship may not be causal. When day type is accounted for, the apparent positive link weakens considerably.

Test 3: One-Way ANOVA (RQ3*)*

This test compared mean productivity scores across three gaming level groups.

- **Hypotheses:** H_0: Mean productivity is the same across all gaming groups. H_1: At least one group differs.
- **Groups:** No Gaming (n = 20, M = 3.95, SD = 0.89), Low Gaming (n = 16, M = 2.62, SD = 1.02), High Gaming (n = 33, M = 1.85, SD = 0.76).
- **Result:** $F(2, 66) = 37.08$, $p < .001$.
- **Decision:** Reject H_0. Gaming level has a significant effect on productivity scores.

There is a clear downward trend: as gaming increases, productivity drops. Days with no gaming averaged a productivity score of 3.95, while days with high gaming (3+ hours) averaged only 1.85, less than half. Fig. 6 shows this pattern.

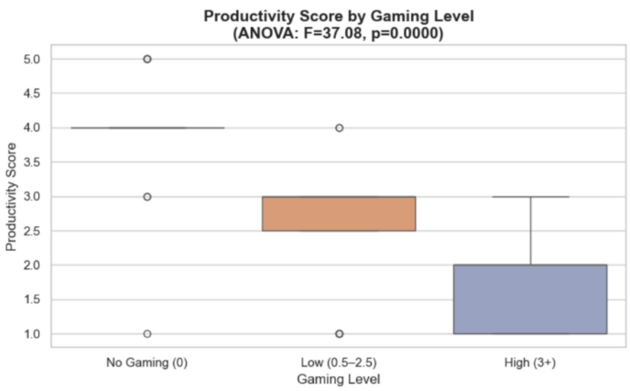


Fig. 6: Productivity Score by Gaming Level

Test 4: Chi-Square Test of Independence

TABLE IV: REGRESSION MODEL PERFORMANCE

METRIC	TRAINING SET (N=55)	TESTING SET (N=14)
R^2	0.9132	0.8619
MAE	0.2951	0.4353
RMSE	0.3498	0.4959

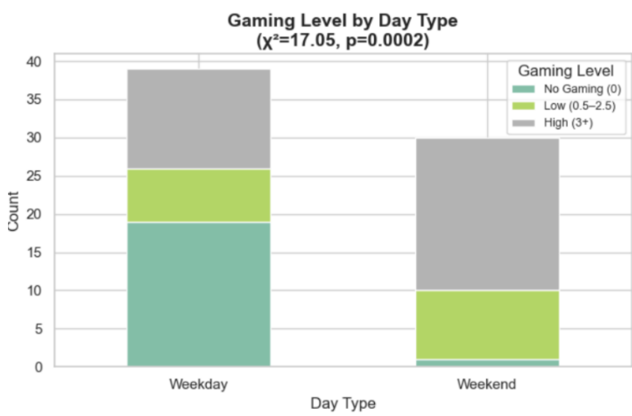
This test examined whether gaming level and day type (weekday vs. weekend) are associated.

- **Hypotheses:** H_0: Gaming level and day type are independent. H_1: They are associated.
- **Result:** $\chi^2(2) = 17.05$, $p < .001$.
- **Decision:** Reject H_0. There is a significant association between gaming level and day type.

TABLE V: REGRESSION COEFFICIENTS

FEATURE	COEFFICIENT	EFFECT
Social_Media_hrs	−0.5955	Strongest negative predictor
Is_Weekday	−0.5079	Negative (after controlling other variables)
Entertainment_hrs	−0.3782	Negative
Sleep_Duration_hrs	−0.2346	Negative (confounded by day type)
Bedtime_Hours	−0.0523	Small negative
Screen_Before_Bed_min	−0.0208	Small negative
Caffeine_Drinks	+0.0789	Small positive
Gaming_hrs	+0.2319	Positive (suppression effect)

On weekdays, 19 out of 39 days had no gaming at all, while on weekends, only 1 out of 30 days had no gaming. High gaming (3+ hours) occurred on 13 of 39 weekdays but 20 of 30 weekends. Gaming behavior is clearly structured



around the weekly schedule. Figures below illustrates this association.

Figure 7a. Gaming Level by Day Type: Count Distribution ($\chi^2 = 17.05$, $p = 0.0002$)

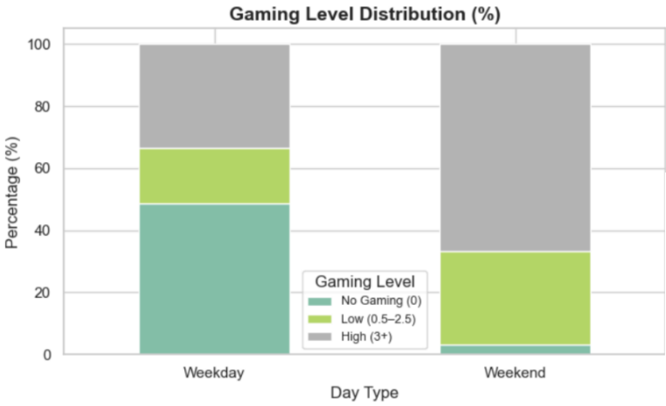


Figure 7b. Gaming Level by Day Type: Percentage Distribution

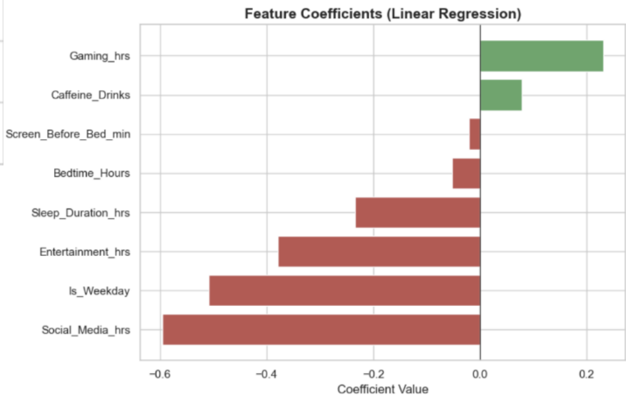
E. Regression Model (RQ4)

A multiple linear regression model was trained to predict daily Productivity_Score using eight features: Gaming_hrs, Social_Media_hrs, Entertainment_hrs, Screen_Before_Bed_min, Sleep_Duration_hrs,Caffeine_Drinks,Is_Weekday, and Bedtime_Hours.

The model explained 86.2% of the variance in productivity on unseen test data, which is a strong result for self-reported behavioral data.

The model intercept was 7.01. Social media hours had the largest negative coefficient (−0.60), meaning that each additional hour of social media was associated with about a 0.6-point drop in productivity. The positive coefficient for Gaming_hrs (+0.23) differs from its strong bivariate negative correlation ($r = −0.78$). This is a suppression effect: after controlling for social media, entertainment, and sleep, the residual effect of gaming flips slightly positive, suggesting that moderate gaming on otherwise structured days is not necessarily harmful. Figures below shows the feature importance and actual-versus-predicted plots.

Figure 8a. Feature Coefficients of the Linear Regression Model



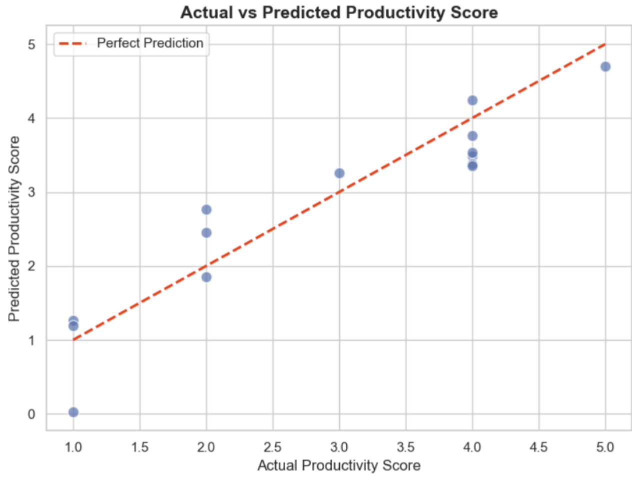
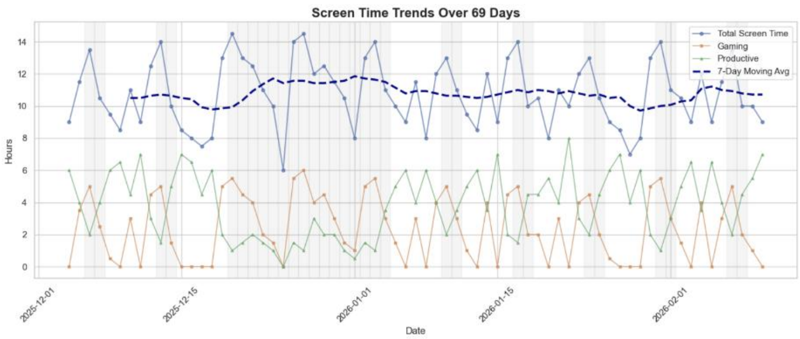


Figure 8b. Actual vs Predicted Productivity Score

F. Time-Series Trends (RQ5)

Screen time patterns showed a clear shift across the 69-day period. During the holiday break (approximately Days 19–32, corresponding to



late December and early January), total screen time and gaming hours were consistently high, productive screen time was near zero, and productivity scores were at their lowest. Once classes resumed in early January, weekday patterns returned: productive screen time increased, gaming dropped on school days, and productivity scores rose.

The 7-day moving average for total screen time showed a gradual stabilization in the final third of the observation period, suggesting that the participant settled into a more regular routine as the new semester progressed. Fig. 9 displays these trends.

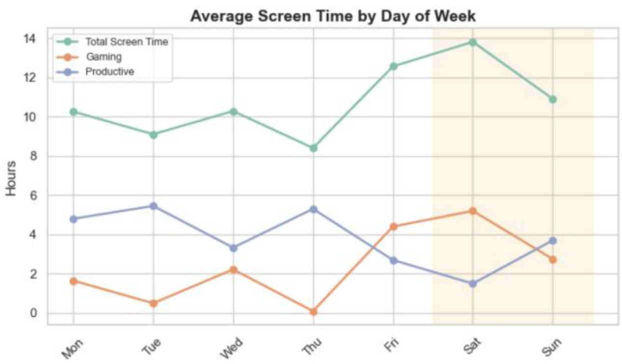
Fig. 9: Screen Time Trends Over 69 Days

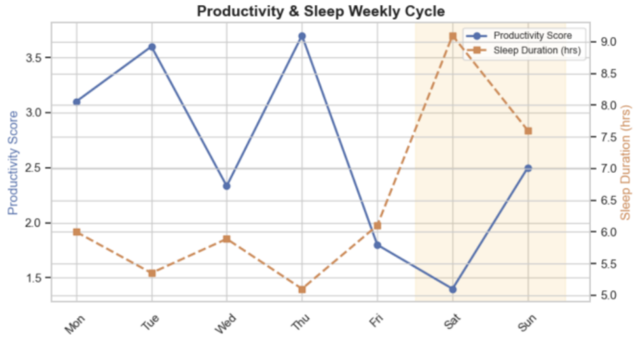
G. Weekly Seasonality

TABLE VI: WEEKLY AVERAGES BY DAY OF WEEK

DAY	SCREEN TIME (HRS)	GAMING (HRS)	PRODUCTIVITY	SLEEP (HRS)
Monday	10.25	1.65	3.10	6.00
Tuesday	9.10	0.50	3.60	5.35
Wednesday	10.28	2.22	2.33	5.89
Thursday	8.40	0.10	3.70	5.10
Friday	12.55	4.40	1.80	6.10
Saturday	13.80	5.20	1.40	9.10
Sunday	10.90	2.75	2.50	7.60

Saturday had the highest average screen time (13.80 hrs) and gaming (5.20 hrs), along with the lowest productivity (1.40). Thursday had the lowest screen time (8.40 hrs), almost no gaming (0.10 hrs), and the highest productivity (3.70). This weekly cycle repeated consistently throughout the observation period. Fig. 10 illustrates these weekly patterns.





V. DISCUSSION

A. Interpretation of Results

The results paint a clear picture of two distinct behavioral modes: a productive weekday mode and a leisure-heavy weekend mode. On weekdays, the participant slept less (5.1 hrs vs. 8.3 hrs), drank more caffeine (1.9 vs. 0.5 drinks), studied more (4.1 vs. 1.4 hrs), and reported higher productivity (3.3 vs. 1.7). On weekends, gaming increased by 2.4 times, entertainment hours doubled, and productivity dropped sharply.

The finding that total screen time is significantly higher on weekends (RQ1) is consistent with Lund, Sølvhøj, Danielsen, and Andersen [3], who reported that leisure screen time peaks during unstructured days. The weekday-weekend gap of nearly 2 hours is meaningful because it represents time shifted away from productive activities.

The positive correlation between screen before bed and sleep quality (RQ2) was unexpected and contradicts Höhn, Hahn, Gruber, and Pletzer [7], who found that evening smartphone use delays sleep onset and reduces sleep quality. However, this apparent contradiction is explained by a confounding variable: day type. On weekends, the participant stayed up later with screens but also slept much longer (8.3 hrs vs. 5.1 hrs), which naturally results in higher self-rated sleep quality. The positive correlation reflects the weekend effect rather than the genuine benefit of screen use before bed. This highlights the importance of controlling confounds in observational studies.

The ANOVA result for RQ3 strongly supports the conclusion that gaming reduces productivity. Days with no gaming had an average productivity score of 3.95, compared to 1.85 on high-gaming days, a drop of more than two full points on the 5-point scale. This is consistent with Alzahrani and Griffiths [10], who found that excessive gaming was associated with worse academic outcomes. The chi-square test further confirmed that gaming behavior is strongly tied to day type, with heavy gaming concentrated on weekends.

The regression model (RQ4) achieved an R^2 of 0.86 on test data, which is strong for behavioral self-report data. Social media hours emerged as the single biggest predictor of lower productivity, which aligns with Gong, Guo, and Tan's [5] findings that social media use is negatively related to academic performance. The suppression effect observed for gaming (positive coefficient in the multivariate model despite a negative bivariate correlation) demonstrates why multivariate analysis is important, as the relationship between any one variable and the outcome can change when other variables are accounted for.

The time-series analysis (RQ5) revealed that the holiday break created a distinct period of high screen time and low productivity. Once the academic schedule resumed, the participant's weekday behavior returned to a more productive pattern. This suggests that external structure (class schedules, deadlines) plays an important role in regulating screen time behavior, a finding consistent with Balasubramanian [11], who showed that reducing smartphone use was associated with improved academic focus and engagement. Fig. 11 presents a behavioral pattern analysis showing relationships among key lifestyle and screen time variables.

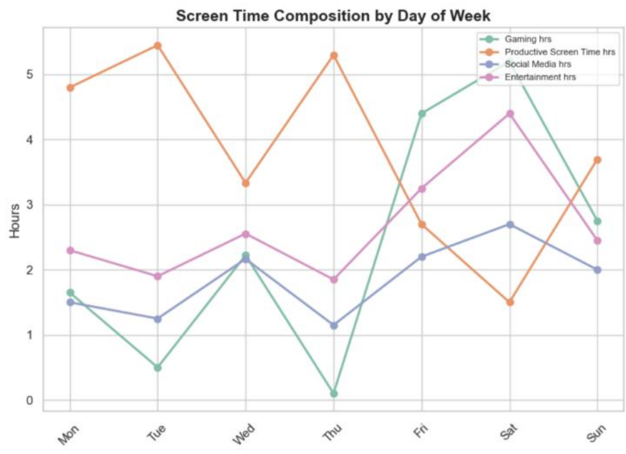


Figure 11a. Screen Time Composition by Day of Week (Gaming, Productive, Social Media, Entertainment)

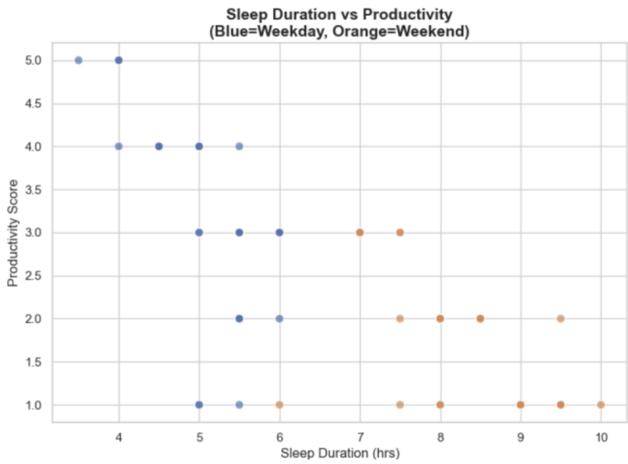


Figure 11b. Sleep Duration vs Productivity Score by Day Type

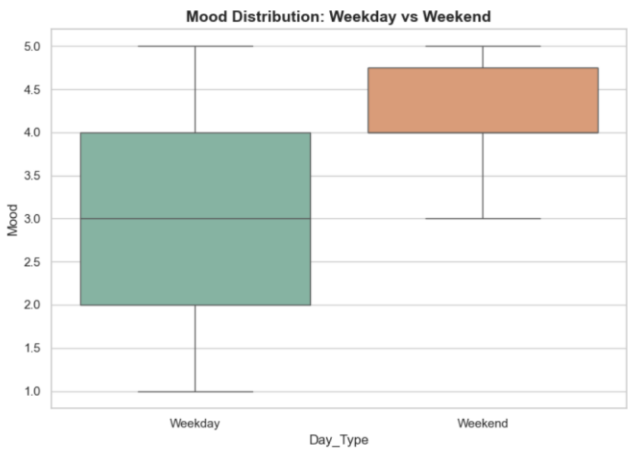


Figure 11c. Mood Distribution: Weekday vs Weekend

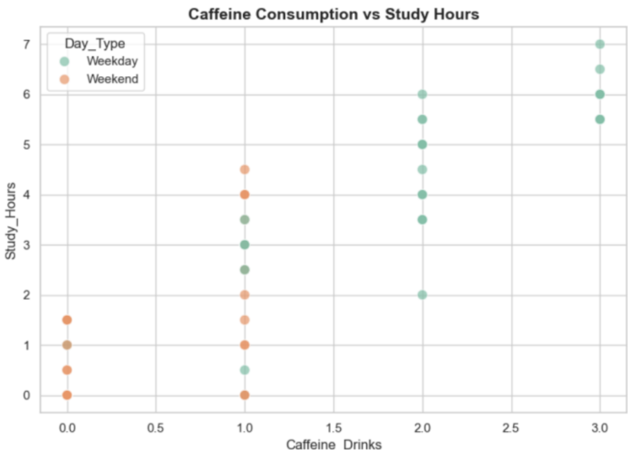


Figure 11d. Caffeine Consumption vs Study Hours by Day Type

B. Comparison to Related Work

The results of this study align with the broader literature in several ways. Like Lund, Sølvhøj, Danielsen, and Andersen [3], this study found that more screen time before bed is linked to sleep-related outcomes, though the specific direction was complicated by confounding. Like Gong, Guo, and Tan [5], social media emerged as a major negative factor for productivity. Like Alzahrani and Griffiths [10], gaming showed a dose-response relationship with academic output: the more gaming, the less productive the day.

However, this study goes further than most prior work by tracking multiple screen time categories simultaneously over 69 days and using regression to separate their effects. The finding that social media is a stronger negative predictor than gaming (in the multivariate model) is a useful addition to the literature, as most screen-time research focuses heavily on gaming as the primary concern.

C. Limitations

1. **Sample size:** The study uses data from a single participant (n = 1). Results cannot be generalized to other students or populations. Individual habits, schedules, and responses to screen time vary widely.
2. **Self-report bias:** All variables except Date and Day_of_Week were self-reported. The participant may have under-reported gaming or social media time and over-reported study hours, either intentionally or unintentionally.
3. **Missing entries:** Three values were missing from the dataset. While median imputation is a reasonable approach, it introduces estimated data points that may not reflect reality.
4. **Short observation window:** The 69-day period covers approximately two months. Longer tracking (e.g., a full semester or academic year) would provide more reliable patterns and allow for seasonal analysis.
5. **No causal claims:** This is an observational study. The correlations and regression results show associations, not cause-and-effect relationships. For example, low productivity on gaming days may be because gaming takes up time, but it could also be that the participant chose to game on days when they had fewer academic tasks.
6. **Confounding variables:** The positive correlation between screen before bed and sleep quality (RQ2) is a clear example of confounding. Other unmeasured confounds (e.g., social activities, exercise, illness) may also affect the results.
7. **Ordinal scales treated as numeric:** Mood, Stress_Level, Productivity_Score, and Sleep_Quality were measured on 1–5 ordinal scales but analyzed using methods designed for continuous data (Pearson correlation, linear regression). While this is common in behavioral research, it is a technical limitation.

D. Recommendations and Future Work

1. **For students:** Reducing social media and entertainment screen time on weekdays could improve daily productivity. Setting a daily limit on non-productive screen time (e.g., under 3 hours) may help. Keeping gaming to weekends and limiting session length could maintain a healthy balance between leisure and academics.
2. **For future research:** Future studies could include multiple participants to

allow generalization. Using automated tracking tools (e.g., RescueTime, Apple Screen Time API) instead of manual logging would reduce self-report bias. Including additional variables such as exercise, social interactions, and academic deadlines would provide a more complete picture.

3. **Methodological improvements:** A longer data collection period (at least one full semester) would strengthen the analysis. Using time-lagged analysis (e.g., does screen time on Day N affect sleep on Day N or productivity on Day N+1?) would help address questions of temporal ordering and potential causation. Mixed-effects models could also be explored for studies with multiple participants.
4. **Screen time interventions:** Controlled experiments where a student deliberately reduces screen time for a set period and tracks the effect on sleep and productivity would provide stronger evidence for causation than observational data alone.

VI. Conclusion

This study analyzed 69 days of tracked screen time data to understand how different types of screen use affect sleep quality and academic productivity in a college student's daily life. Five research questions were investigated using a combination of statistical tests and a regression model.

The key findings are:

1. **Screen time is significantly higher on weekends than weekdays** ($t(67) = -4.34$, $p < .001$), with weekends averaging 11.87 hours compared to 9.91 hours on weekdays. This difference is driven by increased gaming and entertainment.
2. **Screen time before bed shows a positive correlation with sleep quality** ($r = 0.614$, $p < .001$), but this is likely confounded by day type. Weekends have both more screen time before bed and better sleep due to longer sleep duration.
3. **Gaming significantly reduces productivity** ($F(2, 66) = 37.08$, $p < .001$). Days with no gaming had an average productivity score of 3.95, while heavy gaming days averaged only 1.85.
4. **Screen time variables can predict 86.2% of the variance in daily productivity** ($R^2 = 0.86$). Social media hours and entertainment hours are the strongest negative predictors, while caffeine and productive screen time are positive predictors.
5. **Screen time patterns follow a clear weekly cycle** and shift noticeably between holiday periods and academic periods, suggesting that external structure helps regulate behavior.

At the individual level, this analysis showed that the biggest threat to the participant's productivity was not total screen time itself, but how that time was divided. Days where screen time was mostly productive (studying, coding, research) were the most productive days overall, even if total hours were high. Days where screen time was dominated by social media, entertainment, and gaming were consistently the least productive, regardless of how much total time was spent on screens.

The practical takeaway is straightforward: it is not about reducing screen time overall; it is about shifting screen time from non-productive to productive activities. A student who spends 10 hours on screens for studying is in a much better position than one who spends 8 hours on social media and gaming. Managing the *type* of screen use matters more than managing the *amount*.

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