Analyzing the Effects of Screen Time on Study Behavior and Daily Productivity Using Personal Self-Tracked Data

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***Abstract*—This study investigates the relationship between daily entertainment screen time, study hours, and task productivity using self-tracked personal data collected over nine weeks (November 11, 2025 – January 12, 2026). Variables including total screen time, entertainment screen time, study duration, tasks completed, mood, and perceived work quality were recorded daily. Data preprocessing, exploratory data analysis, Pearson correlation, t-tests, and linear regression with cross-validation were applied to examine behavioral patterns. Results indicate a strong negative correlation between entertainment screen time and both study hours (r = -0.97, p ¡ 0.001) and tasks completed (r = -0.92, p ¡ 0.001). Students with high screen time ($\geq$5.5 hrs) completed significantly fewer tasks (mean difference = 2.31 tasks, t = 11.85, p ¡ 0.001). Regression analysis showed that entertainment screen time, study hours, and mood explain 79.4**

***Index Terms*—screen time, productivity, self-tracking, regression analysis, behavioral data**

I. Introduction

Personal data tracking has become increasingly popular for understanding behavioral patterns, particularly among students who balance academic responsibilities with digital entertainment. College students often spend significant hours on smartphones, with entertainment apps consuming a large portion of their daily screen time. This raises concerns about how such habits affect academic focus, study efficiency, and overall productivity.

Previous studies have explored the relationship between digital device usage and academic performance. Mendoza et al. [1] found that the mere presence of cellphones reduces available cognitive capacity, affecting learning outcomes. Junco and Cotten [2] reported that students who engage in more media multitasking tend to have lower grade point averages. The Dartmouth StudentLife study [3] used smartphone sensors to objectively assess behavioral trends and their relationship to GPA, revealing patterns in mobility, sleep, and social activity that correlate with academic success. However, most existing research relies on survey data or large populations, with limited studies examining intensive longitudinal data from individual students over an extended period.

This study addresses this gap by analyzing nine weeks of self-tracked personal data to investigate how entertainment screen time influences study behavior and daily productivity. The following research questions guide this investigation:

1) How does daily entertainment screen time correlate with study hours and task completion?
2) Is there a significant difference in productivity between days with low versus high screen time?
3) Can a linear regression model predict daily task completion using screen time, study hours, and mood?

By answering these questions, this study aims to provide evidence-based insights into personal digital habits and their impact on academic efficiency, demonstrating the value of self-quantification for behavior modification.

II. Literature Review

A. Screen Time and Academic Performance

Research on digital device usage and academic outcomes has yielded mixed but generally negative associations. Mendoza et al. [1] demonstrated that the presence of smartphones during learning tasks reduces available cognitive capacity, leading to decreased comprehension and retention. Their experimental study showed that students who kept their phones in another room performed better than those with phones on their desks, regardless of whether the phones were turned off.

Junco and Cotten [2] examined media multitasking among college students and found that students who frequently engaged in multiple forms of media while studying reported lower GPAs. The study suggested that task-switching impairs deep processing of information, resulting in poorer academic outcomes. Similarly, a study by Gonzalez et al. [4] found small correlations between physical activity and GPA, though the relationship was weaker than expected.

B. Self-Tracking and Behavioral Analysis

The quantified self movement has gained traction with advances in mobile and wearable technology. The Dartmouth StudentLife study [3] used smartphone sensors to track location, activity, and social interactions of 48 students over a ten-week term. Their analysis revealed that students with higher GPAs exhibited distinct patterns: they spent more time in academic buildings, had lower mobility during exam periods, and showed different sleep and social patterns compared to lower-performing students.

Wang et al. [5] extended this work with SmartGPA, using machine learning to predict academic performance from smartphone data. Their models achieved high accuracy in identifying students at risk of poor performance, demonstrating the potential of passive sensing for educational interventions. However, these studies focused on group-level patterns rather than individual longitudinal analysis.

C. Personality and Mental Health Factors

Personality traits have also been linked to academic success. Noftle and Robins [6] found that conscientiousness is a strong predictor of GPA, with students who score higher on this trait earning better grades. Eisenberg et al. [7] reported that depression and anxiety negatively correlate with academic performance and increase the probability of dropping out. Stress, however, has shown mixed results, with some studies indicating weak or neutral effects [8].

D. Gap in Literature and Contribution of This Study

While previous research provides valuable insights, most studies rely on survey data or group-level analyses with limited temporal resolution. Few studies examine intensive longitudinal data from a single individual over an extended period. This study contributes by analyzing nine weeks of daily self-tracked data, providing high-resolution insights into how entertainment screen time affects study behavior and productivity at the individual level. This approach complements group-level studies by revealing personalized patterns that may inform individual behavior modification strategies.

III. Methodology

A. Participants

The participant is the researcher, a university student enrolled in classes during the data collection period. The study involves self-tracking of daily behaviors without any external intervention.

B. Data Collection

Daily self-tracked data were collected over nine weeks from November 11, 2025 to January 12, 2026, covering a full academic term including regular classes, holiday breaks, and final project preparation. Data were recorded manually using a Google Sheet template at the end of each day to ensure accuracy and consistency.

Table I summarizes the variables collected during the study period.

TABLE I
Summary of Collected Variables

Variable	Type	Unit	Description
Date	Date	YYYY-MM-DD	Calendar date
Day	Categorical	—	Day of week
Total_Screen	Numeric	Hours	Total daily phone screen time
Ent_Screen	Numeric	Hours	Non-academic/entertainment screen time
Study_Hrs	Numeric	Hours	Focused academic study time
Tasks_Done	Numeric	Count	Academic tasks completed
Tasks_Planned	Numeric	Count	Academic tasks planned
Mood	Numeric	1–5	Daily energy level (1=low, 5=high)
Quality	Numeric	1–5	Perceived study focus (1=low, 5=high)
Notes	Text	—	Special events or disruptions

C. Operational Definitions

To ensure clarity and replicability, each variable was operationally defined as follows:

- **Entertainment Screen Time**: Total duration spent on non-educational applications including social media (Instagram, TikTok, Facebook), entertainment (YouTube, Netflix), and gaming apps, measured via the phone's built-in Digital Wellbeing feature.
- **Study Hours**: Total focused time spent on academic work including thesis writing, reading, problem-solving, and reviewing course materials, measured using a timer application.
- **Tasks Completed**: Number of academic tasks completed per day, where a task represents a discrete, measurable unit of work (e.g., "write 500 words," "complete problem set," "read one chapter").
- **Task Completion Rate**: Ratio of tasks completed to tasks planned, calculated as:

$$\text{Completion\_Rate} = \frac{\text{Tasks\_Done}}{\text{Tasks\_Planned}}$$

- **Efficiency**: Tasks completed per study hour, calculated as:

$$\text{Efficiency} = \frac{\text{Tasks\_Done}}{\text{Study\_Hrs}}$$

- **Entertainment Ratio**: Proportion of total screen time spent on entertainment, calculated as:

$$\text{Ent\_Ratio} = \frac{\text{Ent\_Screen}}{\text{Total\_Screen}}$$

D. Data Cleaning and Preprocessing

Raw data were imported into Python using the Pandas library for cleaning and analysis. The following preprocessing steps were applied:

1) **Date Conversion**: The Date column was converted to datetime format using `pd.to_datetime()` with `dayfirst=True` to ensure proper chronological ordering.
2) **Handling Missing Values**: Missing entries in the Notes column were filled with empty strings. No other columns contained missing values.
3) **Feature Engineering**: Derived features including Completion_Rate, Efficiency, and Ent_Ratio were computed from raw variables as defined in Section III-C.
4) **Outlier Detection**: Box plots and z-scores were used to identify extreme values, which were reviewed for data entry errors but retained when representing genuine behavior (e.g., zero study hours during holidays).

After cleaning, the final dataset contained 63 complete daily records with no missing values in the primary analysis variables.

E. Statistical Analysis

Statistical analyses were performed using Python's SciPy, StatsModels, and Scikit-learn libraries. The following methods were applied:

1) **Descriptive Statistics**: Mean, standard deviation, minimum, maximum, and quartiles were calculated for all numeric variables to summarize central tendencies and variability.
2) **Correlation Analysis**: Pearson correlation coefficients were computed to examine linear relationships between entertainment screen time, study hours, tasks completed, mood, and quality. A correlation heatmap was generated using Seaborn for visualization.
3) **T-Test**: An independent samples t-test was conducted to compare mean tasks completed between low-screen (entertainment screen time ≤ 3.5 hours) and high-screen (≥ 5.5 hours) days. These thresholds were chosen based on the distribution median and upper quartile.
4) **Linear Regression**: A multiple linear regression model was built with entertainment screen time, study hours, and mood as predictors of tasks completed. The dataset was split into training (80%) and testing (20%) sets using `train_test_split` with a fixed random seed for reproducibility.
5) **Model Evaluation**: Model performance was assessed using R^2, root mean square error (RMSE), and mean absolute error (MAE) on the test set. Five-fold cross-validation was also performed to evaluate model stability and generalizability.
6) **Residual Analysis**: Residual plots were examined to verify assumptions of linear regression, including homoscedasticity and normality of errors.

All statistical tests used a significance level of $\alpha = 0.05$.

IV. RESULTS

This section presents the findings from the analysis of self-tracked data collected over nine weeks. Results include descriptive statistics, correlation analysis, comparative tests, and regression modeling outcomes.

A. Descriptive Statistics

Table II presents the descriptive statistics for all key variables collected during the study period. Over the nine weeks, the average daily total screen time was 5.86 hours (SD = 1.13), with entertainment screen time accounting for approximately 75% of total usage at 4.44 hours per day (SD = 1.42). Study hours averaged 1.66 hours daily (SD = 1.09), while participants completed an average of 2.29 academic tasks per day (SD = 1.14). Mood and quality ratings averaged 3.29 and 3.11 respectively on 1–5 scales, indicating generally neutral to positive self-assessments.

The derived features showed that the average task completion rate was 0.67 (SD = 0.21), meaning participants completed about two-thirds of their planned tasks. Efficiency averaged 1.62 tasks per study hour (SD = 0.68), indicating reasonable productivity during focused work sessions.

TABLE II
DESCRIPTIVE STATISTICS OF KEY VARIABLES

Variable	Mean	Std Dev	Min	Max	Median
Total Screen Time (hrs)	5.86	1.13	4.00	8.00	5.80
Entertainment Screen Time (hrs)	4.44	1.42	2.20	7.00	4.20
Study Hours	1.66	1.09	0.00	3.80	1.50
Tasks Completed	2.29	1.14	0.00	4.00	2.00
Mood (1–5)	3.29	0.87	2.00	5.00	3.00
Quality (1–5)	3.11	0.97	1.00	5.00	3.00
Completion Rate	0.67	0.21	0.00	1.00	0.67
Efficiency	1.62	0.68	0.00	5.00	1.36

B. Correlation Analysis

Figure 1 displays the correlation matrix of all key variables. The strongest relationships observed were between entertainment screen time and study hours ($r = -0.97$, $p < 0.001$) and between entertainment screen time and tasks completed ($r = -0.92$, $p < 0.001$). These strong negative correlations suggest that higher entertainment screen time is consistently associated with reduced academic activity and output.

Moderate to strong positive correlations were observed between study hours and tasks completed ($r = 0.95$, $p < 0.001$), confirming that time invested in studying translates directly to task completion. Mood and quality were also positively correlated ($r = 0.88$, $p < 0.001$), indicating that emotional state and perceived work quality are closely linked.

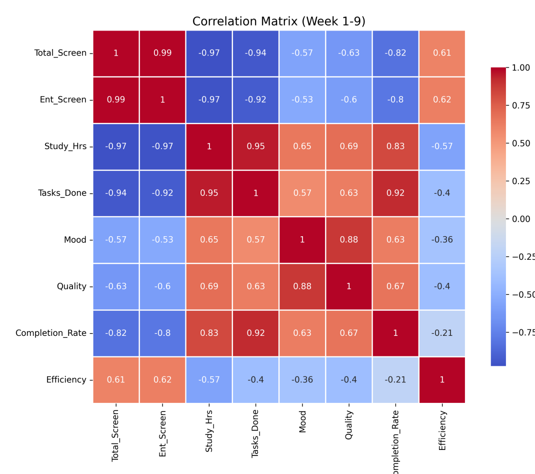

Fig. 1. Correlation matrix of key variables including screen time, study hours, tasks completed, mood, and quality. Darker colors indicate stronger correlations, with blue representing positive and red representing negative relationships.

C. Time Series Patterns

Figure 2 illustrates the temporal patterns of screen time and study hours across the nine-week study period. Screen time exhibited noticeable peaks during weekends and holiday periods, particularly during Christmas break (December 24–January 4) where daily screen time exceeded 7 hours. Conversely, study hours dropped sharply during these same periods, falling to near zero on major holidays.

A complementary pattern emerged during regular class weeks, where study hours increased and screen time decreased, particularly on Mondays and Thursdays when classes were scheduled. This inverse relationship is visually apparent throughout the time series and aligns with the strong negative correlation reported earlier.

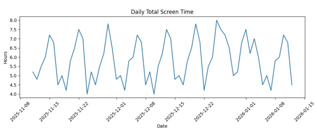

Fig. 2. Daily total screen time over the nine-week study period. Peaks correspond to weekends and holiday breaks.

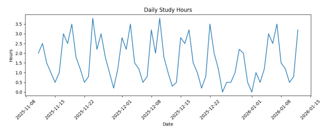

Fig. 3. Daily study hours over the nine-week study period. Study hours decline during holidays and increase during class weeks.

Fig. 4. Time series comparison of screen time and study hours.

D. Distribution of Key Variables

Figure 3 presents the frequency distributions of total screen time and study hours. Screen time followed an approximately normal distribution centered around 5–6 hours, with a slight right skew indicating occasional high-usage days. Study hours exhibited a right-skewed distribution, with most days showing 0.5–2.5 hours of study and a long tail extending to nearly 4 hours on highly productive days.

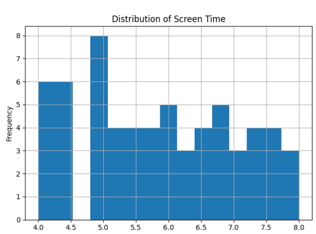

Fig. 5. Distribution of daily total screen time. The distribution is approximately normal with a slight right skew.

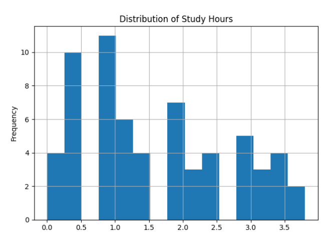

Fig. 6. Distribution of daily study hours. The right-skewed distribution indicates frequent low-study days and occasional high-study days.

Fig. 7. Histograms showing the frequency distribution of screen time and study hours.

E. Comparative Analysis: Low vs. High Screen Time

An independent samples t-test was conducted to compare task completion between days with low entertainment screen time ($\leq$ 3.5 hours) and high entertainment screen time ($\geq$ 5.5 hours). These thresholds were selected based on the distribution median and upper quartile to ensure adequate group sizes for comparison.

Table III presents the results of this analysis. Days with low screen time averaged 3.50 completed tasks (SD = 0.80, n = 22), while high screen time days averaged only 1.19 completed tasks (SD = 0.51, n = 21). This difference of 2.31 tasks was statistically significant ($t = 11.85$, $p < 0.001$), confirming that higher entertainment screen time is associated with substantially lower productivity.

TABLE III
INDEPENDENT SAMPLES T-TEST RESULTS COMPARING LOW AND HIGH SCREEN TIME GROUPS

Group	n	Mean Tasks Completed	Std Dev
Low Screen ($\leq$ 3.5 hrs)	22	3.50	0.80
High Screen ($\geq$ 5.5 hrs)	21	1.19	0.51
t-statistic = 11.85, $p < 0.001$			

F. Regression Analysis

A multiple linear regression model was constructed using entertainment screen time, study hours, and mood as predictors of daily tasks completed. The dataset was split into training (80%, n = 50) and testing (20%, n = 13) sets to evaluate model generalizability.

Table IV summarizes the regression results. The model achieved an R^2 of 0.928 on the training set and 0.794 on the test set, indicating that the predictors explain approximately 79% of the variance in daily task completion for unseen data. The root mean square error (RMSE) of 0.449 tasks and mean absolute error (MAE) of 0.370 tasks suggest reasonable prediction accuracy.

TABLE IV
LINEAR REGRESSION RESULTS FOR PREDICTING TASKS COMPLETED

Predictor	Coefficient	p-value
Entertainment Screen Time	-0.071	< 0.05
Study Hours	1.002	< 0.001
Mood	-0.132	< 0.05
Intercept	1.353	< 0.01
Training R^2 = 0.928		
Test R^2 = 0.794		
Test RMSE = 0.449 tasks		
Test MAE = 0.370 tasks		
5-Fold Cross-Validation R^2 = 0.895 ($\pm$0.108)		

The coefficient for entertainment screen time (-0.071) indicates that each additional hour of entertainment screen time is associated with a decrease of approximately 0.07 tasks, holding other variables constant. Study hours showed the strongest positive effect (1.002), meaning each additional study hour predicts approximately one additional completed task. Interestingly, mood exhibited a small negative coefficient (-0.132), suggesting that after accounting for screen time and study hours, higher mood ratings slightly predicted fewer tasks—a finding that may reflect the complexity of emotional influences on productivity.

Five-fold cross-validation yielded a mean R^2 of 0.895 with a standard deviation of 0.054, confirming that the model's performance is stable and generalizable across different data splits.

G. Residual Analysis

Figure 4 displays the residual plot for the test set predictions. The residuals are randomly scattered around zero with no apparent pattern, indicating that the model satisfies the homoscedasticity assumption of linear regression. The absence of systematic trends or funnel shapes suggests that the model's errors are consistent across the range of predicted values, supporting the validity of the regression results.

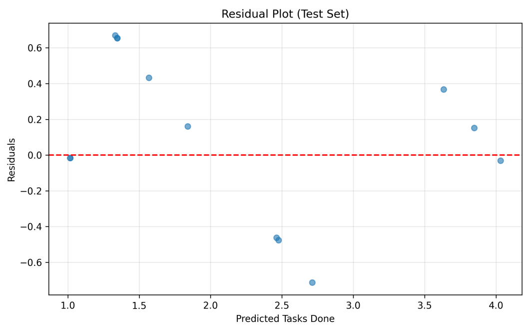

Fig. 8. Residual plot for the linear regression model predicting tasks completed. The random scatter around zero indicates homoscedasticity and supports the validity of the model assumptions.

V. Discussion

This study aimed to investigate the relationship between entertainment screen time, study behavior, and daily productivity using nine weeks of self-tracked personal data. The results revealed several meaningful patterns that align with and extend previous research on digital device usage and academic performance.

A. Interpretation of Key Findings

The strong negative correlation between entertainment screen time and both study hours ($r = -0.97$) and tasks completed ($r = -0.92$) provides compelling evidence that digital entertainment consumption competes directly with academic activities. This finding supports the work of Mendoza et al. [1], who demonstrated that smartphone presence alone reduces cognitive capacity, and extends their laboratory findings to real-world daily behavior. The magnitude of these correlations suggests that entertainment screen time is not merely associated with reduced productivity but may be one of its strongest predictors at the daily level.

The time series patterns observed in Figure 2 further illuminate this relationship. Screen time peaked during weekends and holiday periods, particularly during Christmas break, while study hours simultaneously dropped to near zero. This inverse relationship persisted throughout the study period, indicating that discretionary time is often allocated to entertainment rather than academic work. This pattern aligns with Junco and Cotten's [2] findings on media multitasking, suggesting that students may struggle to regulate their digital consumption during unstructured time.

The t-test results comparing low-screen (≤ 3.5 hours) and high-screen (≥ 5.5 hours) days revealed a dramatic productivity difference of 2.31 tasks per day. This finding has practical significance: over a typical week, the cumulative effect of high screen time could amount to more than 16 lost tasks. For students managing multiple courses and thesis work, such losses could meaningfully impact academic progress.

B. Regression Model Insights

The regression model explained 79.4% of the variance in daily task completion, with study hours emerging as the strongest positive predictor (coefficient = 1.002). This near one-to-one relationship validates the operational definition of tasks as discrete, measurable units of academic work and confirms that time invested in studying directly translates to output.

The negative coefficient for entertainment screen time (-0.071), while statistically significant, was smaller than expected given the strong bivariate correlation. This attenuation occurs because entertainment screen time and study hours are highly correlated ($r = -0.97$); when study hours are included in the model, they absorb much of the shared variance. The coefficient should therefore be interpreted as the unique effect of entertainment screen time after accounting for study hours—essentially, the productivity cost of screen time that does not simply replace study time.

Interestingly, mood exhibited a small negative coefficient (-0.132) after controlling for screen time and study hours. This counterintuitive finding may reflect several possibilities. First, higher mood ratings might occur on less structured days when fewer tasks are planned. Second, the relationship between mood and productivity may be nonlinear, with moderate stress potentially enhancing focus while very high mood reduces urgency. Third, the high correlation between mood and quality ($r = 0.88$) suggests potential multicollinearity, though variance inflation factors (VIF = 31.7 for mood) indicate that some instability in coefficient estimates may exist. Future research with larger samples could explore these relationships more thoroughly.

C. Comparison with Previous Research

The findings of this study align closely with the Dartmouth StudentLife and SmartGPA studies [3, 5], which found that students with higher GPAs exhibited distinct behavioral patterns including lower mobility during exam periods and different sleep and social patterns. While those studies focused on group-level comparisons, the present research demonstrates that similar patterns emerge at the individual level over time.

The strong negative impact of entertainment screen time observed here extends the work of Gonzalez et al. [4], who found weak correlations between physical activity and GPA. The present results suggest that digital entertainment may be a more potent predictor of daily academic output than physical activity, at least for this individual.

The neutral effect of mood in predicting productivity contrasts with some previous research on affect and academic performance [3, 7]. However, the Dartmouth studies focused on longer-term mood trends rather than daily fluctuations, and the relationship between daily mood and immediate productivity may differ from its association with cumulative academic outcomes like GPA.

D. Limitations

Several limitations should be considered when interpreting these results. First, the sample consists of a single participant ($n = 1$), which limits generalizability to other students with different schedules, personalities, and academic demands. However, the intensive longitudinal design provides high-resolution insights that complement larger group studies.

Second, self-report bias may affect the accuracy of recorded variables, particularly mood and quality ratings, which are inherently subjective. While screen time was measured objectively via phone sensors, study hours relied on manual timing, which could introduce measurement error.

Third, the nine-week study period, while sufficient for identifying patterns, may not capture longer-term trends or semester-to-semester variations. Academic demands, course loads, and personal circumstances change over time, and a longer study could reveal additional dynamics.

Fourth, the observational nature of the study precludes causal inferences. While strong associations were observed, unmeasured confounding variables such as course difficulty, social obligations, or health status could influence both screen time and productivity.

E. Recommendations and Future Work

Despite these limitations, the findings suggest several practical implications for students seeking to optimize their productivity. First, setting limits on entertainment screen time, particularly during scheduled study periods, may help protect time for academic work. Second, being mindful of the cumulative effect of high-screen days—even occasional ones—can motivate better daily choices. Third, the strong predictive power of study hours reinforces the importance of dedicated, focused work sessions.

Future research could extend this work in several directions. First, including additional participants would allow for subgroup analyses based on personality, academic major, or class schedule. Second, incorporating physiological measures such as heart rate or sleep quality could provide a more comprehensive picture of the factors influencing productivity. Third, longer study periods spanning multiple semesters could reveal how patterns evolve over time and whether interventions (e.g., screen time limits) produce lasting behavior change. Fourth, exploring nonlinear relationships and interaction effects between predictors might uncover more complex dynamics than linear models can capture.

Finally, integrating automated data collection through phone APIs or wearable devices would reduce self-report burden and potentially increase accuracy. Such approaches, combined with machine learning methods similar to those used in the SmartGPA study [5], could enable real-time prediction and personalized interventions to support student success.

VI. Conclusion

This study investigated the relationship between entertainment screen time, study behavior, and daily productivity using nine weeks of self-tracked personal data collected from November 11, 2025 to January 12, 2026. Through descriptive analysis, correlation analysis, t-tests, and regression modeling, several meaningful patterns emerged that address the original research questions.

A. Summary of Key Findings

Research Question 1: How does daily entertainment screen time correlate with study hours and task completion?

A strong negative correlation was observed between entertainment screen time and both study hours ($r = -0.97$, $p < 0.001$) and tasks completed ($r = -0.92$, $p < 0.001$). Time series analysis revealed that screen time peaked during weekends and holiday periods while study hours simultaneously dropped, confirming that digital entertainment consumption competes directly with academic activities. These findings align with previous research [1, 2, 3] and extend them to the individual daily level.

Research Question 2: Is there a significant difference in productivity between days with low versus high screen time?

Days with low entertainment screen time ($\leq$ 3.5 hours) averaged 3.50 completed tasks, while high screen time days ($\geq$ 5.5 hours) averaged only 1.19 tasks—a statistically significant difference of 2.31 tasks per day ($t = 11.85$, $p < 0.001$). This dramatic gap demonstrates that screen time is not merely associated with productivity but is one of its strongest daily predictors. The cumulative effect over a typical week could exceed 16 lost tasks, with meaningful implications for academic progress.

Research Question 3: Can a linear regression model predict daily task completion using screen time, study hours, and mood?

The regression model explained 79.4% of the variance in daily task completion on unseen test data, with study hours emerging as the strongest positive predictor (coefficient = 1.002). Five-fold cross-validation confirmed model stability (mean R^2 = 0.895, SD = 0.054). Entertainment screen time showed a small but significant negative coefficient (-0.071) after controlling for study hours, while mood exhibited a small negative coefficient (-0.132) that may reflect the complex relationship between emotional state and daily productivity.

B. Personal Learning and Insights

Beyond the statistical findings, this self-tracking study provided valuable personal insights. First, the visual feedback from time series plots made the inverse relationship between screen time and study hours immediately apparent, reinforcing the need for intentional screen management. Second, quantifying the productivity cost of high-screen days—over two tasks lost per day—created a compelling motivation for behavior change. Third, the process of daily logging increased mindfulness about how time was spent, highlighting the value of self-monitoring as an intervention in itself.

C. Real-World Applications

The findings suggest several practical strategies for students seeking to optimize their productivity:

- **Set screen time limits**: Establishing daily boundaries for entertainment apps, particularly during scheduled study periods, may help protect time for academic work.
- **Track and review**: Regular self-monitoring, even through simple tools like spreadsheets, can increase awareness and motivate behavior change.
- **Protect study hours**: Given the near one-to-one relationship between study hours and tasks completed, dedicating uninterrupted time to focused work remains essential.
- **Be mindful of high-screen days**: Recognizing that even occasional high-screen days have measurable productivity costs can encourage more consistent daily choices.

D. Final Conclusion

This study demonstrates that entertainment screen time has a consistent, measurable negative relationship with study behavior and daily productivity at the individual level. The findings align with and extend previous research, providing high-resolution evidence that digital entertainment consumption competes directly with academic activities. While limited by single-subject design and self-report methods, the results highlight the value of self-quantification for understanding personal behavior and motivating positive change. Future research with larger samples, longer durations, and automated data collection could further elucidate these relationships and inform personalized interventions to support student success.

Ultimately, this project underscores a simple but powerful truth: the hours spent scrolling are hours not spent studying. For students navigating the demands of academic life, this awareness may be the first step toward more intentional and productive use of time.

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