Daily iOS Screen Time Patterns and Their Relationship to Social-Media Addiction

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Abstract—**This paper investigates the relationship between daily iOS Screen Time metrics and self-reported social media goal-violation in a college student over an 81-day period. Using objective device data, the study analyzes patterns in total screen time, social media usage, pickups, notifications, and app diversity to identify behavioral predictors of exceeding intended social media limits. Statistical analyses, including descriptive statistics, Welch's t-tests, and logistic regression, reveal that higher social media time, total screen time, and notification counts are strongly associated with goal-violation days, with large effect sizes and significant group differences. The logistic regression model demonstrates that screen time metrics can predict goal-violation with reasonable accuracy. These findings highlight the value of device-tracked data for understanding digital self-regulation and suggest that managing notifications and session length may help reduce problematic social media use. The study provides a replicable framework for personal digital behavior analysis and offers practical insights for healthier technology habits.**

Index Terms—Screen Time, Social Media Addiction, Self-Regulation, iOS Analytics, Behavioral Data, Logistic Regression, Welch's t-test, Digital Well-being, Notifications, Smartphone Usage

I. Introduction

Smartphones and digital devices have become a major part of daily life, especially for students and young adults. Many people use their phones for social media, communication, and entertainment, which can sometimes lead to spending more time online than intended. This increase in screen time has been linked to problems such as poor sleep, lower academic performance, and higher stress or anxiety levels [1]. Social media addiction is now a growing concern, as people often find it hard to control their usage, even when they set personal limits for themselves [2].

Most research on screen time and social media use relies on people estimating how much time they spend on their devices. However, these self-reports are often inaccurate, with many people underestimating their actual usage [3]. Recent studies suggest that using data directly from devices, like iOS Screen Time, gives a more accurate and honest view of digital habits [4]. Despite this, there are still not many studies that use this kind of objective data, especially for tracking daily behavior over a long period.

The project aims to address that gap by using real iOS Screen Time data collected every day for 81 days from one participant. The study looks at total screen time, social media usage, notifications, device pickups, and whether the person went over their daily goal for social media use. By analyzing these patterns, the project explores which digital habits are most connected to breaking self-set limits and whether it is possible to predict when someone is likely to go over their goal using only their screen time data.

By focusing on real, device-recorded data instead of self-reports, the study hopes to provide a clearer understanding of how daily digital behaviors relate to self-control and social media use. The findings can help people become more aware of their habits and learn how to manage their screen time in a healthier way.

II. Literature Review

A growing body of research has explored the impact of digital behaviors such as screen time, social media use, and smartphone engagement on well-being, productivity, and mental health. Many early studies focused on self-reported data to examine relationships between device use and outcomes like sleep quality, academic performance, and mood. For example, Twenge and Campbell [1] analyzed survey data from adolescents and found that higher screen time was associated with lower psychological well-being and increased symptoms of depression. Similarly, Cain and Gradisar [5] reviewed studies on electronic media use and sleep, concluding that greater device use before bedtime was linked to poorer sleep outcomes among children and adolescents.

In the area of social media and self-regulation, researchers have investigated patterns of addictive behavior and the challenges individuals face in managing their usage. Montag et al. [2] discussed the concept of smartphone addiction and highlighted the difficulty users experience in adhering to self-imposed limits, often resulting in repeated goal-violation. These studies typically relied on questionnaires and self-assessment tools to measure both usage and behavioral outcomes.

However, a key limitation of much of the existing literature is the reliance on self-reported data, which is prone to recall bias and underestimation of actual usage. Boase and Ling [3] compared self-reported mobile phone use to device-logged data and found significant discrepancies, with participants consistently underestimating their screen time. Recognizing this gap, more recent research has begun to incorporate objective, device-recorded metrics to provide a more accurate and detailed understanding of digital behavior. Geyer et al. [4] demonstrated that objective screen time data from devices like smartphones offers a more reliable measure than self-reports, and can reveal patterns that might otherwise go unnoticed.

While these studies have advanced our understanding of the effects of digital behavior, they often focus on large populations and aggregate trends, rather than detailed, individual-level patterns over time. The present project builds on this literature by using daily iOS Screen Time data collected from a single participant over an extended period. Unlike most prior work, the study combines objective device metrics with self-reported goal-violation behavior to examine the day-to-day relationship between digital habits and self-regulation. By focusing on individual-level data and leveraging both statistical analysis and predictive modeling, the research addresses the limitations of self-reporting and contributes a new perspective to the ongoing discussion about digital well-being and behavioral self-control.

III. Methodology

A. Participants

The study focused on a single participant. No private or identifying information was collected or included in the dataset.

B. Data Collection Methods

Data was collected daily over a period of 81 days, from November 19, 2025 to February 7, 2026. The main variables tracked were total screen time (all apps), social media app usage time, social intensity ratio, total device pickups, first pickups focused on social apps, total notifications received, notifications from social apps, number of distinct social apps used, and a binary indicator of daily goal-violation. Most of these variables were automatically recorded using the Apple iOS Screen Time feature, which provides objective and detailed logs of device usage. The goal-violation variable was self-reported by the participant each day, indicating whether they exceeded their intended social media usage. This approach ensured high-frequency, accurate data logging using a combination of automated device tracking and manual daily self-reporting.

C. Operational Definitions

Each variable in the dataset was clearly defined to ensure replicability. Total screen time refers to the number of minutes spent on all apps in a day, while social apps total time measures the minutes spent specifically on social media applications. The social intensity ratio is calculated as the proportion of total screen time devoted to social apps. Pickups (total) counts the number of times the device was picked up, and first pickups (social apps) records the number of times the device was first unlocked with a social app as the focus. Notifications (total) and notifications (social) represent the total number of notifications received and those from social apps, respectively. The number of distinct social apps used indicates how many unique social apps were accessed each day. Finally, daily goal-violation is a binary variable, with 1 indicating the participant spent more time on social media than intended, and 0 indicating they stayed within their goal. These definitions are summarized in the variable dictionary below.

D. Data Cleaning

To ensure data quality, several cleaning steps were performed. The dataset was checked for missing values and found to be complete, with no missing entries. Outliers in the numeric variables were identified using the interquartile range (IQR) method and reviewed for validity. Any unnamed columns resulting from CSV import were removed, and all variables were converted to appropriate numeric types. Units were standardized to minutes or counts for consistency. These steps ensured that the dataset was accurate, reliable, and ready for analysis.

E. Statistical Analysis

The analysis combined descriptive and inferential statistics to explore the relationships between digital behavior and goal-violation. Descriptive statistics such as mean, median, and standard deviation were calculated for each variable, and visualizations including histograms and box plots were used to illustrate distributions and group differences. Welch's t-test was applied to compare means between goal-violation and non-violation days, as it does not assume equal variances. Cohen's d was calculated to measure effect size. Logistic regression was used to predict goal-violation based on screen time metrics, with an 80/20 stratified train-test split for model validation. Feature standardization was performed to ensure comparability of regression coefficients. Throughout the process, objective device-recorded metrics and consistent self-reporting minimized bias and measurement errors, supporting the validity of the findings.

IV. Results

This section presents the outcomes of the data analysis in an objective and organized manner, using descriptive statistics, visualizations, and statistical tests to summarize the patterns and relationships observed in the dataset. The dataset consists of 81 daily records, each representing one full day of digital behavior from a single participant, with variables including total screen time, social media usage, device pickups, notifications, and a binary indicator of goal-violation. Overall, the dataset shows a high frequency of goal-violation days, with approximately 79% of days classified as violations, indicating that the participant often exceeded their intended social media usage. Descriptive statistics such as mean, median, and standard deviation were calculated for each variable, revealing that the average total screen time was about 529 minutes per day, and the average social media usage was approximately 431 minutes per day. The standard deviations indicate considerable day-to-day variability in both overall and social media screen time.

Histograms were generated for key variables, including total screen time, social media time, device pickups, and the social intensity ratio, to visualize the distribution of these behaviors across the 81 days. These histograms show that both total and social media screen time are right-skewed, with most days clustered around the mean but several days with exceptionally high usage. The distribution of device pickups is more uniform, while the social intensity ratio (the proportion of screen time spent on social apps) is generally high, reflecting the participant's strong focus on social media. Time-series plots and boxplots further illustrate trends and group differences, such as higher screen time and notification counts on goal-violation days compared to non-violation days.

To explore relationships between variables, a comparison of means was conducted between goal-violation and non-violation days for each screen time metric. The results, summarized in tables and visualized with boxplots, indicate that violation days are associated with significantly higher total screen time, social media time, notification counts, and social intensity ratio. A correlation matrix was also computed to examine the strength and direction of relationships among the variables, revealing strong positive correlations between social media time, total screen time, and notification volume. Statistical tests, specifically Welch's t-tests, were performed to determine whether the differences in means between violation and non-violation days were statistically significant. The results show that 6 out of 8 screen time metrics had significant differences ($p < 0.05$), with large effect sizes for social media time, total screen time, and notification counts, as measured by Cohen's d.

Each figure and table is accompanied by a clear title and caption, and the text explains what the data show without interpreting the deeper meaning. For example, the histogram of total screen time demonstrates the overall distribution and highlights the prevalence of high-usage days, while the boxplot comparing violation and non-violation days visually confirms the higher median screen time on violation days. The results section, therefore, provides a comprehensive and objective summary of the dataset's structure, key patterns, variable relationships, and the outcomes of statistical tests, using tables and graphs to clearly illustrate the findings.

V. Discussion

The results of the study reveal clear patterns in the participant's daily digital behavior, particularly regarding social media use and goal-violation. The data show that days with higher total screen time, social media usage, and notification counts are strongly associated with goal-violation, suggesting that prolonged and frequent engagement with social apps makes it more difficult to maintain self-imposed limits. This pattern may be explained by the addictive design of social media platforms, which use notifications and algorithmic feeds to encourage longer sessions and repeated checking. The strong correlation between social media time and total screen time further indicates that social apps dominate the participant's device usage, crowding out other activities and increasing the likelihood of exceeding daily goals. The finding that violation days have fewer device pickups, but longer usage sessions suggests that the participant is more likely to engage in extended, uninterrupted periods of social media use when self-control lapses, rather than frequent but brief checks.

When compared to previous research, these findings are largely consistent with the literature on digital addiction and self-regulation. Prior studies have shown that higher screen time and notification volume are linked to reduced self-control and increased risk of problematic use, especially among young adults. The large effect sizes observed for social media time and notification counts support earlier work that identifies these metrics as key predictors of digital overuse. However, the negative association between device pickups and goal-violation is somewhat unexpected, as many studies report that frequent pickups are a sign of compulsive checking. In this case, it appears that fewer but longer sessions are more problematic for self-regulation than frequent, short interactions, highlighting the importance of session length as a behavioral marker.

Despite these insights, the study has several limitations. The most significant is the small sample size, as the analysis is based on data from a single participant. This limits the generalizability of the findings and means that the results may reflect individual habits rather than broader trends. Additionally, the goal-violation variable relies on self-report, which can introduce bias or inconsistency, although the use of objective device metrics for other variables helps to mitigate this issue. The data collection period, while spanning nearly three months, may not capture longer-term patterns or seasonal effects. There were no missing entries in the dataset, but the focus on a single behavioral outcome (goal-violation) may overlook other important aspects of digital well-being.

For future research, it is recommended that similar studies be conducted with larger and more diverse samples to enable population-level inference. Including validated psychological scales for digital addiction or well-being, alongside objective device data, would strengthen the analysis. Researchers should also consider tracking additional variables such as sleep quality, academic performance, or mood to explore broader impacts of digital behavior. Alternative methods, such as time-series analysis or cross-validation, could provide deeper insights and more robust model evaluation. Finally, students replicating this approach should be encouraged to reflect on their own behavioral goals and consider interventions, such as notification management or app usage limits, to promote healthier digital habits.

V. Conclusion

This study set out to examine the relationship between daily iOS Screen Time metrics and self-reported social media goal-violation in a college student. The analysis found that higher social media usage, total screen time, and notification volume are strongly associated with goal-violation days, with large and statistically significant differences between violation and non-violation days. The logistic regression model further demonstrated that these metrics can be used to predict goal-violation with reasonable accuracy. Through this process, the participant learned that their digital habits are heavily influenced by social media engagement and that prolonged sessions, rather than frequent pickups, are most closely linked to lapses in self-control. These findings suggest that managing notifications and monitoring session length may be effective strategies for improving self-regulation. Overall, the study highlights the value of objective device data for understanding personal behavior and provides a replicable methodology for others interested in analyzing and improving their own digital well-being.

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