Exploratory Analysis of Personal Smartphone Usage Patterns Using iPhone Screen Time Data

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***Abstract*— This study analyzes personal smartphone usage using objective Screen Time data to examine how total screen time relates to notifications, pickups, app categories, and day-of-week variation. Daily usage metrics were collected and analyzed using descriptive statistics, correlation analysis, ANOVA, and regression techniques. Results show that screen time is significantly higher on weekends and positively correlated with notifications and pickups, indicating that digital interruptions and unstructured time strongly influence usage behavior. The findings demonstrate how personal data analytics can provide meaningful insights into digital habits and support more mindful technology use.**

***Index Terms*— Smartphone usage, screen time, notifications, correlation analysis, ANOVA, behavioral analytics, data science.**

I. Introduction

The rapid proliferation of smartphones has fundamentally reshaped how individuals communicate, work, learn, and entertain themselves. This study focuses on the exploratory analysis of personal smartphone usage patterns using Apple iPhone Screen Time data, with particular emphasis on daily screen time, app usage categories, notifications, and user interaction frequency. As smartphones have become deeply embedded in everyday life, understanding personal digital behavior through data-driven approaches has become increasingly relevant in the field of data science.

Smartphone usage is an important area of study because excessive or unregulated screen exposure has been associated with reduced productivity, sleep disturbances, increased stress levels, and diminished academic or work performance. According to a report by the Pew Research Center, a significant proportion of adults report being online "almost constantly," highlighting the intensity of digital engagement in modern society [1]. Furthermore, research published in journals such as Computers in Human Behavior has linked high smartphone dependency with lower self-regulation and increased psychological distress [2]. These findings underscore the importance of understanding behavioral patterns embedded in daily device interactions.

Prior studies have commonly relied on surveys or self-reported measures to assess smartphone addiction, digital well-being, and productivity impacts. While these approaches provide useful insights, they are often limited by recall bias and subjective inaccuracies. More recent research has emphasized the value of objective behavioral logs, such as passive sensing data and screen tracking metrics to obtain more accurate representations of digital behavior [3]. With the introduction of Apple's Screen Time feature in iOS, users now have direct access to detailed logs of daily screen minutes, app categories (e.g., social, entertainment, productivity), pickup frequency, and notification counts, creating new opportunities for individualized behavioral analytics.
Despite the growing body of literature on smartphone usage, there remains a gap in personalized, small-scale exploratory studies that apply data science techniques to individual-level longitudinal screen time datasets. Many large-scale studies focus on population-level trends, but fewer projects demonstrate how individuals can leverage their own behavioral data to uncover actionable insights. This project addresses that gap by applying exploratory data analysis (EDA) techniques to a personal iPhone Screen Time dataset, transforming raw usage logs into interpretable behavioral patterns.

The primary goal of this research is to explore, visualize, and interpret patterns in personal smartphone usage using statistical summaries and exploratory data analysis methods. Specifically, this study aims to:

1. Quantify daily screen time trends and category-level usage distributions.

2. Identify peak usage periods and potential sudden spikes in activity.

3. Examine relationships between pickups, notifications, and total screen time.

4. Assess how usage distribution across social, entertainment, productivity, travel, and gaming categories reflects behavioral priorities.

Based on these goals, the study seeks to answer the following research questions:

1. What are the dominant patterns in daily smartphone usage as recorded by iPhone Screen Time data?

2. Are there identifiable spikes or anomalies in usage behavior across specific dates?

3. How strongly are notifications and pickup frequency associated with total screen time?

4. Which application categories consume the largest proportion of daily device interaction?

5. What behavioral insights can be derived from analyzing personal smartphone usage data?

By addressing these questions, this research demonstrates how personal digital trace data can be leveraged through data science methodologies to promote self-awareness, digital well-being, and informed behavioral change. The findings contribute to the growing discourse on quantified self-analytics and highlight the practical application of exploratory data analysis in everyday life contexts.

II. LITERATURE REVIEW

The increasing ubiquity of smartphones has generated a substantial body of research examining their influence on human behavior, including sleep quality, mood regulation, gaming engagement, productivity, and physical activity. This section reviews prior studies related to behavioral metrics that align with the variables in the present dataset, namely screen time duration, notifications, pickups, and application usage categories. It synthesizes the methodologies used, key findings, and limitations identified in previous work, and situates this project within the broader academic discourse.

A. Smartphone Usage and Sleep Patterns

One of the most extensively studied areas in smartphone research is its relationship with sleep. Studies have examined how prolonged screen exposure, particularly before bedtime, affects sleep latency, duration, and overall sleep quality. The National Sleep Foundation has reported that increased evening screen time is associated with delayed sleep onset due to blue light exposure and cognitive stimulation [1].

Exelmans and Van den Bulck [2] investigated bedtime mobile phone use among adolescents using survey-based measures and found significant associations between nighttime phone use and reduced sleep quality. Similarly, Levenson et al. [3] utilized self-reported screen time and standardized sleep questionnaires to demonstrate that higher social media use correlated with increased sleep disturbances.

Although this study does not directly measure mood, it analyzes digital engagement intensity, which has been linked to emotional well-being in prior research. The exploratory framework provides foundational behavioral insights that could support future mood-related predictive modeling.

B. Smartphone Use, Mood, and Psychological Well-Being

Research has also examined the psychological consequences of excessive smartphone use. Elhai et al. [4] found that problematic smartphone use is associated with anxiety, depression, and fear of missing out (FOMO). Using validated psychological scales combined with usage frequency measures, the study established correlations between emotional distress and higher digital engagement.

The American Psychological Association has highlighted concerns regarding digital overuse and mental health, particularly among young adults [5]. Moreover, the “Student Life” study by Wang et al. [6] used smartphone sensor data including GPS, call logs, and activity levels to predict mental health and academic performance among university students.

C. Gaming Behavior and Entertainment Consumption

Mobile gaming and entertainment applications contribute significantly to total smartphone screen time. Research has shown that gaming engagement may provide short-term stress relief but can also lead to addictive behaviors when excessive. Kuss and Griffiths [7] examined Internet gaming disorder and highlighted behavioral dependency symptoms linked to extended playtime.

Additionally, usage reports from the Pew Research Center indicate that entertainment and social media apps dominate daily smartphone engagement [8]. Studies analyzing app-level logs have found that entertainment apps contribute disproportionately to screen time spikes, especially during weekends or holidays.

This research similarly categorizes usage into social, entertainment, productivity, travel, and gaming segments. However, it uniquely emphasizes exploratory visualization of sudden spikes and anomalies within a personal dataset, rather than focusing solely on addiction metrics.

D. Productivity and Digital Distraction

Smartphones are both productivity tools and sources of distraction. Duke and Montag [9] examined how frequent phone checking behaviors reduce task efficiency and increase cognitive load. Studies suggest that notification interruptions significantly decrease attention span and workflow continuity.

Mark et al. [10] studied workplace interruptions and found that task-switching due to digital notifications leads to measurable productivity declines.

The inclusion of pickups and notification counts in this project enables exploratory assessment of potential digital distraction patterns. Unlike controlled experiments, this study analyzes naturalistic, real-world data collected passively from iPhone Screen Time.

E. Quantified Self and Personal Analytics

Quantified self-movement promotes the use of personal data to understand behavioral trends. Lupton [11] discusses how self-tracking technologies empower individuals to make data-informed lifestyle changes. Modern smartphones provide built-in analytics dashboards, including Apple’s Screen Time, allowing users to access daily summaries without third-party applications.

Recent data science research has encouraged exploratory data analysis (EDA) as a first step toward behavioral modeling, anomaly detection, and predictive analytics [12].

F. Research Gap and Contribution

Across the literature, previous studies have extensively examined sleep disruption, mood changes, gaming addiction, and productivity decline associated with smartphone usage. They have employed methods such as surveys, wearable sensors, passive smartphone logs, and machine learning algorithms. While findings consistently suggest associations between high screen engagement and behavioral or psychological impacts, several limitations remain:

- Overreliance on self-reported data.
- Limited personalization in behavioral analytics.
- Focus on predictive modeling rather than foundational exploratory analysis.

This project differs in several key ways:

- It utilizes objective iPhone Screen Time logs instead of survey-based measures.
- It focuses on exploratory data analysis rather than predictive modeling.
- It emphasizes individualized behavioral interpretation rather than population generalization.
- It incorporates detection of sudden spikes and temporal anomalies in daily usage patterns.

III. Methodology

This chapter describes the procedures used to conduct the exploratory analysis of personal smartphone usage patterns using iPhone Screen Time data. It provides a detailed explanation of the participant, data collection process, operational definitions of variables, data preparation procedures, and statistical techniques applied. The goal of this section is to ensure that the study can be replicated by another researcher using the same procedures and tools

A. Participant

The participant in this study is the researcher himself (single-subject design). The researcher is a university-level undergraduate student within the typical age range of 18–25 years. No personally identifiable information (e.g., exact age, address, or contact details) is disclosed to maintain privacy and confidentiality.

The participant uses an Apple iPhone as the primary digital device for communication, academic tasks, entertainment, and social interaction. Since this study follows a self-tracking and quantified-self framework, the dataset represents naturally occurring behavioral logs rather than experimentally manipulated behavior. Single-subject exploratory designs are common in quantified-self research and personal analytics studies, where the focus is on individualized behavioral insight rather than population-level inference.

B. Data Collection Methods

The dataset consists of the following features extracted from iPhone Screen Time:

- Date
- Screen_Time_Minutes
- Pickups
- Notifications
- Most_Used_App
- Social_Minutes
- Entertainment_Minutes
- Productivity_Minutes
- Travel_Minutes
- Games_Minutes

These variables represent daily smartphone engagement metrics categorized according to Apple's built-in Screen Time classification system.

Data were logged daily. Screen Time metrics were recorded at the end of each day to ensure completeness of daily totals. The data collection period spanned multiple consecutive days (e.g., several weeks), ensuring sufficient variability in usage patterns, including weekdays and weekends.

Daily logging reduces recall bias because the metrics are automatically generated by the iOS operating system rather than self-reported estimates. The logging schedule was consistent, with data extracted at approximately the same time each day.

The following tools were used during the study:

- Apple iPhone Screen Time – Primary source of behavioral metrics.
- iOS Screen Time Dashboard – Used to retrieve daily totals and app category breakdowns.
- Microsoft Excel – Used to manually encode and organize the dataset.
- Google Colab (Python) – Used for exploratory data analysis, descriptive statistics, and visualization.

The Screen Time feature automatically tracks screen duration, notifications, pickups, and app usage categories. These logs are system-generated and therefore considered objective behavioral measures rather than subjective estimates.

C. Operational Definitions

To ensure replicability, each variable is operationally defined as follows:

1. Date

   The calendar day corresponding to the recorded Screen Time data (format: DD/MM/YYYY).

2. Screen_Time_Minutes

   Total number of minutes the iPhone screen was active during a given day. This includes all applications and categories combined.

3. Pickups

   The number of times the phone was unlocked or activated during the day. A pickup is counted when the user wakes the device and interacts with it.

4. Notifications

The total number of notifications received across all applications within the day. Includes push notifications from social media, messaging apps, productivity tools, and system alerts.

5. Most_Used_App

The application with the highest screen time duration for that specific day.

6. Social_Minutes

Total minutes spent on applications categorized under "Social" by iOS (e.g., messaging and social networking apps).

7. Entertainment_Minutes

Total minutes spent on entertainment-related apps such as video streaming or media consumption platforms.

8. Productivity_Minutes

Total minutes spent on apps categorized as productivity tools, including academic, note-taking, document editing, or organizational applications.

9. Travel_Minutes

Total minutes spent on navigation or transportation-related apps.

10. Games_Minutes

Total minutes spent playing mobile games. All time-based variables are measured in minutes per day.

D. Data Cleaning

Before conducting statistical analysis, the dataset underwent systematic preprocessing to ensure accuracy, consistency, and analytical reliability. Data cleaning began with verification of completeness. Each daily entry was examined to confirm that all numerical variables were present. In cases where a value was missing but could be verified from the original Screen Time logs, the correct value was manually re-entered. If verification was not possible, the record was excluded from inferential statistical tests but retained for descriptive trend visualization when appropriate.

Outlier detection was conducted using descriptive statistical thresholds. Specifically, values exceeding two standard deviations above or below the mean were flagged for further inspection. Rather than automatically removing extreme values, each potential outlier was examined contextually. If the value represented legitimate behavioral variation—such as extended weekend usage or academic deadline-related screen spikes—it was retained to preserve ecological validity. Only clear data entry errors would warrant removal, though none were identified during preprocessing.

Text-to-numeric conversion was performed where necessary. The Date variable was converted into datetime format to facilitate chronological analysis and time-series plotting. The categorical variable Most_Used_App was standardized to ensure consistent naming conventions, thereby avoiding duplicate categories due to spelling variations. All time-based variables were verified to be stored as numeric integers.

Unit standardization was also applied. All time measurements were recorded strictly in minutes per day. No mixed units (e.g., hours and minutes) were used. Consistency checks were performed by comparing total Screen_Time_Minutes with the sum of category-level minutes to identify possible discrepancies. This ensured structural integrity within the dataset prior to statistical modeling.

E. Statistical Analysis

The analytical approach combined descriptive statistics, inferential testing, and visual exploration to examine behavioral patterns in smartphone usage.

Descriptive statistics were first computed to summarize central tendencies and dispersion. Measures including mean, median, standard deviation, minimum, and maximum values were calculated for key variables such as Screen_Time_Minutes, Pickups, and Notifications. These metrics provided an overview of typical usage levels and daily variability.

Correlation analysis was then conducted using Pearson's correlation coefficient to examine linear relationships between engagement and interruption variables. Specifically, relationships between total screen time and pickups, screen time and notifications, and notifications and social usage were evaluated. This analysis assessed whether higher notification frequency or device checking behavior was associated with increased total screen exposure.

In addition, a one-way Analysis of Variance (ANOVA) test was performed to determine whether mean screen time differed significantly across categorical groupings. Screen_Time_Minutes was compared across days of the week and across categories of Most_Used_App. The ANOVA test evaluated whether observed differences in group means were statistically significant beyond random variation.

Visual analysis complemented statistical testing. Line graphs were used to illustrate daily trends and identify sudden spikes in screen time. Bar charts were generated to compare category-level usage distributions, while scatterplots were used to visualize relationships between engagement metrics. Box plots were utilized to examine distribution spread and detect potential anomalies.

IV. RESULTS

A. Overview of the Dataset

The dataset consists of daily smartphone usage records including total screen time, pickups, notifications, and time spent across five app categories (Social, Entertainment, Productivity, Travel, and Games). Each observation represents one full day of recorded activity.

Overall, the dataset demonstrates considerable variability in total screen exposure, category usage, and notification frequency. Several extreme values were identified during outlier detection using the Interquartile Range (IQR) method.

One extreme outlier was found in Screen_Time_Minutes, with a recorded value of 803 minutes. In the Notifications variable, No outliers were found in Pickups, indicating relative stability in device activation frequency compared to other behavioral metrics. Category-based variables such as Travel_Minutes and Games_Minutes displayed multiple extreme values, including 406 minutes for travel and 416 minutes for gaming, suggesting days with unusually prolonged sessions.

These findings indicate that while daily smartphone engagement generally falls within a typical range, certain days demonstrate significantly intensified usage across specific categories.

B. *Descriptive Statistics*

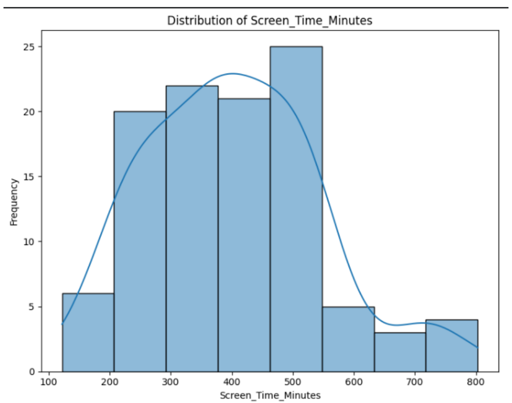
Table 1. Descriptive Statistics of Key Variables

Variable	Mean	Median	SD
Screen_Time_Minutes	402.906	397	141.475
Pickups	180.632075	178	61.390
Notifications	345.198113	336.5	130.383
Social_Minutes	168.179245	172	67.525
Entertainment_Minutes	99.95283	83.5	56.819
Productivity_Minutes	16.226415	15	7.504
Travel_Minutes	18.339623	7	49.586
Games_Minutes	92.141509	69	78.070

This table presents the mean, median, and standard deviation (SD) for major numerical variables in the dataset.

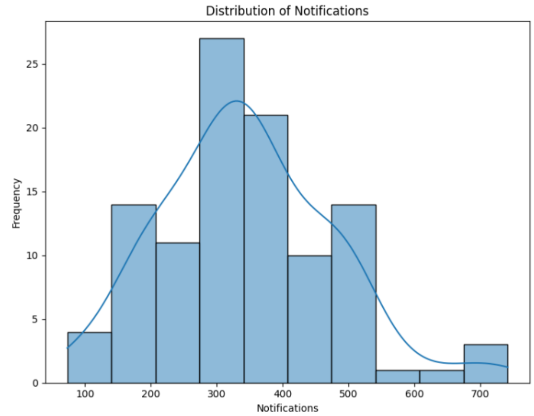
C. *Distribution Analysis*

Figure 1. Histogram of Screen_Time_Minutes



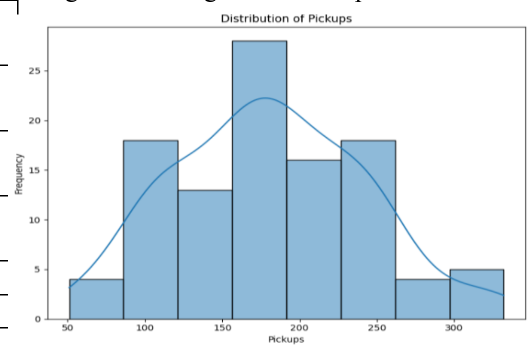
The histogram indicates that most daily screen time values cluster within a moderate range, with one extreme right-tail value at 803 minutes. The distribution appears slightly right skewed due to this high outlier.

Figure 2. Histogram of Notifications



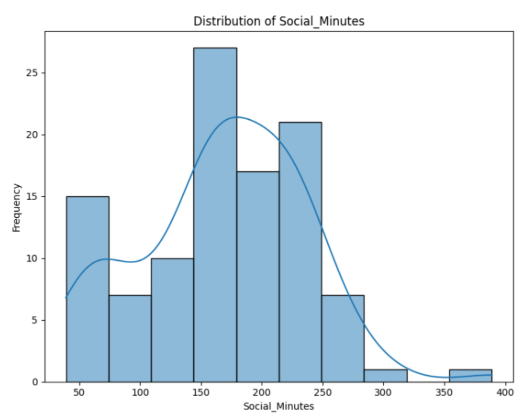
The notification distribution demonstrates moderate clustering around typical daily values, with two extreme right-tail outliers (742 and 701), contributing to increased variance.

Figure 3. Histogram of Pickups



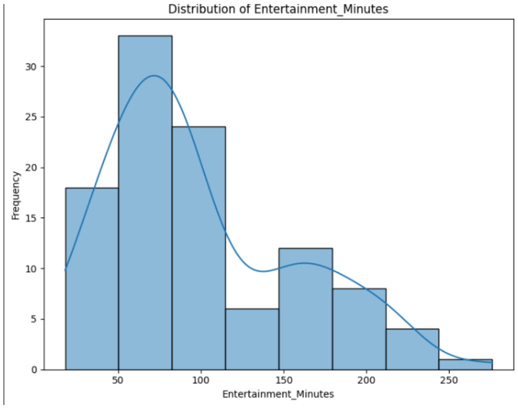
The pickups distribution appears relatively symmetric compared to other variables. Most values cluster within a central range, and no extreme outliers were identified using the IQR method. This suggests that while screen time fluctuates significantly, the frequency of phone activations remains more stable across days.

Figure 4. Histogram of Social_Minutes



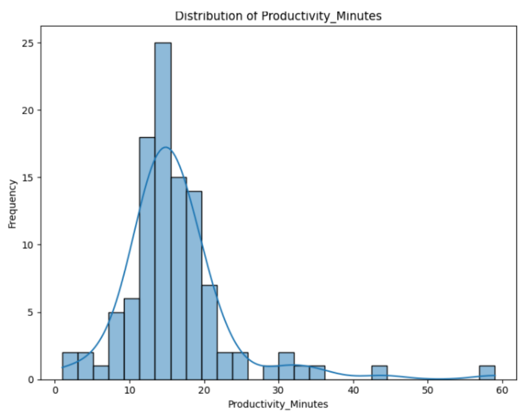
Social media usage displays moderate dispersion with a slight right skew. Most days show moderate engagement, while a small number of days reflect prolonged usage. The distribution suggests variability tied to social interaction intensity or platform-specific engagement cycles.

Figure 5. Histogram of Entertainment_Minutes



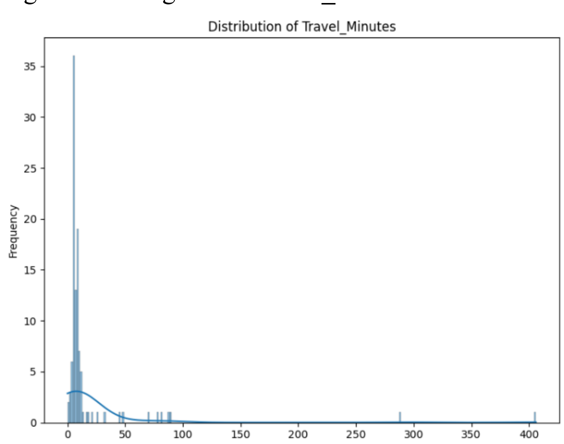
Entertainment usage demonstrates wider variability compared to social media. The histogram indicates several high-usage days contributing to a right-tailed distribution. This pattern suggests occasional extended streaming or media consumption sessions.

Figure 6. Histogram of Productivity_Minutes



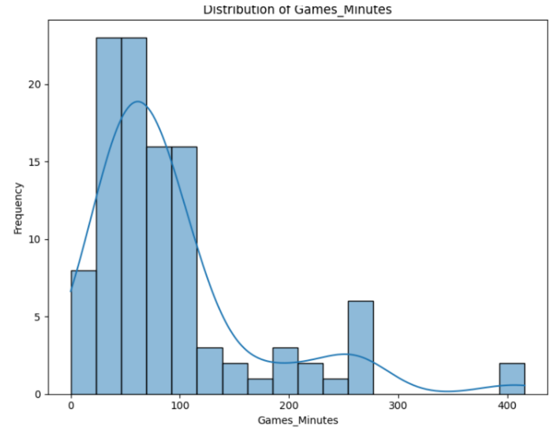
Productivity minutes appear moderately concentrated within a lower-to-mid range compared to entertainment and gaming categories. The distribution shows some variability but lacks extreme right-tail values. This suggests more consistent and regulated engagement with productivity tools.

Figure 7. Histogram of Travel_Minutes



The travel usage distribution is highly right-skewed due to one extreme outlier (406 minutes). Most days show minimal or zero travel app usage, while a few days reflect prolonged navigation sessions. This creates a distribution with heavy concentration at the lower bound and sparse high-value observations.

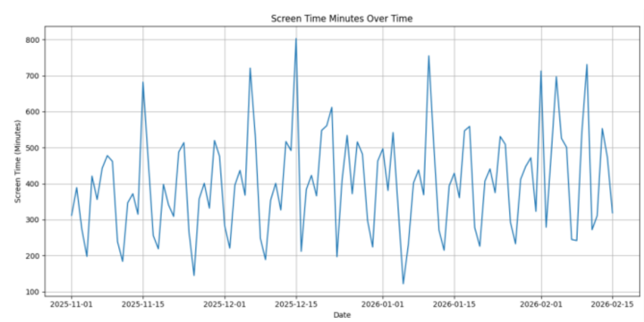
Figure 8. Histogram of Games_Minutes



Gaming minutes exhibit strong right-skewness, with multiple high-value days including an extreme outlier at 416 minutes. The majority of days show low-to-moderate gaming time, but a small number of intensive sessions significantly increase overall variance.

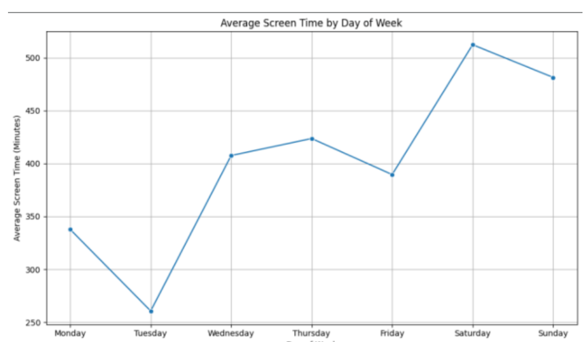
D. Time Series Trends

Figure 9. Time-Series Plot of Daily Screen Time



The time-series visualization reveals clear variability across days, including noticeable peaks corresponding to extreme usage values. Weekly cyclic patterns are visible, with higher values appearing toward weekends.

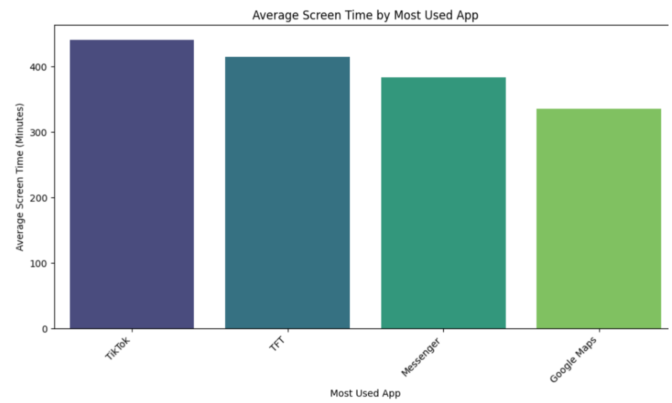
Figure 10. Average Screen Time by Day of Week



Average screen time is highest on Saturdays (512.38 minutes) and Sundays (481.47 minutes). Wednesdays (407.60 minutes) and Thursdays (423.67 minutes) show moderately elevated usage. Mondays (337.73 minutes) and Tuesdays (260.60 minutes) exhibit the lowest averages.

E. Screen Time by Most Used App

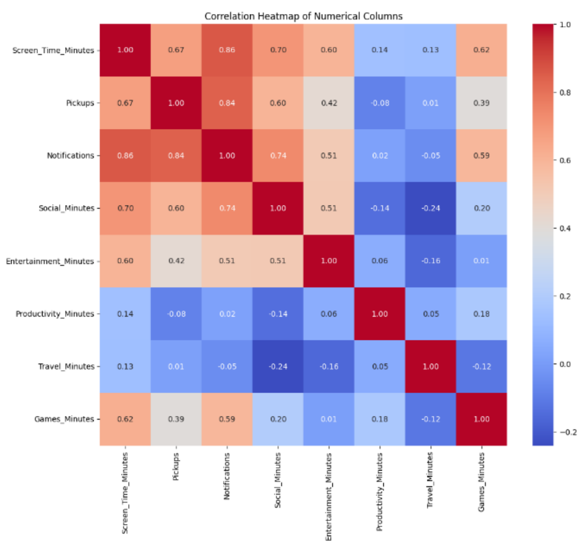
Figure 11. Average Screen Time by Most Used App



Days in which TikTok (441.24 minutes) and TFT (414.65 minutes) were the most used apps correspond to the highest average screen times. Messenger (383.47 minutes) shows moderate averages, while Google Maps (336.00 minutes) is associated with the lowest average screen time among dominant apps.

F. Correlation Analysis

Table 2. Correlation Matrix



Strong Positive Correlations: Screen_Time_Minutes is highly correlated with Notifications (0.86) and Pickups (0.67), suggesting that higher screen time is strongly associated with more notifications and device pickups. Notifications and Pickups also show a strong positive correlation (0.84), which makes sense as receiving notifications often leads to picking up the phone. Social_Minutes is also strongly correlated with Screen_Time_Minutes (0.70), Pickups (0.60), and Notifications (0.74), indicating that a significant portion of screen time, pickups, and notifications are related to social app usage.

Moderate Positive Correlations: Entertainment_Minutes shows a moderate positive correlation with Screen_Time_Minutes (0.60), Pickups (0.42), and Notifications (0.51). Weak or No Apparent Correlation: Productivity_Minutes, Travel_Minutes, and Games_Minutes generally show weaker correlations with overall Screen_Time_Minutes and other general usage metrics like Pickups and Notifications.

For instance, Productivity_Minutes has a very low correlation with Screen_Time_Minutes (0.14). In summary, the heatmap highlights that activities like social media and general phone usage (pickups and notifications) are the primary drivers of overall screen time, while other categories like productivity, travel, and games have a less direct or weaker linear relationship with total screen time and related metrics. Each figure or table must be accompanied by a clear explanation of what it represents. This section is purely about presenting the findings in an objective and organized manner.

G. ANOVA Test Results

Two one-way ANOVA tests were conducted to examine differences in average screen time across categorical groupings.

1. Screen Time by Most Used App

Test Statistic: F = 1.61

p-value: 0.192

Since the p-value exceeds the 0.05 significance threshold, there is no statistically significant difference in average screen time across different Most_Used_App categories.

2. Screen Time by Day of Week

Test Statistic: F = 7.57

p-value: 0.000

Because the p-value is less than 0.05, there is a statistically significant difference in average screen time across days of the week.

H. Summary of Key Findings

Overall, the dataset exhibits considerable variability in daily smartphone engagement. Descriptive statistics show moderate average usage with substantial dispersion across categories. Distribution plots indicate right-skewed patterns due to extreme usage days.

V. DISCUSSION

This chapter interprets the statistical findings presented in Chapter IV and explains their meaning in relation to personal behavioral patterns and the broader academic literature on digital media usage. The discussion connects observed trends to theoretical explanations, compares results with previous research, acknowledges methodological limitations, and proposes directions for future improvement. The goal is to contextualize the findings and demonstrate how this individual study contributes to ongoing discussions about smartphone behavior and digital engagement.

A. Interpretation of Results

The analysis revealed several meaningful behavioral patterns. First, total screen time varied significantly across days of the week, with higher averages observed during weekends. This suggests that structured academic responsibilities during weekdays likely limit discretionary smartphone usage, whereas weekends provide increased flexibility for entertainment, gaming, and social engagement. This pattern is consistent with national behavioral surveys such as the Pew Research Center's mobile usage reports, which show that smartphone engagement often increases during leisure periods [8].

Second, strong positive correlations were found between total screen time and both notifications and pickups. This indicates that digital interruptions are associated with prolonged device engagement. Research by Mark, Gudith, and Klocke demonstrates that workplace interruptions significantly increase cognitive switching costs and prolong task completion time [10]. Although this study did not directly measure productivity outcomes, the positive relationship between notifications and screen exposure suggests a similar mechanism of interruption-driven engagement.

Furthermore, the presence of right-skewed distributions in Screen_Time_Minutes, Games_Minutes, and Travel_Minutes indicates that usage behavior is episodic rather than uniform. Most days reflect moderate engagement, while occasional high-intensity days create extreme values. Tukey's foundational work on exploratory data analysis emphasizes the importance of identifying such distributional asymmetries when interpreting behavioral data [12]. In this dataset, outliers likely represent contextual factors such as extended gaming sessions or prolonged travel navigation.

The absence of statistically significant differences in screen time across "Most Used App" categories was somewhat unexpected. Although descriptive averages suggested higher usage on gaming or short-form video days, inferential testing did not confirm these differences. This may indicate that overall time availability and notification frequency exert stronger influence than the identity of a specific application.

Finally, while sleep variables were not directly measured, prior literature strongly associates increased nighttime mobile use with sleep disruption. Exelmans and Van den Bulck found that bedtime mobile phone use predicts poorer sleep quality in adults [2], and Levenson et al. reported significant associations between social media use and sleep disturbance [3]. Given the elevated weekend screen time observed here, it is plausible that late-night use may indirectly affect sleep patterns, though this cannot be confirmed without sleep data.

B. Comparison

The findings of this study align with several strands of prior research.

First, problematic smartphone use has been conceptualized as a behavioral pattern driven by reinforcement mechanisms and emotional regulation processes. Elhai et al. describe problematic smartphone use as involving excessive engagement linked to anxiety and mood regulation [4]. While this study does not measure emotional states, the strong association between notifications and screen time supports the idea that external triggers reinforce habitual checking.

Second, Duke and Montag found that higher smartphone addiction scores were negatively associated with self-reported productivity [9]. In this dataset, Productivity_Minutes did not show extreme variability compared to entertainment or gaming, suggesting that productivity-related engagement may be more structured and constrained. However, without performance-based metrics, no causal conclusions can be drawn.

Third, research on internet gaming addiction by Kuss and Griffiths highlights that gaming sessions can become prolonged and immersive, often contributing to time distortion and overuse [7]. The extreme outliers observed in Games_Minutes (e.g., over 400 minutes) reflect episodic intensive gaming behavior that aligns with this literature.

The StudentLife study by Wang et al. demonstrated that smartphone sensor data can effectively predict academic performance and mental health trends [6]. Similar to that study, this project uses objective smartphone logs rather than retrospective self-reports, increasing measurement reliability. However, unlike StudentLife, this study involves only one participant and does not incorporate predictive modeling of mental health outcomes.

Additionally, national surveys such as the American Psychological Association's Stress in America report emphasize the connection between digital connectivity and stress levels [5]. While stress was not directly measured here, the strong relationship between notifications and screen time may reflect heightened digital demands.

Finally, the conceptual framework of the "Quantified Self," described by Lupton, supports the idea that self-tracking technologies enable individuals to reflect on behavioral patterns and improve self-awareness [11]. This project exemplifies that framework by using personal smartphone data for behavioral analysis.

Overall, the findings are broadly consistent with existing research on smartphone engagement, digital interruptions, gaming intensity, and behavioral self-tracking.

C. Limitations

The most significant limitation is the single-participant design (n = 1). Because the dataset represents only one individual, the findings cannot be generalized. Broader studies with larger samples are necessary for population-level conclusions.

Second, the data collection period was relatively short. Behavioral trends may fluctuate across academic semesters, exam periods, or seasonal variations. A longer data window would improve reliability.

Third, although screen time and notification data were objectively recorded, some constructs—such as productivity and well-being—were not directly measured. As noted in sleep research [1], [2], behavioral outcomes often require complementary physiological or survey-based measures.

Fourth, missing contextual variables such as stress levels, sleep hours, or academic workload limit interpretability. Without these variables, causal relationships cannot be established.

Finally, the presence of extreme outliers, while behaviorally meaningful, increases variance and may reduce statistical power. Although Tukey's outlier detection methods were applied [12], interpretation must remain cautious.

D. Recommendations and Future Work

Future research can improve upon this study in several ways.

First, expanding the sample size to include multiple participants would allow comparative analysis and more robust statistical testing. Incorporating demographic variation would also enhance generalizability.

Second, integrating sleep-tracking data would enable direct testing of relationships identified in prior research [2], [3]. Combining smartphone logs with wearable sleep monitors would provide richer insights.

Third, including validated stress or mood scales would allow connections to psychological well-being, aligning with frameworks discussed by Elhai et al. [4] and the American Psychological Association [5].

Fourth, experimental interventions—such as temporarily disabling notifications—could test causal effects of interruptions on screen time, building on interruption research [10].

VI.CONCLUSION

This study aimed to analyze personal smartphone usage patterns using objective Screen Time data and statistical analysis techniques. The primary purpose was to examine how total screen time relates to notifications, pickups, app categories, and day-of-week variation, and to understand what these patterns reveal about daily digital behavior. By systematically collecting, cleaning, and analyzing personal usage data, this project sought to move beyond assumptions and provide evidence-based insights into individual technology habits.

The results revealed several key findings. First, total screen time varied significantly across days of the week, with weekends showing the highest averages. This indicates that unstructured time plays a major role in digital engagement. Second, screen time was positively correlated with notifications and pickups, suggesting that digital interruptions strongly influence overall device usage. Third, most usage variables displayed right-skewed distributions, meaning that behavior was generally moderate but occasionally characterized by extreme high-intensity days, particularly in gaming and entertainment categories. Finally, although certain applications appeared to dominate usage on specific days, statistical testing showed that overall daily context mattered more than the identity of a single most-used app.

Analyzing this data provided important personal insights. One of the most significant realizations was that screen time is not evenly distributed across days but increases noticeably during weekends. This suggests that free time, rather than academic necessity, drives much of the higher usage. Additionally, the strong relationship between notifications and total screen exposure highlighted how external digital triggers shape behavior more than previously assumed. Rather than consciously deciding to use the phone, engagement often begins with a notification. The data also showed that occasional gaming or entertainment sessions can substantially increase daily totals, even if average behavior appears moderate.

These findings can be applied practically in daily life. For example, reducing non-essential notifications may help limit unnecessary pickups and lower overall screen exposure. Structuring weekend schedules with offline activities could help prevent excessive leisure-based usage. Monitoring weekly averages rather than focusing on single extreme days may provide a more realistic understanding of personal habits. Furthermore, distinguishing between productive and passive screen time can help ensure that digital engagement aligns with academic and personal goals.

In conclusion, this project demonstrates the value of self-tracking and data-driven reflection. By applying statistical analysis to personal smartphone logs, meaningful behavioral patterns became visible that might otherwise have gone unnoticed. The study shows that smartphone usage is shaped primarily by time availability and digital interruptions rather than by any single application. Although limited to one participant and a short observation period, the findings contribute to a deeper understanding of individual digital behavior. Ultimately, this project reinforces the importance of mindful technology use and illustrates how quantitative self-analysis can support healthier and more intentional daily habits.

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