Mobile Usage Data Analysis

Table of Contents

Abstract

Smartphones are becoming a necessary component of modern day life, influencing work, play, and communication. Nonetheless, there is still much to learn about how mobile use affects network traffic, user efficiency, and battery performance. Using a dataset that contains important parameters including app use time, screen-on length, battery drain, and network consumption, this research seeks to study smartphone usage trends. We want to provide practical insights on enhancing smartphone efficiency, cutting down on needless battery drain, and raising user engagement by spotting important patterns in mobile behavior. In order to find common patterns and their impacts, our study will classify users according to behavior categories, ranging from mild to excessive use. The results of this study will assist manufacturers, researchers, and developers improve mobile experiences by providing insightful information on how people engage with their devices.

Introduction

Since smartphones are being used more and more for both personal and professional purposes, it is essential to comprehend user behavior in order to increase mobile device efficiency. Excessive screen time, ineffective app use, and network activity patterns have been shown to have a major negative influence on user productivity and battery life. The purpose of this study is to examine how people use their cellphones on a daily basis in order to find ways to maximize smartphone utilization.

<u>Our research is driven by the need to:</u>

- Determine the main causes of high battery drain.
- Analyze WiFi and mobile data consumption trends.
- Recognize how various apps affect the device's overall performance.
- Give consumers suggestions based on data to enhance their smartphone experience.

In order to do this, we will examine 700 user data samples that span a variety of topics, including screen-on time, app use length, and battery drain patterns. We want to classify various user kinds and thoroughly examine their activity patterns by using this data.

Manufacturers of mobile devices, app developers, and academics who want to improve smartphone performance and maximize battery life may find this study very pertinent. It may also be used as a basis for predictive modeling to assist consumers in better controlling how they utilize their devices.

Dataset

Our group will examine how people use smartphones on a regular basis, paying particular attention to screen time, battery life, network activity, and user conduct. By using this information, we want to find patterns and insights that will help us better understand user interaction with mobile devices, optimize battery use, and increase the efficiency of smartphone usage. The dataset offers comprehensive surveillance of how users engage with their smartphones, including records of network activity, battery drain trends, screen time, and app use.

Additionally, the dataset includes user behavior classification, which, when linked to screen time, may yield more profound insights. The higher screen time shown on some devices may be explained if a sizable portion of users fall into the "heavy user" group. On the other hand, devices in the "light usage" category that have a higher user base can inherently have shorter screen-on times.

All things considered, the graphic provides a clear comparison of mobile usage trends, highlighting the ways in which various smartphone models accommodate differing degrees of user engagement.

Analysis

The dashboard provides an interactive analysis of user behavior, app usage, battery drain, and data consumption. It allows filtering insights based on the device model, operating system, age, gender, and behavior class. By leveraging these filters, we can identify variations in smartphone usage patterns across different demographics and hardware configurations.

User Behavior Trends: The dashboard highlights key behavioral differences in smartphone engagement. Younger users exhibit higher screen time and app-switching tendencies, while older users tend to have more stable app engagement patterns.

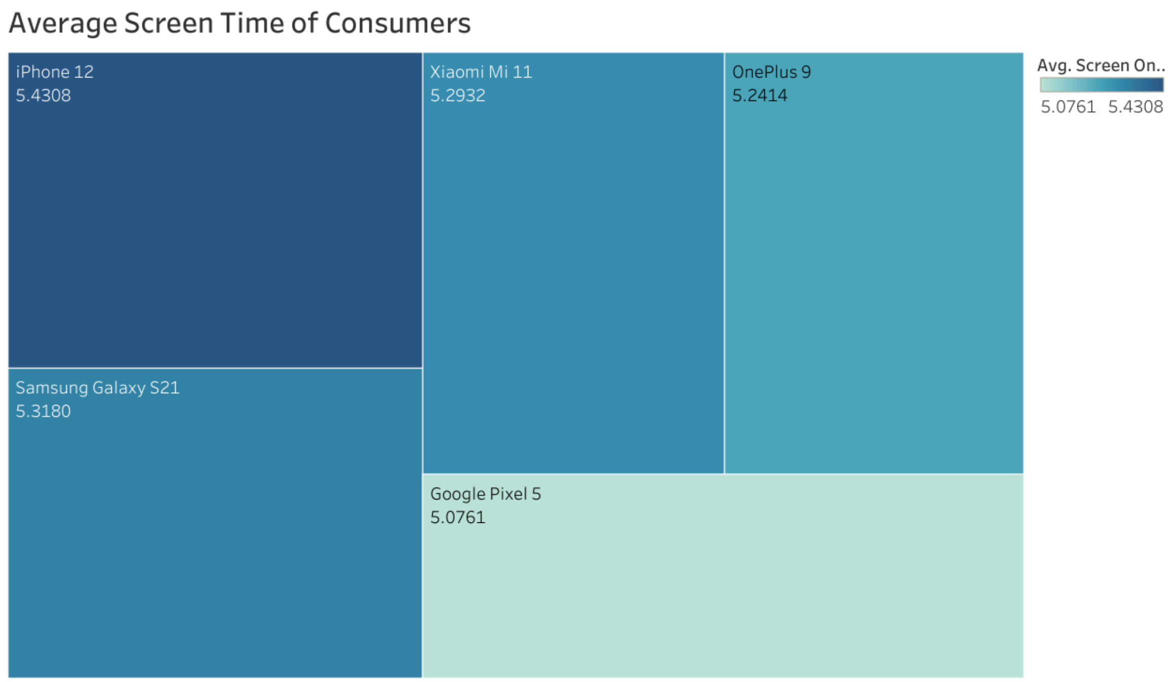
App Usage Patterns: Variations based on age and gender show that entertainment applications are more popular among younger demographics.

Battery Drain and Consumption: Battery performance varies significantly based on device model and app engagement. High-performance devices tend to have better optimization, whereas older models exhibit faster battery depletion.

Data Consumption Insights: Users relying more on mobile data experience higher battery drain than those predominantly.

Result

Starting with the picture below, tableau's visualization shows how people engage with their smartphones by highlighting the variations in average screen-on time across different smartphone models. With the greatest average screen-on time of 5.4308 hours per day, the iPhone 12 indicates that iPhone owners frequently spend a lot of time using their smartphones. Ecosystem participation, improved battery life, or the kinds of apps that iPhone consumers favor could all have an impact on this.



Device Model and average of Screen On Time (hours/day). Color shows average of Screen On Time (hours/day). Size shows average of Screen On Time (hours/day). The marks are labeled by Device Model and average of Screen On Time (hours/day).

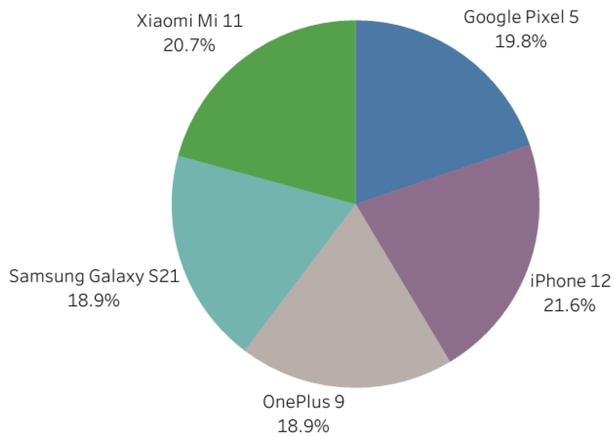
On the other hand, Google Pixel 5 users display the lowest average screen-on time at 5.0761 hours/day, which is notably lower compared to other models. This can be a sign of a user base that values efficiency over extended use, software optimizations, or variations in user behavior.

The remaining Android phones are in a comparable range:

- The average OnePlus 9 user spends 5.2414 hours a day in front of a screen.
- Users of the Samsung Galaxy S21 report 5.3180 hours a day on average.
- Xiaomi Mi 11 users had a somewhat lower but comparable screen time of 5.2932 hours/day.

With only about 0.35 hours separating the greatest and lowest figures, the variations in screen-on time across these devices are still quite minor. This implies that overall user engagement levels among smartphone users are quite similar, notwithstanding differences in brand and model.

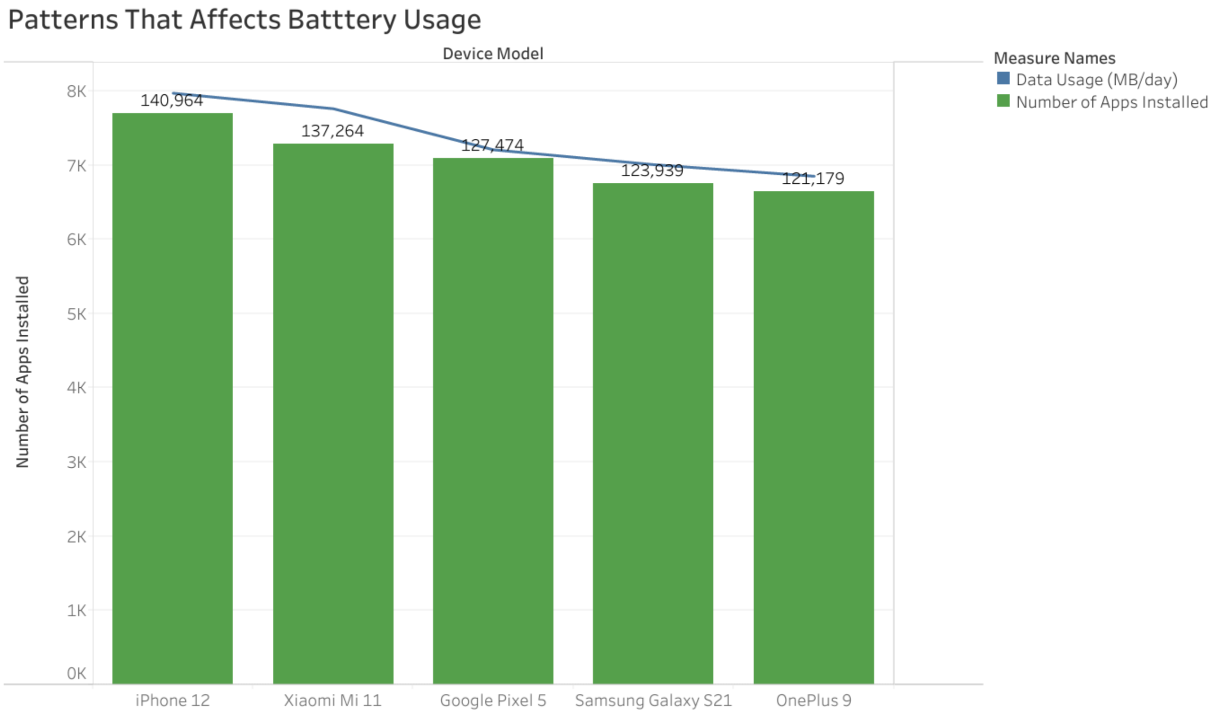
Device Model vs. User Behaviour Class



Device Model and % of Total User Behavior Class. Color shows details about Device Model. Size shows sum of User Behavior Class. The marks are labeled by Device Model and % of Total User Behavior Class.

The goal is to analyze user behavior class to determine how each model impacts the behavior patterns of users. Specifically, does the model affect the screen time of consumers? According to the pie chart, the iPhone, with 20.6%, is one of the phones that significantly influences user behavior, followed closely by the Xiaomi Mi 11, also at 20.6%. Google pixel 5 at a 19.8%, followed by samsung Galaxy s21 and OnePlus at 18.9%,

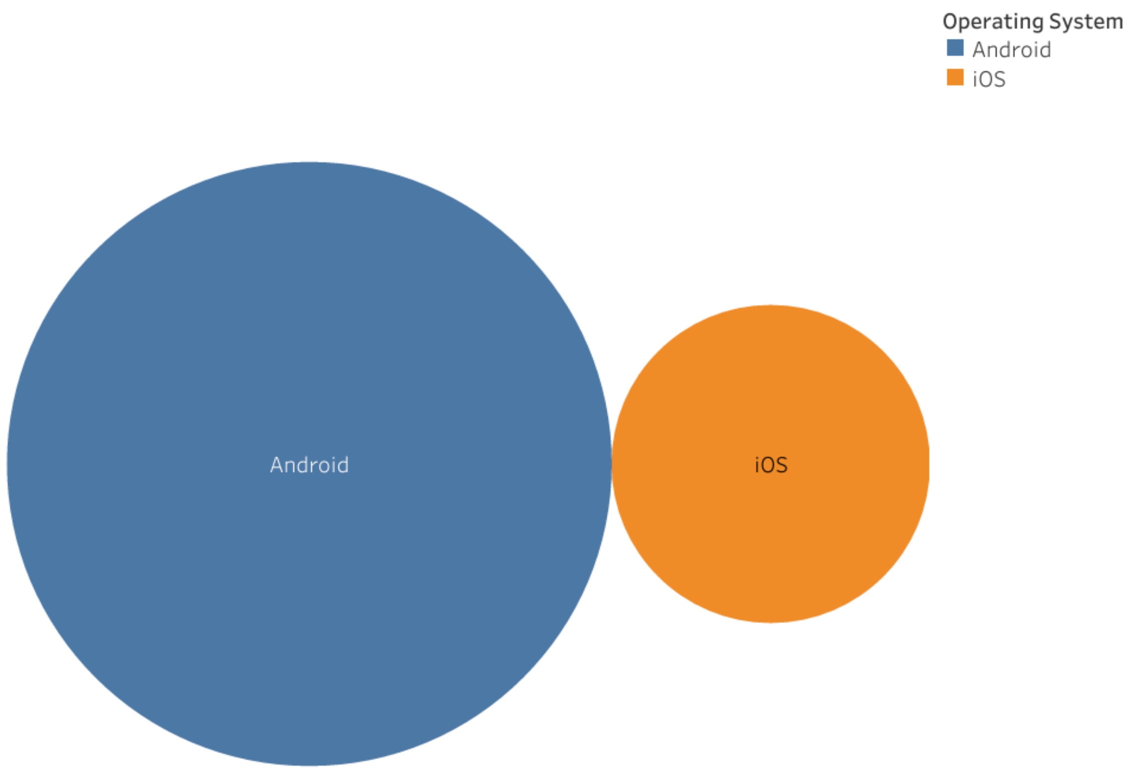
The above visualization approach allows for a comprehensive understanding of how user behavior classes are distributed across different device models, facilitating targeted analysis and informed decision making.



The trends of Number of Apps Installed and Data Usage (MB/day) for Device Model. Color shows details about Number of Apps Installed and Data Usage (MB/day). For pane Sum of Number of Apps Installed: The marks are labeled by Data Usage (MB/day).

The visualization illustrates the correlation between the number of installed applications on various smartphone models and their corresponding data usage that results in battery drain rates. Notably, models such as the iPhone 12 exhibit the highest number of app installations and data usage followed by Xiaomi 11 with a total of 137,264, Google Pixel 5 127,474 Samsung Galaxy 123,939, Oneplus 9 121,179. This elevated app count contributes to increased battery consumption, primarily due to numerous applications running background processes that continuously consume power.

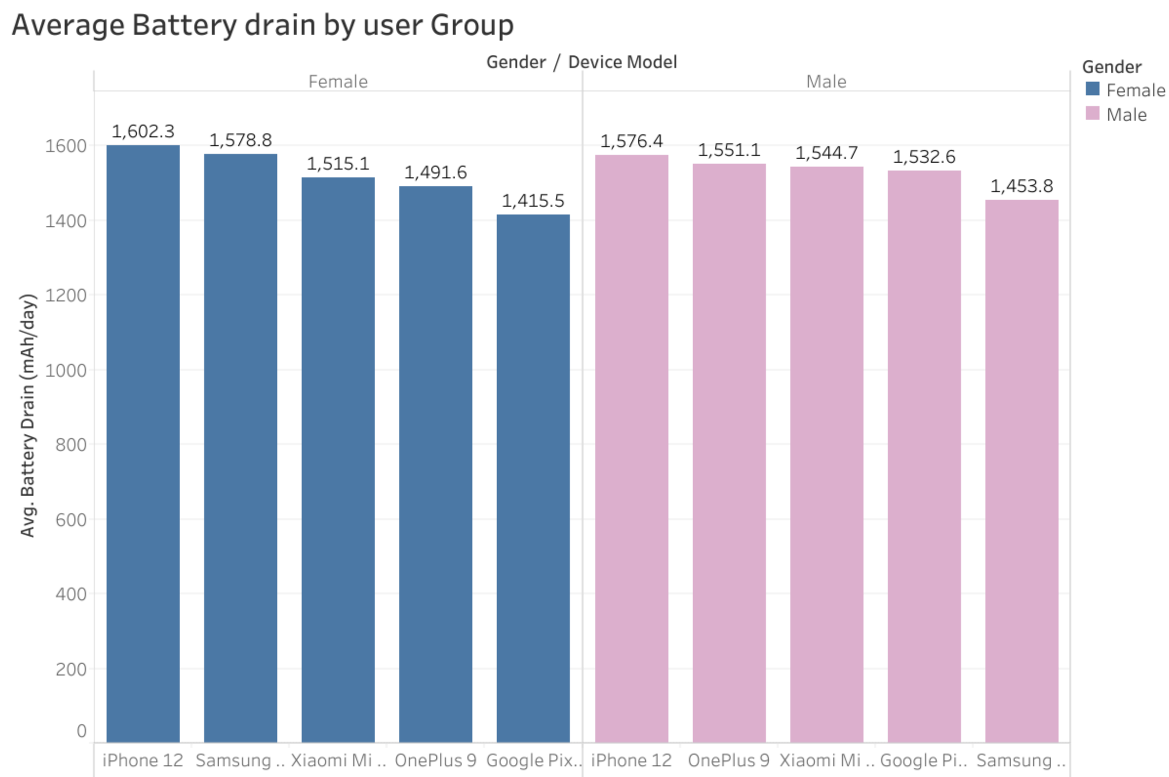
Battery drain vs. App usage



Operating System. Color shows details about Operating System. Size shows sum of App Usage Time (min/day). The marks are labeled by Operating System. The view is filtered on sum of Battery Drain (mAh/day), which ranges from 232,069 to 835,542.

The visualization focuses on the Operating System, where color represents details about the Operating System, and size indicates the total App Usage Time (min/day). Each mark is labeled by the Operating System. The view is filtered based on the sum of Battery Drain (mAh/day), with values ranging from 232,069 to 835,542.

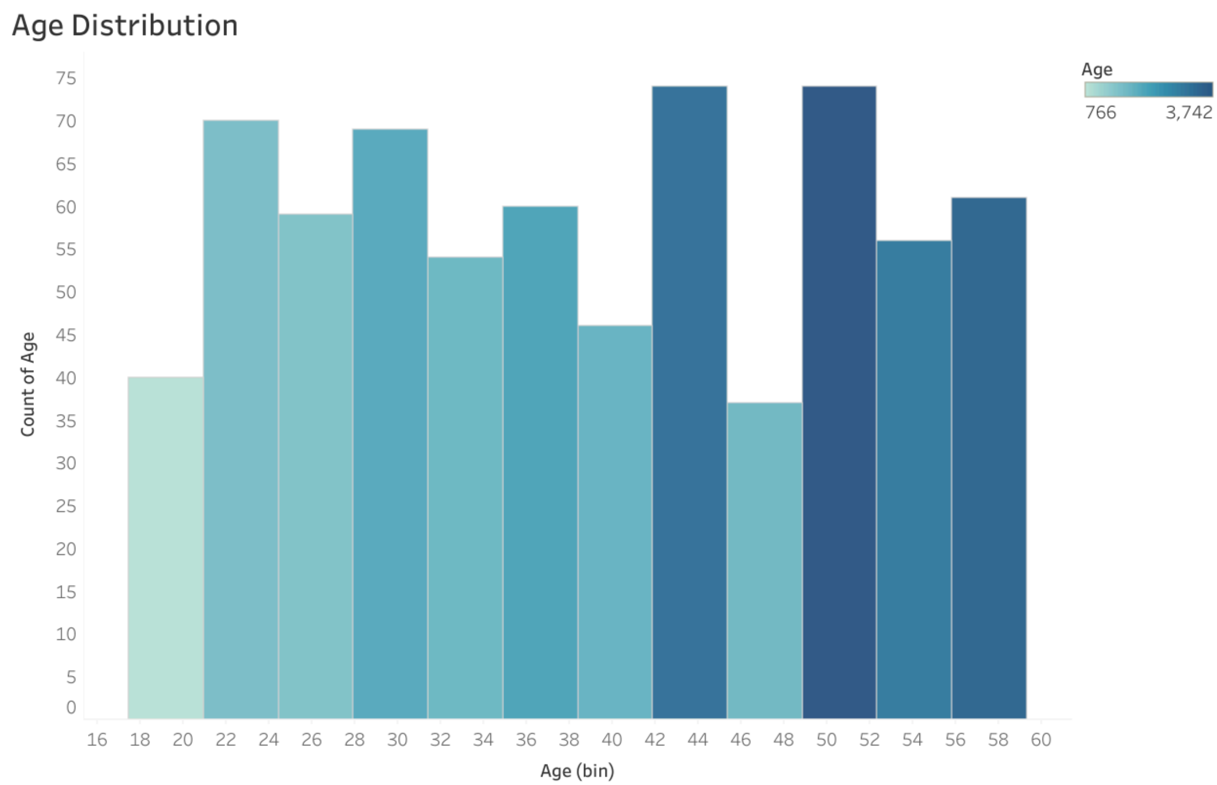
This analysis explores the relationship between operating systems, app usage time, and battery drain. It reveals how different operating systems influence app usage patterns and battery consumption, providing insights into user behavior and device performance.



Average of Battery Drain (mAh/day) for each Device Model broken down by Gender. Color shows details about Gender. The marks are labeled by average of Battery Drain (mAh/day).

The visualization displays the average Battery Drain (mAh/day) for each Device Model, segmented by Gender. Color is used to differentiate gender categories, and the marks are labeled with the average Battery

In addition, the analysis examines the average battery drain across different device models, categorized by gender. It highlights potential variations in battery consumption patterns between genders, offering insights into how device usage and energy efficiency may differ based on device model.



The trend of count of Age for Age (bin). Color shows sum of Age.

The visualization depicts the age distribution of mobile users and how it correlates with battery drain. The x-axis represents age bins (e.g., 0-10, 10-20, etc.), while the y-axis shows the count of users in each age group. The color intensity reflects the sum of ages within each bin, highlighting which age groups contribute more to the overall age distribution. This helps identify trends in mobile usage across different age groups and their potential impact on battery drain.

These trends could be explained by a number of variables. Because smartphones with longer battery life encourage prolonged screen usage, battery performance is important. Operating system variations could also be a factor, as users of iOS and Android have distinct interaction patterns. Additionally, individuals who use social media, streaming, or gaming apps more frequently may favor particular devices, which could have an impact on the total amount of time spent on screens.

Limitations and Conclusion

While our dashboard offers valuable insights into smartphone usage patterns, it is essential to acknowledge certain limitations that may influence the interpretation and generalizability of the findings.

The dataset utilized in our analysis may not fully represent the entire population of smartphone users, as it relies on specific sample groups. Factors such as age, and technological proficiency can influence smartphone usage behaviors, leading to potential biases in the collected data. For instance, individuals without mobile phones, including young children, the elderly, or certain socioeconomic groups, are inherently excluded from the dataset, limiting the comprehensiveness of the analysis.

Also, data collection is subject to privacy regulations, which may limit the granularity of the collected information. Privacy concerns necessitate measures such as data anonymization and aggregation, potentially leading to a loss of detailed insights. Additionally, users' awareness of data collection practices can influence their behavior, introducing response biases that affect the authenticity of the data.

Recognizing these limitations is crucial for contextualizing the findings of our analysis. Future research should aim to address these challenges by employing more representative sampling methods, integrating objective usage data, considering device-specific factors, incorporating contextual information, and adhering to ethical data collection practices that respect user privacy.

Conclusion

The analysis of smartphone user behavior, app usage, and battery drain patterns reveals significant insights into how device models, operating systems, and user demographics influence engagement and energy consumption. iPhone 12 users exhibit the highest screen-on time and app engagement, leading to greater battery drain, likely due to their active participation in the iOS ecosystem and preference for app-heavy usage. In contrast, Google Pixel 5 users demonstrate more efficient usage patterns, with lower screen-on time and battery consumption, potentially due to software optimizations and a focus on streamlined functionality.

Other Android models, such as the Xiaomi Mi 11, Samsung Galaxy S21, and OnePlus 9, show moderate engagement levels, with Xiaomi devices closely mirroring iPhone usage patterns. The correlation between app installations, data usage, and battery drain highlights the impact of background processes on energy consumption, particularly in devices with higher app counts like the iPhone 12 and Xiaomi Mi 11.

Additionally, the analysis underscores the role of operating systems in shaping app usage and battery efficiency, with iOS devices generally consuming more power due to higher engagement. Gender-based differences in battery drain further suggest that usage patterns vary across demographics, offering opportunities for targeted optimizations.

Reference

Mobile Device Usage and User Behavior Dataset. (2024, September 28). Kaggle.https://www.kaggle.com/datasets/valakhorasani/mobile-device-usage-and-user-behavior-dataset