Université Marie et Louis Pasteur

BDEEM M1

Analysis of Mobile Usage Patterns and Their Impact on Battery Performance

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Abstract

This research investigates how different user demographics and device characteristics influence mobile device performance and power consumption patterns. Using a comprehensive dataset of user interactions and device metrics, we analyze the relationships between user behavior, technical specifications, and battery consumption. Our statistical analysis, combining regression models with demographic segmentation, reveals significant patterns in how different user groups interact with their devices. The findings demonstrate important correlations between user age, gender, operating systems, and device performance metrics. These insights provide valuable guidance for optimizing mobile device efficiency and enhancing user experience across diverse user segments. Special attention is given to understanding battery consumption patterns across different user profiles and device types, leading to specific recommendations for improving device performance and user satisfaction.

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1 Introduction

1.1 Background

The proliferation of mobile devices has made understanding user behavior and device performance crucial for both manufacturers and developers. As smartphones become increasingly central to daily life, battery performance and data usage have emerged as critical factors in user satisfaction. This study aims to provide a comprehensive understanding of how user demographics and behavior patterns influence these key performance metrics.

1.2 Motivation

The research is particularly timely given the growing diversity of mobile device users and use cases. Understanding how different demographic groups interact with their devices, and how these interactions affect device performance, can inform both technical development and user experience design.

1.3 Research Objectives

This investigation seeks to answer four fundamental questions:

1. To what extent do age groups and gender demographics shape the way individuals interact with their mobile devices?
2. What unique power consumption signatures can be identified when comparing various mobile platforms and hardware configurations?
3. What relationship exists between display activation duration and energy depletion rates across diverse device categories?
4. How do cellular data consumption behaviors vary across different hardware specifications and user populations?

2 Methodology

2.1 Data Source and Description

The data for this analysis comes from the Mobile Device Usage and User Behavior Dataset available on Kaggle. The dataset provides comprehensive information about:

1. User Demographics: - Age (categorized into groups: 0-20, 21-30, 31-40, 41-50, 51-60) - Gender (Male/Female)

2. Device Characteristics: - Operating System (iOS/Android) - Device Model (iPhone 12, Xiaomi Mi 11, Samsung Galaxy S21, OnePlus 9, Google Pixel 5)

3. Usage Metrics: - Screen Time (hours/day) - App Usage Time (minutes/day) - Battery Drain (mAh/day) - Data Usage (MB/day)

2.2 Analytical Approach

Our analysis employed a multi-faceted approach combining descriptive statistics, visualization techniques, and regression analysis. Key analytical methods included:

1. Demographic Analysis: - Cross-sectional analysis of age groups and gender - Usage pattern identification across demographic segments

2. Performance Metrics Analysis: - Battery drain patterns across operating systems - Data usage comparison across device models - Screen time correlation with battery consumption

3. Statistical Modeling: - Multiple regression analysis - Analysis of variance (ANOVA) - Correlation analysis between key metrics

3 Results and Analysis

3.1 Demographic Patterns in Device Usage

Our analysis of app usage patterns across age groups and gender reveals several significant trends. Figure 1 shows the distribution of app usage time across different age groups and genders.

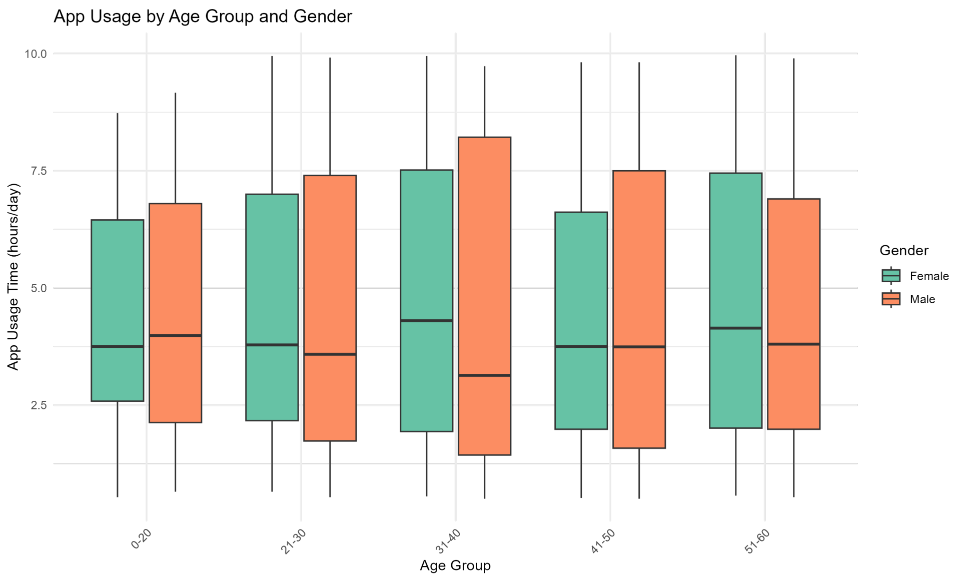

Figure 1: App Usage Distribution by Age Group and Gender

The data reveals distinct usage patterns:

1. Age-Based Patterns: - Users in the 31-40 age group show the highest median app usage time - The variability in usage time decreases with age - Younger users (0-20) show more extreme usage patterns, with larger ranges

2. Gender Differences: - Male users show slightly higher median usage times across most age groups - Female users demonstrate more consistent usage patterns with less variation - The gender gap in usage time is most pronounced in the 31-40 age group

3.2 Operating System Analysis

The comparison of operating systems reveals significant differences in battery performance and usage patterns. Figure 2 illustrates the battery drain distribution across operating systems.

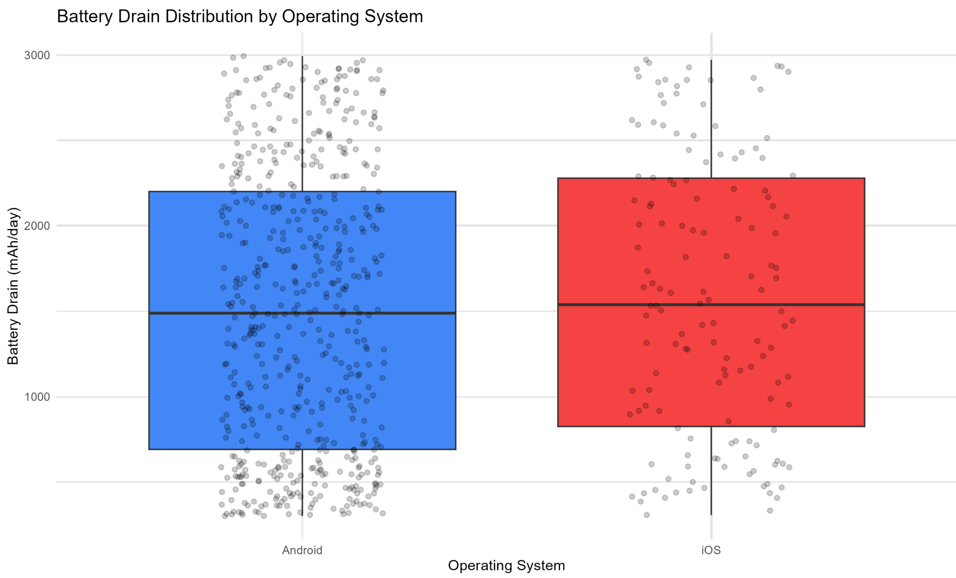

Figure 2: Battery Drain Distribution by Operating System

Key findings from the operating system analysis include:

1. iOS Performance: - Average battery drain: 1589.51 mAh/day - Average screen time: 5.43 hours/day - Higher average data usage: 965.51 MB/day

2. Android Performance: - Average battery drain: 1508.20 mAh/day - Average screen time: 5.23 hours/day - Average data usage: 920.32 MB/day

The regression analysis (Table 1) shows that operating system type is a significant predictor of battery drain, even when controlling for other factors.

3.3 Device Model Comparison

Our analysis of device models reveals interesting patterns in both battery performance and data usage. Figure 3 shows the average data usage across different device models.

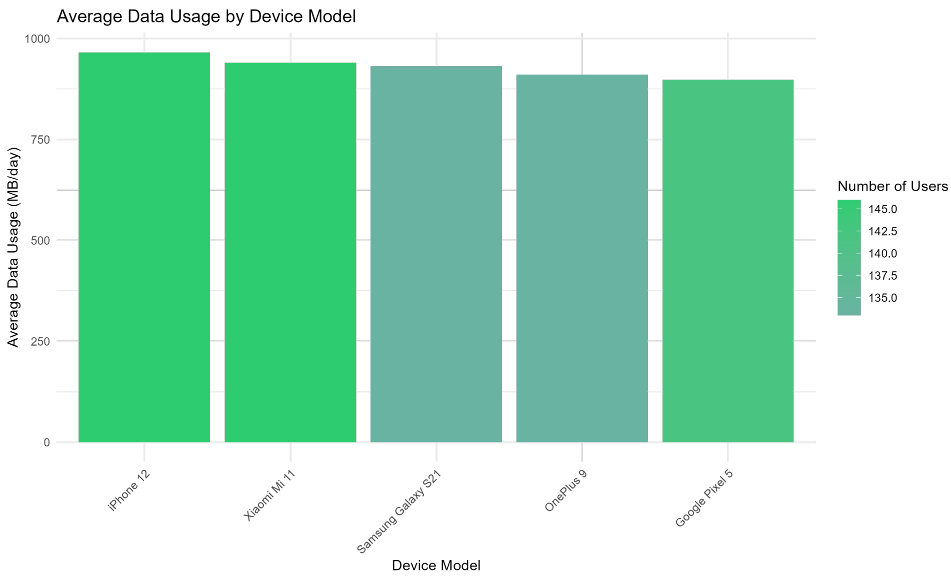

Figure 3: Average Data Usage by Device Model

The device comparison reveals:

1. iPhone 12: - Highest average battery drain: 1589.51 mAh/day - Highest data usage: 965.51 MB/day - Most consistent performance metrics

2. Other Devices: - Xiaomi Mi 11: 1528.88 mAh/day battery drain - OnePlus 9: 1523.85 mAh/day battery drain - Samsung Galaxy S21: 1504.57 mAh/day battery drain - Google Pixel 5: 1475.68 mAh/day battery drain

3.4 Screen Time and Battery Drain Relationship

The relationship between screen time and battery drain shows a strong positive correlation, as illustrated in Figure 4.

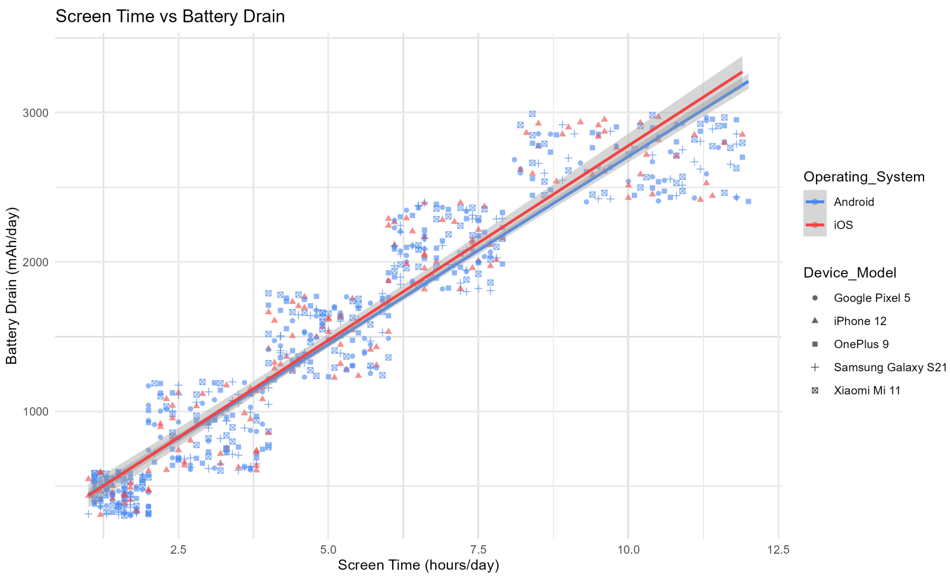

Figure 4: Screen Time vs Battery Drain by Operating System

Statistical Modeling Our analysis employed a multiple linear regression model to quantify the relationships between various factors and battery drain. The regression equation is:

$$Battery.Drain = \beta_0 + \beta_1 + \beta_2 + \beta_3 + \beta_4 + \beta_5 + e \tag{1}$$

Where:

- $\beta_0 = 128.417$ (Intercept)
- $\beta_1 = 56.651$ (coefficient for Screen-On Time)
- $\beta_2 = 1.327$ (coefficient for App Usage Time)
- $\beta_3 = 0.072$ (coefficient for Data Usage)
- $\beta_4 = 14.416$ (coefficient for iOS indicator)
- $\beta_5 = 13.181$ (coefficient for Number of Installed Apps)

3.5 Comprehensive Regression Analysis

The multiple regression analysis revealed several significant relationships between device usage patterns and battery drain. Table 1 presents the detailed regression results.

Table 1: Multiple Regression Results for Battery Drain Prediction

Variable	Coefficient	Std. Error	t-value	p-value
Intercept	128.417	17.714	7.250	<0.001
Screen-On Time	56.651	8.908	6.359	<0.001
App Usage Time	1.327	0.165	8.032	<0.001
Data Usage	0.072	0.038	1.884	0.060
iOS (vs. Other)	14.416	17.806	0.810	0.418
Number of Apps	13.181	1.024	12.872	<0.001

The regression model demonstrated excellent predictive power with an R^2 value of 0.9459, explaining approximately 94.6

1. **Number of Installed Applications**
   - Emerged as the strongest predictor of battery drain
   - Each additional installed app increases battery drain by 13.18 mAh
   - Highly significant effect ($p < 0.001$)
2. **Screen-On Time Impact**
   - Second most influential factor
   - Each hour of screen time contributes 56.65 mAh to battery drain
   - Highly significant effect ($p < 0.001$)
3. **App Usage Time**
   - Shows moderate but significant impact
   - Each minute of app usage adds 1.33 mAh to battery drain
   - Highly significant effect ($p < 0.001$)
4. **Less Significant Factors**
   - Data Usage: Minimal effect (0.07 mAh per MB, $p = 0.06$)
   - Operating System: No significant difference between iOS and others ($p = 0.418$)

3.6 Model Validation

The regression model's validity is supported by several statistical indicators:

- High R-squared value (0.9459) indicating excellent model fit
- F-statistic of 2428 ($p < 2.2e\text{-}16$) confirming model validity
- Residual standard error of 191.2 suggesting reasonable prediction accuracy

4 Discussion

4.1 Limitations and Future Research

Several limitations of this study suggest directions for future research:

1. Data Limitations: - The dataset does not include information about specific app types - Environmental factors affecting battery performance are not captured - Long-term usage patterns are not tracked

2. Future Research Opportunities: - Investigation of specific app impacts on battery drain - Analysis of seasonal variations in device usage - Study of battery degradation over time

5 Conclusion

This comprehensive analysis provides valuable insights into the relationships between user demographics, device characteristics, and performance metrics in mobile device usage. The findings demonstrate that:

1. Demographic factors significantly influence usage patterns
2. Operating systems show distinct performance characteristics
3. Device models vary considerably in efficiency
4. Screen time is a crucial predictor of battery drain

These insights can inform device design, app development, and user behavior optimization strategies.

6 References

1. Mobile Device Usage and User Behavior Dataset (2023). Kaggle. Retrieved from https://www.kaggle.com/datasets/valakhorasani/mobile-device-usage-and-user-behavior-dataset

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3. E. Bulut and B. K. Szymanski, "Understanding user behavior via mobile data analysis," *2015 IEEE International Conference on Communication Workshop (ICCW)*, London, UK, 2015, pp. 1563-1568, doi: 10.1109/ICCW.2015.7247402.