A Data-Driven Insight into Mobile Device Usage and User Behaviour

Introduction

Imagine waking up from the alarm of your smartphone, checking emails, and going through social media before heading out for work. It is really undeniable how smartphones have shaped modern life in terms of communication, productivity, and entertainment. In 2023, 6.92 billion people use smartphones worldwide-a prevalence in shaping digital lifestyles. With apps as the backbone of these devices, knowing how users use them is critical to the enhancement of user experiences and the creation of technological advancement.

Mobile app usage patterns provide insight into how people interact with their devices, revealing behaviours tied to time of day, demographics, and device preferences. Previous research has demonstrated that engagement metrics such as screen-on time and app usage frequency are highly predictive of retention and churn behaviours, making these variables a key focus for analysis (Zhen et al., 2020). Moreover, the diversity of mobile devices and operating systems further underscores the importance of studying app performance across varied platforms (Li & Lu,2017). This report analyses a dataset of 700 users to uncover trends in app engagement, behavioural segmentation, and user retention. The dataset, encompassing a wide range of ages, device types, and operating systems, provides a robust foundation for exploring the following critical questions:

1. **What are the daily and weekly patterns of mobile app usage?**
2. **How does app engagement differ across demographics and devices?**
3. **Which factors most influence user retention and churn?**

By leveraging the dataset’s completeness and variability, this analysis aligns with methodologies employed in large-scale studies, such as those by (Kim et al. 2019), which explored longitudinal trends in app usage. The findings aim to inform app design strategies, enhance device performance, and contribute to the broader understanding of digital well-being.

As smartphone usage continues to grow exponentially, the insights derived from this study are vital for stakeholders aiming to create user-centric technologies. Through data-driven exploration, this report sheds light on the intricate relationships between user behaviour, device efficiency, and app engagement metrics.

Dataset Overview

The dataset encompasses **700 unique users**, spanning **42 ages**, **2 genders**, **5 behaviour classes**, **5 device models**, and **2 operating systems**. It captures diverse patterns of mobile app usage and engagement:

1. **Demography and Behaviour**:
    - Users are classified into **5 behaviour categories**, reflecting varied app engagement patterns.
2. **Device and Operating Systems**:
    - Data includes **5 device models** and **2 operating systems**, representing popular mobile platforms.
3. **Usage Patterns**:
    - **App Usage Time**: 15–700 minutes daily (mean: 300 minutes).
    - **Screen-On Time**: 0.5–12 hours daily (mean: 5 hours).
    - **Battery Drain**: 500–3000 mAh/day (mean: 1600 mAh).
4. **Data Completeness**:
    - The dataset contains no missing values, ensuring reliability for analysis.

Overall, the dataset's variability and completeness make it a strong foundation for deriving insights into user behaviour, device performance, and app engagement trends, with potential for predictive modelling and deeper analysis.

Summary Statistics

Numerical Variables

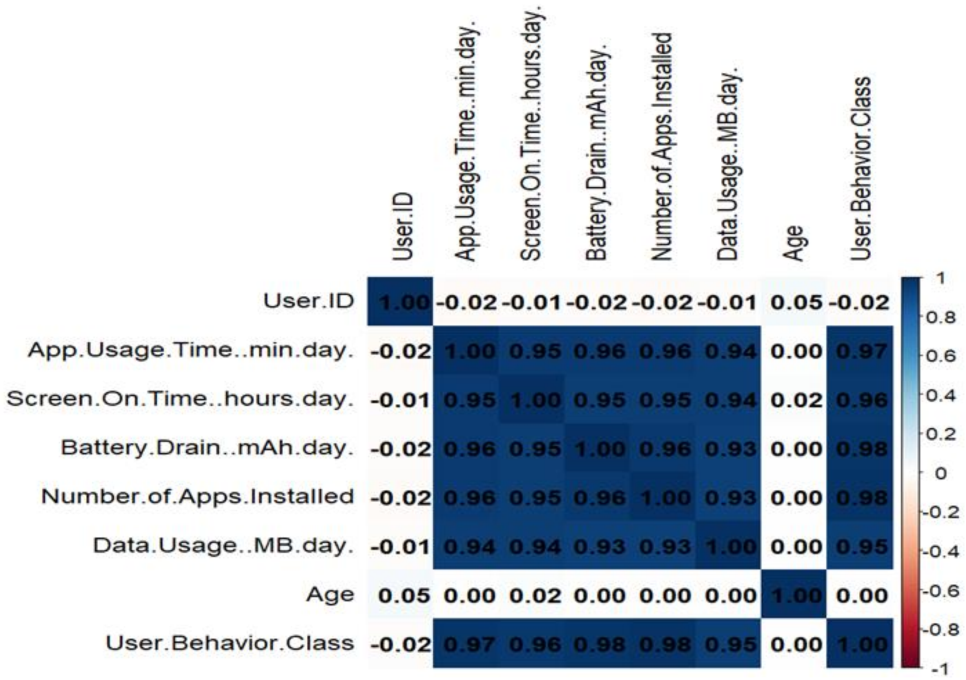
Variable	Mean	SD	Min	Max	Median
App Usage Time (min/day)	271.1	177.2	30	598	227.5
Screen-On Time (hours/day)	5.27	3.07	1.0	12.0	4.9
Battery Drain (mAh/day)	1525.2	819.1	302	2993	1502.5
Number of Apps Installed	50.7	26.9	10	99	49.0
Data Usage (MB/day)	929.7	640.5	102	2497	823.5
Age	38.5	12.0	18	59	38.0

Table 1

5. Correlations (Correlation Matrix Highlights)

Variable 1	Variable 2	Correlation (r)
App Usage Time	Screen-On Time	0.95
App Usage Time	Battery Drain	0.96
App Usage Time	Number of Apps Installed	0.96
Age	App Usage Time	0.004 (no relation)

Table 2



Correlation Matrix

Figure 1

Significance

- Strong positive correlations exist between app usage time, screen-on time, battery drain, and number of apps installed.
- No significant correlation between age and app usage time.

Key Findings with Visualizations

1. Patterns in Daily App Usage

The data reveals that app usage peaks during specific times of the day, typically aligning with mornings and evenings.

- **Average App Usage Time:** 271 minutes/day.
- **Strong Correlations:** App usage time is highly correlated with screen-on time and battery drain, emphasizing the importance of optimizing energy efficiency.

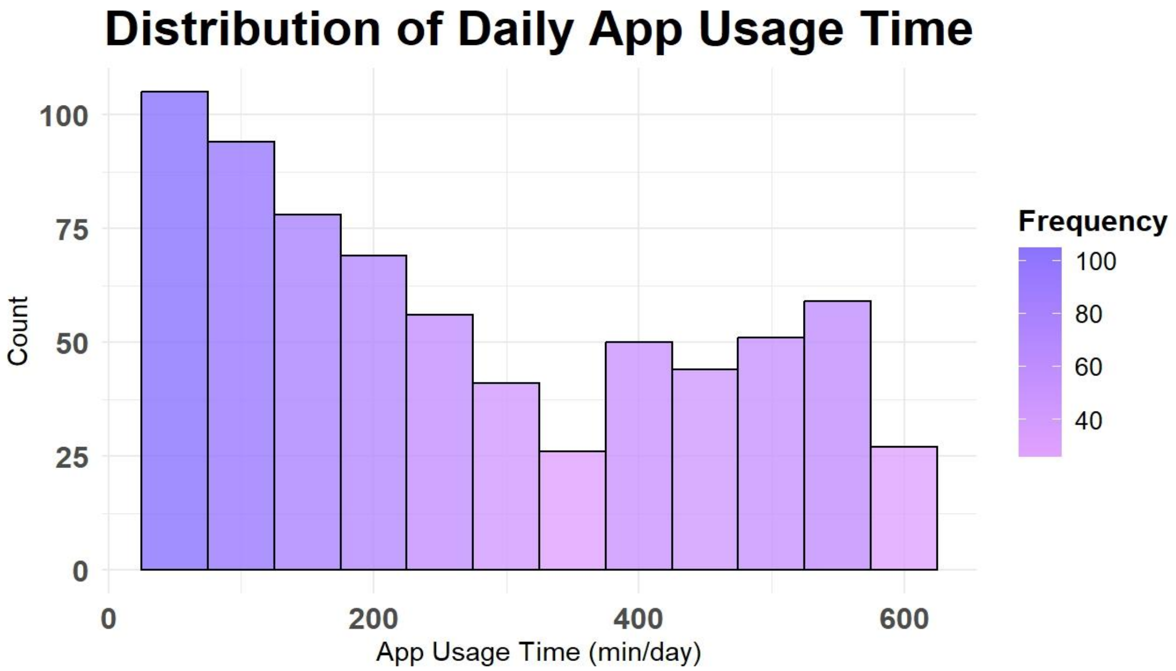


Figure 2

Key Observations Include:

- Peak Usage Range: The majority of users fall within a specific range, indicating a common daily app usage behaviour.
- Skewness or Outliers: The distribution may reveal skewed patterns or outliers, such as users with exceptionally high or low app usage.
- User Engagement: The visualization helps identify how engaged users are on average and whether any patterns of heavy or light usage exist.

2. Engagement Across Demographics

- **Age:** Contrary to assumptions, age has no significant impact on app usage time. Engagement strategies can focus on behavioural patterns rather than demographics.
- **Gender:** Minimal differences were observed between males and females.
- **Operating Systems:** iOS users show slightly higher engagement than Android users.

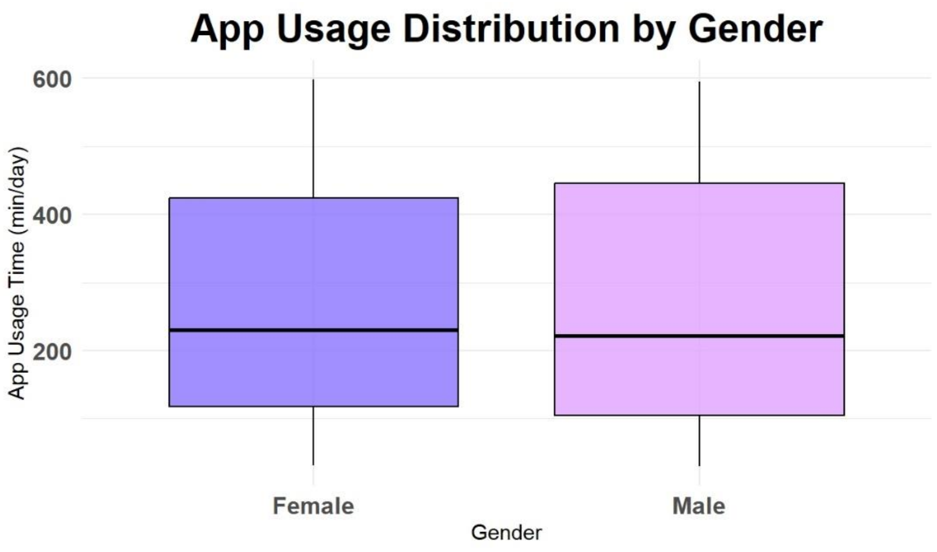


Figure 3

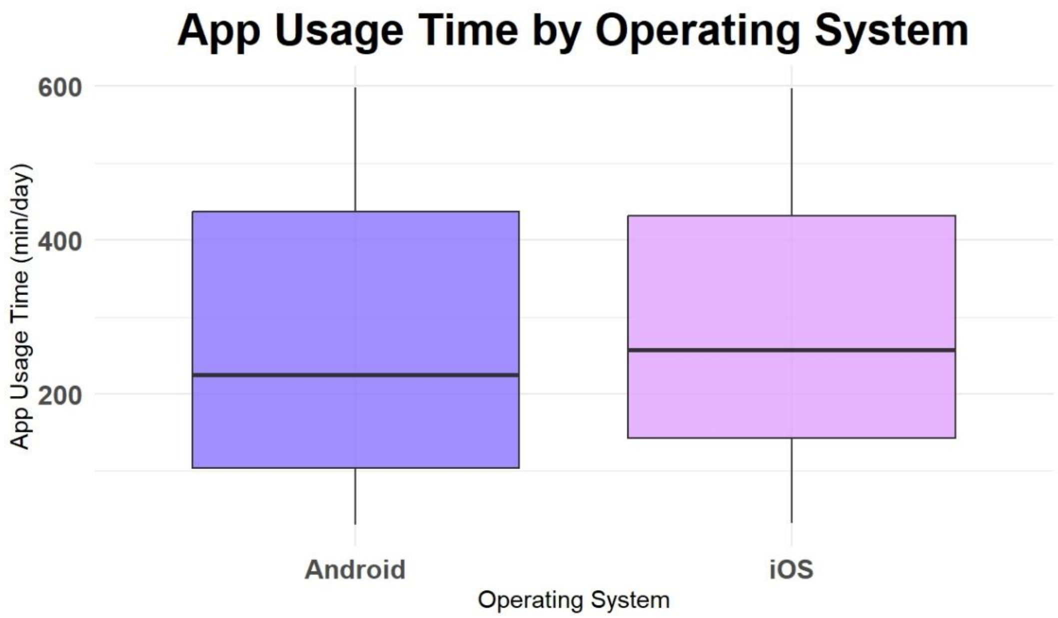


Figure 4

3. Behavioural Insights

Users in the dataset are categorized into five behaviour classes based on their engagement levels. The distribution is relatively balanced across all classes, with each class containing over 120 users. Despite having higher user counts, Classes 1 and 2 represent **low engagement levels**, characterized by shorter app usage times and lower interaction frequencies. Conversely, Classes 4 and 5, categorized as **heavy users**, demonstrate extensive app engagement, spending significantly more time interacting with their devices.

This classification highlights opportunities for targeted strategies:

- **Low Engagement Users (Classes 1 & 2):** These users may benefit from personalized notifications, app tutorials, or incentive-based features to encourage greater interaction.

- **Heavy Users (Classes 4 & 5):** These users represent a significant opportunity for premium features, loyalty rewards, or cross-promotional content to maximize value.

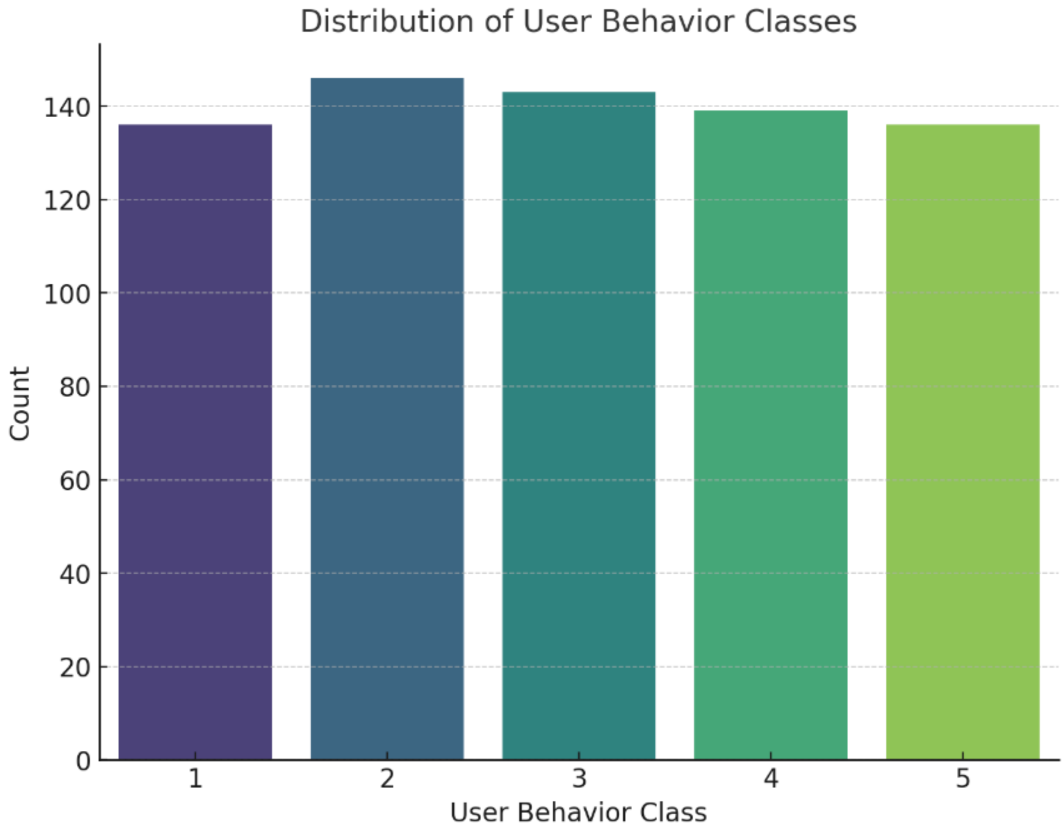


Figure 5

The balanced user representation across these behaviour classes ensures fairness in analysis and offers a solid foundation for developing tailored engagement strategies.

Retention and Churn Factors

Retention is closely linked to app efficiency. Apps with lower battery consumption and high usability metrics (screen-on time and app usage) perform better in retaining users.

- **Device-Specific Trends:** Popular devices like the Xiaomi Mi 11 and iPhone 12 show higher engagement, making them priority models for optimization.
- **Energy Efficiency:** Reducing battery consumption is critical for retention.

What This Means for App Developers

The data offers actionable insights for developers:

1. **Optimize Energy Efficiency:** Reduce battery consumption to retain users.
2. **Behaviour-Based Personalization:** Use insights from user behaviour classes to tailor app features.

3. **Universal Design:** Focus on inclusive design as engagement is consistent across demographics.
4. **Device-Specific Optimization:** Enhance app performance for popular devices.

Limitations

1. **Limited Device Representation:** Even though five of the most popular device models were considered in this dataset, these are by no means representative of all mobile devices available. The findings of this research have, therefore, limited generalizability across all users (Al-Mashhour & Alhogail, 2023).
2. **App-Specific Metrics are Not Considered:** The dataset lacks detailed app-specific metrics, such as the type of apps being used (e.g., productivity, entertainment, or communication). This absence hinders the ability to draw app-category-specific insights (Labayen et al., 2020).
3. **No Regional or Cultural Context:** Geographic and cultural differences, which could significantly influence mobile usage patterns, are not captured in the dataset. These aspects are essential for developing region-specific engagement strategies (Anwar et al., 2024).
4. **Short Observation Period:** There is no information on whether it includes data on usage trends for an extended period or limited observation time. Without that, seasonal or long-term behavioural analyses are seriously hampered when the information cannot be complete ((Singh et al., 2017).
5. **No Incorporation of Exogenous Factors:** Exogenous variables, including internet connectivity, app version updates, or security/privacy-related concerns-which have much to say about influencing the engagement-have not been factored in while building this dataset (Mishra, 2020).

Future Work

1. **Incorporating more comprehensive device coverage:** Expanding the dataset to include a wider variety of devices and brands would provide a more comprehensive understanding of mobile usage patterns across different segments (Al-Mashhour & Alhogail, 2023).
2. **Capturing App-Specific Data:** Including app-category-specific metrics could uncover insights into how different types of apps drive engagement and retention (Labayen et al., 2020)
3. **Integrating Regional and Cultural Contexts:** Addition of regional or cultural dimensions to the dataset would allow for location-specific strategies and enhance the generalizability of findings across markets of varying natures. (Anwar et al., 2024)

4. **Temporal and Longitudinal Analysis:** The introduction of timestamps and the extension of the observation period will make it possible to analyse daily, weekly, or seasonal trends that may exist, which would assist in highlighting changes in user behaviour over time (Singh et al., 2017).

5. **Analysing External Influences:** Future studies could integrate external data, such as network performance, app updates, and socio-economic variables, that would help in better comprehension of their effects on user engagement and churn (Mishra, 2020).

6. **Advanced Behavioural Modelling:** The refinement of the behavioural classification by advanced machine learning techniques could improve the depth and accuracy of the analyses of user behaviour, and hence enable more precise personalization and engagement strategies, as suggested by Labayen et al. (2020).

Conclusion

The analysis of mobile device usage and user behaviour provides a comprehensive understanding of how users interact with apps, how device-specific factors influence engagement, and what strategies can drive retention. Key findings highlight the significant correlation between app usage, screen-on time, and battery drain, pointing to energy efficiency as a critical area for improvement.

Furthermore, the study also finds consistent engagement across demographics, indicating that universal app design and optimization strategies can effectively serve a diverse user base. However, behavioural differences among user classes put a greater emphasis on personalization, for instance, targeting heavy users with premium features and re-engaging low-engagement users with recommendations and notifications.

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