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A Study On Mobile Usage Differences By Gender And Device Model Using Regression Machine Learning Models

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Abstract: In the modern digital era, mobile phones have become indispensable, shaping communication, entertainment, and productivity. However, mobile usage patterns are influenced by various factors, including gender and device model. This study investigates the impact of these factors on mobile usage by analyzing key aspects like screen-on time, app usage, battery consumption, and data usage. A dataset of 700 users from Kaggle was employed, encompassing five smartphone models and both male and female users. To predict mobile usage trends, multiple machine learning models were implemented, including Linear Regression, K-Nearest Neighbors (KNN) Regression, Lasso Regression, and Support Vector Machine Regression (SVR). Among these, KNN exhibited the highest predictive accuracy with an R^2 score of 95%, followed closely by Lasso Regression and Linear Regression.

Key findings: Highlighted that males tend to have higher data consumption and screen-on time than females, while certain device models show higher app usage across genders. The study examines the importance of considering gender and device-specific factors in mobile application development and device optimization. These insights can assist mobile manufacturers, app developers, and policymakers in designing more personalized and efficient mobile experiences.

Future research: This study can be enhanced by incorporating a wider range of device models, including emerging smartphones with advanced features, and integrating additional behavioral factors such as socioeconomic status, geographical location, and cultural influences. Moreover, leveraging deep learning techniques for more precise predictions could further refine mobile usage pattern analysis.

Keywords: Mobile usage, SVM Regression, KNN Regression, Machine learning, Linear Regression, Lasso Regression.

I INTRODUCTION

In the digital era, mobile phones have become essential for daily tasks such as social networking, banking, and shopping. In the modern digital era, mobile phones have become an important part of our daily lives, and their use has brought great convenience to our daily activities. Most of our daily activities or tasks depend on mobile phones for various activities, including social networking, entertainment, accessing bank services, shopping, and productivity. However, mobile usage behavior is not the same among users. Mobile phone usage was influenced by multiple factors, including gender, age, device model, and so on. The modern era keeps people connected online every day, resulting in a daily increase in mobile phone users. According to recent data from Statista and GSMA, around 70% of the world’s population is currently smartphone users. According to world-statistics.org, mobile cellular subscriptions grew nearly fivefold between 2008 and 2018. Research also shows that the average daily smartphone usage is about 3 hours and 45 minutes. Currently, around 4.69 billion people own a smartphone, a number expected to rise to 5.83 billion by 2028.

In today's world, there has been a rapid advancement in mobile technology; in this situation, understanding the mobile usage patterns of users becomes a crucial area of study. However, a gap remains in current research on mobile usage in understanding how gender and device model jointly influence user behavior.

Research suggests that gender plays an efficient role in how individuals interact with mobile devices. Men and Women both exhibit different preferences in terms of app usage, screen on time, battery drain, data usage, etc. For instance, males are more likely to use mobile phones than females. This study explores the relationship between gender, mobile device model, and screen-on-time(mobile usage) to fill the current research gap.

The remainder of the paper is structured as follows: Section 2- Literature survey: Overview of previous studies related to mobile usage, Gender-based differences, and device model on user engagement. Section 3- Materials and methods: Describes the research dataset identification, analysis techniques, and methods used to predict mobile usage based on gender and device model. Section 3- Results and Discussion: The predictions of the study are presented and discussed in this section. Section 5- Conclusion: This section includes key findings, limitations, and future research directions.

II LITERATURE SURVEY

Hwang et. al [1] empirically investigate the effect of mobile app types the moderating effect of mobile app types and the moderating effect of gender and age on mobile app usage. The result of this study demonstrates that all of the mobile app dimensions were significantly affected by the type of mobile app, with the extension of specific mobiles in each dimension. Vanden Abeele et. al [2] examine discrepancies between self-reported mobile phone use and network provider data in a survey. Significant differences were found for all numbers and duration. Light users overestimate, while heavy user underestimates their mobile phone usage. Females were more likely to underestimate calls. This research, by José Liébana-Cabanillas et. al[3] explores factors influencing the adoption of new mobile payment systems. It tests a model considering ease of use, attitude, usefulness, trust, risk, and gender. A web experiment with the general population shows that gender affects the relationship between system features and adoption. The study by Li et. al[4] examined gender differences in the adoption and use of mobile commerce with 372 respondents. Both gender has similar adoption rates of about 30%. Males and Females adopted m-commerce in a similar pattern, with entertainment services being the most popular. However, males used more communication information and transaction services, suggesting they adopted m-commerce faster than females. This paper by T. J. Neal et al.[5] explores gender-related behavioral patterns in mobile device usage, focusing on Bluetooth and Wi-Fi data. Using 19 months of data from 189 subjects, gender classification achieved up to 91.8% accuracy. Finally, it discusses impersonation attacks, examining if one gender is more vulnerable to unauthorized access on mobile devices. Baron et. al[6] examine gender differences in mobile phone use. The study analyzes communication purpose, politeness, contact management, and usage volume, along with complaints about dependency and reachability. Results show gendered patterns, through cultural factors may sometimes better explain differences than gender itself. This study, done by Mariano et. al [7] examines the impact of mobile apps on a company's brand image. Using a structural equation model and data from 350 mobile device users, the research found that apps influence 30.5% of brands' images. The result suggests that mobile apps are becoming as important as websites and social media. To succeed, companies must build a solid brand image that emotionally connects with a customer, alongside high performance and quality standards. This study by Sakkthivel et. al [8] explores the influence of gender on the technology acceptance model for smartphone use, involving 296 participants. Using SEM, the result shows that gender negatively influenced perceived usefulness; males had a positive influence on perceived ease of use, whereas females had a negative influence on perceived ease of use. M. Shahin et. al [9] analyzed gender-related discussions in app reviews to better understand user perspectives on gender inclusion using machine learning and deep learning classifiers. The analysis revealed six key topics in gender discussions: add features, appearance, content, company, etc. Based on these findings, we offer practical recommendations for creating gender-inclusive apps. Lee, et. al [10] explore gender differences in mobile phone aesthetics, categorized into visual, auditory, and tactile senses, using the AHP methodology. The findings indicate significant differences, with visual aesthetics being the most important, suggesting that mobile phone companies should consider these preferences in design. Wang et. al [11] examine user satisfaction with the University of Ha'il's mobile banner system, highlighting female students' concerns. A survey of 235 students evaluated six key aspects, offering insights for future improvements.

According to this study, current limitations include;

- Lack of Device Model Analysis – Most existing research focuses on gender-based mobile usage patterns but does not explore how different device models may influence these behaviours.
- Limited Gender-Device Interaction Analysis – Few studies examine whether specific mobile devices cater more
  effectively to gender-based preferences, highlighting a research gap this study aims to address.

III **RESEARCH METHODOLOGY**

Mobile phones are integral to modern life, yet usage patterns differ by gender and device model. This study analyzes variations in screen-on time, app usage, battery consumption, and data usage to understand user behavior and support better mobile experience design.

3.1 *DATASET*

The dataset was sourced from Kaggle and includes 700 users (364 males, 336 females) aged 18–59 (mean age: 38.48, SD: 12). Devices used include Google Pixel, iPhone 12, OnePlus 9, Samsung Galaxy F21, and Xiaomi Mi11.

3.2 *DATA PREPROCESSING*

The dataset was cleaned and transformed to remove irrelevant data. A check for null values revealed none, ensuring readiness for analysis.

3.3 FEATURE SELECTION

Relevant features were selected to improve model performance. Irrelevant attributes like user ID were removed. Key features used include device model, gender, app usage time, battery drain, data usage, and age.

3.4 MODEL SELECTION

Algorithm selection involves determining the structure of the learning function and choosing the best algorithm based on various performance parameters. This is a critical step in building an effective supervised learning model. In this study, four regression models were used to predict mobile usage (screen-on time) based on gender and device model.

- LINEAR REGRESSION MODEL

Linear Regression depicts the relationship between a dependent variable and one or more independent variables. Simple Linear Regression uses one predictor, while Multiple Linear Regression uses two or more. Since this study involves multiple influencing factors, Multiple Linear Regression was applied to estimate mobile usage patterns. It is a commonly used, interpretable model for predicting continuous variables.

- LASSO REGRESSION MODEL

Lasso (Least Absolute Shrinkage and Selection Operator) Regression enhances the performance of Linear Regression by adding L1 regularization. This regularization helps shrink less important feature coefficients to zero, effectively performing feature selection. It improves model accuracy, reduces overfitting, and simplifies the model, making it suitable for datasets with many features.

- SUPPORT VECTOR REGRESSION MODEL

Support Vector Regression (SVM) is an extension of the Support Vector Regression algorithm for regression tasks. It aims to find a function that approximates the target values within a specified margin of error. SVR can handle both linear and nonlinear relationships by using kernel functions to project data into higher-dimensional spaces. It is robust to outliers and effective in capturing complex data patterns.

- K-NEAREST NEIGHBOUR REGRESSION MODEL

This is a non-parametric method that predicts the value of a new data point by averaging the values of its k nearest neighbors in the dataset. It uses distance metrics like Euclidean distance to identify neighbors and is suitable for nonlinear relationships. While easy to implement and effective, KNN can be computationally expensive and sensitive to irrelevant or unscaled features

3.5 *MODEL TRAINING*

The selected machine learning algorithms were trained on a dataset split into training and testing subsets. Feature selection was applied to identify the most relevant variables affecting mobile usage.

Table 1: Training and Testing data used

Algorithm	Training data	Testing data	Random state
Linear Regression	90	10	540
KNN Regression	90	10	560
Lasso Regression	90	20	230
SVM Regression	90	10	120

Models used include Linear Regression, KNN Regression, Lasso Regression, and SVM Regression. Grid Search was applied for hyperparameter tuning to optimize performance. The goal was to minimize errors and achieve a high R^2 score by evaluating model generalization on unseen data.

3.6 MODEL EVALUATION

Models were evaluated using R^2 Score, Mean Absolute Error (MAE), and Mean Squared Error (MSE).

- R^2 Score assessed the overall performance.
- MAE measured average prediction errors.
- MSE penalized larger errors for better precision.

Results were analyzed by gender and device model to detect performance variation. Adjustments such as feature tuning and preprocessing were considered if large discrepancies appeared. As a sample, Table 2 illustrates the performance analysis of the Linear Regression algorithm.

Table 2: Performance of Linear Regression algorithm

Metrics	Values
R2 Score	92
Mean Absolute Error (MAE)	0.60
Mean Squared Error (MSE)	0.54

IV. RESULTS AND DISCUSSION

With the rise of smartphones in communication, work, and entertainment, usage patterns differ across genders and device types. This study addresses the gap in existing research by analyzing mobile usage based on screen-on time, app usage, and battery consumption. Key findings show that male and female users differ in data use and engagement levels, while device models also affect usage behavior. These insights can support developers and manufacturers in designing more personalized and efficient mobile experiences

4.1 Comparative analysis of mobile usage based on gender and device model

Mobile devices offer a range of features that cater to varied user preferences. This section explores how mobile usage differs based on gender and device model, focusing on six key aspects:

4.1.1 Device preference by gender

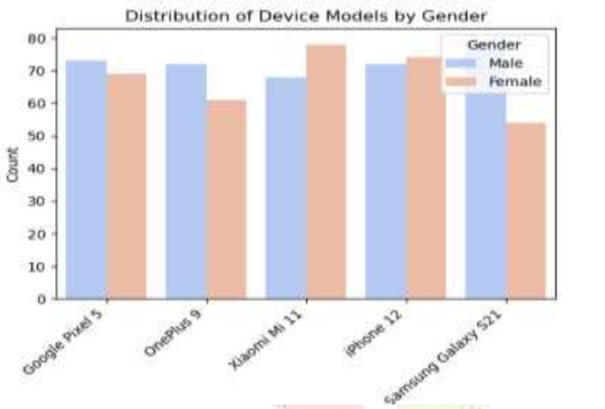


Figure 1 shows the distribution of smartphone models (Google Pixel 5, OnePlus 9, Xiaomi Mi 11, iPhone 12, Samsung Galaxy S21) by gender. Most models show distinct usage trends—for example, the OnePlus 9 is predominantly used by males, while the Xiaomi Mi 11 is more popular among females.

Figure 1: Device preference by gender

4.1.2 SCREEN ON TIME

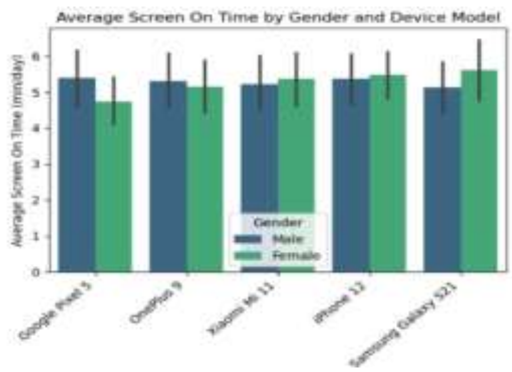


Figure 2 compares daily screen-on time by gender. While usage is similar across genders, males show slightly higher screen time on the Google Pixel 5, whereas females lead for Xiaomi Mi 11.

Figure 2: Screen on time

4.1.3 APP SCREEN

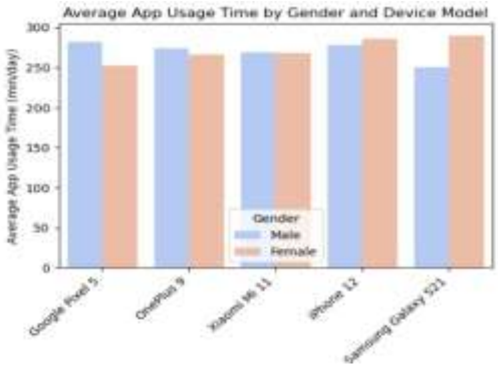


Figure 3 illustrates daily app usage. Males use more apps on the Google Pixel 5, while females lead with the iPhone 12 and the Samsung Galaxy S21. Other models show balanced usage.

Figure 3: APP Screen

4.1.4 BATTERY DRAIN

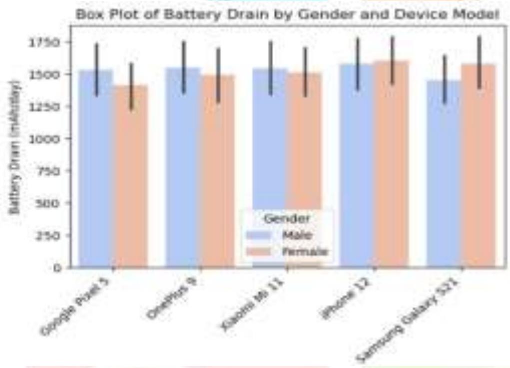


Figure 4 presents daily battery consumption. Males show higher drain on Pixel 5 and OnePlus 9; females on iPhone 12 and Galaxy S21. Overall, differences are minimal

Figure 4: Battery Drain

4.1.5 NUMBER OF APPS INSTALLED

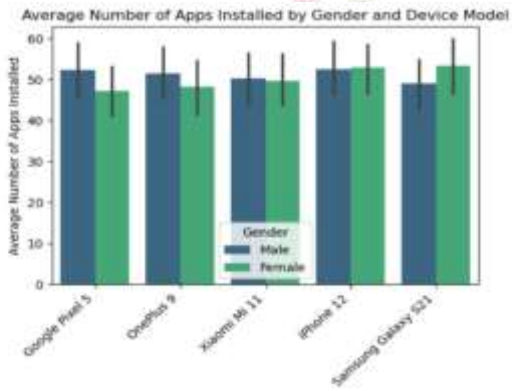


Figure 5 shows that males install more apps on the Pixel 5 and OnePlus 9, while females lead slightly on the iPhone 12 and Galaxy S21.

Figure 5: Number Of Apps Installed

4.1.6 DATA USAGE

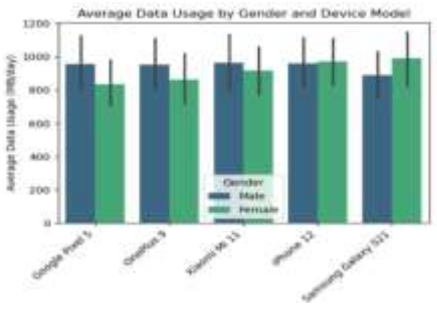


Figure 6: Data Usage

Figure 6 compares average data consumption. Males generally consume more data, except for the iPhone 12 and Galaxy S21, where females consume slightly more.

4.2 AGE DISTRIBUTION

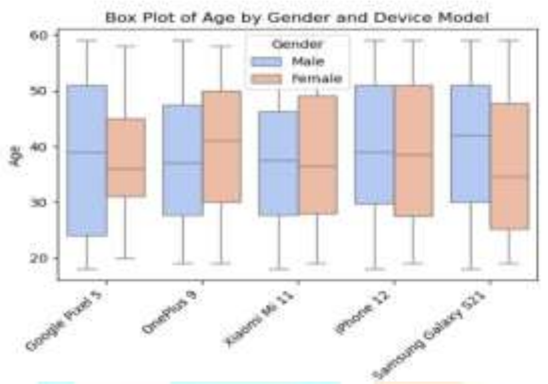


Figure 7: Age distributions across genders and models

Figure 7 (Box plot) reveals similar age distributions across genders and models. No significant gender-based age preference is observed.

4.3 MODEL EVALUATION

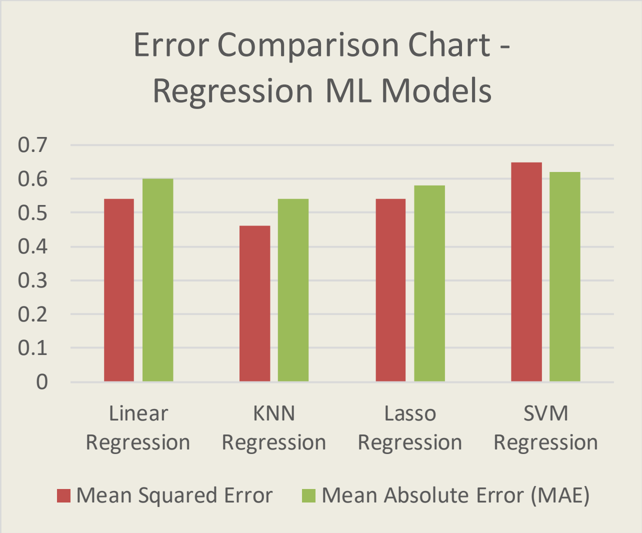
To evaluate predictive accuracy in identifying mobile usage patterns based on gender and device model, four regression algorithms were used: Linear Regression, K-Nearest Neighbors (KNN) Regression, Lasso Regression, and Support Vector Machine (SVM) Regression. These models were assessed using R^2 Score, Mean Squared Error (MSE), and Mean Absolute Error (MAE). Linear Regression achieved an R^2 score of 92, with an MSE of 0.54 and MAE of 0.60. It offers a simple, interpretable approach but may not effectively model complex relationships. KNN Regression performed the best, with an R^2 of 95, MSE of 0.46, and MAE of 0.54, indicating high predictive accuracy and low error margins. Lasso Regression recorded an R^2 of 94, with MSE and MAE values of 0.54 and 0.58, respectively. It benefits from L1 regularization, making it useful for feature selection. SVM Regression resulted in an R^2 of 93, but showed higher error values—MSE of 0.65 and MAE of 0.62— suggesting the need for better kernel or parameter tuning.

4.3 COMPARATIVE ANALYSIS OF MODEL PERFORMANCE

Evaluating multiple regression models is vital for identifying the most accurate method to predict mobile usage patterns based on gender and device model. In this study, Linear Regression, K-Nearest Neighbors (KNN) Regression, Lasso Regression, and Support Vector Machine (SVM) Regression were assessed using three key metrics.

Table 3: Overall Performance of Machine Learning Algorithms

ML Model	**R2 Score**	**Mean Squared Error (MSE)**	**Mean Absolute Error (MAE)**
Linear Regression	92	0.54	0.60
KNN Regression	95	0.46	0.54
Lasso Regression	94	0.54	0.58
SVM Regression	93	0.65	0.62



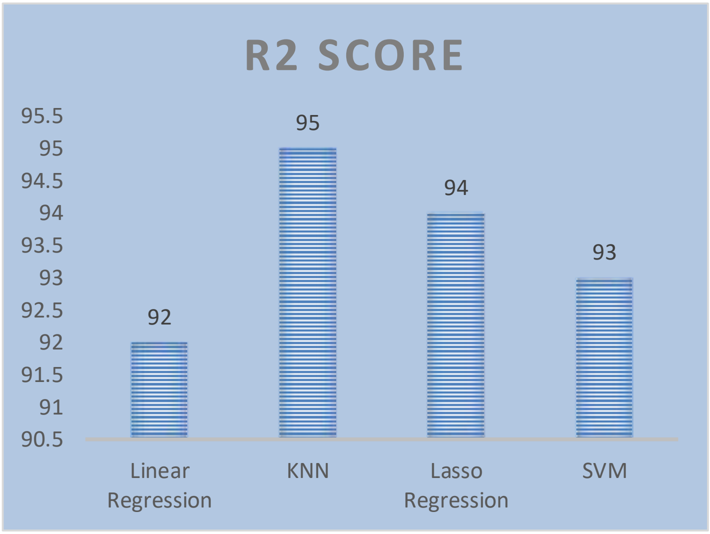


Figure 8: ***Error Metric Comparison of Regression Machine Learning Algorithms***

KEY INSIGHTS WITH REFERENCE TO TABLE 3 AND FIGURE 8

- KNN Regression performed the best, achieving the highest R² score (95%) and the lowest MSE (0.46) and MAE (0.54), making it the most reliable model for predicting mobile usage.
- Lasso Regression closely followed, benefiting from L1 regularization, which aids in feature selection, though with slightly higher error margins.
- Linear Regression provided interpretable results with solid performance but may struggle with non-linear patterns.
- SVM Regression had the lowest performance, showing higher error rates and requiring further tuning of the kernel and hyperparameters.

V CONCLUSION

This study presents a detailed analysis of mobile usage patterns based on gender and device model, revealing notable differences in screen-on time, app engagement, battery consumption, and data usage. The results show that males and females display distinct interaction trends, influenced by specific smartphone models. Machine learning models were used to predict usage behavior, with KNN Regression achieving the highest predictive accuracy. These findings highlight the need for device and gender-specific considerations in mobile app development and user experience design. Key findings include:

- Gender Differences: Males generally show higher data usage and screen-on time, while app engagement varies by device.
- Device Influence: Some models promote greater screen time and app use across both genders.
- Best Model: KNN Regression was most effective for forecasting usage patterns.

Future work could expand the dataset to include more devices and incorporate real-time tracking and advanced models, such as deep learning, to improve prediction accuracy.

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