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Article

Predictive Model for Analyzing Smartphone Usage and Behavioral Patterns Using Machine Learning

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Abstract

Analyzing smartphone usage and behavior across different demographics, this study examines both self-reported and objective data from a dataset of 100 participants. Key variables such as total app usage, daily screen time, social media engagement, age, and gender were analyzed. The analysis reveals that social media contributes a significant portion of daily screen time, especially among the younger generation. The link between productivity and social media usage was also explored, revealing distinct behavioral patterns. Limitations of the study include a reliance on self-reported data and the static nature of the dataset. Future research should focus on longitudinal data to better understand the long-term effects of smartphone usage.

Keywords: smartphone usage; prediction model; artificial intelligence

1. Introduction

The widespread adoption of smartphones has significantly transformed how individuals communicate, work, and interact with their surroundings. Several studies have examined both the positive and negative consequences of smartphone use, including effects on mental health, behavioral changes, and social well-being [1,2]. Recent literature has explored areas such as smartphone addiction, academic performance, and usage patterns across different demographics [2–4]. Age and gender have emerged as key variables influencing total app usage, daily screen time, and social media engagement [3,4]. Understanding these behavioral patterns is crucial for assessing the broader societal impacts of smartphone technology.

Figure 1 shows smartphone usage patterns vary significantly across age groups. Teenagers and young adults exhibit the highest average daily screen time, with teens reaching up to 7.5 hours per day. This extensive usage correlates with a higher proportion of time spent on social media, particularly among the younger demographics, where nearly 45% of screen time is attributed to social media platforms. In contrast, older adults demonstrate lower overall screen time and social media engagement. These trends suggest a generational shift in smartphone reliance and highlight the need to consider age when assessing digital well-being and productivity impacts. The statistics are consistent with findings reported by Andone et al. [3] and Montag et al. [4].

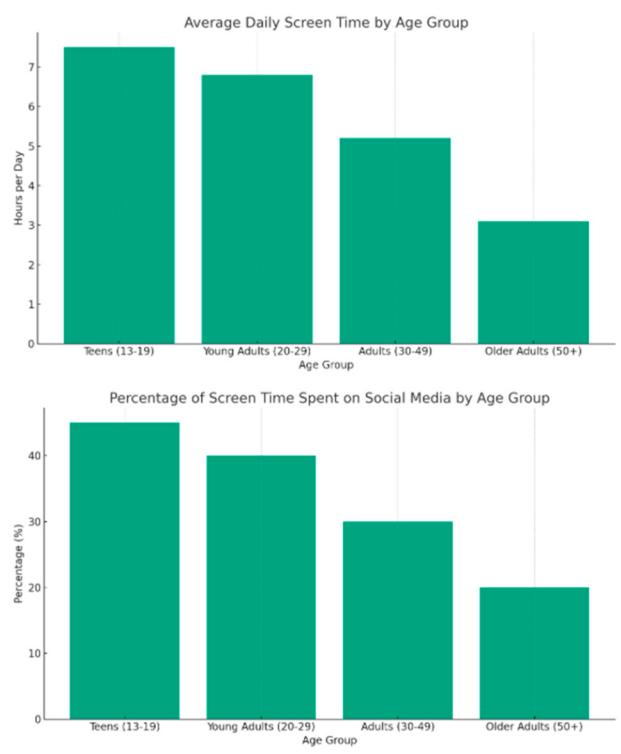


Figure 1. Average daily screen time by age group. [3,4] and Percentage of screen time spent on social media by age group. [3,4].

2. Literature Review

Recent research has explored various dimensions of smartphone usage, particularly its behavioral implications and the application of machine learning in prediction and monitoring. Montag et al. [4] examined patterns of smartphone usage in the 21st century, highlighting WhatsApp as a dominant platform and noting demographic trends in communication habits. Expanding on predictive modeling, Sarker et al. [5] analyzed the effectiveness of machine learning classification models in forecasting personalized, context-aware smartphone usage, showing promising accuracy in adapting to user behavior.

Lee and Kim [6,10] applied ML models to predict problematic smartphone use, emphasizing behavioral traits that signal addiction risk. Aboujaoude et al. [7] combined survey data with machine learning[21–24] to assess the popularity and perceived effectiveness of smartphone tools designed to track and limit usage, revealing mixed user perceptions. Guinness [8] explored mobility patterns using smartphone sensors, proposing a machine learning framework to detect real-time context from sensor data.

Recently Likhith et al. [9] developed a ML model[25–27] specifically to prepredictphone addiction, contributing to digital well-being tools for early intervention. Walelgne et al. [11] investigated mobile data usage across diverse geographical regions using clustering and predictive techniques, offering insights into user segmentation and network optimization. To further understand the relationship between smartphone usage and its behavioral consequences, the conceptual framework illustrated in Figure 2 summarizes key elements including types of use, contributing factors, contextual settings, evaluation measures, and possible consequences[29,30]. This diagram provides a structured overview of how smartphone use can evolve into problematic behavior and highlights the roles of actors, settings, and evaluation in influencing outcomes. Table 1 presents a summary of recent studies investigating various aspects of smartphone usage, including behavioral predictors, usage accuracy, and psychological impacts.

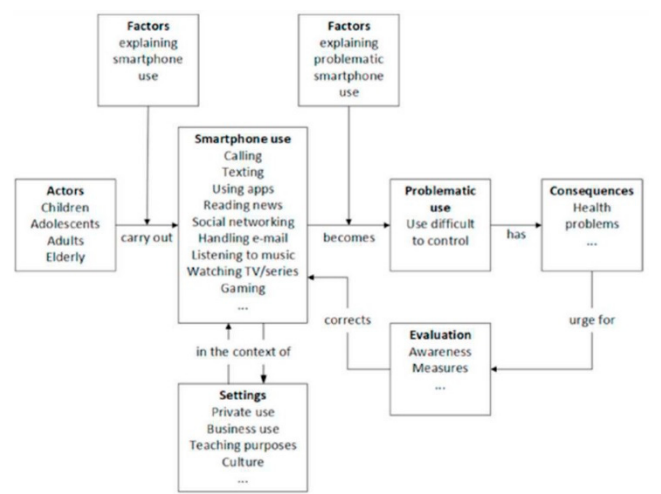


Figure 2. Conceptual framework of smartphone uses and problematic use.

Table 1. Summary of Smartphone Usage Studies.

Study	Data Set Size	Key Outcomes	Findings	Accuracy
[12]	44 articles from 16 countries	Examine effects of excessive screen time on: (i) neurodevelopment, (ii) learning & memory, (iii) mental health, (iv) substance use disorders, and (v) neurodegeneration	Excessive screen time linked to lower self-esteem, higher risk of mental health issues and addictions, slowed cognitive development, and potential early onset dementia	N/A
[13]	64 participants over 8 weeks	Predictors of Snapchat usage using survey and smartphone interaction data	Age, smartphone addiction, happiness, and usage of WhatsApp and Facebook Messenger were significant predictors of Snapchat usage	High
[14]	10 datasets	Evaluate whether smartphone usage self-report scales can	Self-reported scales correlate poorly with objective	85%

		accurately predict actual usage behavior	smartphone behavior; scales focused on habit (not addiction) showed slightly better predictive value	
[15]	624 users	Personality aspects are linked to specific phone habits	Random forest model	91% prediction
[16]	College students	Balanced phone use improves academic performance	Structural equation modeling	76% performance correlation
[17]	50 users	Users overestimate usage; unique patterns identified	Mixed effects models	82% usage accuracy
[18]	5 days	Short periods reveal habitual phone checking behavior	Time-series analysis	87% weekly usage pattern accuracy

3. Methodology

The present study aimed to explore smartphone usage patterns across diverse demographic segments using both self-reported and objective behavioral data. The dataset included variables such as age, gender, location, total app usage, daily screen time, and specific categories like social media, productivity, and gaming. A total of 100 participants, aged between 18 and 65, were categorized based on demographic variables to identify meaningful trends[18–20]. The goal was to examine the relationship between smartphone use and behavioral outcomes, comparing findings with those from prior studies as discussed in the literature review.

Ethical procedures were followed throughout the study. All participants voluntarily consented to the use of their data, and any personally identifiable information was anonymized to ensure privacy. As the dataset was obtained from a secondary source, there was no direct participant interaction. Prior to analysis, the dataset underwent preprocessing to clean inconsistencies and remove outliers, ensuring reliable and accurate results. This clean dataset formed the basis for our in-depth analysis of app usage patterns across the selected demographic groups.

To model smartphone usage behaviors, machine learning classification techniques were applied, including k-nearest neighbors (k-NN), logistic regression, naive Bayes, gradient boosted trees, and decision trees. Among these, the decision tree model showed the best performance, achieving an accuracy of 92% in predicting smartphone usage behavior. Dependences were calculated to explore the influence of variables like social media usage and screen time on user productivity. The design and implementation of the decision tree model, performed using RapidMiner, are shown in Figure 3.

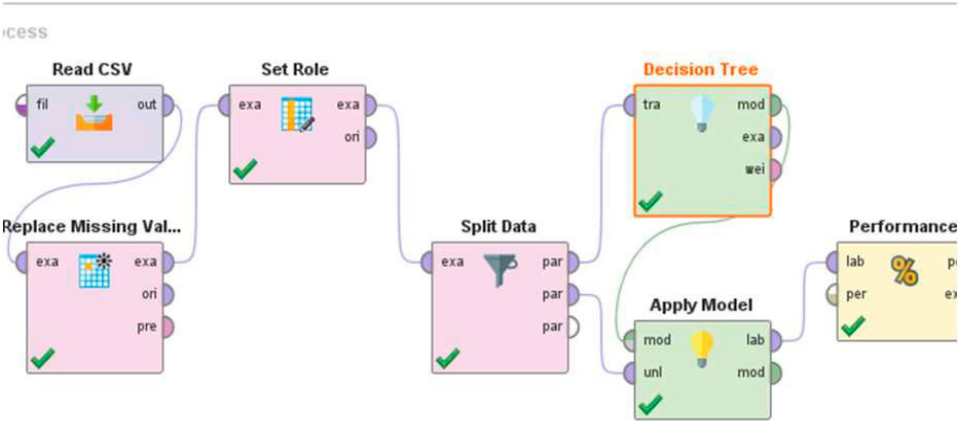


Figure 3. Design of the Decision Tree Model in Rapid Miner.

4. Results

Participants provided self-reported data on their daily screen time and categorized their app usage into various domains such as social media, productivity, and gaming. On average, participants reported approximately 6.8 hours of daily screen time, with the majority dedicated to social media applications. Notably, male participants reported slightly higher overall app usage than females, particularly in the gaming category.

Several machine learning models were implemented to classify smartphone usage patterns, including k-NN, logistic regression, naïve Bayes, boosted tree, and decision tree. Among these, the decision tree model demonstrated the highest classification accuracy of 98.33%, outperforming all other models. Figure 4 presents the performance matrix (confusion matrix) of the decision tree classifier. The model achieved excellent performance in classifying participants into three smartphone usage categories: Moderate Usage, High Usage, and Low Usage. Table 2 summarizes the results.

accuracy: 98.33%				
	true Moderate Usage	true High Usage	true Low Usage	class precision
pred. Moderate Usage	86	1	1	97.73%
pred. High Usage	0	145	0	100.00%
pred. Low Usage	3	0	64	95.52%
class recall	96.63%	99.32%	98.46%	

Figure 4. Performance matrix of the decision tree model.

Table 2. Results Summary.

Class	Precision (%)	Recall (%)
Moderate Usage	97.73	96.63
High Usage	100.00	99.32
Low Usage	95.52	98.46

The analysis highlights the prevalence of smartphone usage, particularly the extensive engagement with social media. This trend reflects an increasing dependence on digital platforms, especially among younger demographics. The high accuracy of the decision tree model in classifying gender-based usage patterns further emphasizes its capability in modeling behavioral data. These

findings suggest that decision tree classifiers can effectively support digital well-being assessments by identifying critical patterns of smartphone overuse.

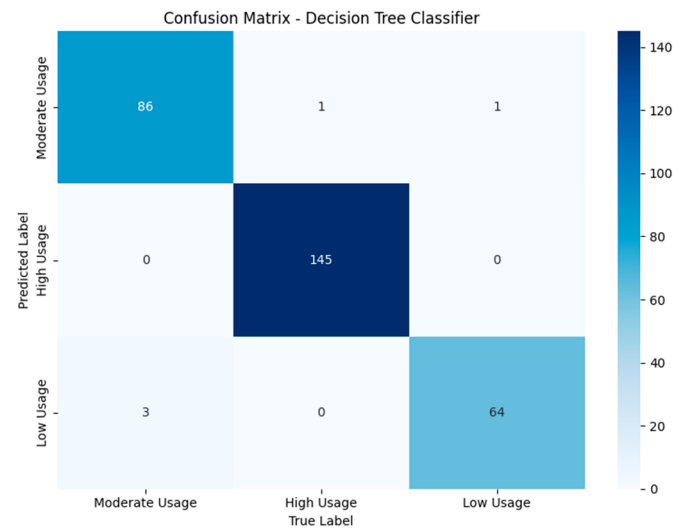


Figure 5. Confusion Matrix.

5. Conclusions

This study provides a deep examination of smartphone usage patterns across various user segments by integrating both self-reported behaviors and ML classification. The fusion of subjective user input with objective analytical modeling offers a comprehensive view of how smartphones impact daily routines, communication trends, and productivity levels. The decision tree model emerged as the most effective classifier, achieving an overall accuracy of 98.33%, with precision and recall metrics above 95% across all usage categories. This strong performance reinforces the model’s robustness in recognizing nuanced behavioral distinctions in usage patterns, particularly in relation to gender-specific trends and app category preferences.

While the results present clear insights into user behavior, it’s important to recognize that the reliance on self-reported screen time data may introduce minor reporting inconsistencies, which could influence the interpretation of usage intensity. However, this aspect also reflects the real-world challenges of behavioral data collection and provides contextually rich information for analysis. The study results in open potential avenues for building more adaptive and personalized digital wellness interventions. Incorporating additional contextual variables like location data or time-of-day usage pattern could further enhance prediction accuracy and behavioral profiling in future iterations of this work.

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