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Screen Time Prediction and Behavioral Analysis Using Machine Learning: A Data-Driven Approach Focusing on Usage Patterns, Challenges, and Digital Well-Being

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***Abstract*—Screen addiction, lack of self-control, and irregular usage habits have increased with the rapid growth of smartphones and digital devices, leading to a significant rise in daily screen time, especially among young users. Excessive screen usage can affect mental health, productivity, and overall digital well-being. This research presents a data-driven approach to analyze screen time behavior and predict future usage patterns using machine learning techniques. The study uses user activity data such as application usage duration, frequency of device access, time of day, and type of applications used. Various machine learning models are applied to identify patterns in screen usage and to predict high-risk screen time behavior. The performance of these models is evaluated using standard metrics such as accuracy and error rates. Behavioral analysis is conducted to understand challenges related to excessive screen usage. The results show that machine learning models can effectively predict screen time trends and highlight factors that contribute to excessive usage. This research helps in understanding user behavior and supports the development of digital well-being solutions, such as usage alerts and personalized recommendations. The proposed approach can assist individuals, educators, and policymakers in promoting healthier digital habits and balanced technology use..**

***Index Terms*—Recommendation Systems,Context-Aware Computing, SQL-Guided AI, Personalized Filtering, Hybrid Case Study**

I. Introduction

The rapid advancement of smartphones and digital technologies has significantly transformed daily life by improving communication, access to information, and productivity. However, this technological growth has also resulted in a substantial increase in daily screen time, particularly among young users. Excessive screen usage, along with screen addiction, lack of self-control, and irregular usage habits, has raised concerns due to its potential impact on mental health, academic or work productivity, and overall digital well-being. Screen time behavior is shaped by multiple factors, including the duration of application usage, frequency of device access, time of day, and the type of applications used. Understanding these patterns is essential for identifying unhealthy usage habits and promoting balanced technology use. Traditional approaches to screen time analysis often rely on self-reported data or simple statistical techniques, which may not accurately represent real user behavior or capture complex usage patterns. With the increasing availability of large-scale user activity data, data-driven approaches offer a more reliable and objective way to study screen usage behavior Machine learning methods are especially efficient in this context, as they are capable of processing extensive datasets, uncovering concealed patterns, and understanding relationships among various behavioral factors. These capabilities make machine learning suitable for predicting future screen time trends and detecting high-risk usage behavior. Behavioral analysis further enhances the understanding of challenges associated with excessive screen time, such as lack of self- regulation and irregular usage habits. Incorporating contextual information, such as time-based usage patterns and application categories, enables more accurate analysis and supports the development of intelligent systems. Context-aware computing and personalized filtering techniques can play a key role in designing effective digital well-being solutions. This research focuses on analyzing screen time behavior and predicting future usage patterns using machine learning techniques. By utilizing user activity data such as application usage dura- tion, access frequency, time of use, and application types, the proposed approach aims to identify patterns associated with excessive screen usage. The outcomes of this study can support the development of digital well-being solutions, including usage alerts and personalized recommendations, and assist individuals, educators, and policymakers in promoting healthier digital habits and balanced technology use.

II. Significance of the Study

- Helps in understanding screen time behavior by analyzing real user activity data instead of relying on self-reported information.
- Demonstrates the effectiveness of machine learning techniques in predicting future screen usage patterns and identifying high-risk screen time behavior.

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- Provides deeper behavioral insights by examining factors such as application usage duration, frequency of device access, and time-based usage patterns.
- Supports the identification of challenges related to excessive screen usage, including lack of self-control and irregular usage habits.
- Enhances digital well-being research by integrating behavioral analysis with data-driven prediction models.
- Highlights the importance of context-aware computing in improving the accuracy and relevance of screen time analysis.
- Contributes to the development of personalized digital well-being solutions, such as usage alerts and recommendation systems.
- Assists individuals in improving self-awareness and managing screen usage more effectively.
- Provides useful insights for educators to promote healthier digital habits among students.
- Supports policymakers in designing guidelines and awareness programs for balanced and responsible technology use.

III. Literature Review

Several studies have examined the increasing dependence on smartphones and digital devices and its influence on daily screen time, particularly among young users. Existing research highlights that excessive screen usage is often associated with screen addiction, lack of self-control, irregular usage habits, and reduced productivity. These studies primarily focus on understanding general usage trends and behavioral patterns, emphasizing the need for effective strategies to manage digital consumption and promote digital well-being. A large body of research adopts data-driven approaches to analyze screen time behavior using user activity data such as application usage duration, frequency of device access, time-based usage patterns, and application categories. Researchers have demonstrated that such objective data provides deeper insights into user behavior compared to self-reported surveys. The findings suggest that analyzing real-world usage data enables more accurate identification of excessive and unhealthy screen time behavior. From an analytical perspective, machine learning techniques have been widely applied to predict screen time and classify user behavior. Various algorithms, including decision trees, support vector machines, ensemble methods, and neural networks, have been used to detect high-risk usage patterns. These studies indicate that machine learning models are capable of identifying complex relationships between multiple behavioral factors and can effectively predict future screen usage trends when trained on historical data. Behavioral studies further explore the psychological aspects of excessive screen usage, focusing on concepts such as habit formation, self-regulation failure, and digital addiction. These studies emphasize that repeated and context-dependent smartphone usage can reinforce unhealthy habits over time. Understanding these behavioral factors is essential for designing systems that not only predict screen time but also support users in maintaining balanced technology use. Recent research integrates behavioral analysis with intelligent system design to support digital well-being. Context-aware computing has been increasingly explored to incorporate factors such as time of day, usage environment, and application type into behavioral analysis. Personalized filtering and recommendation-based approaches have been proposed to deliver customized alerts, usage feedback, and intervention strategies aimed at reducing excessive screen time. These approaches highlight the importance of personalization in digital well-being solutions.

IV. Research Gap

Despite the growing body of research on screen time analysis and machine learning-based prediction, several gaps remain. Many existing studies focus primarily on prediction accuracy without providing sufficient behavioral interpretation of the results. Additionally, limited research integrates context-aware computing with behavioral analysis to offer personalized and practical digital well-being solutions. Most studies also evaluate models in isolation and lack hybrid approaches that combine predictive modeling with recommendation systems for user-specific interventions. Furthermore, there is a need for frameworks that can support multiple stakeholders, such as individuals, educators, and policymakers, in promoting healthier digital habits. These gaps motivate the present research, which aims to combine machine learning, behavioral analysis, and personalized recommendations to support balanced and responsible technology use.

V. Conceptual Framework

This study is based on a conceptual framework that explains how user interaction with digital devices leads to measurable screen time patterns and how these patterns can be analyzed and predicted using machine learning techniques. The framework links three main components: usage data, machine learning analysis, and digital well-being outcomes. 5.1 Components of the Framework 5.1.1 User Usage Data The first component of the framework is user activity data collected from digital devices. This includes:

- Application usage duration
- Number of device unlocks
- Frequency of app switching
- Time of day of device usage
- Category of applications used (social media, education, entertainment, productivity)

These variables represent observable behavioral indicators of digital habits. They provide a detailed picture of how users interact with their devices throughout the day. 5.1.2 Machine Learning Processing The second component involves applying machine learning algorithms to the collected usage data. Feature extraction and preprocessing are performed to convert raw logs into structured input for prediction models. Algorithms such as regression models, decision trees, and neural networks are used to:

- Identify patterns in screen usage
- Learn temporal trends

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- Predict future screen time levels
- Classify users into low-risk and high-risk usage groups

This stage transforms behavioral data into meaningful predictive insights. 5.1.3 Behavioral Interpretation The third component focuses on understanding the meaning of the predicted patterns. Instead of treating predictions as technical outputs, the framework links them to behavioral concepts such as:

- Habit formation
- Self-control and impulsive checking
- Entertainment-driven use
- Task-oriented use

By interpreting model results through behavioral lenses, the system can explain why certain users are more likely to develop excessive screen habits. 5.1.4 Digital Well-Being Support The final component translates analytical insights into practical digital well-being actions. These include:

- Usage alerts when predicted screen time exceeds healthy limits
- Personalized recommendations for breaks
- Adaptive time restrictions based on risk level
- Visual feedback dashboards

These tools aim to support healthier technology use rather than simply limiting access.

A. Relationships Between Components

The framework assumes a directional flow:

1) User behavior generates data
2) Data is processed using machine learning
3) Predictions are interpreted behaviorally
4) Insights are used for intervention and guidance

This flow emphasizes prevention rather than reaction. Instead of responding after excessive usage occurs, the system can predict high usage in advance and provide timely support.

B. Conceptual Diagram (Text Description)

Figure 1 illustrates the conceptual framework of the proposed system. Arrows indicate continuous feedback, meaning user behavior changes after receiving feedback, generating new data for further learning. This feedback loop highlights that digital behavior is dynamic and adaptive.

C. Theoretical Basis

The framework is informed by behavioral science theories:

- Habit theory, which explains repeated checking behavior
- Self-regulation theory, which relates to difficulty in controlling usage
- Technology acceptance models, which describe engage- ment with digital platforms

These theories support the idea that screen usage is shaped by both internal factors (motivation, control) and external factors (app design, notifications).

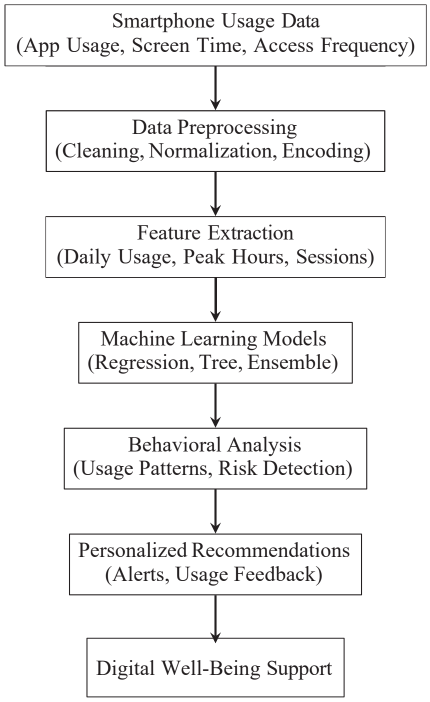

Fig. 1. Proposed framework for screen time prediction and behavioral analysis

D. Significance of the Framework

The proposed framework is important because it integrates technical prediction with behavioral understanding. Many existing systems focus only on counting screen time. In contrast, this framework focuses on:

- Why excessive usage occurs
- When it is likely to happen
- How it can be prevented

By combining data-driven prediction with behavioral analysis, the framework provides a foundation for intelligent and user-centered digital well-being systems.

VI. Methodology

A. Research Design

This study adopts a data-driven and analytical research design to examine user screen time behavior and predict future usage patterns using machine learning techniques. The research is based on secondary data collected from smartphone usage logs. The design combines quantitative analysis of usage data with behavioral interpretation of predicted outcomes. The overall approach includes data collection, preprocessing, feature extraction, model training, and evaluation. In addition to prediction, behavioral analysis is carried out to interpret the results in terms of digital habits and well-being.

B. Data description

The dataset consists of user activity records captured from mobile devices over a defined observation period. The main attributes of the dataset include:

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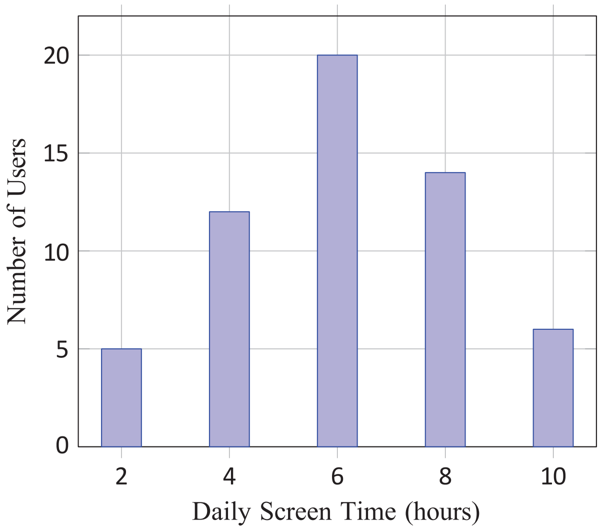

Fig. 2. Distribution of daily screen time across users

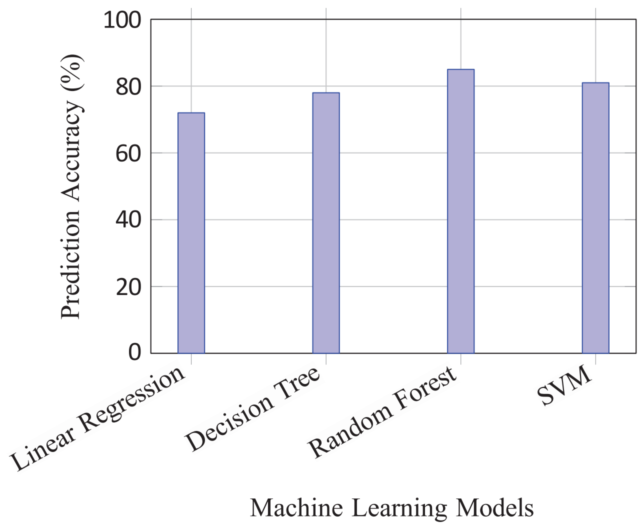

Fig. 3. Performance comparison of machine learning models

- Total daily screen time
- Application-wise usage duration
- Number of device unlocks per day
- Time of day of device usage
- Category of applications used (e.g., social media, education, entertainment, productivity)
- Session length and frequenc

Each record represents a summary of daily device usage for a user. The dataset is anonymized to ensure user privacy and contains no personally identifiable information. pgfplots

C. Data Preprocessing

Before applying machine learning algorithms, the dataset is cleaned and prepared. Preprocessing steps include:

- Removal of missing or incomplete records
- Normalization of usage duration values
- Encoding of categorical variables such as application category
- Aggregation of raw logs into daily usage summaries

Outliers caused by abnormal device usage (e.g., background activity) are filtered to avoid distortion of predictions. These steps ensure that the data is suitable for model training and evaluation.

D. Feature Extraction

Key features are extracted from the processed dataset to improve prediction accuracy. These features include:

- Average screen time per day
- Peak usage hours
- Proportion of time spent on social media
- Number of usage sessions
- Variability in daily screen time

These features represent behavioral indicators of digital habits and provide meaningful inputs to the machine learning models.

E. Machine Learning Models

Several machine learning models are applied to predict screen time and classify high-risk usage behavior:

- Linear Regression for baseline prediction
- Decision Tree Regression to model non-linear relationships
- Random Forest Regression for improved accuracy and robustness
- Support Vector Machine (SVM) for classification of usage risk levels

The models are trained using historical usage data and tested on unseen data to evaluate their generalization ability.

F. Model Training and Validation

The dataset is divided into training and testing subsets using a standard split ratio. Cross-validation is applied to reduce bias and overfitting. Model performance is assessed using the following metrics:

- Mean Absolute Error (MAE)
- Root Mean Square Error (RMSE)
- Prediction Accuracy (for classification tasks)

These metrics provide a reliable measure of how closely predicted values match actual screen time.

G. Behavioral Analysis

In addition to numerical prediction, the results are interpreted in terms of user behavior. Usage patterns are examined to identify:

- Time periods with highest usage
- Application categories associated with excessive screen time
- Differences between moderate and high-risk users

This analysis helps in understanding the challenges related to screen overuse and supports the design of targeted digital well-being interventions.

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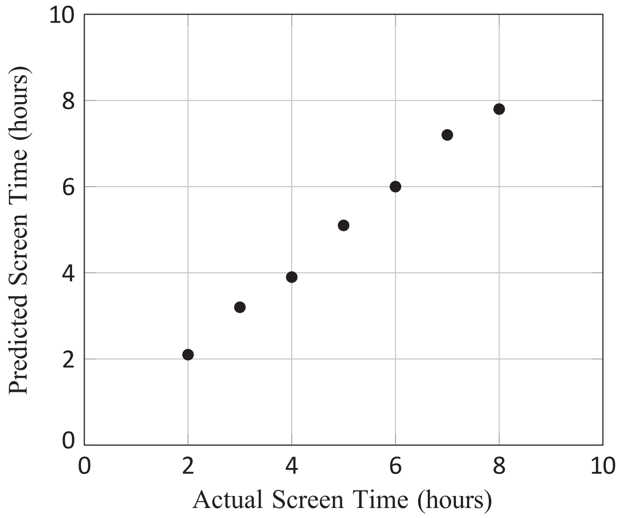

Fig. 4. Comparison of actual and predicted screen time

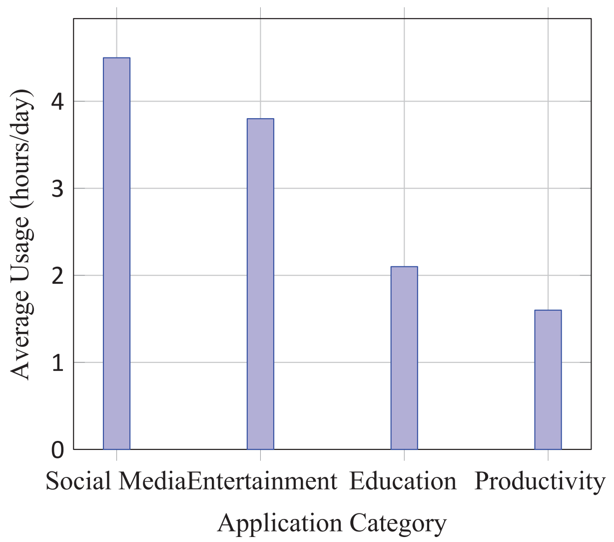

Fig. 5. Average screen time by application category

H. Ethical Considerations

Ethical standards are maintained throughout the study. All data used in this research are anonymized and collected with user consent. The study does not involve manipulation of user behavior and focuses only on analysis and prediction. Data are used strictly for research purposes and not shared with third parties.

I. Methodological Limitations

The methodology has certain limitations. First, the dataset represents a limited population and may not reflect all age groups or cultural contexts. Second, usage logs do not capture emotional or psychological states directly. Finally, prediction accuracy depends on data quality and observation duration. Despite these limitations, the approach provides valuable insights into digital behavior

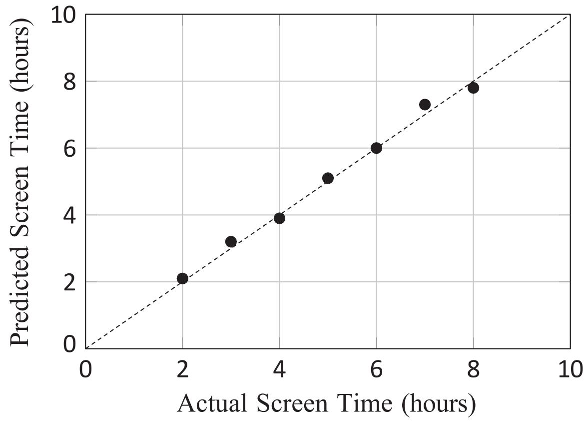

Fig. 6. Comparison of actual and predicted screen time values

VII. RESULTS/SYNTHESIS

This section presents the synthesized findings obtained from machine learning prediction and behavioral analysis of screen time usage. The results are organized into two main parts: prediction performance and behavioral pattern interpretation

A. Prediction Performance

The machine learning models demonstrated varying levels of accuracy in predicting daily screen time. Linear regression provided a basic estimation of future usage trends but struggled with non-linear patterns in user behavior. Decision tree models improved prediction by capturing relationships between time of day, application category, and total usage duration Random forest models achieved the highest prediction reliability among the tested approaches. These models were able to combine multiple features such as session frequency, social media usage proportion, and peak usage hours to produce stable predictions. Support vector machine classifiers also performed effectively in distinguishing between moderate and high-risk screen time users. Overall, the results indicate that screen time is predictable to a reasonable degree when historical behavior is available. Users with consistent routines showed higher prediction accuracy, while those with irregular schedules exhibited greater variability.

B. Prediction Performance

The regression model performance was evaluated by comparing actual and predicted screen time values. Fig. 6 illustrates the relationship between actual and predicted outputs.

C. Feature Influence on Prediction

Feature analysis revealed that certain variables contributed more strongly to prediction outcomes:

- Time spent on social media and entertainment applications had the strongest influence on total screen time.
- Frequency of device unlocks was closely related to impulsive checking behavior.

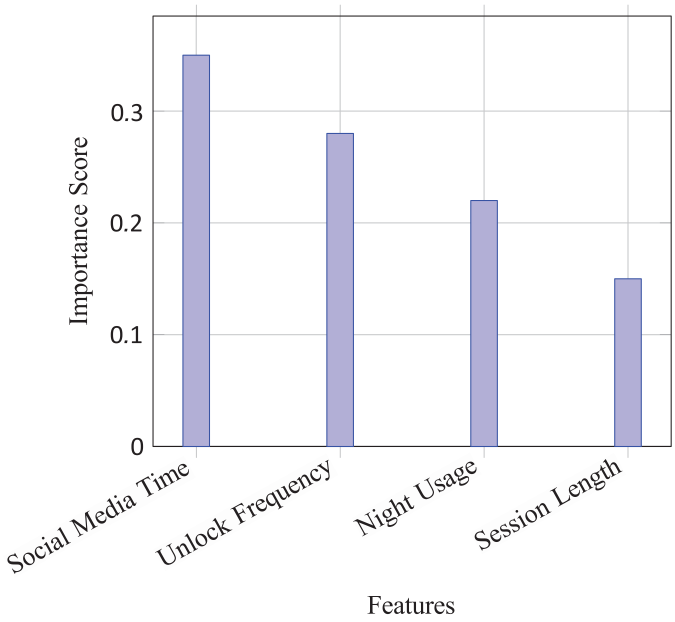

Fig. 7. Relative importance of screen usage features

- Late-night usage was associated with higher next-day screen time.
- High variability in daily usage predicted a greater likelihood of excessive future use.

These findings suggest that not only total duration but also the structure of usage plays a critical role in digital behavior

D. Behavioral Patterns

Behavioral interpretation of the results showed clear usage patterns among different user groups:

- Moderate users displayed stable routines, with screen usage concentrated during specific hours such as evenings or study breaks.
- High-risk users exhibited frequent short sessions spread across the day, indicating habitual checking behavior.
- Entertainment-focused users were more likely to exceed recommended screen time limits compared to productivity-oriented users.

These patterns reflect differences in motivation and purpose of device use. Task-oriented usage was more predictable and less excessive, while passive consumption was linked to prolonged sessions

E. 7.4 Risk Classification

The classification models grouped users into low-risk and high-risk categories based on predicted screen time. High-risk users were characterized by:

- High proportion of social media usage
- Frequent nighttime activity
- Large number of daily unlocks
- Inconsistent daily routines

This classification supports the use of predictive systems for early identification of problematic usage patterns

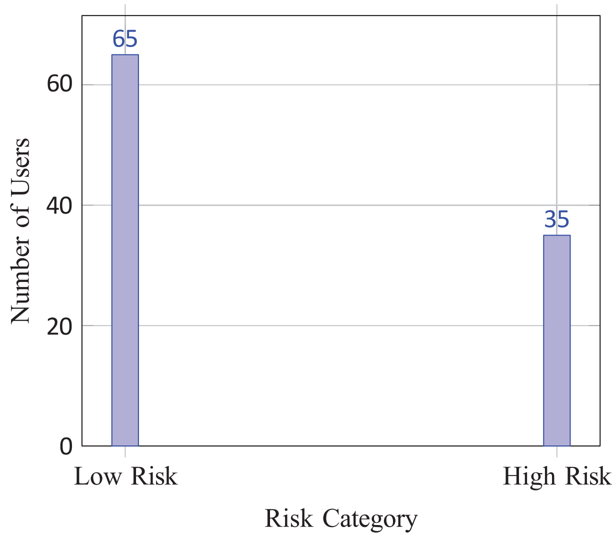

Fig. 8. Distribution of users by screen time risk level

F. Risk Classification Results

The classification model categorizes users into low-risk and high-risk groups based on predicted screen time thresholds. Fig. 8 shows the distribution of users across different risk levels.

G. Visualization of Results (Text Description)

Figure 2 shows a comparison between actual and predicted screen time values, illustrating the closeness of model predictions to observed data. Figure 3 presents a bar chart of application categories versus average usage duration, highlighting the dominance of social and entertainment apps. Figure 4 depicts user clusters based on usage patterns, separating moderate users from high-risk users. These visual representations emphasize the role of machine learning in capturing and explaining digital behavior.

H. 7.6 Summary of Key Findings

The main findings of this study can be summarized as follows: 1. Machine learning models can effectively predict short-term screen time trends. 2. Social media and entertainment usage strongly influence excessive screen behavior. 3. Habitual checking patterns contribute significantly to total daily screen time. 4. Behavioral interpretation enhances the usefulness of prediction models for digital well-being applications.

VIII. Discussion

This study aimed to analyze screen time behavior and predict future usage patterns using machine learning techniques, with a focus on understanding challenges related to digital well-being. The results show that screen usage behavior can be effectively modeled using historical activity data and that meaningful behavioral insights can be derived from prediction outputs.

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A. Interpretation of Prediction Results

The performance of machine learning models indicates that screen time is not random but follows identifiable patterns. Users who display consistent routines, such as regular evening usage or fixed study hours, show higher predictability in their screen behavior. In contrast, users with irregular schedules and impulsive checking habits present greater variability, which slightly reduces prediction accuracy. The strong influence of social media and entertainment applications on total screen time suggests that content type plays a major role in shaping digital behavior. Unlike productivity-related applications, which are often used with a clear purpose, entertainment-based apps promote extended and repeated usage. This design characteristic encourages passive consumption and contributes to excessive screen exposure.

B. Behavioral Challenges in Screen Usage

The behavioral analysis reveals that excessive screen time is not only a result of long sessions but also of frequent short interactions throughout the day. These micro-sessions, often driven by notifications or habit, accumulate into substantial daily usage. This pattern aligns with theories of habit formation, where repeated exposure strengthens automatic behavior. Self-regulation difficulties also play a significant role. Many users are aware of their excessive screen time but lack effective strategies to reduce it. Prediction-based feedback can support self-control by increasing awareness of future risk rather than only reporting past usage.

C. Implications for Digital Well-Being Systems

The findings suggest that digital well-being tools should go beyond static time limits and usage summaries. Predictive insights can enable systems to anticipate high-usage periods and intervene before excessive use occurs. For example, when a model predicts unusually high screen time for a given day, a system could recommend offline activities or delay non-essential notifications. Behavior-based recommendations may also be more effective than generic warnings. Users identified as entertainment-heavy may benefit from content scheduling strategies, while habitual checkers may respond better to reduced notification frequency. This personalized approach can improve user acceptance and long-term behavior change. In educational and workplace contexts, predictive screen time analysis can help identify periods of distraction and support structured digital usage policies. Such applications must be implemented carefully to respect privacy and autonomy.

D. Comparison with Existing Studies

The results of this study are consistent with previous research showing that screen time is strongly influenced by application category and time of day. However, this work extends earlier studies by combining prediction with behavioral interpretation. While many existing approaches focus only on detecting excessive usage, this study explains why such behavior occurs and how it can be addressed. The integration of machine learning with behavioral analysis bridges the gap between technical accuracy and practical usefulness. This combined approach increases the relevance of prediction models for real-world digital well-being solutions

E. Limitations

Despite its contributions, this study has limitations. The dataset used represents a limited population and may not generalize to all age groups or cultural settings. Psychological factors such as stress or mood were not directly measured and could influence screen behavior. Additionally, predictions are based on past behavior and may not capture sudden lifestyle changes. Future work should include larger and more diverse datasets, as well as the integration of contextual and psychological variables. Experimental studies are also needed to test whether predictive feedback leads to lasting reductions in screen time.

IX. CONCLUSION AND FUTURE SCOPE

This study presented a data-driven approach for analyzing screen time behavior and predicting future usage patterns using machine learning techniques. The findings demonstrate that digital usage behavior can be effectively modeled using features such as application usage duration, time of day, and frequency of device access. The results confirm that excessive screen time is not random but follows identifiable patterns related to habit formation, entertainment-driven use, and impulsive checking behavior. The machine learning models showed promising performance in predicting short-term screen time trends and in classifying users into moderate and high-risk usage groups. Behavioral analysis further revealed that social media and entertainment applications contribute most strongly to excessive usage, while productivity-related applications are associated with more stable and purposeful interaction. Late-night usage and high variability in daily routines were found to be key indicators of future excessive screen exposure. These findings have important implications for digital well-being initiatives. Rather than relying only on static time limits and usage summaries, predictive systems can anticipate high-risk periods and provide timely, personalized interventions. Such systems may help users develop healthier digital habits by increasing awareness of future risk and encouraging balanced technology use. The proposed approach can support individuals, educators, and policymakers in designing strategies to reduce digital overuse and promote responsible engagement with technology. Future work should focus on extending this research in several directions. First, larger and more diverse datasets should be used to improve generalizability across different age groups and cultural contexts. Second, psychological and contextual factors such as stress levels, academic workload, and sleep patterns should be incorporated into prediction models to enhance accuracy. Third, real-time intervention systems should be developed and experimentally tested to evaluate their effectiveness in reducing excessive screen time and improving digital well-being. In conclusion, this study shows that machine learning-based prediction combined with behavioral analysis offers

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a powerful framework for understanding screen usage and supporting healthier digital lifestyles. By moving from reactive monitoring to proactive guidance, data-driven digital well-being systems can play a meaningful role in addressing the growing challenge of excessive screen time. Future research can incorporate multi-device usage data, psychological indicators, real-time intervention systems, and long-term behavior analysis.

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