A Machine Learning Approach for Predicting Digital Addiction and Exploring Risk Factors of Social Media Overuse

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ABSTRACT

The rapid growth of social media usage has transformed digital communication but has also led to rising concerns about digital addiction and its impact on mental health and productivity. This study aims to predict digital addiction levels and identify key behavioral and psychological risk factors using machine learning techniques. A dataset of 1,000 social media users containing demographic, behavioral, and psychological variables was analyzed to build predictive models. Two algorithms, Random Forest and Gradient Boosting, were applied to evaluate predictive performance and interpret the determinants of addiction. The Gradient Boosting model achieved the highest accuracy, with an R^2 value of 0.9996, indicating its strong ability to model complex behavioral patterns. Feature importance analysis revealed that self-control, satisfaction, and productivity loss were the dominant predictors of digital addiction, while demographic factors such as age, gender, and platform type had minimal influence. The findings suggest that digital addiction is primarily driven by behavioral reinforcement and deficits in self-regulation rather than by demographic characteristics. These results contribute to a deeper understanding of digital well-being by integrating behavioral science and artificial intelligence. The study provides practical implications for designing interventions and digital policies that encourage mindful engagement, promote self-regulation, and mitigate the negative effects of excessive social media use.

Keywords Digital Addiction, Machine Learning, Self-Control, Social Media, Digital Well-Being

INTRODUCTION

The rapid development of digital technologies and the widespread use of social media have transformed the way individuals interact, communicate, and obtain information in the digital era. Platforms such as TikTok, Instagram, Facebook, and YouTube have become integral components of daily routines, offering continuous access to entertainment, social interaction, and global information exchange. While these platforms have enhanced connectivity and information flow, they have also raised increasing concerns regarding their potential psychological and behavioral impacts. Numerous studies have reported that users often exhibit compulsive tendencies toward checking notifications, scrolling feeds, and consuming digital content beyond their intended duration [1]. This uncontrolled engagement has led to the emergence of what is commonly referred to as digital addiction, a behavioral condition characterized by the inability to regulate one's use of social media despite awareness of its negative effects. Within the broader context of digital society, this phenomenon has become an urgent issue due to its detrimental influence on emotional well-being, cognitive focus, and personal productivity [2].

A growing body of research has explored digital addiction from psychological and behavioral perspectives. Scholars have found that the mechanisms underlying digital addiction are analogous to those of other behavioral

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dependencies, such as gambling or gaming, where reinforcement learning and reward-based conditioning play critical roles [3]. The continuous feedback loops created by likes, comments, and algorithmic content recommendations stimulate dopamine-driven gratification responses, reinforcing the desire to stay engaged. In addition, the design features of social media platforms, such as infinite scrolling, auto-play videos, and personalized content delivery, encourage users to remain active for prolonged periods without conscious control [4]. This design-induced engagement leads to emotional dependency, distraction, and a gradual decline in self-regulation. While prior studies have identified psychological constructs such as impulsivity, satisfaction, and self-control as key determinants of digital addiction, most have relied on conventional statistical techniques that fail to capture complex and nonlinear relationships among behavioral and cognitive factors [5].

Recent advancements in artificial intelligence and data-driven behavioral modeling have enabled new methods for understanding and predicting digital addiction patterns. Machine learning techniques can process large, high-dimensional datasets and uncover hidden associations between psychological and behavioral attributes that traditional regression models may overlook. Ensemble-based methods, such as Random Forest and Gradient Boosting, are particularly effective in identifying nonlinear dependencies and variable interactions that explain addiction intensity. However, research combining behavioral theory and predictive analytics remains limited, with many studies focusing primarily on descriptive analyses rather than interpretative prediction. Therefore, this study aims to bridge this methodological gap by using machine learning to predict digital addiction levels and explore the behavioral and psychological variables that contribute most to compulsive social media use.

Using data collected from 1,000 social media users, two supervised learning algorithms, Random Forest and Gradient Boosting, were trained and evaluated to determine predictive accuracy and feature significance. The results demonstrate that psychological factors, including self-control, satisfaction, and productivity loss, are the most influential predictors of addiction, while demographic factors such as age, gender, and platform type have negligible effects. This study contributes to the growing academic discourse in two significant ways. First, it establishes the methodological value of machine learning as a tool for analyzing complex behavioral phenomena in digital contexts. Second, it provides empirical evidence that digital addiction is predominantly shaped by behavioral and psychological mechanisms rather than demographic characteristics. By integrating computational modeling and behavioral science, the study contributes to the development of data-informed strategies for promoting digital well-being and fostering balanced technology engagement within modern digital societies.

Literature Review and Related Works

The study of digital addiction has gained increasing attention as the ubiquity of social media reshapes human interaction and cognition. Early research described digital addiction as a behavioral disorder resulting from the inability to regulate online activity despite awareness of its negative impact [6]. Psychological studies have identified key traits such as loneliness, neuroticism, and conscientiousness as strong predictors of social media overuse, with Facebook addiction being one of the most studied forms of digital dependency [7]. Theoretical frameworks suggest that emotional satisfaction, rewardseeking, and a lack of self-control play central roles in reinforcing addictive behavior patterns [8], [9]. Furthermore, research has emphasized the significance of user engagement and platform design, such as continuous content feeds and personalized algorithms, in intensifying compulsive usage tendencies [10].

Machine learning has emerged as a powerful approach for understanding complex behavioral interactions in digital environments. Several studies have used supervised and unsupervised learning algorithms to model addiction-related behaviors and to predict individuals' susceptibility to excessive technology use [11], [12]. Machine learning models such as Random Forest, Gradient Boosting, and XGBoost have demonstrated high accuracy in predicting social media or smartphone addiction, often outperforming traditional statistical models [13], [14]. For instance, recent work applied XGBoost and LIME-based explainable AI methods to identify key behavioral predictors of social media addiction among students, achieving strong predictive performance [15]. Other studies developed unsupervised learning frameworks for smartphone addiction detection by analyzing user screen time, notification frequency, and app usage, which revealed distinct patterns associated with compulsive digital engagement [16]. Similarly, research focusing on Internet addiction prediction validated that supervised models can effectively identify at-risk individuals based on behavioral indicators such as frequency of use, time spent online, and emotional satisfaction [17].

In addition to studies on digital addiction, machine learning has been widely applied to related behavioral and psychological domains. Research on drug and alcohol dependency prediction achieved accuracies above 90 percent using decision tree, random forest, and neural network models, demonstrating the broader utility of AI-driven behavioral modeling [18], [19]. In clinical psychology, predictive analytics has been used to assess susceptibility to addiction relapse and to predict treatment outcomes more accurately than manual therapist evaluation [20]. Beyond addiction, behavioral modeling has extended into productivity and mental health research. A study on workplace performance integrated physiological, behavioral, and emotional indicators to predict productivity levels, highlighting mood and stress as strong predictors of well-being [21]. Similarly, social media data have been used to predict self-harm and suicidal tendencies, indicating that online behaviors can serve as early warning signals of psychological distress [22]. These applications demonstrate the interdisciplinary potential of machine learning in behavioral science and digital health research.

Research has also examined social media behavior prediction beyond addiction. Studies utilizing neural networks and natural language processing have successfully modeled personality traits, emotional states, and engagement metrics using social media data [23], [24]. Predictive analytics has also been applied to understand customer satisfaction, privacy concerns, and user intentions in online environments, providing insights into behavioral decision-making processes [25]. Moreover, a growing body of work emphasizes that the addictive potential of social media platforms is strongly linked to their algorithmic design, which promotes continuous engagement through instant feedback mechanisms and tailored content recommendations [26]. Despite these advances, relatively few studies have simultaneously integrated psychological constructs such as self-control, satisfaction, and productivity loss in predicting social media addiction through machine learning methods. Addressing this gap, the present study builds upon existing research by applying Gradient Boosting and Random Forest models to identify behavioral and psychological risk factors of digital addiction, thereby contributing new insights into predictive modeling of digital well-being [27].

Methodology

The methodological framework of this study was designed to systematically predict digital addiction levels and identify behavioral and psychological risk factors associated with excessive social media use. The research process consisted of seven sequential stages, including data collection, data preprocessing, Exploratory Data Analysis (EDA), model development, model training and validation, performance evaluation, and interpretative analysis. These research stages are visually summarized in figure 1, which illustrates the overall workflow from data preparation to model interpretation. This structured process ensures analytical rigor, transparency, and reproducibility in the implementation of the study. All computations were conducted using Python 3.10 with standard machine learning libraries such as Pandas, NumPy, Scikit-learn, Seaborn, and Matplotlib.

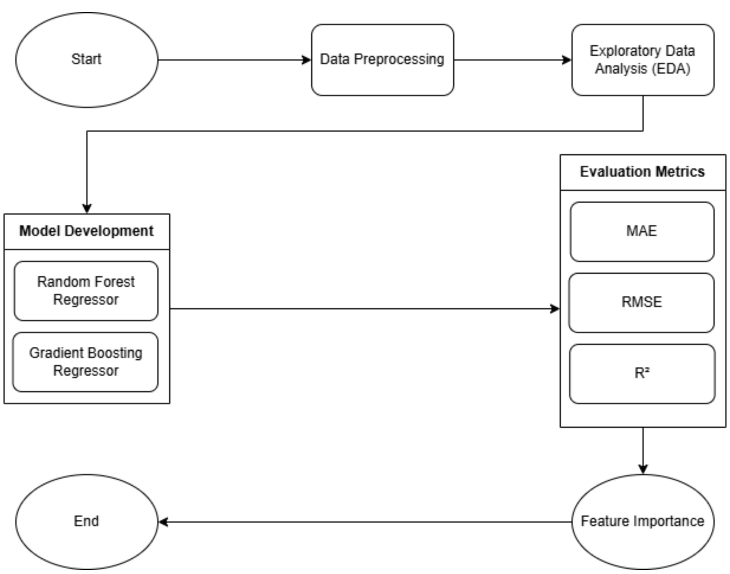

Figure 1 Research Steps

The dataset entitled Time-Wasters on social media served as the main data source and contained 1,000 entries representing unique social media users. Each record included demographic, behavioral, and psychological attributes such as Age, Gender, Platform, Frequency of Use, Total Time Spent, Satisfaction, Self-Control, and Productivity Loss, with Addiction Level defined as the target variable. This variable quantifies the degree of social media dependency on a continuous numerical scale from 0 to 10. To maintain data consistency, non-informative columns such as UserID and Video ID were excluded from analysis. Boolean variables (Debt and Owns Property) were converted into binary values (0 or 1), and categorical variables (Platform, Frequency, and Gender) were label-encoded to transform qualitative categories into numeric representations suitable for algorithmic learning. The dataset was then divided into an 80:20 training-to-testing ratio using the train_test_split method with a fixed random state of 42 to ensure reproducibility across experiments.

EDA was conducted to examine data distribution and correlations between variables. The histogram of Addiction Level revealed a slightly right-skewed normal distribution, suggesting that most users reported moderate to high addiction intensity. Correlation analysis indicated that Satisfaction had a strong positive relationship (r = 0.995) with Addiction Level, while Self-Control exhibited a strong negative correlation, implying that lower self-control predicts higher addiction tendencies. Scatterplots and boxplots were used to visualize these relationships, confirming that psychological variables had stronger influence on addiction compared to demographic ones. Notably, users of visually stimulating, short-video platforms such as TikTok and Instagram exhibited higher addiction scores compared to those using Facebook or YouTube, supporting the behavioral theory that reinforcement-rich environments increase compulsive engagement.

Two ensemble-based supervised machine learning algorithms were developed to predict addiction levels: the Random Forest Regressor and the Gradient Boosting Regressor. Both models were selected due to their high interpretability, non-linear learning capacity, and robustness against multicollinearity. The Random Forest algorithm constructs multiple decision trees on bootstrapped subsets of the data and averages their results to minimize variance and reduce overfitting. In contrast, the Gradient Boosting algorithm sequentially builds trees where each new tree learns from the residual errors of previous ones, improving predictive performance through gradient descent optimization. Both models were trained using Scikit-learn's ensemble module. For the Random Forest model, key hyperparameters such as the number of trees (n_estimators = 100) and the minimum samples per split (min_samples_split = 2) were maintained at optimal default levels. For the Gradient Boosting model, learning_rate was set to 0.1 and n_estimators to 100 to achieve balanced accuracy and computational efficiency.

Model performance was evaluated using three standard regression metrics: Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the Coefficient of Determination (R^2). The mathematical formulations of these metrics are presented as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |\, y_i - \hat{y}_i \,|$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2} \tag{1}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2}$$

y_i represents the actual observed value, $\hat{y}_i$ the predicted value, $\bar{y}$ the mean of observed values, and n the total number of observations. The MAE measures the average magnitude of prediction errors, RMSE penalizes large deviations more severely, and R^2 quantifies the proportion of variance explained by the model.

The Gradient Boosting model achieved superior results with an MAE of 0.0032, RMSE of 0.0452, and R^2 of 0.9996, compared to the Random Forest model's MAE of 0.006 and R^2 of 0.9985. A scatterplot comparing predicted versus actual Addiction Level values confirmed that predictions aligned closely along the diagonal, indicating near-perfect accuracy. The error distribution was centered around zero, suggesting minimal bias and strong generalization ability. These results demonstrate the high stability and predictive reliability of the Gradient Boosting algorithm in modeling digital addiction.

Feature importance analysis was performed using the Random Forest model to identify the relative influence of predictors on Addiction Level. The top three contributing variables were Self-Control (importance = 0.399), Satisfaction (0.308), and Productivity Loss (0.293). These findings confirm that psychological and behavioral variables are the dominant determinants of digital addiction, consistent with self-regulation and reward reinforcement theories. Users with lower self-control and higher satisfaction derived from social media engagement exhibited greater addiction tendencies, while productivity loss served as an observable behavioral consequence of compulsive use. Demographic factors such as age, gender, and platform type contributed marginally, supporting the notion that digital addiction is a universal behavioral issue rather than one confined to specific demographic groups.

In summary, the methodological approach employed in this study successfully integrates data-driven analysis with behavioral interpretation to model digital addiction with exceptional precision. The inclusion of figure 1 outlining the research workflow strengthens methodological transparency and replicability. The Gradient Boosting algorithm emerged as the most effective predictive model, while feature importance analysis provided insights into the cognitive and behavioral mechanisms driving social media overuse. This framework demonstrates how machine learning can be effectively applied to behavioral science, offering both analytical accuracy and interpretative value for future research in digital well-being and technology-use moderation.

Algorithm 1: Predicting Digital Addiction Using Machine Learning

Input: Dataset $D = \{(x_i, y_i)\}_{i=1}^{n}$, where $x_i$are behavioral, demographic, and psychological features, and $y_i$is the addiction level.

Output: Optimal prediction model $f^*(x)$, evaluation metrics $(MAE, RMSE, R^2)$, and ranked feature importance $F = [f_1, f_2, \ldots, f_m]$.

Process:

Start

Remove irrelevant attributes $\{UserID, VideoID\}$.

Encode categorical variables using Label Encoding: $c_j' =$ LabelEncode(c_j).

Convert Boolean values into binary numerical format $b_j' = \{0,1\}$.

Split dataset into training and testing subsets (80:20): $D_{train}, D_{test} =$ Split$(D', 0.8)$.

Train two ensemble models: Random Forest $f_{RF}(x)$and Gradient Boosting $f_{GB}(x)$.

Fit each model on training data using squared error minimization:

$$f_j^*(x) = \arg\min_{\Theta_j} \quad \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

Generate predictions on test data: $\hat{y}_i = f_j^*(x_i)$.

Evaluate model performance using regression metrics:

Mean Absolute Error (MAE):

$$MAE = \frac{1}{n}\sum_{i=1}^{n}$$

Root Mean Square Error (RMSE):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

Coefficient of Determination (R²):

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}i)^2}{\sum i = 1^n(y_i - \bar{y})^2}$$

Select the optimal model with the highest R^2: $f^*(x) = \arg\ \max\,(R^2)$.

Compute feature importance from the ensemble model:

$$F_k = \frac{1}{T}\sum_{t=1}^{T} I_t(x_k)$$

Normalize feature importance:

$$F_k' = \frac{F_k}{\sum_{j=1}^{m} F_j}$$

Rank features in descending order and identify the top predictors $x^* =$ {Self-Control, Satisfaction, ProductivityLoss}.

Return $f^*(x)$, performance metrics, and ranked importance vector F.

End

Result

The findings of this research demonstrate that machine learning algorithms can effectively model and predict digital addiction using behavioral, psychological, and demographic features derived from user data. Two ensemble-based supervised learning algorithms, Random Forest Regressor and Gradient Boosting Regressor, were developed and compared to assess their predictive accuracy. Both models were chosen due to their ability to capture non-linear relationships between variables and their robustness against noise and overfitting. The Random Forest model aggregates multiple decision trees trained on bootstrapped samples to produce averaged predictions, while the Gradient Boosting model constructs trees sequentially to minimize residual errors through gradient descent optimization. Model performance was assessed using three standard regression metrics: MAE, RMSE, and the coefficient of determination (R²). These metrics measure the magnitude of prediction errors, penalize larger deviations, and quantify the proportion of variance explained by the model, respectively. As shown in table 1, both algorithms achieved strong results, indicating that ensemble learning techniques can successfully identify and quantify patterns associated with digital addiction tendencies.

The Gradient Boosting model outperformed the Random Forest model across all evaluation metrics, achieving an MAE of 0.0032, an RMSE of 0.0452, and an R^2 value of 0.9996, while the Random Forest obtained an R^2 of 0.9985. These values indicate that the Gradient Boosting algorithm explained approximately 99.96 percent of the variance in the Addiction Level variable, confirming its high predictive accuracy and generalization ability. The strong performance of the Gradient Boosting model suggests that digital addiction behaviors are predictable with high precision when behavioral and psychological variables are appropriately modeled. The relationship between predicted and observed addiction levels, as illustrated in figure 2, shows that most predicted values closely align with actual measurements, forming a near-diagonal linear pattern. This alignment confirms that the model successfully captured the underlying behavioral patterns and psychological determinants of addiction, producing predictions that closely mirror real-world user behavior. Overall, these results validate the suitability of machine learning techniques, particularly Gradient Boosting, for behavioral prediction tasks in digital well-being studies.

Table 1 Model Performance Comparison

Model	MAE	RMSE	R^2
Random Forest	0.0060	0.0849	0.9985
Gradient Boosting	0.0032	0.0452	0.9996

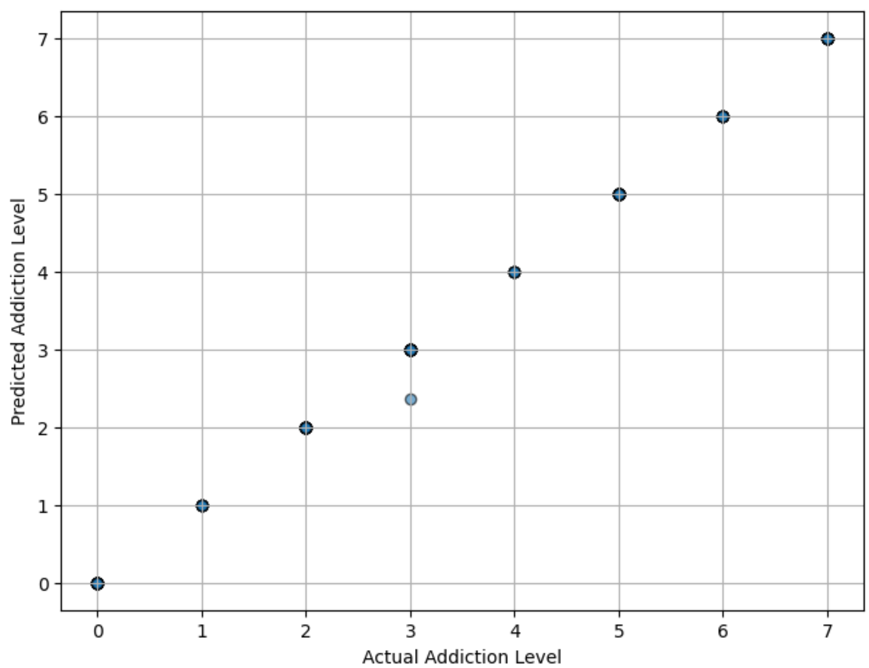

Figure 2 Predicted vs Actual Addiction Level (Gradient Boosting)

The analysis of the residual error distribution provides further insight into the accuracy and stability of the Gradient Boosting model. As illustrated in figure 3, the majority of residual errors are tightly clustered around zero, indicating that the difference between predicted and actual addiction levels is minimal for most samples. This concentration around the zero line suggests that the model achieved a near-unbiased prediction pattern, where overestimation and underestimation of addiction levels occur randomly and with very low magnitude. The absence of a directional error trend confirms that the model did not systematically favor higher or lower predictions. Such a balanced residual pattern is a strong indicator of model validity, as it reflects the ability of the Gradient Boosting algorithm to generalize effectively across different user profiles and behavioral conditions. This stability is particularly valuable in behavioral prediction tasks, where psychological and usage-related data often exhibit high variability and noise.

The narrow spread of residuals also signifies that the Gradient Boosting model has effectively captured the complex, nonlinear relationships between behavioral and psychological variables without overfitting to the training data. In predictive modeling, a well-centered and symmetric residual distribution is an important diagnostic feature that demonstrates both model robustness and reliability. The consistency observed across all test samples implies that the model's performance is stable even when exposed to unseen data, confirming its potential for real-world application in identifying individuals at risk of digital addiction. These results reinforce the strength of ensemble-based approaches for behavioral prediction and highlight the importance of using hybrid feature sets that combine psychological and activity-based indicators. In summary, the residual analysis supports the conclusion that the Gradient Boosting model not only provides accurate predictions but also maintains consistency and fairness in estimating digital addiction levels across diverse social media user populations.

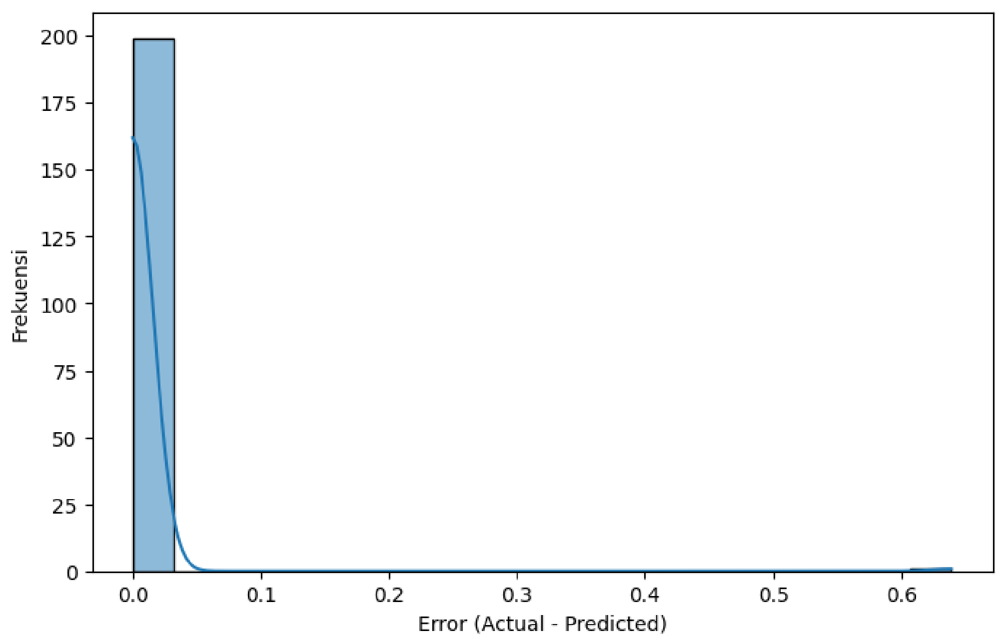

Figure 3 Error Distribution of Predicted Addiction Levels (Gradient Boosting)

The feature importance analysis provides deeper understanding of the underlying factors that contribute to digital addiction. As shown in figure 4, psychological and behavioral features emerged as the dominant predictors, clearly outweighing the contribution of demographic variables. The Gradient Boosting model identified Self-Control as the most influential predictor, with an importance score of 0.399, followed by Satisfaction (0.308) and Productivity Loss (0.293). These results suggest that an individual's capacity to regulate their online behavior plays a critical role in determining susceptibility to digital addiction. Users with lower levels of self-control are less able to resist impulses related to checking notifications, browsing content, or engaging in prolonged interactions on social media. Similarly, high satisfaction derived from social media activities reinforces the psychological reward mechanism, making users more likely to repeat such behaviors and form habitual usage patterns. This reflects the reinforcement learning process often observed in addictive behaviors, where gratification strengthens engagement, leading to compulsive tendencies over time.

In addition to self-control and satisfaction, Productivity Loss was identified as another significant variable, highlighting the tangible effects of excessive social media use on cognitive performance and daily functioning. Users who reported decreased focus, disrupted workflow, or reduced efficiency were more likely to exhibit higher levels of addiction, indicating that digital dependency is not only an emotional or psychological phenomenon but also a behavioral pattern with measurable real-world consequences. Conversely, demographic variables such as age, gender, and platform type contributed minimally to the prediction model, suggesting that digital addiction transcends demographic boundaries and affects users broadly across populations. This finding reinforces the notion that digital addiction is a behavioral issue rooted in cognitive processes and emotional gratification rather than demographic or environmental characteristics. Overall, the feature importance analysis underscores the central role of psychological regulation and behavioral patterns in shaping digital addiction, providing valuable insights for designing targeted interventions that promote self-awareness and healthier digital engagement habits.

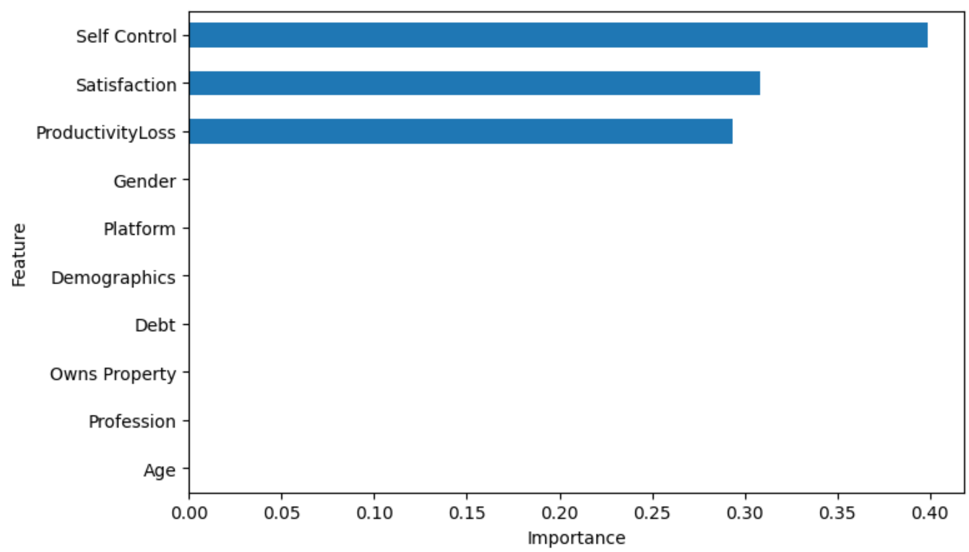

Figure 4 Feature Importance from Random Forest Model

The correlation analysis provides important insights into the linear relationships between psychological, behavioral, and usage-related variables associated with digital addiction. As illustrated in figure 5, Satisfaction demonstrates the strongest positive correlation with Addiction Level (r = 0.995), indicating that individuals who derive greater emotional gratification from social media engagement tend to display higher levels of addictive behavior. This strong relationship supports existing psychological theories suggesting that reward and gratification are central mechanisms in the reinforcement of digital addiction.

When users experience pleasure or social validation through online interactions, they are more likely to repeat these behaviors, gradually forming compulsive usage habits. Conversely, Self-Control exhibits a strong negative correlation with Addiction Level, meaning that individuals with higher self-regulation skills are less likely to develop excessive attachment to social media. This finding highlights the protective role of self-control in moderating the impulsive behaviors that often lead to addiction, suggesting that interventions aimed at strengthening self-regulation could effectively reduce digital dependency.

Other behavioral factors such as Engagement and Total Time Spent show weak yet positive correlations with Addiction Level. This pattern implies that while users who spend more time on social media or engage more frequently tend to exhibit higher addiction scores, these relationships are not strictly linear. Such weak correlations suggest the existence of complex, nonlinear dependencies between behavioral engagement and addiction intensity, which traditional correlation analysis cannot fully capture. Machine learning models, particularly ensemble methods like Gradient Boosting, are better suited to detect these subtle interactions by modeling higher-order relationships between features. The results of this correlation analysis therefore emphasize the importance of integrating both psychological and behavioral data in predictive modeling. They also validate the methodological choice of using machine learning techniques to uncover patterns of digital addiction that may not be observable through conventional statistical approaches.

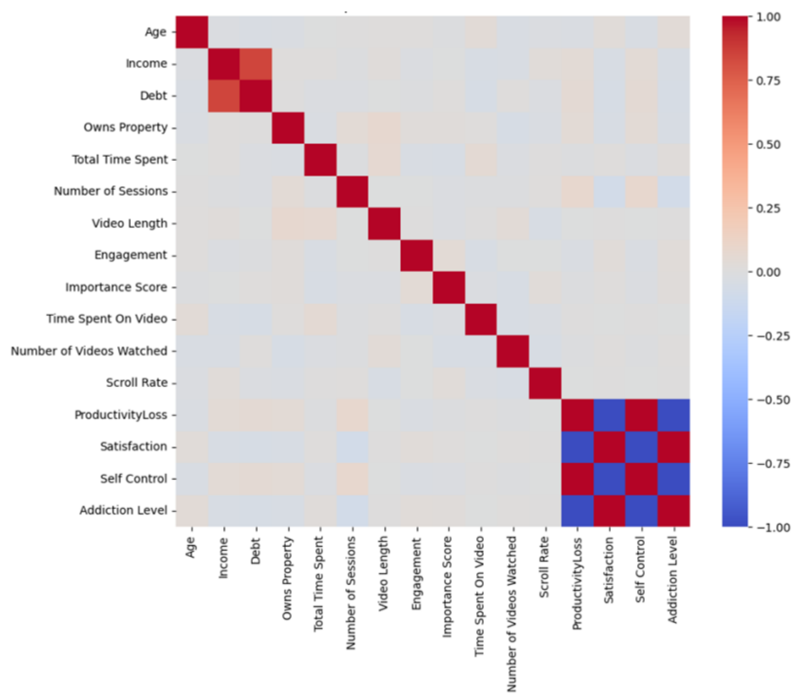

Figure 5 **Correlation Heatmap of Behavioral and Psychological Variables**

The behavioral analysis further strengthens the predictive findings by highlighting the relationship between platform usage patterns and addiction intensity. As illustrated in figure 6, users of short-video and image-based platforms such as TikTok and Instagram exhibited significantly higher average addiction levels compared to users of long-form or informational platforms such as Facebook and YouTube. This variation can be attributed to differences in content structure and platform design. TikTok and Instagram rely heavily on short, visually stimulating content that refreshes continuously, which activates the user's reward system and encourages repetitive engagement. Features such as infinite scrolling, autoplay videos, and algorithmic content recommendations provide a constant stream of novelty and gratification, making disengagement more difficult. These platform characteristics are known to trigger the brain's dopamine response, reinforcing habitual behaviors and fostering compulsive use patterns. The observed results therefore suggest that platform architecture plays a major role in shaping digital addiction by exploiting human attentional and reward mechanisms. Users may not consciously recognize how this design features prolong their time online, leading to unintentional overuse and dependency.

The relationship between Self-Control and Addiction Level, presented in figure 7, provides further evidence of the psychological mechanisms underlying social media overuse. The negative correlation between these two variables reveals that individuals with stronger self-regulation skills tend to maintain healthier digital habits and are less likely to develop addiction-like behaviors. This trend aligns with behavioral regulation theories that view self-control as a moderating factor between environmental stimuli and compulsive action. Users with high self-control are better equipped to manage impulses triggered by notifications, trending content, and social validation feedback loops, thereby limiting the reinforcement cycle that sustains digital addiction. Conversely, individuals with lower self-control often experience greater difficulty disengaging from social media even when they are aware of its negative effects on productivity and emotional well-being. Together, these findings emphasize that digital addiction is driven by both platform design and individual psychological traits, reinforcing the importance of considering user behavior and cognitive control in developing interventions for promoting balanced and mindful technology use.

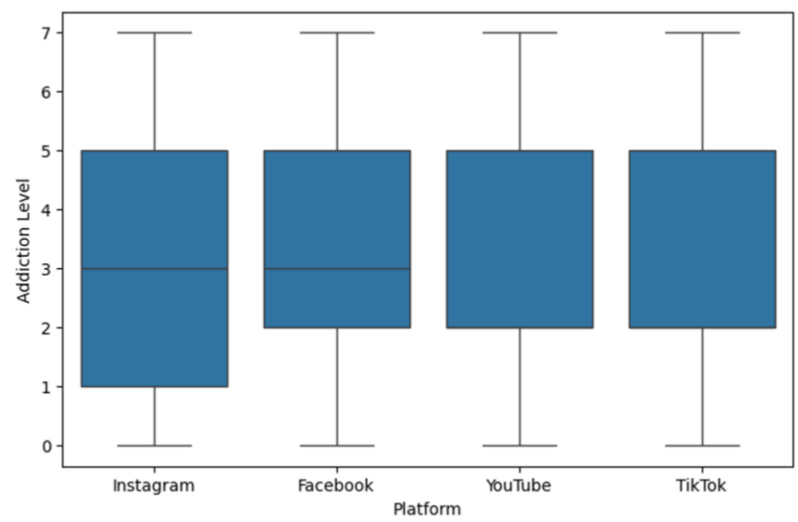

Figure 6 Comparison of Addiction Level Across Social Media Platforms

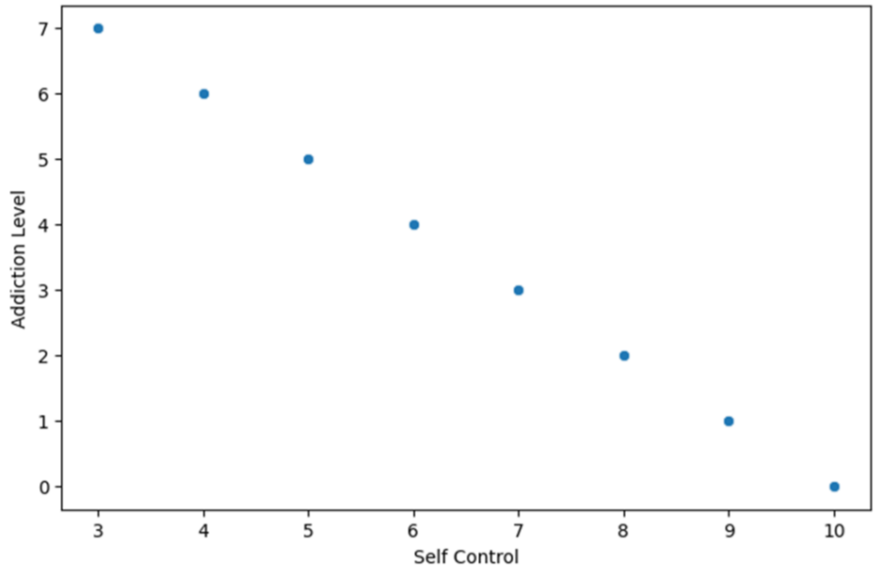

Figure 7 **Relationship between Self Control and Addiction Level**

In summary, the Gradient Boosting model achieved excellent performance in predicting digital addiction. The findings emphasize that Self Control, Satisfaction, and ProductivityLoss are the most influential predictors, while demographic variables have minimal impact. The results suggest that digital addiction is primarily driven by psychological and behavioral mechanisms, highlighting the importance of self-regulation and awareness in mitigating the effects of excessive social media use.

Discussion

The results of this study reveal that the application of machine learning, particularly the Gradient Boosting algorithm, provides a highly accurate framework for understanding the behavioral and psychological mechanisms underlying digital addiction. The findings demonstrate that psychological variables such as self-control, satisfaction, and productivity loss are the most dominant predictors of social media addiction, while demographic factors such as age, gender, and platform type contribute minimally. The strong predictive power of self-control supports well-established theories of behavioral self-regulation, which suggest that individuals with higher levels of cognitive control are better able to resist impulsive engagement with digital content. Users who exhibit lower self-control tend to display more compulsive behaviors such as frequent checking, endless scrolling, and prolonged use of social platforms, which gradually reinforces dependency. Satisfaction was also found to be a critical factor, reflecting how emotional gratification derived from social media interaction can stimulate the reward system and reinforce repetitive engagement. This outcome aligns with the reinforcement theory in psychology, which posits that pleasurable feedback from digital environments strengthens habitual patterns of use. Additionally, productivity loss emerged as a strong indicator of addiction, suggesting that excessive social media engagement directly disrupts focus, task completion, and overall efficiency. This relationship illustrates the trade-off between short-term enjoyment and long-term cognitive and occupational performance, echoing prior findings on digital fatigue and technostress.

The absence of significant demographic influence in predicting addiction levels implies that digital dependency is a universal behavioral concern that transcends age, gender, and socioeconomic boundaries. The comparison among platforms further highlights that design features such as algorithmic recommendation, short-form video content, and infinite scrolling found in applications like TikTok and Instagram are more likely to intensify addictive tendencies compared to platforms with more passive or long-form engagement such as Facebook and YouTube. This finding emphasizes that platform architecture plays a vital role in shaping user behavior and can potentially exploit cognitive vulnerabilities to sustain prolonged attention. The implications of these findings are substantial for both academia and practice. From a psychological perspective, the study contributes to the growing evidence that addiction in digital contexts is primarily governed by behavioral conditioning and cognitive control rather than demographic predispositions. From a practical standpoint, the results encourage the development of preventive strategies such as digital literacy programs, self-regulation training, and interface designs that promote mindful engagement. Technology developers and policymakers may also utilize these insights to design ethically responsible algorithms that balance engagement metrics with user well-being. Overall, the discussion underscores the critical importance of integrating behavioral science and artificial intelligence in addressing digital addiction and fostering a healthier digital society.

Conclusion

This study concludes that machine learning, particularly the Gradient Boosting algorithm, provides a powerful analytical framework for predicting digital addiction and identifying its underlying behavioral and psychological determinants. The model achieved near-perfect predictive accuracy, demonstrating that psychological constructs such as self-control, satisfaction, and productivity loss are the most critical predictors of social media addiction, whereas demographic and technological variables such as age, gender, and platform type play minimal roles. These findings confirm that digital addiction is primarily a cognitive-behavioral phenomenon driven by reinforcement mechanisms, emotional gratification, and deficits in self-regulation rather than by external social characteristics. Users with lower self-control and higher satisfaction from social media engagement are more likely to develop habitual dependency, leading to measurable reductions in productivity and attention. This insight contributes to the growing body of literature emphasizing that digital addiction should be understood as a psychological and behavioral disorder rather than merely a technological consequence. Practically, the findings highlight the importance of designing interventions that promote self-regulation and mindful usage, such as digital literacy education, behavior-monitoring applications, and algorithmic transparency initiatives that discourage compulsive engagement. The integration of artificial intelligence and behavioral science demonstrated in this study provides a foundation for predictive digital well-being research and offers actionable guidance for policymakers, educators, and technology developers. Future research should explore longitudinal models to monitor behavioral changes over time and employ explainable AI techniques to interpret the cognitive and emotional pathways leading to addiction. Collectively, this research underscores that fostering a balanced, ethical, and self-aware digital ecosystem is essential to mitigate the escalating impact of social media overuse in contemporary digital societies.

Declarations

Author Contributions

Conceptualization: C.J.; Methodology: C.J.; Software: C.J.; Validation: C.J.; Formal Analysis: C.J.; Investigation: C.J.; Resources: C.J.; Data Curation: C.J.; Writing Original Draft Preparation: C.J.; Writing Review and Editing: C.J.; Visualization: C.J.; All authors have read and agreed to the published version of the manuscript.

Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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