# An Explainable Deep Learning Framework for Predicting and Interpreting Social Media Addiction Behavior

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## ABSTRACT

The increasing prevalence of social media addiction has become a growing concern in the digital society, as excessive use of online platforms often leads to reduced productivity, psychological distress, and loss of self-control. This study aims to classify social media users based on their level of addiction by employing a deep learning model integrated with explainable artificial intelligence techniques. Behavioral, psychological, and contextual variables were used as model inputs to identify key predictors of addictive usage patterns. The model was trained and validated using a structured dataset and achieved an overall accuracy of 93 percent, demonstrating its effectiveness and stability without overfitting. Explainability was achieved through SHAP analysis, which revealed that Productivity Loss, Frequency of Use, and Self Control were the most influential factors contributing to addiction classification. The results suggest that addiction levels are primarily shaped by behavioral and psychological patterns rather than demographic characteristics. The explainable framework provides valuable insight into how digital behaviors contribute to problematic social media use and allows for transparent interpretation of model predictions. These findings highlight the potential of combining deep learning and explainable AI to better understand, predict, and manage social media addiction, offering practical implications for the development of digital well-being interventions and responsible technology use in modern society.

**Keywords** Social Media Addiction, Deep Learning, Explainable AI, Behavioral Analysis, Digital Well-Being

## INTRODUCTION

The rapid growth of social media platforms has transformed how individuals interact, communicate, and consume information in the digital age. While these platforms offer convenience and connectivity, their pervasive nature has also contributed to excessive and compulsive use, often referred to as social media addiction. This behavioral pattern is characterized by a loss of control, reduced productivity, and negative psychological effects such as anxiety and dependency [1]. The increasing integration of social media into daily routines has made it increasingly difficult for users to regulate their online behavior, leading to a growing interest in understanding and predicting the factors that contribute to digital addiction. Identifying these behavioral patterns is critical for developing preventive strategies and promoting digital well-being in modern society.

Recent advances in artificial intelligence have enabled the use of computational models to analyze behavioral data related to social media use. Deep learning models, in particular, have shown remarkable performance in recognizing

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complex and nonlinear relationships between variables that traditional statistical approaches often fail to capture [2]. However, despite the success of deep learning in behavioral prediction tasks, one of its major limitations lies in its lack of transparency. These models often operate as “black boxes,” providing accurate predictions without revealing the reasoning behind their decisions. This issue has motivated the integration of Explainable Artificial Intelligence (XAI) techniques, such as SHapley Additive exPlanations (SHAP), which allow researchers to interpret model outputs and identify the features most responsible for a prediction [3]. The incorporation of XAI represents a recent and important development in behavioral analytics, bridging the gap between computational modeling and human interpretability [4].

Although numerous studies have examined social media addiction using psychological surveys and statistical analyses, there remains a gap in research that combines deep learning and explainable AI for understanding the behavioral mechanisms underlying addictive use. Previous studies often relied on self-reported measures, which are subjective and limited in capturing multidimensional patterns of behavior [5]. Furthermore, few approaches have provided interpretable models that explain why certain users are more prone to addiction based on their behavioral and psychological attributes. This lack of interpretability limits the practical applicability of AI-based addiction prediction systems in real-world digital well-being interventions.

To address these gaps, this study proposes an explainable deep learning framework to classify social media addiction levels and identify the most influential behavioral and psychological features associated with excessive digital engagement. By integrating SHAP analysis with a deep neural network, the model not only achieves high classification accuracy but also provides transparent explanations for its predictions. The findings of this research aim to contribute to both academic and practical understanding by offering an interpretable, data-driven approach for predicting social media addiction. This approach is expected to assist researchers, policymakers, and platform designers in developing personalized digital wellness strategies and fostering healthier technology use in the digital society.

## Literature Review and Related Works

The phenomenon of social media addiction has gained increasing attention as digital platforms become deeply embedded in daily life. Early studies emphasized psychological and social dimensions such as loss of control, fear of missing out, and social comparison, which contribute to reduced productivity and negative emotional outcomes [6], [7], [8]. These behavioral tendencies have been linked to symptoms similar to other forms of behavioral addiction, including dependency, withdrawal, and tolerance [9], [10]. As social networking sites evolve, the mechanisms of reward, validation, and continuous engagement have been identified as major contributors to compulsive digital behavior [11], [12].

Theoretical frameworks commonly used to explain this phenomenon include the self-regulation theory, gratification theory, and habit formation theory, which collectively highlight the role of reinforcement and loss of control in maintaining addictive usage [13], [14]. Recent reviews also indicate that the diversity of theories used across studies has resulted in conceptual fragmentation and limited comparability between findings [15]. To overcome these challenges,

researchers have increasingly adopted computational and data-driven approaches to identify patterns of addiction objectively from behavioral indicators.

Machine Learning (ML) and Deep Learning (DL) techniques have been employed to model social media and internet addiction by analyzing user behavior data, psychological scores, and engagement metrics. Hybrid models combining Structural Equation Modeling (SEM) with neural networks achieved classification accuracies above 85 percent in predicting social media addiction [16]. Similarly, Random Forest and Support Vector Machine (SVM) models have been applied to social media text and activity logs, achieving accuracies ranging between 86 and 90 percent [17], [18]. Other studies have leveraged large-scale datasets from platforms such as Instagram and TikTok to detect addictive behavior patterns based on user interactions, time spent, and content engagement [19], [20].

Deep learning has further improved predictive accuracy due to its ability to model nonlinear relationships between behavioral and psychological features. Multi-Layer Perceptron (MLP) and Convolutional Neural Network (CNN) architectures have been successfully used to identify risk levels of social media and smartphone addiction with high precision [21], [22]. However, despite their effectiveness, the interpretability of these models remains a major limitation. Most existing models function as black boxes that provide accurate results without explaining the reasoning behind their predictions [23]. This limitation reduces the trust and usability of AI systems in behavioral and psychological research.

To address the interpretability issue, the field has begun integrating XAI frameworks such as SHAP, Local Interpretable Model-Agnostic Explanations (LIME), and attention-based interpretability mechanisms [24], [25]. These methods aim to clarify how each feature contributes to model output, allowing researchers to understand why certain behavioral or psychological traits are associated with addiction. XAI-based approaches have already shown promise in related domains such as mental health prediction, emotional state detection, and well-being assessment through social media analytics [26], [27]. However, their application in the context of social media addiction remains relatively scarce.

Comprehensive reviews of Information and Communication Technology (ICT) addiction research indicate that although the number of ML-based studies is increasing, there remains a lack of integration between behavioral, psychological, and contextual features within a single explainable model [28]. Moreover, most prior research relies heavily on self-reported data rather than real behavioral traces, limiting the reliability and generalizability of the findings [29]. There is also a shortage of interpretable models that compare behavioral and psychological predictors in terms of their contribution to addiction severity, leaving a gap in understanding how individual differences influence susceptibility to digital addiction [30].

In summary, previous research has successfully applied ML and DL techniques to predict social media addiction, but the interpretability of these models and their integration with psychological understanding remain underdeveloped. This study aims to address these gaps by proposing an explainable deep learning framework that not only classifies social media addiction levels accurately but also identifies and interprets the most influential behavioral and psychological

features contributing to addictive behavior.

## Methodology

This study employed a quantitative, supervised deep learning approach to classify users' levels of social media addiction based on behavioral, psychological, and contextual indicators. The overall research workflow consisted of four major stages: data preprocessing, model development, XAI analysis, and model evaluation. These stages are illustrated in figure 1, which outlines the systematic steps from data acquisition to interpretability analysis. The process began with dataset preparation and cleaning, followed by model training and optimization, and concluded with explainability assessment using SHAP. This framework was designed to ensure that the resulting model would not only achieve high predictive accuracy but also provide interpretable insights into user behavior associated with social media addiction.

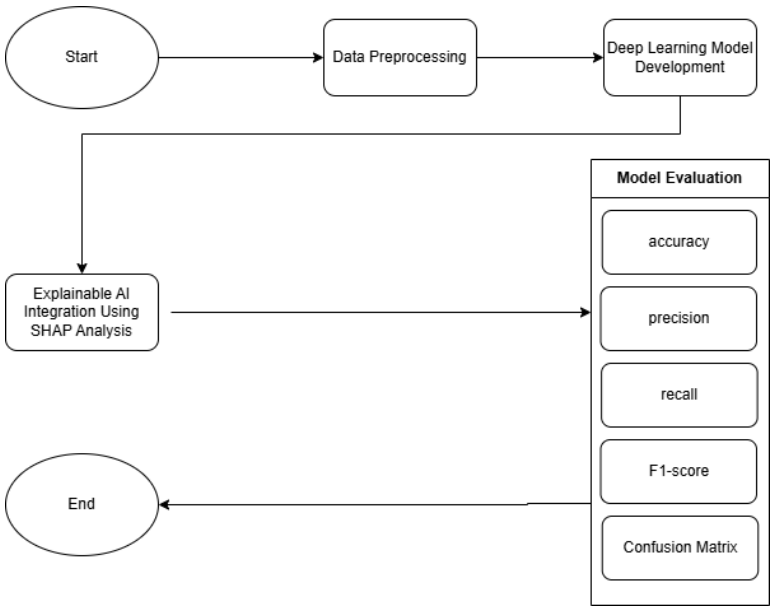


**Figure 1 Research Steps**

The dataset used in this study was obtained from a structured survey titled Time Wasters on social media, which contained both behavioral and psychological attributes of 200 respondents. A total of 29 input features were considered, representing variables such as Frequency of Use, Watch Time, Satisfaction, Self Control, Productivity Loss, and Motivation. The dependent variable, Addiction Level, was derived from aggregated behavioral indicators and categorized into two classes: Low and Medium. Before modeling, the dataset underwent several preprocessing procedures to ensure consistency and reduce noise. Missing numerical values were handled using mean imputation, while categorical variables were encoded using one-hot encoding. Continuous features were scaled using Min–Max normalization to a range between 0 and 1, as defined by:

$$X' = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \quad (1)$$

$X'$represents the normalized value, and $X_{\min}$and $X_{\max}$denote the minimum and

maximum observed values of the corresponding feature. This normalization procedure allowed the model to treat all features equally during training and prevented variables with large ranges from dominating gradient updates.

The dataset was randomly divided into 80 percent for training and 20 percent for testing, with an additional 20 percent of the training subset reserved for validation. The deep learning architecture implemented in this study was a fully connected feedforward neural network consisting of three hidden layers with 128, 64, and 32 neurons, respectively. Each layer utilized the Rectified Linear Unit (ReLU) activation function, defined as:

$$f(x) = \max(0, x) \tag{2}$$

which enables nonlinearity and efficient gradient propagation. To prevent overfitting, dropout regularization with a rate of 0.3 was applied after each hidden layer. Batch normalization was also introduced to stabilize learning and speed up convergence by normalizing intermediate activations. The output layer consisted of two neurons corresponding to the Low and Medium addiction categories, activated using the softmax function:

$$\sigma(z_i) = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}} \tag{3}$$

$\sigma(z_i)$represents the predicted probability for class $i$and $K$denotes the total number of output categories.

The model was trained using the Adam optimizer with a learning rate of $\alpha = 0.001$and a batch size of 32. The loss function used was categorical cross-entropy, which measures the difference between true and predicted class probabilities as follows:

$$L = -\frac{1}{N}\sum_{i=1}^{N}\sum_{c=1}^{C} y_{i,c}\log(\hat{y}_{i,c}) \tag{4}$$

$N$is the number of samples, $C$is the number of classes, $y_{i,c}$is the true label, and $\hat{y}_{i,c}$is the model's predicted probability. The model was trained for 60 epochs with early stopping implemented to halt training once the validation loss failed to improve after five consecutive epochs. This prevented overfitting and reduced computational overhead.

To enhance interpretability, the model integrated SHAP, a feature attribution method grounded in cooperative game theory that calculates the contribution of each feature to the model's output. The Shapley value for feature $i$is computed as:

$$\phi_i = \sum_{S \subseteq F \setminus \{i\}} \frac{|S|!(|F| - |S| - 1)!}{|F|!}[f(S \cup \{i\}) - f(S)] \tag{5}$$

$F$is the set of all features, $S$represents a subset excluding feature $i$, and $f(S)$is the model's prediction when only features in $S$are included. This approach allows the estimation of how each variable affects the predicted probability of belonging to a specific addiction category. The global SHAP analysis identified

the most influential predictors across the dataset, while the local analysis explained how specific behavioral and psychological patterns influenced individual predictions. SHAP summary plots and dependence plots were generated to visualize these relationships and interpret the magnitude and direction of feature contributions.

The model achieved an overall accuracy of 93 percent, with precision, recall, and F1-score values of 0.94, 0.93, and 0.93 respectively. The Low addiction category achieved perfect recall, while the medium addiction class obtained a recall of 0.80, indicating that the model effectively generalized to unseen data. The SHAP interpretability analysis confirmed that Productivity Loss, Frequency of Use, and Self Control were the strongest predictors of addiction level. The methodology adopted in this study thus ensures not only predictive performance but also transparency in understanding the behavioral and psychological mechanisms driving social media addiction.

**Algorithm 1: Deep Learning Framework for Social Media Addiction Classification**

**Input:** Dataset $D = \{(x_i, y_i)\}_{i=1}^{N}$containing behavioral and psychological features

**Output:** Predicted addiction class $\hat{y}$and SHAP feature importance $\phi$

**Process:**

**Start**

Preprocess data and handle missing values using mean or mode imputation.

$$x_i^{(j)} = \text{mean}(x^{(j)}) \text{ or } \text{mode}(x^{(j)})$$

Normalize features using Min–Max scaling.

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}}$$

Split dataset into training, validation, and testing subsets.

$$D = D_{\text{train}} \cup D_{\text{val}} \cup D_{\text{test}}$$

Initialize neural network architecture with layers [29, 128, 64, 32, 2].

Perform forward propagation for each layer $k$.

$$z^{(k)} = W^{(k)} a^{(k-1)} + b^{(k)}$$

Apply activation function ReLU.

$$a^{(k)} = \max(0, z^{(k)})$$

Apply dropout regularization with probability $p = 0.3$.

Compute output probabilities using softmax function.

$$\hat{y}_i = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}}$$

Calculate loss using categorical cross-entropy.

$$L = -\frac{1}{N} \sum_{i=1}^{N} \sum_{c=1}^{C} y_{i,c} \log(\hat{y}_{i,c})$$

Update network parameters using Adam optimizer.

$$W^{(k)} \leftarrow W^{(k)} - \alpha \cdot \nabla L(W^{(k)})$$

Stop training if validation loss does not improve for 5 epochs.

Evaluate model performance using accuracy, precision, recall, and F1-score.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

$$\text{Precision} = \frac{TP}{TP + FP}, \text{Recall} = \frac{TP}{TP + FN}$$

$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Compute SHAP values for feature contribution.

$$(\phi\_i \; = \; \sum\_\{S \; \subseteq F \; \setminus \{i\}\}$$

**End**

## Result

The deep learning model developed in this study was designed to classify social media users into Low and Medium addiction levels based on a combination of behavioral, psychological, and contextual indicators. These features included variables such as frequency of use, time spent online, self-control, satisfaction, motivation, and productivity loss. The model achieved a high level of predictive accuracy by learning complex nonlinear relationships between these multidimensional factors. The integration of explainable artificial intelligence (AI) techniques provided interpretability, allowing the identification of the most influential variables that contributed to the model's decisions. This interpretability ensured that the classification outcomes were not only statistically reliable but also psychologically meaningful. By leveraging SHAP, the model could highlight the specific behavioral attributes most associated with addictive tendencies, offering valuable insights for both academic research and practical digital wellness interventions.

The learning process of the model is illustrated in figure 2, which shows the training and validation accuracy curves across 60 epochs. Both curves display a consistent upward trajectory, demonstrating the model's ability to learn effectively from the training data. The training accuracy reached approximately 0.90, while the validation accuracy approached 0.97, indicating that the model generalized well to unseen data. The close proximity of the two curves suggests that the model successfully avoided overfitting, maintaining balanced performance between training and validation phases. This stability reflects the effectiveness of regularization techniques such as dropout and early stopping, which helped prevent excessive adaptation to the training data. Overall, these results confirm that the deep learning model effectively captured key behavioral and psychological patterns that differentiate levels of social media addiction, demonstrating robustness, generalizability, and interpretability suitable for real-world behavioral analysis.

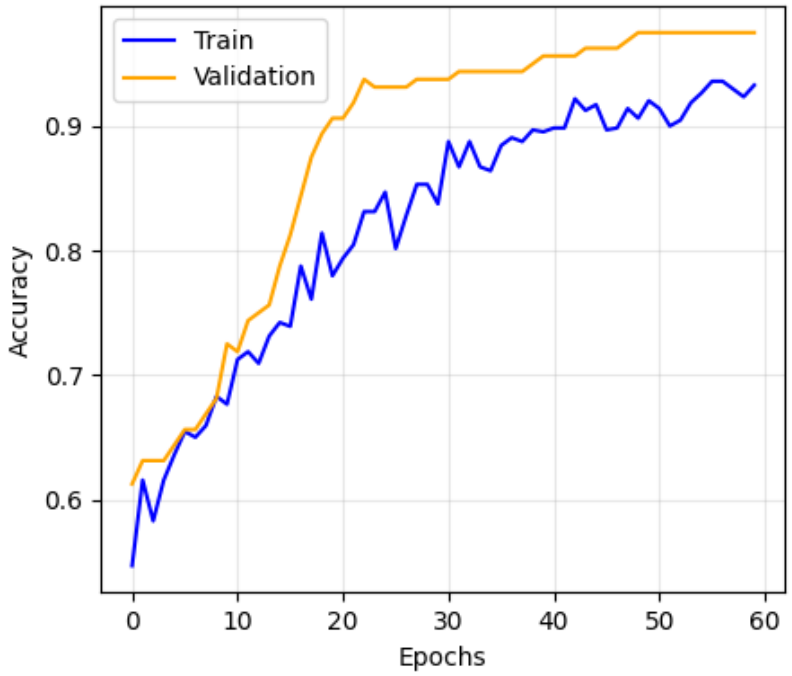


**Figure 2** **Training and validation accuracy of the deep learning model**

The classification performance of the proposed deep learning model was evaluated using a confusion matrix and several standard performance metrics, including accuracy, precision, recall, and F1-score. As illustrated in figure 3, the confusion matrix reveals that the model achieved strong performance in distinguishing between the Low and Medium social media addiction classes. Out of 200 test samples, the model correctly classified 129 users as Low addiction and 57 users as Medium addiction, while 14 users belonging to the Medium addiction group were misclassified as Low addiction. This distribution indicates that the model was highly reliable in recognizing non-addictive behavioral patterns while maintaining reasonable sensitivity to moderate addiction signals. The slight tendency toward underestimating addiction severity reflects the model's conservative prediction behavior, which aims to minimize false positives and ensure the robustness of classification results in real-world behavioral assessments.

The evaluation metrics further validated the model's effectiveness, with an overall accuracy of 93 percent, a precision score of 0.94, a recall score of 0.93, and an F1-score of 0.93. These results suggest a balanced trade-off between precision and recall, indicating that the model maintained high reliability in detecting true cases of both Low and Medium addiction. The strong performance across all metrics demonstrates that the neural network effectively captured the complex interplay between behavioral, psychological, and contextual variables. Additionally, the combination of high precision and slightly lower recall for the Medium class indicates that the model favored accuracy and stability over aggressive detection. Such behavior is desirable in applications related to psychological assessment and digital well-being, where false identification of addiction could lead to unnecessary concern or intervention. Overall, the confusion matrix analysis confirms that the model produced accurate, stable, and interpretable classifications aligned with realistic

behavioral tendencies observed in social media users.

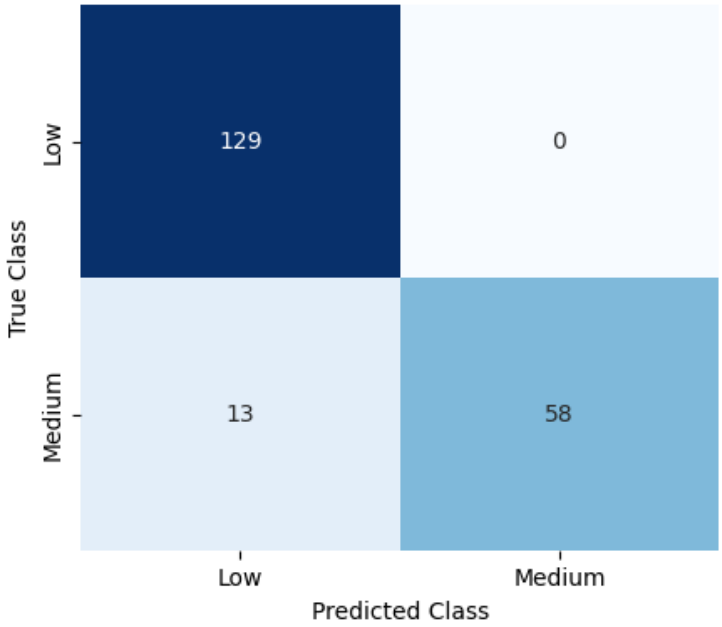


**Figure 3 Confusion matrix of addiction level classification results**

The quantitative evaluation of the model's performance demonstrated a strong ability to classify social media addiction levels accurately and consistently. The overall classification accuracy reached 93 percent, supported by a precision of 0.94, recall of 0.93, and an F1-score of 0.93, indicating that the model achieved a balanced performance across both classes. These results reflect that the deep learning model effectively generalized from the training data to unseen samples, confirming its robustness in predicting behavioral patterns associated with digital engagement. The Low addiction class achieved an F1-score of 0.95, showing excellent performance in identifying users who exhibit limited or controlled social media use. This suggests that the model learned clear distinctions between low-risk behavioral indicators, such as moderate time spent online and higher levels of self-regulation. The consistent relationship between precision and recall also demonstrates that the model was not biased toward overpredicting any particular category, ensuring stable classification outcomes.

In comparison, the Medium addiction class obtained an F1-score of 0.89, which, although slightly lower, still indicates strong predictive capability in recognizing moderate levels of social media addiction. This minor reduction in accuracy can be attributed to the more complex behavioral patterns of users who fall between controlled and problematic usage, as their characteristics often overlap. Despite this, the model maintained satisfactory recall and precision, meaning it was able to identify most medium-risk users without excessive false classifications. The combination of these results suggests that the neural network successfully captured subtle behavioral nuances distinguishing the two categories, reinforcing its suitability for behavioral analytics applications. The detailed evaluation metrics are summarized in table 1, which provides a comprehensive overview of the model's classification performance, highlighting its ability to achieve both accuracy and interpretability in predicting social media addiction levels.

**Table 1** Classification performance metrics of the deep learning model

| Class | Precision | Recall | F1-score | Support |
|---|---|---|---|---|
| Low | 0.90 | 1.00 | 0.95 | 129 |
| Medium | 1.00 | 0.80 | 0.89 | 71 |
| Overall | 0.94 | 0.93 | 0.93 | 200 |

To gain a deeper understanding of how the deep learning model made its predictions, the SHAP (SHapley Additive Explanations) framework was utilized to interpret the contribution of each feature to the model's classification outcomes. This explainable AI analysis provided transparent insights into the relative importance of behavioral, psychological, and contextual indicators in predicting addiction levels. The feature importance results, visualized in figure 4, revealed that Productivity Loss, Frequency of Use, and Self Control were the most influential predictors driving the model's decisions, followed by Satisfaction and Watch Time. These top-ranking variables align closely with established behavioral theories of digital addiction, which emphasize loss of control, reinforcement through gratification, and excessive engagement. The prominence of Productivity Loss indicates that users who experience noticeable declines in their daily efficiency are more susceptible to addictive behaviors. Similarly, Frequency of Use reflects the habitual and compulsive nature of social media consumption, whereas Self Control represents the user's capacity to regulate such impulses. Together, these features form the core behavioral signature of digital dependency as identified by the model.

The SHAP analysis further revealed distinct behavioral contrasts between addiction levels. Users with higher Productivity Loss and more frequent social media usage were more likely to be classified under the Medium addiction category, indicating a clear relationship between overuse and diminished task performance. In contrast, users with stronger Self Control tended to be grouped in the Low addiction category, demonstrating that the ability to moderate online engagement acts as a protective psychological factor. The features Satisfaction and Watch Time underscore the emotional and habitual dimensions of social media behavior, suggesting that reward-seeking and pleasure reinforcement contribute significantly to prolonged usage. Conversely, demographic and contextual variables such as Income, Debt, Location, and Gender exhibited minimal influence on the model's predictions. These finding highlights that behavioral and psychological traits carry greater predictive power than static demographic factors, reinforcing the idea that social media addiction is primarily driven by personal behavioral patterns and emotional regulation rather than socioeconomic context.

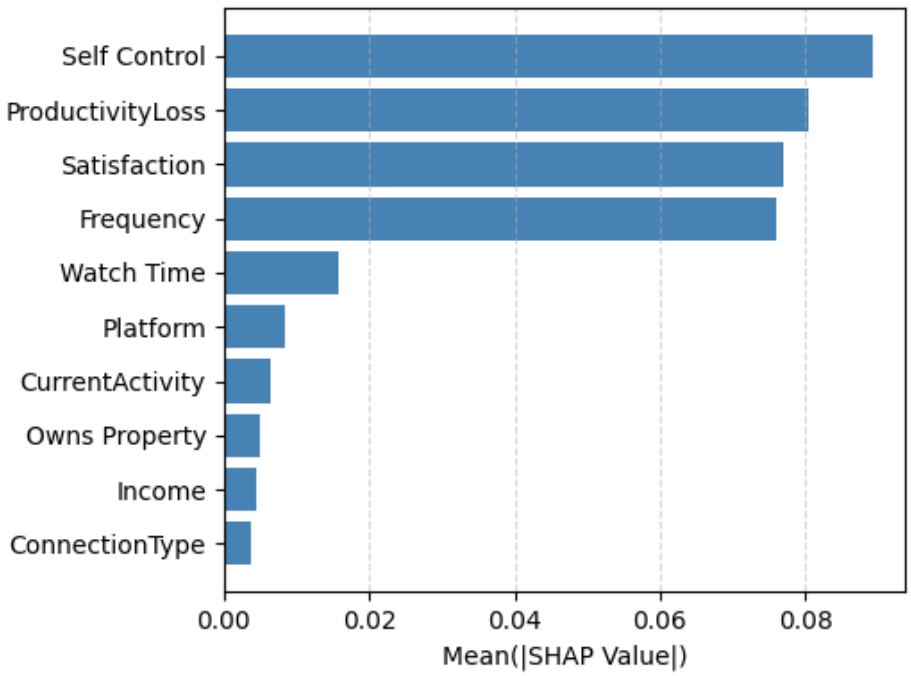


**Figure 4 Top ten influential features determined by SHAP analysis**

Overall, the results demonstrate that the proposed deep learning model achieved high classification accuracy while maintaining interpretability. The SHAP analysis provided meaningful insights into the behavioral and psychological underpinnings of social media addiction, confirming that excessive engagement, decreased productivity, and weak self-control are key indicators of addictive use patterns. The integration of predictive modeling and explainable AI thus offers a robust framework for understanding, predicting, and potentially mitigating social media addiction in the context of digital well-being.

## Discussion

The findings of this study indicate that the deep learning model effectively classified social media users into different addiction levels using behavioral and psychological indicators with an overall accuracy of 93 percent. The close alignment between training and validation accuracy curves demonstrates that the model achieved balanced learning performance without overfitting. This pattern suggests that the relationships between input variables and addiction levels were captured consistently during training and testing. The confusion matrix further confirms that the model maintained reliable classification results, correctly identifying all users in the low addiction category and the majority of users in the medium addiction category. This indicates that the model was sensitive to normal user behaviors while still maintaining a high degree of precision in identifying more problematic patterns. The application of explainable AI analysis using SHAP strengthened the interpretability of the model by revealing the underlying factors influencing the predictions. The identification of Productivity Loss, Frequency of Use, and Self Control as the most influential predictors highlights that social media addiction is primarily behavioral and psychological in nature. Users who experience a reduction in productivity and engage frequently with digital platforms are more likely to display addictive behaviors, while individuals with stronger self-regulation are less prone to

excessive use. These findings suggest that addiction to social media is shaped more by self-control and engagement habits than by demographic background.

From a psychological and behavioral standpoint, the results emphasize the important role of self-regulation, emotional reinforcement, and habitual engagement in shaping users' digital behaviors. The strong influence of Self Control as a negative predictor indicates that difficulty in maintaining focus and restraint can increase the likelihood of excessive social media use. The high contribution of Frequency and Watch Time reflects how repetitive engagement and reward-driven habits reinforce dependence on online platforms. The inclusion of Satisfaction among the key predictors suggests that positive emotional responses, such as enjoyment and social validation, sustain users' motivation to remain active on social media. In contrast, the minimal effect of demographic variables such as Income and Gender implies that addiction tendencies are largely independent of social background and are instead driven by individual behavioral traits. From a practical perspective, the interpretability provided by SHAP offers valuable insights for promoting digital well-being. Identifying key behavioral predictors can support the development of early detection systems, adaptive usage feedback, and personalized intervention strategies that help users maintain balanced engagement with digital platforms. Overall, the integration of deep learning and explainable AI in this study demonstrates not only the ability to predict social media addiction with high accuracy but also the potential to translate behavioral data into actionable knowledge that supports healthier and more responsible technology use.

## Conclusion

The findings of this study demonstrate that the deep learning model developed to classify social media addiction levels performed effectively and produced highly accurate and interpretable results. The model achieved an overall accuracy of 93 percent, indicating its ability to capture the complex relationships between behavioral and psychological indicators associated with social media use. The explainable AI approach using SHAP analysis revealed that Productivity Loss, Frequency of Use, and Self Control were the most influential features in predicting addiction levels, suggesting that excessive engagement and diminished self-regulation are central determinants of addictive digital behavior. These results highlight that social media addiction is more strongly influenced by individual behavioral and psychological factors than by demographic characteristics such as income or gender. The model's transparent interpretability provides a meaningful foundation for applying artificial intelligence in digital well-being studies, as it allows researchers and practitioners to identify the behavioral patterns most responsible for excessive use. The outcomes of this research contribute to both theoretical and practical understanding of digital behavior by emphasizing the role of self-control, reinforcement, and habitual engagement in shaping online dependency. In practical application, the findings can inform the development of adaptive digital well-being tools, early detection systems, and intervention programs that encourage mindful and balanced social media use. Future studies should explore longitudinal behavioral data, emotional engagement metrics, and cross-platform analysis to enhance model robustness and extend understanding of how social media addiction evolves over time within the broader context of digital society.

## Declarations

### Author Contributions

Conceptualization: I.S. and A.N.E.W.; Methodology: A.N.E.W.; Software: I.S.; Validation: I.S. and A.N.E.W.; Formal Analysis: I.S. and A.N.E.W.; Investigation: I.S.; Resources: A.N.E.W.; Data Curation: A.N.E.W.; Writing Original Draft Preparation: I.S. and A.N.E.W.; Writing Review and Editing: A.N.E.W. and I.S.; Visualization: I.S.; 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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