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Modeling Internet Addiction Severity Using Deep Learning: Effects of Impulsivity, Emotional Dysregulation, Reward Sensitivity, and Fear of Missing Out

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ABSTRACT

Objective: The present study aimed to model internet addiction severity using deep learning techniques by examining the combined effects of impulsivity, emotional dysregulation, reward sensitivity, and fear of missing out.

Methods and Materials: This quantitative cross-sectional study was conducted on 412 university students from Mexico selected through stratified convenience sampling. Participants completed standardized self-report measures including the Internet Addiction Test (IAT), Barratt Impulsiveness Scale (BIS-11), Difficulties in Emotion Regulation Scale (DERS), Behavioral Activation System (BAS) scale, and Fear of Missing Out (FoMO) scale. Data were collected via an online survey platform. After preprocessing, including handling missing values and standardization, a deep neural network model was developed to predict internet addiction severity. The dataset was divided into training (70%), validation (15%), and test (15%) sets. Model performance was evaluated using mean squared error (MSE), root mean squared error (RMSE), and coefficient of determination (R^2), and hyperparameters were optimized using grid search techniques.

Findings: The deep learning model demonstrated strong predictive performance, with R^2 values of 0.72, 0.69, and 0.68 in the training, validation, and test sets, respectively, indicating high explanatory power and generalizability. All predictor variables showed significant positive associations with internet addiction severity, with fear of missing out emerging as the strongest predictor, followed by emotional dysregulation, impulsivity, and reward sensitivity. Shapley value analysis confirmed the relative importance of these variables, highlighting a multidimensional pattern of influence. The model exhibited low error rates across datasets, supporting its robustness and stability in predicting internet addiction severity.

Conclusion: The findings indicate that internet addiction severity is best understood as a multidimensional construct influenced by interrelated psychological factors, with fear of missing out and emotional dysregulation playing central roles. The application

of deep learning provides a powerful and accurate approach for modeling complex behavioral phenomena, offering both theoretical insights and practical implications for prevention and intervention strategies.

Keywords: *Internet addiction, deep learning, impulsivity, emotional dysregulation, reward sensitivity, fear of missing out, predictive modeling*

1. Introduction

The rapid proliferation of digital technologies and the ubiquitous integration of internet-based platforms into everyday life have transformed patterns of human behavior, communication, and psychological functioning. While these developments have facilitated unprecedented levels of connectivity and information exchange, they have also given rise to maladaptive patterns of internet use, often conceptualized as internet addiction or problematic internet use. Contemporary research increasingly recognizes internet addiction as a multidimensional behavioral phenomenon characterized by excessive preoccupation with online activities, loss of control over usage, and persistence despite negative consequences (Li & Yang, 2024; Weinstein, 2023). This condition has been associated with a wide range of adverse outcomes, including impaired academic performance, disrupted social relationships, and deteriorating mental health, particularly among adolescents and young adults who represent the most digitally engaged population (Marano et al., 2025; Wacks & Weinstein, 2021).

Recent empirical evidence highlights that internet addiction is not a homogeneous construct but rather a complex interplay of psychological, behavioral, and neurobiological factors. Longitudinal studies have demonstrated that problematic internet use follows dynamic developmental trajectories, influenced by both individual predispositions and environmental conditions (Xiao et al., 2025). Cross-cultural investigations further confirm that while the prevalence and expression of internet addiction may vary across contexts, its underlying psychological correlates remain relatively consistent, emphasizing the role of internal vulnerabilities over purely contextual determinants (Varchetta et al., 2024). Consequently, there has been a growing emphasis on identifying core psychological mechanisms that contribute to the severity of internet addiction, moving beyond descriptive frameworks toward predictive and explanatory models.

Among the most extensively studied predictors of internet addiction is impulsivity, which reflects a tendency toward rapid, unplanned reactions to internal or external stimuli without regard for long-term consequences. Impulsivity has been consistently linked to various forms of behavioral addiction, including problematic internet and gaming

behaviors, due to its association with deficient inhibitory control and heightened reward-seeking tendencies (Chang et al., 2021; Ünübol & Sayar, 2020). Individuals with high impulsivity are more likely to engage in excessive online activities as a means of immediate gratification, often bypassing cognitive regulation processes. This tendency is further reinforced in digital environments characterized by instant feedback, continuous novelty, and low barriers to engagement, which collectively amplify impulsive behavioral patterns (Flayelle et al., 2023).

Closely related to impulsivity is the construct of emotional dysregulation, which refers to difficulties in understanding, managing, and responding to emotional experiences. Emotional dysregulation has been identified as a central mechanism underlying various addictive behaviors, as individuals may turn to internet use as a maladaptive coping strategy to alleviate negative affect or escape from distressing emotions (Benedetto et al., 2024; Quaglieri et al., 2021). Empirical findings suggest that individuals with poor emotional regulation are more vulnerable to excessive internet use, particularly in contexts where online platforms provide temporary emotional relief or distraction (Ntumi et al., 2025). Furthermore, the interaction between emotional dysregulation and environmental triggers, such as social media notifications and algorithm-driven content, may exacerbate compulsive usage patterns, reinforcing the cycle of addiction (Wang & Shen, 2025).

Another critical factor contributing to internet addiction is reward sensitivity, defined as the degree to which individuals respond to rewarding stimuli. Neurocognitive research indicates that heightened reward sensitivity is associated with increased activation of the brain's reward system in response to digital cues, such as likes, comments, and notifications (Deng et al., 2021). This heightened responsiveness can lead to repetitive engagement with online platforms, as individuals seek to maximize rewarding experiences and minimize negative affect. The reinforcing properties of digital environments, combined with individual differences in reward processing, create a powerful mechanism driving sustained and excessive internet use (Flack et al., 2024). Notably, reward sensitivity has been shown to differentiate between high and low levels of problematic smartphone use, underscoring its role as a key predictor of addiction severity.

Fear of missing out (FoMO) has emerged as one of the most salient psychosocial variables associated with internet addiction in recent years. FoMO is conceptualized as a pervasive apprehension that others might be having rewarding experiences from which one is absent, leading to a persistent desire to remain connected to social networks (Elhai et al., 2021). This construct is particularly relevant in the context of social media, where continuous streams of curated content amplify perceptions of social exclusion and inadequacy. Empirical studies have consistently demonstrated strong associations between FoMO and problematic internet use, with FoMO acting as both a direct predictor and a mediating variable linking psychological distress to addictive behaviors (Guan et al., 2023; Servidio, 2021). Moreover, FoMO has been found to interact with emotional dysregulation and impulsivity, creating a synergistic effect that intensifies compulsive internet use (Flack et al., 2024).

In addition to these individual-level factors, emerging research highlights the role of technological design features in facilitating addictive behaviors. Modern digital platforms are intentionally engineered to maximize user engagement through mechanisms such as variable reward schedules, personalized content algorithms, and social validation systems (Flayelle et al., 2023). These features exploit fundamental psychological processes, including reward sensitivity and social comparison, thereby increasing the likelihood of excessive use. The proliferation of short-form video platforms, for instance, has been associated with negative cognitive and mental health outcomes, further illustrating the interaction between technological affordances and psychological vulnerabilities (arouch et al., 2025). Similarly, the rise of platform-specific addictions, such as TikTok overuse, underscores the need to consider both user characteristics and platform dynamics in understanding internet addiction (Maghraoui & Khrouf, 2024).

The psychological consequences of internet addiction extend beyond behavioral patterns, encompassing significant impacts on mental health and well-being. Studies have linked excessive internet use to increased levels of anxiety, depression, and stress, with FoMO often serving as a mediating mechanism in these relationships (Y. Wang et al., 2022). Neurodevelopmental research also suggests that prolonged exposure to digital environments may alter brain structure and function, particularly in regions associated with attention, reward processing, and emotional regulation (Marciano et al., 2021). These findings highlight the

importance of early identification and intervention, as well as the need for comprehensive models that can accurately predict addiction severity based on underlying psychological factors.

Despite the growing body of literature on internet addiction, traditional statistical approaches have limitations in capturing the complex, nonlinear relationships among multiple predictors. In recent years, machine learning and deep learning techniques have gained prominence as powerful tools for modeling complex psychological phenomena. These methods allow for the integration of high-dimensional data and the identification of intricate patterns that may not be detectable by conventional analytical approaches (Wan, 2025; Wang & Shen, 2025). Deep neural networks, in particular, offer significant advantages in predictive modeling due to their ability to learn hierarchical representations of data and capture nonlinear interactions among variables.

The application of deep learning in the context of behavioral addiction research remains relatively nascent but highly promising. Preliminary studies have demonstrated the effectiveness of machine learning models in predicting problematic internet use based on psychological and behavioral indicators, suggesting that these approaches can enhance both theoretical understanding and practical intervention strategies (Ndayambaje & Udohchukwu, 2025; Totur et al., 2025). Furthermore, the integration of explainable artificial intelligence techniques, such as Shapley value analysis, enables researchers to interpret model outputs and identify the relative importance of predictors, thereby bridging the gap between predictive accuracy and theoretical insight.

Given the multifaceted nature of internet addiction, there is a critical need for comprehensive models that integrate key psychological variables within a robust analytical framework. Existing studies often examine predictors in isolation or rely on linear models that may not adequately capture the complexity of their interactions. By incorporating impulsivity, emotional dysregulation, reward sensitivity, and fear of missing out into a unified deep learning model, the present study seeks to address this gap and provide a more nuanced understanding of the determinants of internet addiction severity. This approach not only advances the methodological rigor of the field but also offers practical implications for the development of targeted interventions and prevention strategies.

Therefore, the aim of the present study is to model internet addiction severity using deep learning techniques by

examining the combined effects of impulsivity, emotional dysregulation, reward sensitivity, and fear of missing out.

2. Methods and Materials

2.1. Study Design and Participants

The present study employed a quantitative, cross-sectional design with a predictive modeling approach grounded in deep learning techniques. The target population consisted of university students in Mexico, selected due to their high exposure to digital environments and increased vulnerability to problematic internet use. A total of 412 participants were recruited from three major public universities located in Mexico City, Guadalajara, and Monterrey using a stratified convenience sampling method to ensure representation across academic disciplines and gender. Inclusion criteria required participants to be between 18 and 30 years of age, currently enrolled as full-time students, and regular users of the internet for at least two hours per day. Individuals with self-reported neurological disorders or current psychiatric treatment were excluded to control for confounding clinical effects. Prior to data collection, all participants provided informed consent, and the study protocol adhered to ethical standards for human subject research, including confidentiality and voluntary participation.

2.2. Measures

Data were collected using a structured battery of standardized psychometric instruments administered electronically through a secure online survey platform. Internet addiction severity was assessed using the Internet Addiction Test (IAT), a widely validated instrument that measures the extent of problematic internet use across multiple behavioral domains. Impulsivity was measured using the Barratt Impulsiveness Scale (BIS-11), capturing attentional, motor, and non-planning dimensions. Emotional dysregulation was evaluated using the Difficulties in Emotion Regulation Scale (DERS), which assesses multiple facets including emotional awareness, clarity, and impulse control under distress. Reward sensitivity was measured through the Behavioral Activation System (BAS) scale derived from the BIS/BAS framework, focusing on responsiveness to reward cues and approach motivation. Fear of Missing Out (FoMO) was assessed using the FoMO Scale, which evaluates apprehension about missing rewarding social experiences and its impact on online

engagement. All instruments demonstrated acceptable internal consistency in the current sample, with Cronbach's alpha coefficients exceeding 0.80. Demographic variables such as age, gender, academic field, and daily internet usage were also collected to serve as control variables in the modeling process.

2.3. Data analysis

Data analysis was conducted in two primary stages, combining traditional statistical preprocessing with advanced deep learning modeling. Initially, data were screened for missing values, outliers, and normality assumptions. Missing data were handled using multiple imputation techniques, and all variables were standardized to ensure compatibility with neural network input requirements. Correlation analysis and multicollinearity diagnostics were performed to examine relationships among predictors and ensure model stability. Subsequently, a deep neural network (DNN) model was developed to predict internet addiction severity as a continuous outcome variable. The architecture of the model consisted of an input layer corresponding to the predictor variables, multiple hidden layers with rectified linear unit (ReLU) activation functions, and an output layer with a linear activation function suitable for regression tasks. Dropout regularization and batch normalization were implemented to prevent overfitting and enhance generalization performance. The dataset was split into training (70%), validation (15%), and test (15%) subsets. Model performance was evaluated using mean squared error (MSE), root mean squared error (RMSE), and coefficient of determination (R^2). Hyperparameter tuning, including learning rate, number of neurons, and number of layers, was conducted using grid search optimization. All analyses were performed using Python programming language with libraries including TensorFlow, Keras, and Scikit-learn to ensure robust and reproducible computational procedures.

3. Findings and Results

The final sample consisted of 412 university students from Mexico, with a mean age of 22.47 years ($SD = 3.18$), ranging from 18 to 30 years. Of the participants, 226 (54.85%) were female and 186 (45.15%) were male. In terms of academic fields, 34.22% were enrolled in social sciences and humanities, 28.64% in engineering and technology, 21.36% in health sciences, and 15.78% in business and management programs. The average daily internet usage

reported by participants was 5.73 hours (SD = 2.41), with 61.17% of the sample indicating usage exceeding five hours per day. These characteristics confirm that the sample

represents a population with substantial exposure to digital environments, making it appropriate for examining internet addiction severity.

Table 1

Descriptive Statistics and Correlations Among Study Variables

Variable	Mean	SD	1	2	3	4	5
1. Internet Addiction Severity	49.82	11.36	1.00				
2. Impulsivity	63.47	9.28	0.54	1.00			
3. Emotional Dysregulation	89.15	13.74	0.61	0.48	1.00		
4. Reward Sensitivity	38.92	7.16	0.46	0.52	0.44	1.00	
5. Fear of Missing Out (FoMO)	27.83	6.91	0.67	0.49	0.58	0.51	1.00

Table 1 presents the descriptive statistics and Pearson correlation coefficients among the primary study variables. The results indicate that internet addiction severity had significant positive correlations with impulsivity ($r = 0.54$), emotional dysregulation ($r = 0.61$), reward sensitivity ($r = 0.46$), and fear of missing out ($r = 0.67$). Among the predictors, FoMO exhibited the strongest association with internet addiction severity, suggesting that individuals with higher concern about missing social experiences are more

prone to problematic internet use. Emotional dysregulation also showed a strong relationship, indicating that difficulties in managing emotions are closely linked with excessive internet engagement. Additionally, moderate intercorrelations were observed among the independent variables, with impulsivity and reward sensitivity ($r = 0.52$) and FoMO and emotional dysregulation ($r = 0.58$) showing notable associations, while remaining below critical multicollinearity thresholds.

Table 2

Deep Neural Network Model Performance Metrics

Metric	Training Set	Validation Set	Test Set
Mean Squared Error (MSE)	21.48	24.36	25.12
Root Mean Squared Error	4.64	4.94	5.01
R ²	0.72	0.69	0.68

The performance metrics of the deep neural network model are presented in Table 2. The model demonstrated strong predictive capability, with an R² value of 0.72 in the training set, 0.69 in the validation set, and 0.68 in the test set. The relatively small decline in performance across datasets indicates good generalization and minimal overfitting. The

root mean squared error (RMSE) values remained consistently low, further confirming the model’s accuracy in predicting internet addiction severity. These findings suggest that the selected psychological variables collectively provide substantial explanatory power when modeled using deep learning techniques.

Table 3

Relative Importance of Predictor Variables (Shapley Values)

Predictor Variable	Importance Score
Fear of Missing Out	0.31
Emotional Dysregulation	0.27
Impulsivity	0.22
Reward Sensitivity	0.20

Table 3 reports the relative importance of predictor variables based on Shapley value analysis. Fear of missing out emerged as the most influential predictor (0.31), followed by emotional dysregulation (0.27), impulsivity

(0.22), and reward sensitivity (0.20). This ranking indicates that while all variables contributed meaningfully to the model, FoMO and emotional dysregulation played a particularly critical role in determining internet addiction

severity. The relatively balanced distribution of importance scores also suggests that the model captures a

multidimensional psychological profile rather than relying on a single dominant factor.

Table 4

Hyperparameter Optimization Results

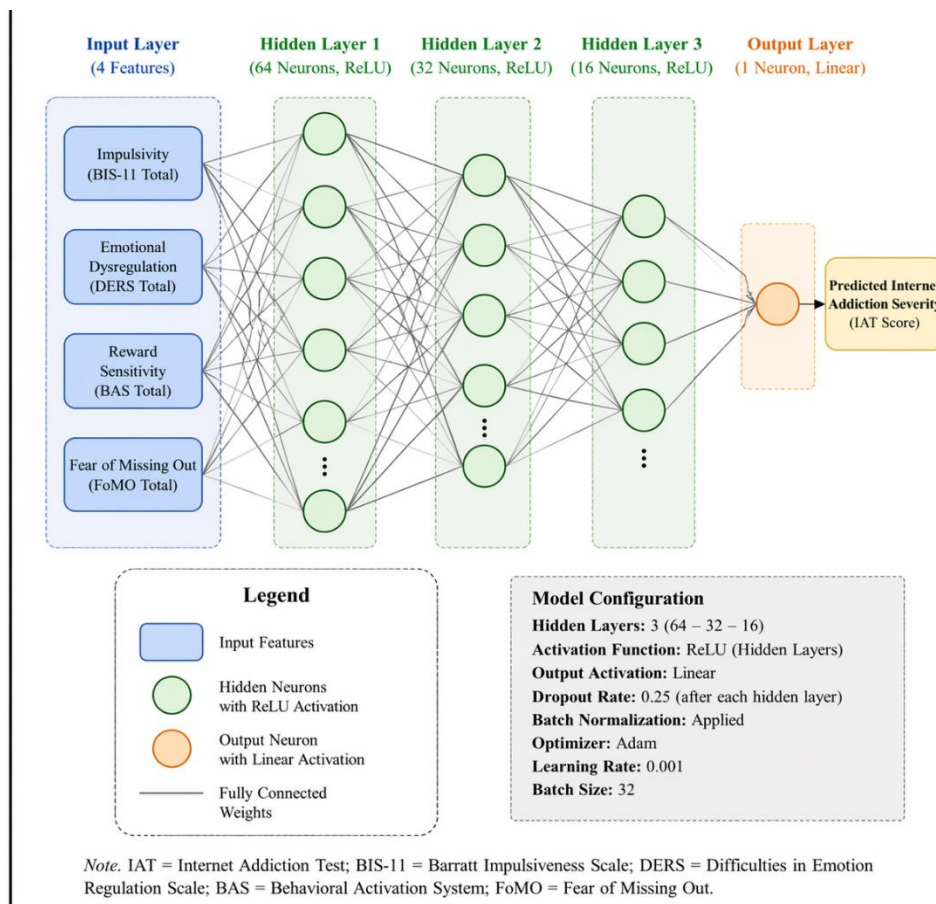
Parameter	Optimal Value
Number of Hidden Layers	3
Neurons per Layer	64–32–16
Learning Rate	0.001
Batch Size	32
Dropout Rate	0.25
Activation Function	ReLU

The results of hyperparameter optimization are presented in Table 4. The optimal model configuration included three hidden layers with decreasing neuron sizes (64–32–16), a learning rate of 0.001, and a batch size of 32. The application of a dropout rate of 0.25 contributed to reducing overfitting, while the use of the ReLU activation function facilitated

efficient gradient propagation. These parameters were selected based on grid search procedures that minimized validation error while maintaining computational efficiency, indicating a well-tuned deep learning architecture for the current dataset.

Figure 1

Deep Neural Network Architecture for Predicting Internet Addiction Severity



The figure illustrates the architecture of the deep neural network model used in this study, including the input layer

with four predictor variables, three hidden layers with nonlinear transformations, and a final output layer

generating continuous predictions of internet addiction severity. The layered structure demonstrates how psychological variables are progressively transformed into higher-level representations, enabling accurate prediction of the outcome variable.

4. Discussion

The present study aimed to model internet addiction severity using a deep learning framework by examining the combined effects of impulsivity, emotional dysregulation, reward sensitivity, and fear of missing out. The findings revealed that all four psychological variables were significantly associated with internet addiction severity, with fear of missing out emerging as the strongest predictor, followed by emotional dysregulation, impulsivity, and reward sensitivity. Furthermore, the deep neural network model demonstrated high predictive accuracy, with strong performance across training, validation, and test datasets, indicating robust generalizability and minimal overfitting. These findings provide empirical support for the multidimensional nature of internet addiction and underscore the value of integrating advanced computational approaches in behavioral research.

The strong association between fear of missing out and internet addiction severity is consistent with a growing body of literature emphasizing FoMO as a central driver of problematic technology use. Individuals experiencing heightened FoMO tend to engage in persistent online monitoring behaviors, driven by the need to remain socially connected and informed about others' activities. This pattern reinforces compulsive internet use and contributes to increased addiction severity (Elhai et al., 2021; Guan et al., 2023). The present findings align with previous studies demonstrating that FoMO not only predicts problematic smartphone and internet use but also mediates the relationship between negative emotional states and excessive online engagement (Servidio, 2021; Y. Wang et al., 2022). Additionally, neurocognitive evidence suggests that FoMO is associated with structural and functional alterations in brain regions linked to social cognition and reward processing, further explaining its strong predictive role (L. Wang et al., 2022). The prominence of FoMO in the current model highlights its importance as a key psychological mechanism underlying internet addiction.

Emotional dysregulation also emerged as a significant predictor of internet addiction severity, supporting the conceptualization of excessive internet use as a maladaptive

coping strategy. Individuals with difficulties in regulating emotions may rely on online environments to escape negative affect or to achieve temporary emotional relief. This interpretation is consistent with prior research indicating that emotional dysregulation is closely linked to problematic internet and social media use, often through its interaction with other psychological vulnerabilities (Ntumi et al., 2025; Quagliari et al., 2021). The current findings further corroborate evidence suggesting that individuals with poor emotional regulation skills are more susceptible to the reinforcing properties of digital platforms, which provide immediate but short-lived emotional rewards (Benedetto et al., 2024). Moreover, the interplay between emotional dysregulation and FoMO may create a feedback loop in which emotional distress increases online engagement, which in turn exacerbates emotional instability (Flack et al., 2024).

Impulsivity was found to have a moderate yet significant effect on internet addiction severity, consistent with its established role in behavioral addictions. Impulsive individuals are more likely to prioritize immediate gratification over long-term consequences, making them particularly vulnerable to the instant rewards offered by online platforms. This finding is in line with previous studies demonstrating that impulsivity is a key predictor of problematic gaming and internet use, reflecting deficits in inhibitory control and decision-making processes (Chang et al., 2021; Ünübol & Sayar, 2020). The digital environment, characterized by rapid feedback and continuous stimulation, may further amplify impulsive tendencies, leading to habitual and excessive use (Flayelle et al., 2023). Although impulsivity was not the strongest predictor in the model, its contribution remains substantial, particularly when considered in conjunction with other variables such as emotional dysregulation and reward sensitivity.

Reward sensitivity also contributed significantly to the prediction of internet addiction severity, highlighting the role of neurobehavioral reinforcement mechanisms. Individuals with heightened sensitivity to rewards are more likely to engage repeatedly in behaviors that provide positive reinforcement, such as receiving social validation or achieving in-game rewards. This finding aligns with neurophysiological research indicating that individuals with problematic smartphone use exhibit increased neural responses to reward-related stimuli (Deng et al., 2021). The reinforcing nature of digital platforms, which often employ variable reward schedules and personalized content, may further enhance this effect, promoting sustained engagement

and increasing the risk of addiction (Flayelle et al., 2023). The relatively balanced importance of reward sensitivity in the model suggests that while it is a critical factor, its influence operates in conjunction with broader emotional and cognitive processes.

The deep learning model employed in this study demonstrated strong predictive performance, indicating that the combination of psychological variables effectively explains variance in internet addiction severity. This finding supports the growing recognition of machine learning approaches as valuable tools for modeling complex psychological phenomena. Unlike traditional linear models, deep neural networks can capture nonlinear relationships and interactions among variables, providing a more comprehensive understanding of behavioral patterns (Wan, 2025; Wang & Shen, 2025). The use of explainability techniques, such as Shapley value analysis, further enhances the interpretability of these models, allowing researchers to identify the relative contributions of individual predictors. The current results align with emerging evidence suggesting that advanced computational methods can significantly improve the accuracy and utility of predictive models in behavioral addiction research (Ndayambaje & Udohchukwu, 2025; Totur et al., 2025).

The findings of this study also contribute to the broader theoretical understanding of internet addiction by integrating multiple psychological perspectives into a unified framework. The results support biopsychosocial models that emphasize the interaction between individual vulnerabilities, emotional processes, and environmental factors in the development of addictive behaviors (Chang et al., 2021). Furthermore, the significant role of FoMO and emotional dysregulation highlights the importance of affective and social-cognitive processes, complementing traditional models that focus primarily on behavioral reinforcement. These findings are consistent with recent reviews suggesting that internet addiction should be conceptualized as a multifactorial phenomenon involving cognitive, emotional, and neurobiological components (Li & Yang, 2024; Marano et al., 2025).

In addition to individual-level factors, the current findings should be interpreted in the context of evolving digital environments that increasingly promote continuous engagement. Technological design features, such as algorithm-driven content and social validation mechanisms, interact with user characteristics to create conditions conducive to addictive behaviors (Flayelle et al., 2023). The rise of short-form video platforms and highly immersive

social media environments further exacerbates this issue, as these platforms are specifically designed to capture and sustain user attention (arouch et al., 2025; Maghraoui & Khrouf, 2024). The integration of psychological and technological perspectives is therefore essential for developing comprehensive models of internet addiction.

5. Conclusion

Overall, the findings of this study underscore the importance of considering multiple psychological factors in understanding and predicting internet addiction severity. By employing a deep learning approach, the study provides a nuanced and empirically robust model that captures the complex interplay among impulsivity, emotional dysregulation, reward sensitivity, and fear of missing out. These insights have important implications for both theory and practice, particularly in the development of targeted interventions aimed at reducing problematic internet use.

6. Limitations & Suggestions

The study is subject to several limitations that should be acknowledged. First, the cross-sectional design precludes causal inferences regarding the relationships among variables, limiting the ability to determine the directionality of effects. Second, the reliance on self-report measures may introduce response biases, including social desirability and recall inaccuracies. Third, the sample was limited to university students in Mexico, which may affect the generalizability of the findings to other populations or cultural contexts. Additionally, although the deep learning model demonstrated strong performance, the complexity of such models may limit their interpretability compared to traditional statistical approaches. Finally, potential confounding variables, such as personality traits or environmental stressors, were not included in the model and may have influenced the results.

Future research should address these limitations by employing longitudinal designs to examine causal relationships and developmental trajectories of internet addiction. Expanding the sample to include diverse age groups and cultural contexts would enhance the generalizability of findings. Additionally, integrating objective behavioral data, such as digital usage logs, could complement self-report measures and improve measurement accuracy. Future studies may also explore additional psychological variables, including personality traits, cognitive biases, and social support, to further refine

predictive models. The application of hybrid modeling approaches that combine deep learning with traditional statistical techniques may provide a balance between predictive accuracy and interpretability. Furthermore, investigating intervention strategies informed by model outputs could contribute to the development of evidence-based prevention and treatment programs.

From a practical perspective, the findings highlight the need for targeted interventions that address the psychological mechanisms underlying internet addiction. Programs aimed at improving emotional regulation skills and reducing fear of missing out may be particularly effective in mitigating problematic internet use. Educational institutions can play a critical role by promoting digital literacy and encouraging balanced technology use among students. Mental health professionals should consider incorporating cognitive-behavioral and mindfulness-based approaches to enhance self-regulation and reduce reliance on digital coping strategies. Additionally, policymakers and technology developers should consider implementing design features that promote healthier usage patterns, such as usage reminders and reduced reliance on variable reward mechanisms.

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Declaration of Interest

The authors of this article declared no conflict of interest.

Ethical Considerations

The study protocol adhered to the principles outlined in the Helsinki Declaration, which provides guidelines for ethical research involving human participants.

Transparency of Data

In accordance with the principles of transparency and open research, we declare that all data and materials used in this study are available upon request.

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Authors' Contributions

All authors equally contributed in this article.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

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