JOURNAL OF SOCIAL COMPUTING
ISSN 2097-5015 07/07 pp359−377

Volume 6, Number 4, December 2025
DOI: 10.23919/JSC.2025.0020

Predicting Digital Addiction Patterns with Machine Learning for Personalised Mental Health Support

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Abstract: The exponential growth of social media has heightened concerns about digital addiction and its mental health consequences, particularly among younger populations. Existing digital health tools, including conversational agents and large language models, offer real-time support but often neglect the predictive value of structured behavioural data. This study introduces a machine learning framework to assess digital addiction risk using 3200 anonymised self-reports comprising screen time, social media engagement, sleep duration, and mental health indicators. Across multiple models, categorical boosting (CatBoost) achieves the highest performance (precision = 85.4%, receiver operating characteristic-area under the curve (ROC-AUC) = 0.93), outperforming extreme gradient boosting (XGBoost) and graph neural networks (GNN). A linear regression model provides interpretable correlations between behavioural variables and addiction risk. Structural equation modelling (SEM) reveals that anxiety and depression mediate the relationship between digital behaviours and addiction risk, offering causal insights into these pathways. Feature importance analysis identified excessive screen time, frequent social media checking, and reduced sleep as the most influential predictors. To translate findings into practice, K-means clustering generated behavioural risk profiles, enabling personalised, data-driven recommendations. While clinical validation remains a next step, this framework demonstrates how predictive modelling and clustering can inform scalable, non-invasive digital health interventions. By integrating machine learning with causal modelling and personalised intervention design, this study advances computational approaches to digital addiction and contributes to the broader discourse on artificial intelligence applications in mental health and social computing.

Key words: digital addiction; machine learning (ML); mental health; personalised recommendations; social media behaviour; predictive modelling; digital wellness

1 Introduction

Mental health is a cornerstone of overall well-being, significantly influencing how individuals think, feel, and function in their daily lives. It encompasses conditions ranging from anxiety and depression to complex

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Manuscript received: 2025-04-05; revised: 2025-08-31; accepted: 2025-09-08

disorders like schizophrenia and bipolar disorder[1]. The World Health Organisation (WHO) defines mental health as the capacity to cope with life's stresses, work productively, and contribute to society[2]. Despite its critical role, mental health challenges are pervasive, with nearly one in five adults experiencing a mental health disorder annually[3]. Addressing these challenges is vital for fostering individual resilience and societal well-being. Among these issues, addiction and dependence stand out for their complexity and profound impact, particularly as digital technology reshapes how people interact with the world[4]. The rise of digital platforms has revolutionised communication and entertainment, but also introduced new stressors. One of the most prominent of these stressors is digital addiction, a behavioural disorder characterised by excessive and compulsive use of digital platforms. This disorder is often marked by a loss of control, a preoccupation with online engagement, and continued use despite negative consequences in social, academic, or psychological domains[5]. Digital addiction goes beyond simply screen time; it encompasses a wider range of compulsive behaviours, including persistent checking, emotional dependency, and withdrawal symptoms when not using digital platforms.

Social media, initially designed to connect users, has been linked to increased anxiety, depression, and other mental health concerns[6]. Generation Z, those born between the mid-1990s and early 2010s, is particularly vulnerable to these effects due to their unprecedented digital exposure. Reports indicate that 95% of Gen Z own a smartphone, with many spending significant hours daily on social media[7]. This constant engagement fosters digital addiction, driven by features like algorithm-driven notifications and psychological rewards such as likes and shares[8, 9]. These behaviours, characterised by compulsive screen use and an overwhelming fear of missing out (FOMO), have significant implications for mental health.

Existing research underscores the dual-edged nature of technological progress but highlights critical gaps in predicting and mitigating digital addiction. Studies often fall short in capturing the behavioural patterns of younger generations or providing scalable, personalised interventions[10, 11]. Recent advances in mental health technology have seen the emergence of conversational agents, large language models (LLMs)[12], and virtual mental health assistants designed to deliver emotional support and cognitive interventions through natural language interaction. Platforms such as Woebot[13], Wysa[14], and Replika employ AI-driven dialogue systems to simulate therapeutic conversations[15], often using reinforcement learning and fine-tuned LLMs, e.g., generative pre-trained transformer (GPT), to detect emotional states and provide real-time coping strategies. Similarly, research in digital psychiatry has explored virtual companions and chat-based assessments that leverage language as a window into mental health conditions[16].

While these innovations represent valuable strides in AI-assisted mental health care, the work here addresses a complementary but distinct problem space. Rather than focusing on real-time conversational interaction, this study emphasises the early prediction of addiction and dependence patterns through structured digital behaviour metrics, such as screen time, social media engagement, and sleep duration. The selection of digital behaviour indicators was guided by their proven association with addictive digital behaviour and mental health outcomes. Previous studies have shown that prolonged screen exposure and frequent social media interaction correlate with anxiety, depression, and compulsive usage patterns[17, 18]. Likewise, sleep disruption has been consistently linked to digital overuse and psychological distress. These features are observable, quantifiable, and early indicators of dependency. The essence is to generate interpretable, personalised recommendations based on quantified behavioural signals without requiring user dialogue or linguistic input. This approach is especially relevant in low-resource environments, wellness platforms, or self-help applications where natural language processing infrastructure is limited or inappropriate. This research gap is particularly pressing, given the rapid evolution of social media platforms and their pervasive role in shaping daily life. Locally, the situation mirrors global trends, with young people reporting escalating mental health challenges linked to their digital habits.

Hence, the research is propelled by three pivotal questions. First, it examines how machine learning (ML) can predict patterns of addiction and dependence linked to digital behaviour. Second, it identifies key factors driving social media addiction, such as screen time, engagement patterns, and psychological triggers, to develop predictive and insightful models. Third, it evaluates personalised recommended support systems to mitigate the mental health impacts of digital addiction, emphasising the importance of actionable, tailored interventions. Consequently, this study aims to address these gaps by leveraging advanced ML techniques to predict patterns of digital addiction and its dependencies among Generation Z. This younger generation, particularly those within Generation Z, is disproportionately affected by digital dependency[19]. Their earlier exposure to technology, higher daily screen usage, and increased reliance on social validation through digital platforms significantly contribute to this vulnerability. Studies have shown that these demographic experience higher levels of anxiety, FOMO, and disrupted sleep due to their online habits[7]. As a result, Generation Z has been prioritised in this research to better understand emerging digital behaviours and to develop timely interventions aimed at addressing the mental health challenges linked to digital addiction.

Using algorithms such as extreme gradient boosting (XGBoost), categorical boosting (CatBoost), and graph neural networks (GNN), the research seeks to identify key drivers of social media addiction and evaluate the efficacy of cluster-driven personalised recommended support. These models are designed to provide actionable, tailored interventions that can mitigate the mental health impacts of digital behaviours. By addressing theoretical gaps and applying innovative ML methodologies, the study not only advances academic understanding but also provides practical tools for policymakers and mental health practitioners. These tools empower targeted interventions, foster healthier digital habits, and enhance societal well-being. Ultimately, this research contributes to a broader vision of sustainable digital engagement, where technology supports rather than undermines mental health. Section 2 presents theories of social media addiction along with related works. Section 3 outlines the methodology, followed by the results in Section 4. Key findings and discussions are covered in Section 5, with the conclusion summarised in Section 6.

2 Literature Review

2.1 Theories of social media addiction and mental health impact

Theories of social media addiction draw from a range of psychological and behavioural frameworks, each contributing a unique perspective on the underlying mechanisms of digital dependency. Behavioural Addiction Theory posits that social media addiction is similar to other behavioural addictions, such as gambling. The theory suggests that social media platforms activate the brain's reward system through variable rewards (e.g., likes and comments), leading to a reinforcement cycle that triggers compulsive use[20]. Social comparison theory emphasises that constant exposure to idealised images and lifestyles on social media can create feelings of inadequacy. This prompts users to engage more intensely with these platforms in an attempt to counteract negative emotions[21]. Self-determination theory further supports this by suggesting that social media satisfies unmet psychological needs for social connection, self-esteem, and competence, which can lead to dependence when these needs remain unfulfilled in real life[22]. FOMO theory highlights that the anxiety of missing important updates or social interactions drives excessive social media use. This fear leads to constant checking and engagement, reinforcing the behaviour[23, 24]. Additionally, attachment theory explains that individuals with insecure attachment styles may rely on social media for emotional validation, potentially leading to dependency on digital interactions for comfort[25].

These theories of social media addiction provide a framework for understanding how excessive usage patterns contribute to negative mental health outcomes, such as anxiety, depression, and diminished well-being. The mental health effects of prolonged screen time and social media usage (SMU) are significant and multifaceted. Extensive exposure to digital platforms has been linked to increased mental health issues, including anxiety, depression, and disrupted sleep patterns[26]. Social comparison on platforms exacerbates feelings of inadequacy and loneliness, particularly when users compare themselves to idealised versions of others. Excessive screen time also disrupts sleep, particularly due to blue light emitted by electronic devices, which suppresses melatonin production and alters circadian rhythms[27]. This can lead to poor sleep quality, reduced focus, and increased stress. Research shows that nighttime social media activity can be particularly harmful, as it heightens anxiety and exacerbates sleep issues, contributing to depressive symptoms and even suicidal thoughts[28]. Also, social comparison on social media can amplify feelings of exclusion and anxiety, particularly among adolescents and young adults[29].

While multiple theories offer valuable perspectives on digital behaviour, this study emphasises behavioural addiction theory and self-determination theory (SDT) as the core conceptual frameworks. These were selected for their comprehensive ability to explain both the reinforcement mechanisms driving compulsive digital use and the underlying psychological motivations that sustain it. Behavioural addiction theory accounts for observable patterns such as persistent engagement and withdrawal symptoms, while SDT addresses the internal frustrations of autonomy, competence, and relatedness that often lead users to seek gratification in digital environments. Other relevant theories, including social comparison theory, FOMO, and attachment theory, are retained in this study as supporting constructs. They offer insights into how emotional and cognitive triggers amplify addictive behaviours, but are considered subordinate to the two core frameworks for purposes of analytical clarity and theoretical focus. In Section 2.2, related works in detecting digital addiction are reviewed.

2.2 Technological advances in detecting digital addiction

Advances in technology, particularly through ML, have improved the clustering and detection of digital addiction and its associated mental health risks[30]. ML techniques, particularly those involving natural language processing (NLP), enable the analysis of large datasets, such as social media posts and health records, to extract insights about individuals' behaviours and mental health[31, 32]. For instance, Ref. [33] develops a neural network based mobile app to detect gaming addiction in children and adolescents using data from 101 participants, including usage patterns, gaming logs, and Chen Internet Addiction Scale responses. The model shows promising accuracy and potential for early, non-invasive intervention, though further validation, and model refinement are recommended.

Similarly, a recent study[34] was conducted in Republic of Korea, where smartphone ownership is nearly universal (95%) and generational gaps in usage are minimal, examined the rising trend of smartphone addiction among adolescents, particularly since the COVID-19 pandemic. Using data from the National Information Society Agency's Smartphone Overdependence Survey (2017–2021), the study applies eight machine learning and deep learning algorithms to predict high-risk groups. Among these, XGBoost achieves the highest precision at 87.6%. Notably, extended use of games, webtoons, and e-books emerges as significant predictors, factors less emphasised in earlier research. The findings highlight the potential of AI-driven approaches for early detection and prevention, emphasising the need for healthy, offline alternatives for youth engagement. No doubt, ML models can uncover complex patterns and relationships between social media usage and mental health, which may not be apparent through traditional analysis[35]. For example, GNNs can model interactions between users and the content they consume, shedding light on how social networks and content virality contribute to addiction[36].

In addition, these models are adaptable, providing personalised feedback based on real-time behavioural data, which are particularly useful for developing dynamic interventions[37]. ML's potential to create adaptive interventions is especially promising. For example, predictive models can identify moments of high emotional distress and trigger interventions to reduce screen time or encourage healthier online activities, addressing both the behavioural and emotional aspects of addiction[38]. Similarly, Ref. [39] demonstrates the feasibility of predicting depression using behavioural markers derived from smartphone sensor data. Analysing data from 629 participants over 22.1 days, the study finds a significant correlation between screen usage patterns and depression levels. Machine learning models achieve high accuracy (up to 98.14%) in detecting depressive symptoms, with screen time and internet use identified as key predictors. These findings suggest that smartphone data can effectively augment traditional depression assessments for early detection and ongoing monitoring.

Existing interventions for digital addiction, including cognitive-behavioural therapy (CBT), mindfulness practices, and digital detox initiatives, provide some relief but are often limited in effectiveness. CBT, while helpful for many addictive behaviours, does not always translate well to digital contexts, as it fails to address the unique triggers of social media addiction, such as exposure to social comparison or the algorithmic design of platforms[40]. With different social media comments having an undertone of emotion, Ref. [41] explores the limitations of existing mental health prediction models that lack emotional attention mechanisms, emphasising the need for approaches that capture contextual and emotional nuances. Using advanced embedding techniques, the authors proposed a contextual emotional transformer-based model (CETM) to enhance predictive accuracy. Also, digital detox programs, though popular, are criticised for being impractical in an interconnected world. Many users find it difficult to completely detach from digital environments due to their professional, academic, and social integration[42].

Furthermore, these interventions tend to overlook the emotional, social, and cognitive factors driving digital behaviours, making them less effective for a wide range of individuals[43]. Emerging technologies, such as apps that track screen time, offer some promise in managing addiction. However, these tools often focus only on surface-level metrics, like time spent on devices, without considering the psychological and emotional factors that underlie specific digital behaviours. This highlights a significant gap in current interventions: the need for more personalised, dynamic solutions that account for emotional and cognitive impacts.

2.3 LLMs and conversational AIs in digital addiction management

LLM and conversational AIs are increasingly recognised for their possible roles in addressing digital addiction, particularly as virtual mental health assistants that can promote the use of healthier technology. Reference [44] analyses the integration of AI tools in mental health care, suggesting that these technologies can offer personalised interventions for people fighting excessive digital commitment. Similarly, Ref. [45] highlights the use of LLM to mitigate the problematic use of social networks among students, indicating a promising way to reduce digital addiction through personalised interaction and support. Reference [46] articulates the duality of the benefits and risks associated with the LLM in mental health interventions, and emphasises the need for careful implementation to maximise the advantages while minimising possible damage. These challenges underline the importance of developing conversation agents with explanation and security in mind, as discussed by Ref. [47]. They identify significant ways for improvement that can improve the effectiveness and acceptance of AI mental health support systems.

Subsequently, Ref. [48] presents a framework for adaptive personality to conversational AI, suggesting that LLMs can be finely tuned to individual personality features, which increases their effectiveness in therapeutic contexts. This adaptability is aligned with the vision proposed by Ref. [49] for the development and responsible evaluation of AI in the medical care of behaviour, urging researchers and professionals to create ethical guidelines. To advance in the state of the mental health dialogue backed by AI, Ref. [50] contributes to the field when entering Counsellme, a set of data designed to compare the performance of the LLM against human interactions. This initiative can further refine the ability of conversation agents to support people in the navigation of their digital behaviours, ultimately promoting the healthiest technology use patterns.

2.4 Personalised decision support systems (PDSS) in mental health

A major gap in digital addiction research is the lack of personalised and precision-based interventions. Most current solutions assume that all users experience addiction in the same way, but digital addiction is highly individualised. People engage with digital platforms differently based on their personality traits, mental health status, and social context[51]. As a result, interventions that apply the same strategy for everyone are often ineffective. Personalisation is crucial for the long-term success of digital addiction treatments. Predictive models that account for an individual's habits, emotional states, and interactions with digital content could lead to more tailored and sustainable outcomes[52]. Moving beyond simply tracking time spent online, these models would integrate emotional and cognitive data to address both the symptoms and root causes of addiction.

PDSS are increasingly used in mental health care to tailor interventions to the specific needs of patients, improving treatment outcomes. These systems leverage AI and machine learning to analyse patient data and provide real-time recommendations[53, 54]. PDSS can assist clinicians in making informed decisions, offering adaptive support, identifying risks early, and delivering customised care for conditions like depression and anxiety[55]. However, even these systems often lack the real-time adaptability required to address the evolving nature of digital addiction. Recent advances, such as using deep learning for dementia screening[56], highlight the potential of ML-driven systems to improve clinical outcomes. However, most existing systems do not yet offer the level of personalisation needed to address the complex, individualised nature of digital addiction. As presented in Section 3, the need for advanced machine learning models and continuous monitoring is clear, as they offer the potential to create truly personalised interventions that can address both the immediate and long-term effects of digital addiction.

3 Methodology

In an era where digital behaviours significantly impact mental health, understanding patterns of addiction and dependence has become crucial. This study focuses on the relationship between social media usage, screen time, and mental health, particularly within Generation Z. To address the growing need for effective tools to predict and manage digital addiction, the research employs advanced machine learning algorithms to analyse complex data and derive actionable insights. The methodology centres on three state-of-the-art models: XGBoost, CatBoost, and GNN, chosen for their ability to handle high-dimensional data, robust predictive performance, and capacity to capture complex behavioural patterns. The following sections outline the data collection, processing, feature engineering, and model development processes, demonstrating how these algorithms contribute to achieving the study's objectives. By integrating these methodologies, the study offers personalised recommended support systems to improve mental health outcomes through targeted interventions.

3.1 Dataset overview

The dataset consists of 3200 anonymous records of self-reported surveys. The survey instrument captured digital behaviour, lifestyle factors, and mental health indicators. Mental health was assessed using validated scales: the PHQ-9 for depression[57] and the GAD-7 for anxiety[58]. Behavioural measures were adapted from established instruments used in digital addiction research, notably those by Ref. [59], ensuring consistency with prior studies. Participants provided data on their social media usage, mental health symptoms (e.g., anxiety, depression, and stress), and demographic information. The survey captured information on physical activity levels, sleep patterns, and social interaction metrics. Brief descriptions of these sampled fields are provided below:

(1) Screen time (hours/day): Average number of hours spent on social media per day.

(2) Social media engagement (checks/day): Number of times that participants check their social media accounts per day.

(3) Sleep duration (hours/night): Average number of hours per night.

(4) Physical activity (steps/day): Average number of steps taken per day, reflecting physical activity levels.

(5) Anxiety level: Score from the generalised anxiety disorder 7-item (GAD-7) scale measuring anxiety levels.

(6) Depression level: Score from the patient health questionnaire 9-item (PHQ-9) scale measuring depression levels.

(7) Stress level: Self-reported stress level on a scale from 1 to 10.

(8) Social interaction (hours/week): Average number of hours spent in face-to-face social interactions per week.

(9) Likes (likes/day): Average number of likes that participants give to posts on social media per day.

(10) Comments (comments/day): Average number of comments that participants make on social media posts per day.

(11) Shares (shares/day): Average number of times participants share posts on social media per day.

(12) Demographic information: Includes age and gender.

Here, standardised mental health assessments, such as the GAD-7 and PHQ-9, are included not as diagnostic tools but as self-reported indicators to provide psychological context to users' digital behaviour. The inclusion of these features supports a more holistic understanding of how patterns of screen time and social media engagement may interact with mental well-being, particularly in non-clinical or pre-clinical populations. This approach reflects the intended use case: digital health and wellness platforms, where individuals voluntarily log their behavioural and emotional experiences.

Importantly, the system is not designed to replace clinical diagnosis, nor does it prioritise digital addiction over clinically diagnosed conditions, such as depression or anxiety. Instead, it complements early detection and behavioural support by identifying individuals who may be at risk of developing unhealthy digital habits alongside emerging psychological symptoms. In settings where formal clinical assessments are available, these would naturally take precedence; however, in digitally mediated wellness environments, the model's purpose is to guide proactive, personalised interventions before issues escalate to clinical severity.

3.2 Dataset preprocessing and feature engineering

The first step is data cleaning, which addresses inconsistencies and missing values. Numerical features, such as screen time and physical activity, are imputed using the mean, ensuring the imputed values represent the distribution. Categorical features, like social media platform types and interaction frequencies, are imputed using the mode to preserve the categorical distribution. Outliers, identified with z-scores (value exceeding ±3 standard deviation), are removed to prevent distortion and ensure the accuracy of subsequent analyses.

After data cleaning, normalisation and scaling are applied to ensure comparability of numerical features. Min-max scaling is used to transform values to a range of 0 to 1, preventing features with larger ranges from disproportionately influencing the results. Here, feature engineering followed, focusing on three key areas:

(1) Behavioural features: Indicators of digital engagement, such as average screen time, frequency of social media checks, and interactions (likes, comments, and shares).

(2) Mental health features: Scores from the GAD-7 and PHQ-9 assessments, providing insights into anxiety, depression, and mental well-being.

(3) Lifestyle features: Data on physical activity (steps/day), sleep quality, and face-to-face interactions, contextualising the impact of digital behaviours on daily life.

These engineered features form the basis for applying machine learning models, enabling more accurate predictions of digital addiction and dependence.

3.3 Machine learning model

To predict addiction and dependence patterns effectively while creating personalised recommended support mechanisms, this study employs three advanced machine learning algorithms: XGBoost, CatBoost, and GNN. Each of these models is selected for its distinct strengths in handling the complexity and high-dimensional nature of the dataset. Sections 3.3.1 to 3.3.3 detail the development process for each model, highlighting their unique methodologies, hyperparameters, and fine-tuning approaches.

3.3.1 XGBoost

XGBoost is used to leverage its powerful ensemble learning capabilities for handling high-dimensional data. The performance of XGBoost hinges on fine-tuning key hyperparameters. Initially set at 100, the number of trees (n_estimators) is optimised to 150, balancing complexity and performance. The learning rate is adjusted from 0.10 to 0.06 to enhance accuracy while minimising overfitting. Increasing the maximum tree depth (max_depth) from 6 to 8 allows the model to capture more complex patterns. To prevent overfitting, subsample and colsample_bytree are both set to 0.8, ensuring variability and robustness by using a fraction of samples and features for each tree. Grid search is used for hyperparameter optimisation, resulting in a configuration that provided the best balance of bias and variance.

3.3.2 CatBoost

CatBoost is selected for its efficiency in handling categorical features directly, which is particularly advantageous given the nature of our dataset. Its performance is fine-tuned by adjusting key hyperparameters. The number of boosting iterations (iterations) is reduced from 1000 to 500, improving efficiency without sacrificing accuracy. The learning rate is adjusted from 0.03 to 0.02 for better generalisation. Tree depth (depth) increases from 6 to 7 to capture more complex patterns, while l2_leaf_reg is optimised from 3 to 5 to minimise overfitting. Then, border_count is increased from 32 to 64, enhancing the model's ability to identify detailed patterns in numerical features. Here, Bayesian optimisation is used to refine these hyperparameters, resulting in an optimal configuration that maximises the model's effectiveness.

3.3.3 GNN

GNNs, as introduced by Ref. [60] are utilised to model the complex relationships and interactions within the data. The GNN is selected due to its ability to capture relational patterns among users by leveraging graph-structured data, making it especially effective in behaviour prediction tasks. Data are structured as graphs where nodes represent individual users, and edges capture interactions or behavioural similarities, such as comparable screen time usage, frequency of social media interactions, and proximity in mental health scores. Node features include behavioural metrics, mental health indicators, and lifestyle factors, like screen time, number of daily checks, anxiety (GAD-7), depression (PHQ-9), sleep hours, physical activity, and social interaction metrics. The GNN model architecture comprises multiple graph convolutional network (GCN) layers followed by a dense layer for classification. This design enables the model to aggregate and transform information from neighbouring nodes, capturing relational patterns effectively.

Training the GNN involves the Adam optimiser with a learning rate of 0.001 and a weight decay of 5×10^{-4}. The GNN model is enhanced by increasing hidden units in the GCN layers from 64 to 128, improving its capacity to learn complex features. The dropout rate is adjusted from 0.5 to 0.4 to reduce overfitting, while the learning rate is fine-tuned from 0.0010 to 0.0005 for better convergence. These optimal settings are identified using Bayesian optimisation, resulting in superior predictive performance. Each algorithm is tailored to leverage its strengths, resulting in a comprehensive analysis of addiction and dependence patterns and contributing to the development of effective, personalised recommendation-support mechanisms. The integration of these advanced algorithms allows for actionable recommendations tailored to individual risk profiles. In addition to predictive modelling, structural equation modelling (SEM) is employed to examine the causal relationships between digital behaviour, sleep patterns, and mental health indicators. SEM enables the modelling of both direct and indirect effects, offering insights into how behavioural patterns influence psychological outcomes.

To account for potential confounding effects, demographic variables (age and gender) and lifestyle indicators (physical activity levels and sleep duration) are included in the SEM as control variables. Multicollinearity diagnostics (assessed using the variance inflation factor (VIF) are performed before estimation, confirming no significant collinearity among the predictors (all VIF < 3). This ensures that the observed relationships between digital behaviour, mental health indicators, and addiction risk reflect robust pathways rather than spurious associations. The model is estimated using maximum likelihood estimation in Python with the semopy library. Model fit is evaluated using standard indices, including root mean square error of approximation (RMSEA), comparative fit index (CFI), and standardised root mean square residual (SRMR). This system not only provides valuable insights into addiction and dependence patterns, but also enables targeted interventions designed to address specific needs. Generally, the methodological framework of this study demonstrates a commitment to leveraging cutting-edge machine-learning techniques to enhance mental health interventions. The outcome is a set of powerful tools that offer a deeper understanding of addiction behaviours and provide meaningful, personalised support mechanisms to improve mental health outcomes, which is discussed in Section 4 below.

4 Result and Evaluation

The results and evaluation section examines the findings from machine learning models, XGBoost, CatBoost, and GNN, applied to a dataset of 3200 samples to predict addiction and dependence patterns. First, linear regression is introduced to provide interpretability and serve as a baseline reference point**,** contrasting the performance of more complex algorithms like CatBoost and GNN. The inclusion demonstrates the direct, linear relationships among key features and addiction risk while reinforcing the value added by non-linear, multi-dimensional models. Later, this section evaluates how well XGBoost, CatBoost, and GNN identify behavioural patterns linked to addiction, assess feature importance, and evaluate the impact of personalised recommended support on user behaviour and mental health. The discussion covers model performance, key predictive features, and interventions supported by case studies demonstrating the practical success of the implemented recommendations.

4.1 Linear regression baseline analysis

To enhance model interpretability and provide a transparent baseline for comparison, a linear regression model is developed using three core features: screen time (hours/day), social media engagement (checks/day), and sleep duration (hours/night). These variables are selected based on their strong behavioural relevance to digital addiction and dependence.

The linear regression analysis reveals the following:

(1) Screen time: Positively associated with addiction risk score ($\beta = 0.42$, $p < 0.001$)

(2) Social media engagement: Positively associated with addiction risk ($\beta = 0.31$, $p < 0.001$)

(3) Sleep duration: Negatively associated with addiction risk ($\beta = -0.29$, $p < 0.001$)

The model achieves an R^2 value of 0.62, indicating that these three variables collectively explain 62% of the variance in addiction risk scores. While the linear model provides a strong starting point, it could not capture non-linear interactions and contextual factors captured by more advanced models, such as CatBoost and GNN. This regression serves as a valuable benchmark, confirming the direct correlation between behavioural patterns and addiction risk, and justifying their inclusion in more complex machine learning models.

4.2 Results for machine learning algorithm

The effectiveness of the machine learning models in predicting addiction and dependence patterns is evaluated using a comprehensive set of performance metrics. Each model is assessed on various metrics, including accuracy, precision, recall, F1-score, and receiver operating characteristic-area under the curve (ROC-AUC), as defined below, to determine their predictive capabilities and performance.

(1) Accuracy: This measures the proportion of correctly classified instances out of the total instances.

(2) Precision: This represents the ratio of true positive predictions (correctly identified risk cases) to the total number of positive predictions made by the model (both true positives and false positives).

(3) Recall: This indicates the ratio of true positive predictions to the total number of actual positives in the dataset (both identified and missed).

(4) F1-score: This is the harmonic mean of precision and recall, providing a single metric to assess the balance between them.

(5) ROC-AUC: It measures the area under the receiver operating characteristic curve, which plots the true positive rate (recall) against the false positive rate at various threshold settings

Table 1 presents the performance metrics for the three machine learning algorithms evaluated in this research: XGBoost, CatBoost, and GNN. The metrics provide insights into how well each model performed in predicting addiction and dependence patterns and guide the selection of the most effective algorithm for personalised recommended support systems.

First, accuracy measures the correctness of the model in classifying addiction and dependence cases. Among the models, CatBoost achieves the highest accuracy at 87.1%, outperforming XGBoost at 85.3% and GNN at 83.9%. This indicates that CatBoost is the most reliable in making correct predictions across all instances. Then, precision, which evaluates the ratio of true positive predictions to the total number of positive predictions made, shows CatBoost leading

Table 1 Performance metrics for ML models.

Algorithm	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	ROC-AUC
XGBoost	84.3	82.5	88.2	85.3	0.91
CatBoost	87.1	85.4	89.1	87.2	0.93
GNN	83.9	80.3	85.0	82.6	0.89

with a score of 85.4%. This result highlights CatBoost's strength in minimising false positives when predicting high-risk cases. Recall, reflecting the model's ability to identify all actual positives in the dataset, is highest for CatBoost at 89.1%. This metric is essential for ensuring that the model detects most of the true risk cases, minimising the number of false negatives. A high recall score indicates that CatBoost effectively identifies nearly all individuals at risk of addiction, which is vital for timely and appropriate interventions.

The F1-score, which balances precision and recall into a single metric, was also highest for CatBoost at 87.2%. This metric provides a comprehensive measure of model performance by combining the effectiveness of both precision and recall. CatBoost's superior F1-score underscores its balanced approach, achieving high accuracy in identifying high-risk cases while minimising both false positives and false negatives. Later, ROC-AUC, measuring the model's ability to distinguish between users at risk of addiction and those who are not, is highest for CatBoost, with a score of 0.93. This score reflects the model's strong discriminative ability across different classification thresholds. A higher ROC-AUC indicates that CatBoost is most effective at separating positive from negative cases, which is crucial for developing a robust and reliable recommended support system. In all, CatBoost consistently outperforms XGBoost and GNN across all performance metrics, accuracy, precision, recall, F1-score, and ROC-AUC. These results highlight CatBoost's effectiveness in predicting addiction and dependence patterns, making it the most suitable model for creating personalised and actionable recommended support mechanisms in this research. Hence, evaluations in Sections 4.4–4.6 are based on CatBoost's algorithm.

4.3 Structural equation modelling result

To address concerns regarding causal interpretation, a SEM approach is implemented. This model aims to evaluate the direct and indirect relationships between digital behaviour (screen time, social media use, and sleep duration) and mental health indicators (GAD-7 and PHQ-9 scores), as well as addiction risk levels. The SEM model reveals that both screen time and frequency of social media checks have significant positive effects on GAD-7 and PHQ-9 scores, while reduces sleep duration negatively affected mental health. Furthermore, both anxiety and depression scores show strong predictive power for addiction risk. These findings support the hypothesis that mental health mediates the relationship between digital behaviours and addiction outcomes. The SEM model thus provides a structured, theory-driven framework for understanding these interactions and reinforces the importance of integrating mental health screening into digital behaviour monitoring, as presented in Table 2.

The model demonstrates an acceptable fit to the data, as indicated by standard SEM fit indices: RMSEA = 0.045, CFI = 0.963, and SRMR = 0.041. These values fall within commonly accepted thresholds (RMSEA < 0.06, CFI > 0.95, and SRMR < 0.08), suggesting that the model adequately represents the observed relationships among the variables. The SEM analysis provides evidence for both direct and indirect relationships between digital behaviour and addiction risk. Higher screen time and more frequent social media checks are significantly associated with increased anxiety (GAD-7) and depression (PHQ-9) scores. Conversely, longer sleep duration is associated with lower levels of both anxiety and depression.

Importantly, both anxiety and depression scores are significant predictors of digital addiction risk. This suggests that mental health acts as a mediator, linking behavioural patterns (like screen time and sleep) to the likelihood of developing addictive or dependent digital behaviours. The model highlights a clear psychological pathway: compulsive digital use, which leads to impaired mental health, ultimately increasing the risk of addiction. These findings underscore the need to monitor not just behaviour, but the mental health context in which it occurs, reinforcing the importance of integrated, personalised interventions.

Table 2 SEM path coefficients and model fit indices.

Path	Coefficient β	Significance
GAD-7 predicted by screen time	0.42	$p < 0.01$
GAD-7 predicted by social media checks	0.39	$p < 0.01$
PHQ-9 predicted by screen time	0.36	$p < 0.05$
PHQ-9 predicted by social media checks	0.33	$p < 0.05$
GAD-7 predicted by sleep hours	−0.30	$p < 0.05$
PHQ-9 predicted by sleep hours	−0.27	$p < 0.05$
Addiction risk predicted by GAD-7	0.44	$p < 0.01$
Addiction risk predicted by PHQ-9	0.47	$p < 0.01$

4.4 Behavioural pattern insights

4.4.1 Identified patterns

The analysis of addiction and dependence patterns uncover key digital behaviours associated with increased addiction risk. The following patterns are identified through the machine learning models:

(1) High screen time: Users with daily screen time exceeding four hours are consistently classified as high-risk for addiction, with corresponding disruptions in physical activity and social interactions.

(2) Frequent social media checks: Individuals checking social media more than 20 times per day display compulsive behaviours linked to higher levels of anxiety and stress, thereby increasing addiction risk.

(3) Compulsive interaction patterns: High engagement in liking, commenting, and sharing leads to a dependency cycle, where the need for immediate gratification increases screen time and reduces real-world social interactions.

(4) Sleep deprivation: Users with less than six hours of sleep per night exhibit compulsive social media behaviours. This extended screen time exacerbates sleep deprivation, further reinforcing digital dependence.

A summary of the addiction of dependencies pattern is presented in Table 3, the distribution of daily screen check in Fig. 1 and the average frequency of social media checks in Fig. 2. These patterns provide critical insights into the behavioural markers of digital addiction, which can inform future predictive models and interventions.

In Fig. 1, a histogram showing the distribution of daily screen time across all users and highlighting the proportion of users falling into the high, moderate, and low screen time categories is presented.

4.4.2 Behavioural trends

Behavioural trends encompass various aspects of digital engagement, including fluctuations in screen time, variations in social media usage, and shifts in interaction patterns over time. This study has identified significant trends that provide a picture of how persistent and evolving digital behaviours impact mental health.

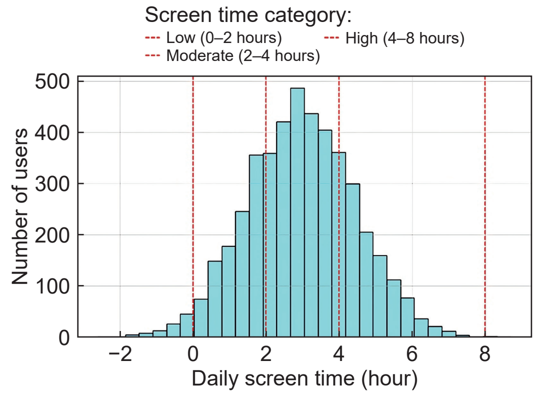

Fig. 1 Distribution of daily screen time across all users.

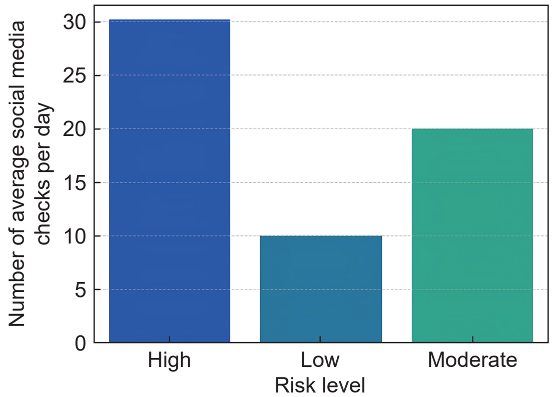

Fig. 2 Average frequency of social media checks by risk level.

In particular, the analysis covers:

(1) Temporal trends in screen time: Examining how average daily screen time changes across different times of day, week, and month, and its impact on addiction risk.

(2) Patterns of social media use: Analysing how variations in the frequency and timing of social media checks influence mental health indicators.

(3) Engagement trends: Investigating how changes in the intensity and type of social media interactions (likes, comments, and shares) correlate

Table 3 Summary of addiction and dependence pattern.

Pattern	Description	Percentage of users (%)
High screen time	Daily screen time exceeding 4 hours	35
Frequent social media check	More than 20 checks per day	40
Compulsive interaction	Excessive liking, commenting, sharing	25
Sleep deprivation	Less than 6 hours of sleep per night	30

with addiction and dependence.

These behavioural trends in Tables 4–6 not only highlight the persistence and variability of digital habits, but also shed light on how these habits evolve and affect mental health. By understanding these trends, we can better inform personalised interventions and support mechanisms aimed at reducing addiction risks and improving mental well-being.

Then, Table 7 presents the relationship between sleep duration and average daily screen time, highlighting how digital engagement patterns correlate with sleep habits. By analysing user data, users are categorised based on their sleep duration and corresponding screen time usage, offering insights into the percentage of users affected in each category. This correlation provides valuable context for understanding the interplay between excessive screen time and its impact on sleep hygiene, a critical factor in assessing addiction risk and overall well-being.

4.5 Feature importance

As part of the model evaluation, feature importance is assessed to identify the key drivers of addiction and dependence predictions. The following features emerge as critical predictors:

(1) Time spent on apps: Prolonged screen time is the most significant predictor, with each additional hour of daily use increasing the risk score.

(2) Engagement frequency: A higher frequency of social media interactions (likes, comments, and shares) is correlated with increased addiction risk and mental health issues.

(3) Sleep duration: Less than six hours of sleep per night significantly raises addiction risk, emphasising the interplay between digital behaviours and physical health.

(4) Mental health indicators: Elevated levels of stress, anxiety, and depression are strongly predictive of higher addiction risk, confirming the relationship between mental health and addictive behaviours.

These insights in Table 8 highlight the key factors influencing addiction and dependence, informing the development of more targeted interventions and predictive models.

By elucidating the importance of these features, valuable insights are gained into the key drivers of addiction and dependence. Understanding these factors allows for more targeted and effective interventions, providing a foundation for personalised recommended support mechanisms that address specific risk factors and promote healthier digital habits.

4.6 Recommended interventions as support mechanisms

The effectiveness of personalised decision support recommendations is a critical measure of the system's

Table 4 Temporal trends in screen time.

Time period	Average daily screen time (hour)	User percentage (%)
Morning (6 AM –12 PM)	1.5	25
Afternoon (12 PM –6 PM)	2.8	35
Evening (6 PM –12 AM)	4.2	30
Late night (12 AM –6 AM)	2.0	10

Table 5 Social media usage pattern.

Usage frequency	Percentage of users (%)	Average daily screen time (hour)	Average number of social media checks per day
Low (0–15 checks)	45	2.0	8
Moderate (16–30 checks)	30	3.5	15
High (>30 checks)	25	4.8	25

Table 6 Engagement trend.

Engagement level	Percentage of users (%)	Average daily screen time (hour)	Average engagement actions per day
Low (1–5 actions)	40	2.2	3
Moderate (6–15 actions)	35	3.4	10
High (>15 actions)	25	4.6	20

Table 7 Sleep duration and screen time correlation.

Sleep duration (hour)	Average daily screen time (hour)	User percentage (%)
< 6	4.5	30
6–7	3.0	40
> 7	2.2	30

Table 8 Feature importance score.

Feature	Importance score	Description
Time spent on apps	0.35	Strongly correlates with addiction risk
Engagement frequency (Number of checks per day)	0.30	Significant predictor of compulsive behaviour
Sleep duration	0.20	Indicates overall well-being and risk level
Mental health indicator	0.15	Reflects relationship between mental health and addiction

success in addressing addiction and dependence related to digital behaviours. This section focuses on translating addiction risk assessment scores into actionable and personalised recommendations aimed at improving mental health outcomes. By integrating data on screen time, social media engagement, sleep patterns, and mental health indicators, targeted strategies that address the specific needs of individuals at varying levels of addiction risk are engendered. The increasing prevalence of digital addiction underscores the importance of personalised interventions. Generic recommendations often fail to account for individual behaviour and mental health, leading to suboptimal outcomes. To address this, the research approach utilises a data-driven framework that aligns intervention strategies with the risk levels identified through the CatBoost model. User risk levels are determined using K-means clustering algorithms, categorising individuals into low, moderate, and high-risk groups based on behavioural patterns. Targeted interventions are designed for each group, addressing key factors such as screen time, social media engagement, and sleep duration.

In addition, activities and mental health support are tailored to each risk level to ensure that the interventions are both relevant and effective. Table 9 outlines recommended interventions based on addiction risk assessment scores and serves as a guide for implementing personalised strategies designed to manage and mitigate addiction risks effectively. The risk classifications (low, moderate, high, and very high) are determined through probability thresholds derived from model outputs, particularly from CatBoost, XGBoost, and GNN classification scores. Each risk level is mapped to behavioural profiles using a combination of:

Feature importance analysis: Using built-in model interpretability tools, key predictors, such as time spent on the app, screen time, number of daily social media checks, and sleep duration, are identified. These features directly influence the grouping into risk categories.

Behavioural trends in dataset: Users with very high screen time (> 6 hours/day), excessive engagement (> 35 checks/day), and poor sleep (< 4 hours) consistently fall into the higher risk categories. These patterns inform the thresholds used in the recommendation structure.

Literature-based guidelines: To ensure relevance and theoretical grounding, risk categories are mapped to behavioural interventions, supported by digital wellness and psychological literature. For instance, mindfulness exercises are recommended for moderate-risk users[59, 60], while digital detox programs and psychiatric support are proposed for very high-risk users[61].

Each recommendation is crafted to align with the identified risk level, ensuring that users receive support tailored to their unique needs and challenges.

It is important to note that the recommendations in Table 8 are proposed, not experimentally validated. They are based on predictive modelling and behavioural theory but have not yet been tested in a clinical or controlled setting. These interventions serve as conceptual outputs intended to guide future implementation. At the same time, they represent an evidence-driven framework with translational potential, enabling clinicians, educators, and digital health practitioners to identify at-risk individuals earlier and tailor interventions to behavioural and psychological profiles. Future work will focus on validating these recommendations in clinical and real-world settings to establish their practical efficacy.

Table 9 Recommended intervention based on user addiction risk assessment.

Addiction risk level	Observed behaviour pattern	Screen time limit (hours/day)	Social media engagement (checks/day)	Sleep duration (hours/night)	Recommended activitie	Mental health support
Low risk	Balanced digital use, low anxiety, depression scores	Maxium 4	<10	>8	Regular physical activity	Periodic check-ins
Moderate risk	Moderate screen time, signs of stress, reduced sleep	Maxium 3	>15	6–7	Mindfulness & exercises	Counselling sessions
High risk	Extended screen use, social withdrawal, disturbed sleep	Minimum 4	>35	4–5	Structured daily routines, physical exercise, regular digital detox periods	Intensive therapy
Very high risk	Excessive use (⩾6 hours), compulsive checking, sleep duration <5 hours	Minimum 6	>60	<4	Comprehensive digital detox programs, intensive hobbies, scheduled offline activities	Psychiatric evaluation

5 Key Finding and Discussion

The addiction risk assessment model developed in this study provides personalised interventions to individuals based on key behavioural factors, including screen time, social media engagement, and sleep duration per cluster. By utilising a combination of machine learning algorithms and clustering techniques, the model classifies users into distinct risk levels, enabling tailored recommendations to mitigate the impact of addictive digital behaviours and improve mental health outcomes. With the model classifying individuals into varying levels of addiction risk based on a combination of screen time, social media engagement, and sleep duration, these behavioural metrics are identified as crucial indicators of addiction risk, with higher levels of screen time and social media engagement, along with inadequate sleep, correlating strongly with an increased likelihood of dependence. For instance, screen time emerges as one of the most influential factors in addiction prediction. Individuals spending more than four hours daily on digital devices are consistently categorised into the high-risk group. Similarly, social media engagement, measured by the frequency of interactions, such as likes, shares, and comments, shows a direct correlation with increased addiction risk. Frequent engagement, especially when exceeding 30 social media interactions per day, is a clear indicator of compulsive behaviour. In addition, sleep duration plays a significant role, with individuals who sleep less than six hours per night exhibiting a heightened risk of addiction, likely due to the reinforcing cycle between late-night screen use and sleep deprivation.

The findings align with and extend existing research linking excessive screen time and social media engagement to increased risks of anxiety and depression. Earlier works, including Refs. [62, 63], identified psychological consequences of digital overuse. Recent studies have further substantiated these effects in diverse populations. For example, Ref. [64] finds that prolonged device use among 3307 Chinese adolescents significantly correlates with anxiety and depression, with sleep duration as a mediating factor. Similarly, Ref. [65] reports longitudinal associations between screen time and mental health symptoms in over 4000 adolescents. These studies reinforce the importance of sleep and digital behaviour in youth mental health. The present study contributes a hybrid framework by combining machine learning predictions, clustering-based personalisation, and SEM to move beyond associations. This integrative approach enables the translation of behavioural risk patterns into tailored mental health interventions, enhancing the state of the art in digital dependency research.

To ensure the interventions are tailored and relevant to each user's unique habits, the clustering process, using K-means, identifies groups of users with similar characteristics in terms of screen time, social media engagement, and sleep. By clustering users based on these features, the model is able to generate personalised risk profiles, allowing for more targeted interventions. For example, one cluster includes individuals with high screen time, frequent social media interactions, and poor sleep habits, placing them in the high-risk category. For this group, interventions focus on reducing screen time, promoting better sleep hygiene, and offering mental health support. Conversely, individuals in a lower-risk cluster, those with moderate screen time and good sleep habits, only require periodic check-ins and recommendations for maintaining their healthy habits.

5.1 Theoretical discussion

From a theoretical perspective, the research supports existing theories on the relationship between digital behaviour and mental health. The findings align with the social comparison theory, which posits that frequent social media use can lead to negative self-perception and increased anxiety. In addition, the research highlights the cyclical nature of digital dependency, where excessive engagement exacerbates mental health issues, confirming the addiction model's emphasis on the reinforcing cycle of digital behaviour. The theoretical integration of feature importance in predicting addiction underscores the multifaceted nature of digital dependency, combining behavioural, mental health, and lifestyle factors.

5.2 Managerial discussion

For managers and digital health practitioners, the research underscores the importance of implementing personalised digital wellness interventions. By tailoring recommendations based on addiction risk levels, organisations can develop targeted strategies that effectively address individual needs. Managers should focus on integrating real-time monitoring tools and personalised feedback systems into their digital platforms to promote healthier user behaviours. The use of predictive models to identify at-risk individuals can guide the development of proactive interventions, such as digital detox programs and mindfulness exercises, enhancing user well-being.

5.3 Clinical discussion

The outputs generated by this model offer meaningful clinical value by functioning as early warning indicators and decision support tools, rather than diagnostic endpoints. For clinicians, the ability to view behavioural data, such as screen time, social media interaction frequency, and sleep duration through the lens of structured risk categories, provides a non-invasive method for identifying individuals who may be developing digital dependence or exhibiting behaviours linked to underlying psychological distress. These features serve as digital phenotypes, a concept increasingly recognised in digital psychiatry, where patterns in digital behaviour are used to infer potential mental health risks and monitor changes over time. For example, excessive screen time or erratic usage patterns may reflect avoidance coping, emotional dysregulation, or early signs of anxiety and depression, constructs already well-established in psychiatric assessment frameworks. Translating these subjective digital behaviours into quantifiable risk profiles allows clinicians to prioritise patients for further evaluation, recommend early interventions, or complement ongoing therapeutic work. By aligning machine learning outputs with familiar psychiatric dimensions, such as compulsivity, withdrawal, and disrupted circadian rhythms, the system bridges the gap between digital lifestyle patterns and clinical decision-making.

5.4 Policy and practical implications

The study's findings also have practical implications for policy development. Policymakers could use these insights to formulate guidelines that encourage responsible digital usage and support mental health. Public health initiatives could benefit from incorporating personalised recommendations into digital health programs, promoting balanced screen time and fostering environments that mitigate the risks associated with excessive digital engagement. Finally, the research highlights the effectiveness of predicting and providing personalised recommendations in managing digital addiction and dependence, providing a comprehensive approach that combines theoretical insights with practical applications for improving mental health outcomes.

6 Conclusion

In the rapidly evolving digital landscape, where screens dominate daily life, the challenge of managing digital addiction and its impact on mental health has never been more pressing. This study offers a personalised roadmap for navigating these complexities by highlighting key behavioural markers (excessive screen time, compulsive social media use, and reduced sleep) as strong predictors of digital addiction and mental health risk. While these relationships remain correlational, they reflect well-established psychological indicators; establishing causality will require longitudinal tracking and more robust inference methods.

Beyond confirming known associations between screen time, social media engagement, and mental health outcomes, this study contributes uniquely to the literature in three ways. First, it integrates machine learning algorithms with SEM, linking predictive accuracy with causal pathways. Second, it applies clustering to generate personalised intervention categories, translating behavioural data into actionable recommendations. Third, it focuses on younger populations, offering new insights into digital dependency patterns in a demographic particularly vulnerable to technology-related mental health challenges. Together, these elements extend existing work by moving from descriptive analysis toward personalised, data-driven decision support.

By leveraging advanced machine learning algorithms, XGBoost, CatBoost, and GNN, this research not only illuminates patterns of digital dependence, but also proposes targeted, individual-level interventions. These recommendations aim not simply to reduce screen time but to foster more meaningful engagement with both digital and real-world activities. In doing so, the study provides a foundation for digital health practitioners and policymakers to design data-driven, empathetic interventions that encourage balanced emotional and mental well-being.

Looking ahead, future research should focus on validating and refining these recommendations through longitudinal studies and larger-scale trials. Examining long-term effects, assessing applicability across diverse populations, and integrating real-time feedback mechanisms will be essential. Furthermore, exploring causal pathways through methods such as time-series modelling, mediation analysis, and counterfactual approaches could deepen our understanding of how digital behaviours influence mental health outcomes. Such advances will strengthen the basis for clinically validated, personalised interventions.

Acknowledgment

The authors would like to express their sincere gratitude to the PRAILAB members for their invaluable support and collaboration throughout this research. Their expertise and insights significantly contributed to the success of this study.

Conflict of Interest

The authors declare no conflict of interest.

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