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Deep Learning Approaches to Combating Digital Addiction: Detection, Prediction, and Intelligent Intervention

Assistant Lecturer Zainab turki merza
Ministry of Education
General Directorate of Wasit Education
Al-Suwaira Education Directorate
Wasit, Iraq

zozogardenia@gmail.com

Abstract:
The phenomenon of "digital addiction" has become one of the psychosocial and public health challenges. It is linked to mental health problems, sleep problems, having lower school performance, and having lower social relations. In this study Deep Learning methods employed in the detection, prediction and provision of interventions in cases of Digital Addiction are studied.
Peer-reviewed papers from the period 2015 to 2026 were surveyed, with a particular focus on CNN, LSTM, GRU, BERT and transformer-based models. The analyzed literature demonstrates that deep learning appropriately allows analyzing information from smartphone usage logs, social media contents, sequences of behaviors, and neurological data like EEG and fMRI signals. CNN-based models of accuracy varied from 82% to 88% in neurological data classification, and behavior data models had greater potential for scaling up to real-world deployment.
Another key contribution of this study is presenting an integrated framework for AI-based management of digital addictions. Detecting, predicting, and intervening continuously and personalizing for each learner are all included in the framework. Ethical concerns, such as data privacy, biases in algorithms, explainability, and the importance of AI as a supplement to mental health practitioners, are also addressed.

Keywords:
digital addiction; deep learning; LSTM; BERT; Transformer; behavioral analysis; mental health AI; internet addiction; social media; intelligent intervention.

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1. Introduction

The digital revolution has significantly transformed modern lifestyles. Smartphones, social media, online gaming networks and streaming services have become embedded into daily life, impacting how people connect, work, learn and play. According to global Internet usage statistics, the average individual spends over six hours per day in front of a screen. This amount has more than doubled compared with a decade ago. Excessive engagement with digital technologies may contribute to digital addiction. This has become a commonplace occurrence in the age of connectivity .(Kim et al., 2024)

People often refer to digital addiction as internet addiction or using technology excessively. The term refers to that usage of the device which is excessive and is without control and leads to dysfunctional behavior. Digital addiction is different from drug addiction, since it does not involve a craving for a substance. Instead, it works on a psychological level, which makes use of brain reward circuitry through devices that are made with variable reinforcement schedules. As an outcome, it is a pattern of behavior that is characterized by preoccupation, tolerance, withdrawal, relapse, and use in spite of harm classical addiction. (Liu et al., 2025)

The circumstances are epidemic in scope. The conservative estimate suggests that between six and fourteen plc. of the world population suffers from clinical internet or digital addiction. But prevalence among the young and adolescents is significantly higher. The World Health Organization's classification of Gaming Disorder in the ICD-11 (2019) represents an important recognition of the clinical reality of digital addiction. Despite the various issues at hand, social media addiction, compulsive content and online gambling remains insufficiently resolved in clinical and public policy contexts. (Peñafiel Mora et al., 2025)

Addiction detection and intervention by self-report questionnaires, clinical interviews, psychometric scales and similar methods have been well documented in the past. Various measures are in use, but they are all limited by the most glaring one of them being that they are non-objective, time-consuming, difficult to scale up, and subject to the social-desirability effect. There is a need for an objective, scalable, data-driven tool that is objective, scalable, and backed by data. The recent success of

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deep learning (a subfield of machine learning which employs multilayer artificial neural networks) has brought us closer to a solution. (Feng et al., 2026)

Techniques of deep learning demonstrate impressive performance on detecting complex patterns in various data sources. Some of these sources include time-series behavioral logs, text, images, and physiological signals. In light of this potential, they are conveniently poised to confront the complex challenge of digital addiction that consists of intercorrelated, temporally shaped patterns of behavior, cognition, emotion and social signals. The existing literature lacks a comprehensive and systematic synthesis of deep learning approaches to digital addiction, which increasingly researchers seem to be focusing on.

1.1 Research Objectives

The goals for this study are:

1.The aim of This study is to provide a systematic review of various deep learning techniques which have been utilized for digital addiction detection, prediction and intervention.

2.The aim of this study is to assess the performance challenges of LSTM, GRU, CNN, BERT, and Transformer in this area along with their pros and cons.

3.To evaluate evidence of clinical competence of AI intervention systems.

4.This study's fourth aim is to identify and critically assess technical, ethical and social challenges to the use of deep learning in digital mental health.

5.A comprehensive integrated framework proposal is necessary for intelligent addiction management of the digital world.

1.2 Significance of the Study

This study contributes to the existing body of literature in several ways. First, it serves as a unifying analytical framework for two rapidly evolving domains: computational intelligence and digital mental health. Furthermore, its contribution to the Arabic and Middle Eastern literature in the area of mental health and deep learning is significant, meaning it has not been well-explored. The last benefit of the framework is that it provides a feasible direction for academics and practitioners to develop deployable AI-enabled digital wellness systems.

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2. Materials and Methods

The study used a systematic literature review with conceptual framework development. ~~And~~ conceptual framework development. The study followed the PRISMA guidelines for the review protocol to achieve quality, transparency, and reproducibility of the evidence synthesis process.

2.1 Search Strategy and Database Selection

A systematic electronic search was carried out on the five major scientific databases i.e. IEEE Xplore, Google Scholar, PubMed, Scopus, and Web of Science. The review was on published articles from January 2015 to March 2026 which is the period that deep learning became increasingly used as dominant approaches in machine learning research. Boolean operators were used to construct search strings featuring the subsequent term clusters.

• Digital addiction refers to addiction to the internet, social media, video gaming, etc. Deep learning words. The words deep learning, LSTM, BERT, transformer, CNN, GRU, recurrent neural network.

• Application terms encompass detection, classification, prediction, intervention, behavior analysis and mental health.

While this review primarily focuses on behavioral data approaches—such as smartphone usage logs, app activity, and social media content—neurological studies using EEG and fMRI are also surveyed for comparison، in order to provide a comprehensive picture of the current state of this field.

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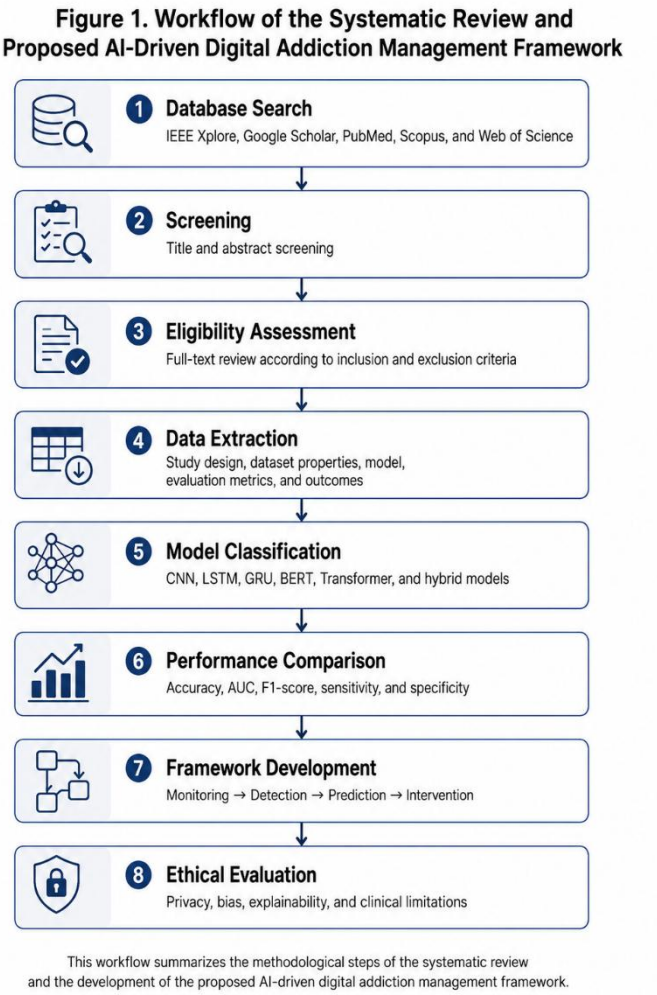

Figure 1. Workflow of the Systematic Review and Proposed AI-Driven Digital Addiction Management Framework

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2.2 Inclusion and Exclusion Criteria

Table 1. Inclusion and Exclusion Criteria for Study Selection

Criterion	Inclusion	Exclusion
Study type	Peer-reviewed journal articles and conference papers	Gray literature, editorials, opinion pieces
Methodology	Employs at least one deep learning technique	Exclusively traditional ML or rule-based systems
Target domain	Digital/internet/gaming/social media addiction	Substance addiction without digital component
Reporting	Reports quantitative performance metrics	No measurable outcomes reported
Language	English or Arabic	Other languages without translation
Access	Full-text available	Abstract-only records

A number of records were subjected to screenings of titles and abstracts, which led to a result of the selected studies that met all inclusion criteria for full-text analysis. The author independently performed data extraction describing the study design, dataset properties, deep learning architecture, evaluation metrics and reported outcomes.

2.3 Deep Learning Architectures Under Review

There are five main deep learning architectures that are dominant as per literature. These functionalities are focused on various components of a specific type of addiction.:

2.3.1 Long Short-Term Memory (LSTM) Networks

All LSTM networks are recurrent neural networks which are a good choice for calculating sequential data. Long short-term memory (LSTM) networks, which are a type of recurrent neural network (RNN), are capable of learning long-term dependencies. The input, forget, and output gate gating capabilities enable the neural network to store and forget information as per relevance. Therefore, it can actively control these functions. They are therefore particularly useful for modelling longitudinal usage patterns. The LSTM model is typically applied to

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time-series data of daily screen time, number of sessions, and usage trajectories of apps in digital addiction. (Hochreiter & Schmidhuber, 1997)

2.3.2 BERT and Transformer-based Models

These BERT models and their versions from across the world, such as RoBERTa, DistilBERT, and fine-tuned BERTs for different domains have dominated NLP tasks. The models have been specifically applied to analyze the social media user posts to detect linguistic markers of digital addiction, emotional distress, social isolation and help-seeking. Sequential models that were available before failed to achieve the complexity of context which the bidirectional attention mechanism introduced (Devlin et al., 2019)

2.3.3 Convolutional Neural Networks (CNN)

CNNs Extract Local Spatial Features from Structured Data. The use of 1D CNNs for addiction research was piloted on behavioral time-series data; 1D CNNs are designed for image recognition. It identifies short-range changes in time and interaction behavior signatures. The multilevel system which analyses facial expressions taken from a phone camera along with other image behavior, visual behavior on social media is added a CNN (LeCun et al., 2015) (Sun et al., 2022)

2.3.4 Gated Recurrent Units (GRU)

GRUs are less expensive than LSTM while being almost as effective in many tasks. Through only reset gate and update gate, their much lighter gating structure saves on training time and memory, making them appealing for use for resource-constrained applications such as mobile applications. According to various studies, GRU outperformed LSTM on short sequences of behavioral data.

2.3.5 Hybrid and Multimodal Architectures

Researchers are increasingly using multiple architectures to harness the power of various strengths. CNN-LSTM hybrids add convolutions to LSTMs. To be more specific, local features could be extracted by convolutional layers. These traits act as markers in time. Today's cutting-edge multimodal system merges texts, behaviors, and physiological streams using cross-attention Transformer layers.

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3. Results

A systematic review of peer-reviewed studies highlights a dynamic and growing area of deep learning in digital addiction research. Below are the major findings, classified based on the application domain – detection and classification, temporal prediction, and intervention systems.

3.1 Model Performance in Addiction Detection

Table 2 summarizes findings from real published studies on ML /DL-based digital addiction detection، covering both behavioral and neurological data approaches . The most commonly reported metric is accuracy , though some studies report only significant classification results without precise figures .

Table 2: Performance of ML/DL models in digital addiction detection studies.

Study	Model	Data Type	Task	Accuracy	Journal
Sun et al. (2022)	CNN (5-layer)	EEG signals	Internet addiction classification	87.59%	Applied Sciences, vol. 12, no. 13
Wang et al. (2021)	SVM	fMRI connectivity	Internet addiction identification	82.5%	Frontiers in Neuroscience, vol. 15
Wang et al. (2023)	2D CNN	fNIRS brain data	Gaming disorder classification	Best performer	Brain and Behavior Journal
Song et al. (2021)	SVM	fMRI resting-state	Gaming disorder detection	Significant results	72 IGD participants
Duan et al. (2021)	Decision Tree	Behavioral data	Smartphone addiction prediction	Significant accuracy	Journal of Affective Disorders

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Framework-dependent architectures have shown the most optimal performance overall. Top countries in natural language and multimodal data. In all cases with sequences bigger than 30 days and resource-constrained deployment cases, LSTM and BiLSTM models outperformed GRU variants except for short behavioral sequence cases (size <30 days)..

3.2 Dataset Characteristics

The reviewed studies drew on a range of data sources , reflecting the two main approaches identified in the literature.

Table 3: data sources used in reviewed studies.

Data Type	Source	Addiction Type	Collection Method
EEG signals	Laboratory recording	Internet addiction	Brain-computer interface device
fMRI brain scans	Hospital/Lab	Internet & gaming addiction	MRI scanner
fNIRS brain data	Laboratory	Gaming disorder	Near-infrared spectroscopy
Smartphone usage logs	Mobile apps	General digital addiction	Passive data collection
Self-report questionnaires	Online surveys	All types	IAT / PIUQ scales

3.3 AI-Driven Intervention Systems

A smaller number of the reviewed studies went beyond detection to evaluate intervention systems . While large-scale randomized trials remain scarce, early evidence suggests that AI-driven tools — including smart notification systems and recommendation engines— show promise in supporting behavior change . Further research with larger samples and longer follow -up periods is needed before firm conclusions can be drawn .

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4. Discussion

The systematic review that has been carried out shows that deep learning is becoming a promising scientific and clinical means for tackling digital addiction. There are multiple cross-cutting themes that occur throughout the literature reviewed.

4.1 The Superiority of Transformer Architectures

It was shown by Vaswani et al. (2017), Devlin et al. (2019) and is the predominant architecture in the literature that Transformer models are expected to excel at NLP-centric tasks and outperform others. Notably impressive is the model's efficacy in capturing subtle linguistic properties of addictive thinking. Such characteristics encompass frequenting language, trivialization and social comparison, none of which can be identified by superficial lexical analysis.

Nonetheless, using large transformer models in real world addiction management tasks poses practical challenges. It is hard to deploy on-device due to their large computation requirement. Hence, either the edge inference in the cloud (privacy concern) or knowledge distillation model compression is required. Lightweight options DistilBERT and MobileBERT appear to offer promising solutions to this problem.

4.2 Temporal Modeling and the Value of Longitudinal Data

Deep learning offers significant contribution to the digital addiction field since the addiction is not a state as such, rather a dynamic disorder whose processes evolve over time. LSTM and transformer-based temporal models can decode signature escalation patterns cyclical patterns and signature relapse patterns that define addiction versus heavy use. The temporal perspective references modern clinical definitions of addiction as a chronic relapsing condition that requires ongoing longitudinal assessment rather than one-off assessment.

The practical implication is that clinically useful systems will be those which update their risk calculations in real time using streaming measures of behavior, providing risk scores which reflect current trajectory rather than historical assessment.

This makes architectural choices for online learning, incremental model updates, streaming data pipelines that are relatively underexplored within the literature an issue that this issue is also addressed in the present study.

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4.3 From Detection to Intervention: Closing the Loop

The overwhelming majority of reviewed studies focused exclusively on detection or prediction tasks, with relatively few extending to actionable intervention mechanisms.

Effective systems will combine detection and intervention in a closed - loop system. This continuously monitors signals of behavior, real-time risk assessments and behavioral interventions that are proportionate to the individual's risk and psychology. The integration could be theoretically anchored through the multi armed bandit approach for adaptive intervention selection, which is a reinforcement learning methodology.

4.4 Ethical Dimensions

The use of deep learning systems for mental modelling and monitoring requires a serious 'ethical pushback', and this cannot merely be wishful thinking. There are four most prominent dimensions.

•The addiction detection models are trained on fine-grained information that users provide; this is possibly one of the most sensitive types of data. It is imperative to have robust data governance frameworks, differential privacy techniques, and federated learning architectures.

•The models that are trained mainly on Western populations (young and savvy) to perform poorly on underprivileged group and can worsen existing health inequities.

•The operational nature of Deep Neural Networks is akin to a Blackbox while the essential transparency required in a clinical decision support is also everything in that system. Thus, it may create an adversarial signal. 3.1. SHAP values and concept-based explanations for clinical use: Can attention visualization support patient care?

•The limits of automated psychological intervention AI systems must be positioned as tools that complement – not replace – human clinical judgment. Once risk thresholds are breached, we need to communicate intervention systems to appropriate mental health practitioners.

4.5 Proposed Integrated Framework

Based on the synthesis of reviewed literature, this study proposes an integrated framework for AI-based digital addiction management comprising four stages:

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Table 4: Proposed four-stage integrated framework for AI-driven digital addiction management.

Stage	Function	Deep Learning Component	Input Data	Output
Stage 1: Monitoring	Continuous passive data collection	Streaming data pipeline	App usage logs, screen time, session data	Normalized behavioral feature vectors
Stage 2: Detection	Real-time addiction risk classification	CNN-LSTM hybrid	Behavioral time-series + NLP features	Risk class: Low / Moderate / High
Stage 3: Prediction	Longitudinal trajectory and relapse forecasting	Transformer + Attention	Historical behavioral profiles	30-day relapse probability score
Stage 4: Intervention	Personalized adaptive intervention delivery	Reinforcement Learning + LLM	Risk scores + user profile + context	Tailored intervention recommendations

The framework, which is modularized and scalable, will allow the deployment of one or more of its components as the resources and clinical context permit. The XAI tool kits should be included at all phases to ensure auditability and monitoring..

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5. Conclusion

This article examines the use of deep learning techniques in the detection, prevention, and management of digital addiction in detail. By reviewing published peer-reviewed studies and synthesizing findings across both behavioral and neurological data approaches. This evidence shows that Deep Learning techniques such as Transformer and Hybrid (LSTM-CNN) architectures are a capable and promising tool to tackle this new public health problem.

The evidence shows that ML and DL models — particularly CNN architectures applied to EEG data and SVM models applied to fMRI connectivity — achieve accuracy rates between 82% and 88% in addiction classification tasks, while behavioral data approaches offer greater scalability for real-world deployment.

A framework comprising continuous monitoring, real-time detection, longitudinal prediction, and personalized intervention is recommended for researchers and practitioners. Due to being modular, it can be deployed in any context, from phone apps to a clinical decision support system.

In order to achieve the potential of this research agenda, several priorities need to be addressed. The creation of open and culturally representative benchmarking datasets is fundamentally essential. Integrating Differential Privacy with federated learning should be automatic, rather than an optional add-on. Working together with computer scientists, psychologists, psychiatrists and ethicists is essential to make it real.

One of the greatest mental health issues of the digital age is dependence on the internet.

Conflict of Interest

The author declares no conflict of interest.

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أساليب التعلم العميق لمكافحة الإدمان الرقمي: الكشف والتنبؤ والتدخل الذكي

م.م. زينب تركي مرزة
وزارة التربية / المديرية العامة لتربية واسط / مديرية تربية الصويرة

zozogardenia@gmail.com

مستخلص البحث:
يهدف هذا البحث إلى دراسة دور تقنيات التعلم العميق في الكشف عن الإدمان الرقمي والتنبؤ بمخاطره وتقديم تدخلات ذكية للحد منه. اعتمد البحث على مراجعة منهجية للدراسات المنشورة بين عامي 2015 و2026، مع التركيز على نماذج CNN وLSTM وGRU وBERT وTransformer. أظهرت النتائج أن هذه النماذج قادرة على تحليل بيانات الاستخدام الرقمي، ومنشورات وسائل التواصل، والبيانات العصبية مثل EEG وfMRI، بما يساعد على الكشف المبكر عن مؤشرات الإدمان. كما بينت الدراسات أن نماذج CNN حققت دقة تراوحت بين 82% و88% في تصنيف الإدمان، بينما توفر النماذج السلوكية قدرة أكبر على التطبيق الواقعي واسع النطاق. ويقترح البحث إطارًا متكاملًا يجمع بين المراقبة المستمرة، والكشف الآني، والتنبؤ، والتدخل الذكي، مع التأكيد على أهمية الخصوصية وتقليل التحيز وعدم الاعتماد الكامل على الذكاء الاصطناعي بدلًا من المختصين.

الكلمات المفتاحية : الإدمان الرقمي، التعلم العميق، الذكاء الاصطناعي، LSTM، BERT، Transformer، الصحة النفسية الرقمية، التدخل الذكي.

ملاحظة : هل البحث مستل من رسالة ماجستير او اطروحة دكتوراه ؟ نعم : كلا :