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"Usage to Addiction": Prediction of Smartphone Addiction using Transformer-based Deep Learning Models

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***Abstract*—Smartphone have become a vital part of modern life. They are affecting almost every aspect of our daily routines. They are essential in areas like education, business, and entertainment. Smartphone are valuable tools for learning, communicating, and relaxing. However, increased dependence on them has sparked serious concerns about smartphone addiction, which can harm mental health, lower productivity, and weaken social ties. This study aims to create a method for predicting smartphone addiction using Transformer-based deep learning models. Unlike older machine learning techniques, Transformers are good at managing time-series and sequential data. They can recognize long-term patterns through self-attention mechanisms. The proposed method involves collecting or simulating smartphone usage data. Then process it into sequential inputs. Train a classification model to predict the likelihood of addiction, which is categorized as Addicted or Not Addicted. The main aim of this study is to develop a smart software system that can analyze user behavior and also detect early signs of addiction. By providing timely insights, this system can serve as a preventive tool. It can help users track their habits, promote self-awareness, and encourage a healthier, more mindful relationship with technology.**

***Keywords*— Transformer, smart software system, classification model, Time Series, Informer, behavior.**

I. Introduction

Smartphones have changed how people interact, learn, and do business. They are now a part of daily life, offering unmatched convenience and connection. Despite their positive effects on education, business, and entertainment, concerns are growing worldwide about the negative consequences of excessive smartphone use. One major issue is smartphone addiction, which has become a serious behavioral and public health problem. This addiction involves compulsive and uncontrolled usage patterns that hurt mental health, productivity, sleep quality, and social relationships [1]. Traditionally, identifying and predicting addiction relied on simple measures like total screen time or self-report surveys. These methods offer basic insights, but they fail to capture the complex and sequential behaviors that result in addiction. Recent breakthroughs in artificial intelligence, especially deep learning, have opened new paths for understanding how people use their smartphones. They use time-series data and self-attention mechanisms to do this.

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By looking at factors like screen time, how often users unlock their phones, app-switching habits, and response times to notifications, these models can predict addiction risks more accurately and intervene sooner than traditional methods.

This review paper summarizes recent research on predicting smartphone addiction, with a focus on Transformer-based deep learning frameworks. It looks at how digital footprints and behavioral data can be used to improve addiction detection and prevention. The goal is to bridge the gap between traditional methods and advanced intelligent systems. Ultimately, the paper seeks to provide insights that help develop tools and strategies for promoting healthier, more mindful digital habits in a world increasingly influenced by smartphone technology.

This project proposes a deep learning framework grounded in Transformer architectures. Transformers are particularly well-suited for this task because of their ability to capture both short-term variations and long-term dependencies in sequential data. By leveraging these strengths, the project aims to move beyond static aggregates and towards a richer, more accurate modeling of behavioral patterns associated with smartphone addiction. Comparative analyses with alternative models may also be conducted to establish the robustness and effectiveness of the proposed approach. Ultimately, the objective is not only to predict smartphone addiction but also to contribute toward early detection and provide a foundation for future intervention strategies that can promote healthier digital habits.

The rapid proliferation of smart-phones has led to widespread concerns about problematic smartphone use (PSU) and smartphone addiction, which negatively impact mental health, sleep quality, productivity, and social relationships. Existing studies primarily rely on psychometric questionnaires such as the Smartphone Addiction Scale (SAS/SAS-SV) to classify users, and employ classical machine learning techniques such as Decision Trees, Random Forests, or Support Vector Machines on aggregated features like total screen time or app usage duration. While these approaches have shown reasonable predictive performance (accuracy in the range of 75 83%), they are limited in two key aspects:

- Static Aggregation of Features: Most prior models treat smartphone usage as static daily or weekly aggregates, ignoring the temporal dynamics (e.g., bursts of late-night activity, frequent app switching, irregular notification response patterns) that are critical indicators of addictive behavior.
- Limited Model Expressiveness: Ensemble methods and shallow classifiers struggle to capture complex, contextual, and sequential dependencies in user behavior, leading to underestimation of addiction risk in real world scenarios. Given these gaps, there is a need for models that can represent and learn from fine-grained temporal sequences of smartphone interactions rather than coarse usage summaries. Transformer-based deep learning architectures, with their self-attention mechanism, provide a promising solution by enabling the model to attend to both short term and long-term dependencies in behavioral sequences. Therefore, the problem addressed in this study is to develop an effective deep learning framework for predicting smartphone addiction by leveraging Transformer-based models on sequential usage data (e.g., unlock events, app-category dwell time, app-switch patterns, notification response latency)and to benchmark its performance against traditional approach

It highlights the significance of secure data storage, network security, and identity management in cloud systems and examines important security concerns such as data breaches, unauthorized access, and insider violations.

Section 2 surveys the literature on our project Section 3 defines deep learning architecture and transformer models.

II. Literature Survey

Predicting smartphone addiction is a major focus of behavioral informatics and mobile health research. As cell phones become more integrated into daily life, it’s important to spot problematic usage habits early to prevent negative impacts on social relationships, productivity, and mental health. Researchers have recently examined both deep learning and traditional machine learning methods to identify and classify behaviors related to addiction based on smartphone interaction data.

Chandra, M. A et al. discussed SVM development, kernel selection, parameter optimization, and advanced variants that improve classification accuracy and machine learning performance. [2] In this study, some key methods for classifying images are discussed. SVM is the most well-known method for machine learning. The Support Vector Machine (SVM) has become a highly effective classification paradigm. The best mathematical model for regression and classification is SVM.

Jang et al. (2021) conducted a large study that collected data from over 27,000 Korean users. They combined behavioral metrics such as screen time, notification checks, and app categories with demographic factors to train several machine learning models, including Random Forest, XGBoost, and Decision Trees. The Random Forest model, achieving an accuracy of 82.6%, significantly outperforming the Decision Tree model's 74.6% is so far observed the best model. Notably, static demographic features like age, gender, and profession did not greatly affect prediction accuracy. In contrast, how often users interacted with their phones and the patterns of app usage over time were stronger indicators of addiction risk. [3]

Giraldo-Jiménez et al. (2022) utilized Random Forest, Logistic Regression, and Support Vector Machines (SVM) with data from 1,228 Colombian university students. This dataset included psychometric assessments, behavioral indicators, and smartphone dependency scores. These models achieved accuracy percentages between 76% and 77%. This indicates that machine learning models trained on behavioral and mental health indicators can effectively identify clients at high risk of smartphone dependence [4]. Raj (2024) utilized Decision Tree, Logistic Regression, and Random Forest algorithms to predict smartphone addiction levels. Further supporting the applicability of this traditional ML techniques [5] .Kim (2024) presented data-driven analysis results for predicting and preventing SA in Korea, using the XGBoost ensemble algorithm which achieved 87.60 %. Precision in identifying participants at risk of future problematic smartphone use. [6]

Peters et al. (2024) utilized LSTM and Transformer models. He did this to analyze app launch sequences as time series data. Their results showed that user logs can reveal patterns. These patterns showed person's usual social media engagement, without requiring any changes. This allowed them to identify repeated behavioral tendencies. [7]

Different methods for natural language processing that use transformers are commonly used. BERT a method which are often used to study content created by users. This includes different types of content found on social media. Content such as text messages and posts. These models can spot language patterns tied to heavy usage. They are also good at picking up subtle emotional hints. They also take up behavioral signals that users might miss. In their research, Sudheesh and Prasad (2023) demonstrated this by revealing signs of smartphone addiction through an analysis of Twitter data with BERT. [8]

Hong et al. (2024) proposed a deep learning technique, the gd-LSTM algorithm. This led to predict internet addiction risk. They highlighted the utility of LSTMs in behavioral addiction contexts through this. [9]

In mobile and wearable sensing domains, hybrid architectures combining CNN and LSTM layers have been widely adopted. Haque et al. (2024) compared the performance of CNN-LSTM and Transformer models .For real-time fall detection using smartwatch accelerometer data. A proxy for modeling sequential behavioral patterns. While CNN-LSTM showed superior accuracy on offline benchmark datasets. The Transformer model demonstrated better real-time robustness. Then particularly in terms of reduced false positives and steadier performance under noisy conditions. [10]

The introduction of Transformer models has changed the way we approach sequence modeling. They first transformed Natural Language Processing (NLP) and are now being used more in time-series and behavioral data. The main advancement of Transformers is their self-attention mechanism. This mechanism helps them assess the importance of different parts of a sequence. It captures both local and global connections efficiently. This design addresses many problems found in RNNs and LSTMs, especially in managing long-range dependencies and allowing for parallel computation. [10]The use of Transformers in modeling user behavior and analyzing time-series data is a growing field.

Li et al. (2024) introduced Atten-Transformer, a new model that combines temporal attention with a Transformer network. This model can dynamically identify and use key app usage patterns for prediction. It shows how Transformers can extract detailed insights from behavioral data. [11]

Kaufman et al. (2025) studied deep Transformer models for time series and found consistent behavior across layers that correspond with performance. This supports their effectiveness for complex temporal data. [12]

Caetano et al. (2025) evaluated various Transformer-based architectures, such as Vanilla Transformer, Informer, Autoformer, ETSformer, and NSTransformer, for probabilistic time-series forecasting. They highlighted these models' strong effectiveness and ability to adapt across different datasets. [13]

Nguyen et al. (2024) introduced BehaveFormer, a spatio-temporal dual attention Transformer. This model is designed to combine multi-sensor time series data to improve security in behavioral biometrics. It shows how versatile Transformers are in handling different behavioral data streams [14].

Zhang et al. (2025) developed a Transformer-enabled smartphone system for smart physical activity monitoring.

This further demonstrates the practical use of Transformers in analyzing continuous behavioral data from mobile devices [15].Beyond general behavior, Transformers are proving to be powerful tools for predicting addiction and mental health outcomes:

Sudheesh et al. (2023) used a BERT (Bidirectional Encoder Representations from Transformers) model to analyze smartphone-related tweets. Their work showed how well Transformers can identify linguistic markers of addiction with high accuracy. They significantly outperformed traditional machine learning models [8].

Curtis et al. (2023) found that AI-based analysis of social media language, likely using Transformer-based models, could predict mental health outcomes. This suggests a similar potential for predicting self-harm from digital text data. [16]

Boopathybalan (2025) looked into Transformer-based deep learning models for mental health assessment. This included early risk detection of self-harm behaviors, with a focus on ethical issues related to data privacy and consent. [17]

The study by Haque et al. (2024) compared CNN-LSTM hybrids with Transformer models for fall detection using smartwatch data, providing important insights. While CNN-LSTM models achieved high offline accuracy, the Transformer model showed better robustness in real-time, on-device testing. It produced steadier performance and fewer false positives. This reliability came from the Transformer's ability to capture long-range temporal context without the strict windowing needed by other models, making it highly suitable for continuous monitoring applications like predicting self-harm [10].

Joseph and Maheswari (2025) suggested a deep learning-based approach for detecting and preventing smartphone addiction through facial emotion recognition. This indicates the multimodal potential of deep learning, where Transformers could play a significant role in processing sequential emotional cues. Their model integrates video-based inputs with a Theory-of-Mind inspired architecture system and monitored the behavioral parameters of the user to infer addiction states. The study demonstrates that emotion patterns (e.g., sustained sadness or disengagement) can serve as predictors of problematic smartphone use. By combining advanced CNN-/search-optimized models for emotion detection with behavioral intervention strategies, the paper offers a novel approach to mitigating smartphone addiction of the user. [18]

Tay et al. (2020) present a comprehensive survey of efficient Transformer architectures designed to reduce computational and memory requirements. The study categorizes optimization strategies, including sparse attention, kernel-based methods, and model compression. It highlights the performance trade-offs between efficiency and accuracy in various NLP tasks. This survey provides guidance for selecting suitable Transformer variants for resource-constrained applications.

III. Deep Learning Model

A deep learning model refers to a multi-layered network .They learn hierarchical feature representations from data. Each of these successive layers transforms raw input into more meaningful representations.

These inputs screen-time logs, app usage patterns, unlock frequency, text responses. In contrast to shallow models (like logistic regression), deep models automatically discover hidden patterns that human feature engineering might miss. Smartphone addiction is a complex behavior influenced by:

- Time-related patterns, including how often and how long devices are used
- Contextual cues, such as the type of applications and the time of day.
- Psychological elements, which can be derived from survey responses and text message logs.
- Routine dependencies that show how usage changes over time.

These interconnected behaviors necessitate a structured model that can capture nonlinear relationships, understand temporal connections, and handle different types of input. This is where deep transformer-based architectures excel.

A. Structure of Deep Transformer Model

A deep learning system uses Transformers to predict smartphone addiction generally contains six of conceptual layers:

- Input Representation Layer: Convert unprocessed behavioral data into embeddings that machines can easily interpret the usage data. Input sources: total screen time, frequency of unlocks transitions between applications, behavior trends over days or weeks, gaps between sessions, and self-evaluations or feedback questionnaires.

  Processing: normalized time-series vectors and embeddings using Tab Transformer or one-hot encoding.
- Positional Encoding Layer: Since Transformers lack recurrence (unlike RNNs/LSTMs), positional encoding is preferred to represent sequential order. For smartphone addiction prediction: Positional encodings capture chronological app usage or daily progression of the user. This enables the model to understand the temporal evolution of usage behavior pattern of user.
- Multi-Head Self-Attention Layer: It is the core of the Transformer. Allows the model to learn which parts of the sequences influence other parts. Example: Excessive night-time usage of app may correlate with low productivity in the morning. Each attention head focuses on a different behavioral aspect of the user:

Head_1→ temporal attention (time of use)
Head_2→ category attention (social media vs. productivity)
Head_3 → duration attention (short vs. long sessions)
This multi-perspective learning makes Transformers ideal for behavioral prediction.

- Feed-Forward Neural Layers: After attention layer, each time-step embedding process passes through fully connected dense neural layers. These layers learn nonlinear feature interactions (e.g., how duration, frequency, and type of app jointly indicate addiction of the user tendencies).They often uses ReLU activation for efficiency.
- Layer Normalization and Residual Connections: Stabilize training by normalizing activations. Residual (skip) connections prevent gradient vanishing in deep architectures. Enable the model to retain both local (short-term) and global (long-term) dependencies in smartphone use behavior.
- Output Layer (Prediction Head):The final layer depends on the prediction goal for the user's addiction:

Binary classification: Addicted vs. Non-addicted of the user (Sigmoid activation)
Multi-class: Mild, Moderate, Severe (Softmax activation)
Regression: Addiction risk score (Linear output) Output can also be integrated into a risk evaluation dashboard.

TABLE I: OVERVIEW OF ML MODELS

Model	Type	Key Strength	Data Type	Advantages	Limitation
Logistic Regression (LR)	Linear	Simple, interpretable; Fast training	Numerical features (usage frequency, duration, unlocks)	Good baseline for binary classification (addicted vs. non-addicted)	Fails on non linear patterns
Decision Tree (DT)	Tree-based	Easy to interpret	Structured data	identify threshold-based patterns	Over fits easily; low generalization
Random Forest (RF)	Ensemble (Bagging)	Reduces overfitting good accuracy	Structured tabular data	Captures feature importance and nonlinear relations	Slower inference; less explainable
Support Vector Machine (SVM)	Kernel-based	Works well for small datasets;	Numerical/categorical behavioral features	Effective in high-dimensional behavioral features	Not scalable for very large data
K-Nearest Neighbors (KNN)	Instance-based	simple and non-parametric	Usage pattern vectors	Learns user similarity patterns intuitively	slow on large data
Naïve Bayes (NB)	Probabilistic	Fast, efficient for text or categorical data	Survey data, categorical features	Can combine with app-category data or self-assessment scores	Assumes feature independence
Gradient Boosting (GBM)	Ensemble (Boosting)	Strong predictive power; customizable	Tabular, structured usage data	Good at handling noisy behavioral data	Risk of overfitting; requires tuning
XGBoost	Advanced GB	Highly optimized	Large tabular data	High accuracy,	Less interpretable; heavy computation

IV. RESEARCH GAPS

Limited Granular Behavioral Analysis with Transformers. Although some studies use Transformers for general user behavior or linguistic analysis, there is a relative scarcity of research that explicitly leverages the self-attention mechanism of Transformers to analyze raw, fine-grained sequential smartphone usage data (e.g., precise app-launch sequences, micro-interactions, dynamic screen unlock patterns) to detect the subtle, evolving behavioral shifts indicative of SA. Most existing ML/DL approaches still rely on aggregated features or self-reported data, missing the intricate temporal dependencies [7].
Scarce focus on long-range temporal dependencies in addiction progression. The development of SA is a slower process, often takes weeks or months. While LSTMs attempt to capture temporal dependencies, their effectiveness diminishes over very long sequences.
There is a need for models that can robustly capture and interpret long-range dependencies in continuous behavioral data to understand the complete trajectory from usage to addiction, a strength inherent to Transformers that is not yet fully exploited in this specific context [9].
It is insufficient to develop real-time prediction frameworks for continuous observation of the user's data. Many prediction models are evaluated on easily available static datasets. For continuous, real-time smartphone usage

monitoring, transformer-based models that can provide quick predictions with few false positives—similar to their efficacy in other real-time use cases like fall detection—must be developed and validated.[4],[5],[6]
Lack of Understanding in Behavioral Addiction Predictive models often become harder to understand as they get more complicated.
Explainable AI techniques are increasingly being applied to Transformer-based prediction models. These methods offer information about the elements that contribute to a specific user being categorized as at-risk or not. [11], [14]
Ethical considerations, ethical handling of user behavioral data, preventing misuse, and maintaining confidentiality throughout model development and deployment, aligning with modern AI ethics and data protection standards.[31]

V. Analysis

- Data Requirements: In Transformers one typically requires a large and labeled dataset for training [7]. This may be difficult to collect due to security concerns. One should be always aware before giving out their own details therefore secure connection between user and the administration. Real-world data requires consent of user and strong anonymization practices along with ethical oversight.
- Computational Resources: Transformers can be computationally intensive, requiring relevant resources for training and inference. High-performance GPUs (new models) are needed for efficient model training and fine-tuning. Higher storage for the process to complete its collection of user data.
- Interpretability: The complexity of Transformers can make it difficult to interpret their predictions. The complexity of Transformer-based architectures makes their decisions harder to explain, which can be a challenge in psychological or behavioral prediction domains.[7]
- Synthetic Data: Begin with datasets that are either publicly available or generated through synthetic methods.
- Ethical Protocol: When collecting real data, follow strict and clear guidelines to obtain explicit informed consent. Processing data directly on devices can reduce the transfer of unprocessed information.[31]
- Data Labeling: The smartphone addiction often comes from subjective self-reported surveys like the SAS-SV, which is type of labeling can introduce noise and bias into the training dataset. The model learns to predict a subjective score rather than an objective medical condition.
- Multi-Modal Labeling: Improve self-reported scores by including objective behavioral metrics, such as late-night usage and how often apps are switched. This creates a more complete and objective label.
- Expert Validation: Work with a domain expert, such as a psychologist or counselor, to evaluate and confirm a sample of the labels.
- Data Imbalance: The class imbalance of truly addicted individuals and non individual cause performances issues like biasing and overfitting of the model therefore struggles to identify minority groups correctly. This results many false negatives.
- Sampling Techniques: Methods like SMOTE (Synthetic Minority Over-sampling Technique) or ADASYN are often used as sampling techniques.
- Loss Functions: Using weighted loss functions like Focal Loss would most likely impose greater penalties for incorrectly classifying the minority group thus increasing the model.

VI. Conclusion

The field of predicting smartphone addiction has gone from simple machine learning models that use combined data to more advanced deep learning architectures. While initial ML and LSTM-based methodologies provided substantial insights about test data, they often didn't capture the complicated, long-term time links that are typical of the gradual onset of addiction.
Transformer models can look at very detailed sequential behavioral data in a way that has never been possible before. This is because they have very strong self-attention mechanisms. This is what makes them perfect for this hard job. This review stresses the need for a specialized Transformer-based framework that can accurately find subtle behavioral patterns, model long-range dependencies, make reliable real-time predictions, and includes explainability and ethical issues. The proposed project aims to fill these research gaps by offering a novel and comprehensive solution for the early diagnosis and intervention of smartphone addiction, thereby contributing and playing a significantly important role to the promotion of digital well-being amid the alarming rise of smartphone usage.

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