International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Analysis and Study of Mobile Phone Addiction in the context of Artificial Intelligence

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ABSTRACT

Smartphone addiction has emerged as a growing concern in modern society, creating a pressing need for advanced methods to analyze and predict addictive behaviors using smart phone usage data. This paper offers a comprehensive survey of machine learning, data mining and deep learning techniques employed to detect and predict smart phone addiction. A variety of algorithms have been applied to diverse datasets, such as usage logs, self-reported information, and behavioral patterns, to derive valuable insights. Supervised learning methods, including Decision Tree, Support Vector Machine, Random Forest, and Neural Networks, have been extensively used to predict addiction by leveraging labeled data. Additionally, unsupervised techniques such as clustering, Principal Component Analysis (PCA), and auto encoders have been utilized to uncover hidden patterns in unlabeled data, enhancing the understanding of behaviors linked to addiction. This survey highlights the critical role of machine learning and deep learning in combating smart phone addiction with qualitative and quantitative analysis. The paper highlights the tools and techniques that form a strong foundation for future research works that form as a foundation to solve real-world problems regarding mobile phone addiction.

Keywords— Mobile Phone addiction, Data Mining, Machine Learning, Deep Learning, Artificial Intelligence

I. INTRODUCTION

This study examines the ways in which smart phones impact our social, emotional, professional, mental, and educational facets of life. Promoting more balanced and healthful smart phone use is the goal. Mok J.Y. et al. [1] explored the key features and functions of smart phones. Their study showed that smart phones are used for a variety of tasks, including making calls, checking emails, browsing the web, and listening to music. The rapid adoption of smart phones has outpaced any other technology in history, and today, smart phones are the most common device for accessing the internet. By early 2012, the global number of smart phone users had surpassed 1.08 billion, and the number continues to grow at a rapid pace. A study by Choi S.W. et al. [2] in the UK showed that 68% of adults owned smartphones, and in South Korea, there were over 39 million smartphone users by 2012. This trend was global. However, their research also raised concerns about increasing smartphone dependence. A 2017 survey by the Korea Internet and Security Agency (KISA), reported by Poushter, J. [3], found that 18.6% of 29,712 smartphone users were at high risk of smartphone addiction, a 1% increase from the previous year, showing a growing problem. Li, Y. et al. [6] looked at how widely smartphones are used in today's society. With the arrival of 5G networks and new technology, smartphones, with their many functions, have become essential. According to the 44th Statistical Report on China's Internet Development, published by the China Internet Network Information Center, 175 million people under 18 in China were internet users by June 2019, making up 93.1% of the country's population. More than 99.1% of these young users access the internet through smartphones, showing that smartphones have overtaken computers as the main device for online access. M. Gülü et al. [7] studied the link between digital game addiction, physical activity, and obesity in teenagers. The study used machine learning to predict addiction levels and identify the main factors contributing to addiction. It also explored how digital habits affect the health and well-being of adolescents. However, the rate of smartphone addiction varies from study to study, with findings ranging from 0% to 38% depending on the methods used. Bian M. Zhou [8] found that the fastest-growing group of smartphone users in China is young people, particularly university students. A 2018 survey showed that 79% of Chinese university students used smartphones in class and spent more than five hours a day on their phones. Public health measures like lockdowns and social isolation during the COVID-19 pandemic made smartphone use increase, leading to more personal and professional use. Surveys during the pandemic found that young people spent more time online for activities like networking, learning, and gaming. This increased smartphone use, along with social isolation, has been linked to mental health issues, including problematic smartphone use (PMPU).

II. LITERATURE SURVEY

Abu-Taieh et al. [22] conducted a study on the predictors of smartphone addiction and social isolation among children and adolescents in Jordan. Using Structural Equation Modeling (SEM) and Machine Learning (ML) techniques, the researchers identified factors contributing to smartphone addiction and social isolation. Published in Big Data and Cognitive Computing, this study aimed to understand the mental and social impacts of smartphone usage on young people. The authors sought to offer insights into the mechanisms behind addiction and isolation in this demographic. Marciano et al. [23] examined how mobile assessments can leverage algorithms to monitor mental health in youth. They highlighted the use of algorithms for real-time data analysis from mobile applications, enabling the identification of patterns and trends in mental health indicators. This approach facilitates early detection of issues and personalized interventions. By integrating machine learning techniques, the study emphasized how individualized data could enhance mental health monitoring and provide more accurate predictions and tailored support for young people. Chen, Nath, and Tang [24] explored the determinants of digital distraction using Structural Equation Modeling (SEM). The study applied SEM to analyze the relationships between factors contributing to digital distraction, such as user habits, cognitive biases, and environmental influences. By using this algorithmic approach, the authors were able to model and quantify both direct and indirect effects of these factors on distraction levels. Their findings provided valuable insights into how automatic thinking processes affect user interactions with technology and contribute to overall distraction, offering a deeper understanding of the dynamics of digital distraction. Yağcı [25] investigated the application of machine learning algorithms in educational data mining to predict students' academic performance. By using algorithms such as decision trees, support vector machines, and neural networks, the study analyzed historical student data to identify patterns. The goal was to predict academic performance by recognizing trends in student behaviors and past achievements. Gülü et al. [7] studied the relationship between obesity, physical activity, and digital game addiction among adolescents. The research, published in Frontiers in Psychology, used machine learning techniques to predict levels of digital game addiction. The study focused on identifying key factors contributing to addiction and its association with physical health issues such as obesity and activity levels. This approach provided deeper insights into how digital behaviors, including gaming, might affect the health and well-being of adolescents. The use of machine learning allowed for more accurate predictions and analysis of addiction patterns.

III. PHONE ADDICTION

This study gathered data from 29,712 participants (14,790 males and 14,922 females) who took part in a survey conducted by KISA in 2017 [5]. The participants, all native Koreans, were aged between 3 and their 60s and lived in metropolitan areas of South Korea. The survey included nine questions from the S-scale to assess smartphone addiction levels, as well as questions about personal information like employment status and monthly income. It also contained 180 questions about smartphone usage, covering topics such as frequency of use on weekdays and weekends, and self-assessment of smartphone content usage. However, only 27 of these questions were used in the smartphone addiction prediction model, as they were the ones that could be matched with smartphone log data.The participants were divided into seven age groups (3–9, 10s, 20s, 30s, 40s, 50s, and 60s). However, only participants in their 10s, 20s, and 30s were included in the prediction model, as the survey focused on individuals under 40. Addiction levels were categorized into three groups: high risk, potential risk, and normal. The "potential risk" group was combined with the normal group due to similar smartphone usage patterns. To ensure consistency in survey responses, Cronbach's alpha was calculated for each age group. In this study, the mean Cronbach's alpha for each age group exceeded 0.8, indicating high internal consistency in the responses about smartphone usage levels across 19 content types, such as news, gaming, social media, and video streaming.

3.1 cell phone addiction and psychological and physiological health in adolescents

According to Augner, C. & Hacker, G. W. [10], there is a link between cellphone addiction and the mental and physical health of teenagers. It's unclear, though, if youth mental or physical health issues are solely related to cell phone use. Two opposing viewpoints are presented in the studies they reviewed. According to one theory, excessive phone use can cause anxiety, sadness, rage, and even suicide, demonstrating a clear correlation between cellphone addiction and mental health problems. In the past few years, the number of suicides has been rising. However, some research points to a beneficial correlation between physical health and cellphone addiction.

3.2 global trends in cell-phone addiction

The relationship between teenagers' emotional and physical well-being and cellphone addiction has been highlighted by Augner, C. & Hacker, G. W. [10]. Nevertheless, it remains unclear whether the adverse mental or physical health outcomes in young individuals can be attributed solely to mobile phone usage. The studies they reviewed present two contrasting perspectives. One perspective suggests a significant link between mental health issues and cellphone addiction, positing that excessive use of mobile devices may lead to anxiety, depression, anger, and even suicidal tendencies. In recent years, there has been an increase in suicide rates. Conversely, other research suggests a positive association between physical health and cellphone addiction.

3.3 smart phones dependency risk analysis using machine-learning predictive models

Gülü, M. and Yagin, F. [7] examined the significant influence of recent technological advancements on various facets of human life, including communication, education, and leisure activities. Nonetheless, the overuse of smartphones, particularly among younger demographics, has resulted in new forms of addiction and a more sedentary lifestyle, adversely affecting both mental and physical well-being. Research indicates that approximately 40% of smartphone users engage in excessive usage, which is closely associated with cognitive impairments, challenges in decision-making, and musculoskeletal problems. Historically, self-reported measures, such as the Smartphone Dependency Test (SDT), have been employed to assess dependency; however, these approaches often necessitate expert intervention for precise outcomes. This highlights the necessity for more objective assessment methods. Recent studies have started to investigate the application of machine learning algorithms to forecast smartphone dependency by integrating self-reported data with personal, familial, and environmental risk factors. Models like support vector machines and random forests have demonstrated encouraging predictive accuracy, with the results underscoring the significance of variable selection over the specific choice of model. This research indicates that self-reported questionnaires can serve as a valuable instrument for predicting dependency levels and sets the stage for future investigations to incorporate more objective measures to mitigate the adverse effects of excessive smartphone usage.

3.4 Understanding and predicting customers' intentions to use smart phone-based online games: A deep-learning-based dual-stage modeling analysis

Chen et al. [24] investigated the rapid advancement of smartphone technology and its profound influence on the online gaming sector. In 2022, the Asia-Pacific region represented approximately 62% of the global revenue generated from app-based games, totaling around USD 63.20 billion (Chen, 2022). This remarkable growth has led marketers to seek a deeper understanding of consumer perceptions regarding smartphone gaming, as these perceptions significantly affect gamers' intentions to participate in gaming platforms. Factors such as perceived flow, cognitive engagement, and overall involvement shape these attitudes, all of which are essential for creating an immersive gaming experience. While prior research has addressed various aspects of online gaming, including player loyalty and user experience, there has been insufficient exploration of the interplay between attitudes, flow, and engagement specifically within the realm of smartphone gaming. This research gap is particularly relevant in emerging markets like Bangladesh, where the online gaming industry is experiencing rapid growth, driven by a substantial and youthful gaming demographic. The present study seeks to address this gap by examining the complex interrelationships among these factors, employing sophisticated analytical methods such as Partial Least Squares Structural Equation Modeling (PLS-SEM) and Artificial Neural Networks (ANN) to gain a comprehensive insight into consumer behavior in the smartphone gaming landscape.

3.5 Influence of Mobile Phone Addiction on Academic Performance Among Teenagers

Osorio et al. [12] emphasize that mobile phone addiction is an escalating issue, particularly concerning its effects on adolescents and their educational outcomes. Over the years, mobile phones have transitioned from basic communication devices to sophisticated tools that offer internet access, social media engagement, and a variety of multimedia applications, leading to considerable distractions. The prevalent use of mobile phones among teenagers has raised significant concerns, as research indicates that excessive engagement with platforms such as Facebook, Twitter, and YouTube can adversely impact students' concentration and academic performance. The inherently addictive qualities of these devices, which deliver immediate gratification through various applications, may diminish productivity, disrupt sleep patterns, and ultimately hinder academic achievement. In certain instances, social media can occupy as much as nine hours of a teenager's daily routine. Although mobile phones have improved communication and connectivity, their excessive use is increasingly associated with social challenges, including reduced family interaction and declining academic performance. Consequently, scholars are advocating for more comprehensive research to investigate the full ramifications of mobile phone addiction and its wider implications for students' academic success and social behavior.

3.6 Multidimensional Health of Children in Rural China

Zhou et al. [16] may have incorporated algorithms in their research. To ascertain this, it is crucial to examine their methodology to determine if they employed data analysis techniques such as machine learning models, statistical algorithms, or moderation analysis tools. Should algorithms have been utilized, they would likely have served to predict, segment, or investigate the relationships among variables such as parental migration, children's health, and mobile phone addiction. In a similar vein, Reza Pour et al. [18] applied machine learning algorithms to analyze extensive data concerning shifts in alcohol consumption patterns among healthcare professionals in the United States during the COVID-19 pandemic. These algorithms were likely used to find important predictors, build prediction models of behavioral changes, and reveal complex patterns that traditional statistical techniques could miss. Support vector machines (SVM), decision trees, random forests, and other machine learning models are commonly used for datasets with several variables.

3.7. Artificial intelligence recommendation and academic procrastination behavior

C. Longoni et al. [4] highlight that while earlier research indicated a general resistance to algorithmic recommendations, with people believing that algorithms cannot improve or learn, this perspective is changing as artificial intelligence (AI) advances rapidly. People are increasingly embracing algorithmic support. Their study found that customers' differing opinions on AI and friend recommendations—specifically in terms of enjoyment and usefulness—play a significant role in shaping the impact of machine learning. Generally, perceptions of AI's enjoyment tend to be higher than those of its usefulness. These AI-driven insights give mobile phones a "soul," making them more engaging and practical. One noticeable effect of mobile phone addiction is the loss of control over screen time, with over 70% of college students admitting to procrastinating on their coursework. Mobile phone usage often leads to the delay of academic responsibilities, including behaviors such as attending classes late, pushing events to the last minute, and deferring homework. Based on these observations, the article proposes the theory that academic procrastination is positively influenced by artificial intelligence.

IV. QUALITATIVE ANALYSIS IN SMART PHONE ADDICTION

TABLE 1: Qualitative analysis of research works from the literature.

Ref. No	**Method**	**Input Dataset**	**Pre-Processing**	**Feature Extraction**	**Classification Clustering**	**Strengths**	**Weaknesses**	**Outcome**
	Descriptive Survey	UG & PG Students (200 total)	Modified Social Media Addiction Scale	4dimensions: virtual tolerance, virtual communication virtual problems, virtual information	Descriptive survey method	Widely used research method in social sciences	Nill	Social Media Addiction level analysis of university students
[6]	**T-test analysis**	Social Media Addiction scores	Data cleaning and standardization	Statistical measures like mean and SD were used	T-test to compare the means of different groups	Clear statistical significance testing	Limited to non-parametric hypothesis testing	Determination of significance between various demographic factors
[7]	**Random Forest**	Large-scale datasets	Handling missing values, bootstrapping	Random subset of features for each tree	Ensemble of Decision trees	Robust to over fitting, can handle large datasets	Slower in prediction, complex model	High accuracy, versatile across classification and regression tasks
[11]	**K-Fold Validation**	Various datasets	Data split into k subsets for validation	N/A	Repeated training/testing on k-1 subsets	Efficient use of all data for training and validation	Computationally expensive for large datasets	Reliable accuracy measurement across all models
[12]	**Decision Tree**	Categorical & numerical data	Handling missing values, normalization	Information Gain, Gini Index	Decision Tree-based splitting	Easy to interpret, handles both types of data	Prone to over fitting, less effective for small datasets	Provides interpretable classification trees, sensitive to data splits

	Gradient Boosting Tree	High-Dimensional data	Data normalization, residual calculation	Gradient-based residual extraction	Iterative boosting with decision trees	Great for complex data, reduces over fitting	Computationally intensive, slower than Random Forest	High performance, accuracy in regression and classification tasks
	Neural Network (MLP)	EEG data or other complex numerical data	Data normalization, noise reduction	Layered neuron-based feature learning	Multilayer perceptron (MLP)	Learns complex patterns, effective in nonlinear data	Requires large datasets, difficult to interpret	High accuracy for complex tasks like addiction detection via EEG
[12]	**Naïve Bayes**	Categorical, binary data	Binning of continuous features, removing noise	Probability estimation based on feature independence	Naive Bayes classifier	Simple, fast, handles small datasets well	Assumes feature independence, may perform poorly if this assumption fails	Good baseline classifier for quick analysis, performs well with small datasets
	Machine Learning for COVID-19 Diagnosis	CT scans, X-rays, clinical data, PCR test results	Data normalization, noise removal, augmentation, missing data imputation	Feature Extraction using CNNs, decision trees, or RF for tabular data	CNN, Random Forest, SVM, KNN for classification tasks	Can handle large-scale, complex medical imaging and clinical datasets	Requires large labeled datasets, computationally intensive	Increased accuracy in COVID-19 detection and screening
[19]	**DNA Sequencing with Deep Learning**	SARS-CoV-2 genome sequences	Noise reduction, normalization, sequence alignment	Sequence features extracted using CNN, RNN, LSTM models	Classification using LSTM, CNN for prediction of virus strains	Can predict mutations, efficient for complex sequence data	Needs significant computational resources	Effective in identifying viral strains and mutation prediction
	Forecasting COVID-19 Spread	Time-series data of COVID-19 cases, infection rates, hospitalization data	Data normalization, noise filtering, handling missing data	Time-series feature extraction using ARIMA, LSTM, or moving averages	Time-series forecasting using ARIMA, LSTM, Prophet	Can accurately forecast COVID-19 case trajectories	Requires a lot of historical data, may not perform well on new variant	Improved understanding of COVID-19's spread patterns over time
	Multi-Layer Perceptron (MLP)	EEG data, numerical datasets	EEG data filtering, normalization	Feature extraction using MFCC,	Neural Network with 2 or 3 layers, training	Learns highly complex patterns,	Computationally expensive,	High accuracy in classifying EEG signals,

				wavelet transforms	with back propagation	good for time-series/EEG data	requires large datasets	particularly for addiction detection
	Decision Tree (DT)	Big Five Inventory (BFI) and Smartphone Addiction Scale (SAS)	Handling missing values, normalization, categorical encoding	Big Five Personality Traits	Decision tree-based classification	Easy to interpret, good for small datasets	Prone to over fitting, low generalization	Moderate accuracy, provided insight into important traits for addiction
[25]	**Random Forest (RF)**	BFI and SAS questionnaires	Handling missing data, data normalization, feature scaling	Extracted personality traits used as features	Ensemble of decision trees, bagging technique for classification	High accuracy, reduces over fitting by averaging trees	Requires more computational power, harder to interpret	Best performance with 89.7% accuracy, 87.3% precision, highest AUC value
	Extreme Gradient Boosting (XGB)	BFI and SAS questionnaires	Missing data imputation, data scaling, normalization	Personality trait data as input features	Boosting technique for classification, improves accuracy over iterations	Efficient in handling high-dimensional datasets, reduces bias	Computationally expensive, sensitive to parameter tuning	Achieved high accuracy, but lower than RF in this context
	Logistic Regression (LG)	BFI and SAS questionnaire es	Data normalization, removing outliers	Personality trait values, linear relationships with addiction outcome	Logistic regression for binary classification	Simple, interpretable model, requires less computational power	Limited to linear relationships, may underperform with complex data	Lower accuracy compared to tree-based methods, but interpretable results

V. QUANTITATIVE ANALYSIS METRICS:

The performance of the algorithms are evaluated using specific metrics Jiméne z et al [11], each with its own corresponding meaning and value in the context of research performance evaluation as illustrated in this table.

TABLE 2: Performance evaluation metrics.

Metric	**Formula**
Accuracy	Accuracy=TP+TN/TP+TTN+FP+FN
Precision	Precision=TP/TP+FP
Sensitivity (Recall)	Sensitivity=TP/TP+FN
Specificity	Specificity=TN/TN+FP
Fall-Out	FallOut=FP/FP+TNFP

VI. CONCLUSION:

The growing concern about teen mobile phone addiction is brought to light by this study, which emphasizes the need for more investigation into the causes of this new problem. The article offers useful information and statistics by introducing a technique for evaluating teenage mobile phone addiction using criteria for addictive disorders. There are still certain restrictions, though, and further study is essential, especially to comprehend the connection between addiction to mobile phones and mental health conditions like anxiety and despair. Rapid improvements in mobile technology, such as internet connectivity and applications like WhatsApp, are changing how people use them, which may make addiction more likely. In order to address this growing issue among teenagers, it is imperative that research be conducted continuously in order to develop effective preventative methods, treatment programs, and diagnostic tools.

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