



Review Article

A review: Machine learning approach to understanding the impact of mobile phone addiction on academic performance, health, and family life

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ABSTRACT

This review explores the impact of mobile phone addiction on studies, health, and home life based on machine learning methods. In contrast to previous research focusing on one aspect, e.g., sleep quality or study stress, the present investigation employs machine learning to detect patterns of phone dependence and its extended effects. Excessive use of mobile phones has been shown to negatively impact academic performance by instigating poor time management, distraction, and sleep deprivation, which translates to decreased grades. It decreases the quality of sleep, causing lethargy and cognitive problems. Additionally, excessive use of mobile phones damages family and social relationships since individuals tend to give preference to online relationships over actual ones. With the application of machine learning models, it is feasible to forecast individuals at risk and negative outcomes, thereby informing targeted interventions. Also, this review compares different methodological strategies, such as ML-based investigations into the detection of depression, overuse of mobile phones, online game addiction, and their effects of health and relationships.

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INTRODUCTION

Communication has been forever changed by the rise of the mobile phone, which allows us to reach anyone in the world at a moment's notice. Apart from being used for speaking on, they are hand-held computers that can be used to gain access to both information and entertainment. However, their commonality has raised concerns about cell phone addiction,

which is a behavior pattern that interferes not only with daily life but also with social interactions, it appears.

Machine learning appears to provide a relatively promising approach, based on creating models that will predict which individuals may be predisposed to mobile phone addiction, taking into account actual mobile phone usage, social media behavior, demographic factors such as age and gender, as well as psychological factors such as anxiety

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[1] and depression. However, in order to create such models, data needs to be collected from a large group of users, including both their patterns of mobile phone usage as well as demographic and psychological information. Such models may prove useful in identifying those who are at risk and developing intervention programs aimed at helping them overcome their addiction [2] which, in turn, would help avoid the consequences of addiction.

Common signs of mobile phone dependence [3] include:

- Unable to minimize phone usage even after trying.
- Failure to keep track of time when using the phone.
- The use of the phone as a way to run away from reality.
- Feeling anxious about running out of battery or losing the phone.
- Favoring virtual communication over face-to-face interaction.
- Overly dependent on checking phones for notifications and messages.

Excessive use of phones leads to many after effects, including headaches and that feeling of tension in relationships, which is definitely not ideal. It is crucial to ensure proper management of phone usage to maintain its usefulness as a tool, without letting it become a nuisance. Machine learning models can be very useful in this regard as they can aid both individuals as well as health care professionals in preventing phone addiction and minimizing the adverse consequences that follow.

Emotional Impact of Mobile phone Addiction

These devices have become an integral part of communication, work, and recreation; therefore, when you think about it, your life is actually quite dependent on mobile phones. Nonetheless, the overreliance on these gadgets has resulted in various adverse effects on the psychological, emotional, social, and behavioral health of users. Mobile phone addiction is a rising issue throughout the world, and it comes out as an emotional echo, where the person becomes dependent rather than using them. These emotional impacts of mobile phone addiction in Figure 1 can be listed as follows:

1. **Nomophobia:** Fear of losing the phone or the feeling of being anxious due to inability to find it [4].
2. **Textaphrenia:** The feeling of receiving messages or the sensation of vibrations when none occurs.
3. **Ringxiety:** Feeling that one's phone rings when it doesn't happen.
4. **Textiety:** The anxiety of not receiving or sending messages.

These behaviors illustrate the extent to which the mental influence exerted by the mobile phones on their users is powerful, such that everything seems to disrupt the normal daily activities as well as the personal relationships. In addressing the problem of mobile phone addiction, one needs to be aware and take measures ahead of time so as to reduce the use of the phones while still retaining them as convenient devices and not sources of stress.

Health Risks with Excessive Mobile Phone Use

Overuse of a mobile phone leads to numerous health issues affecting not only physical well-being but also psychological state. The above-listed risks arise due to the long-term and incorrect use of the smartphone and may result in considerable disruptions in one's everyday activities. Below there is a list of some health conditions associated with excessive use of a mobile phone.

- a) **Text Neck Syndrome:** This condition can be characterized by the strain on neck muscles resulting from constant looking down at the mobile phone screen, which makes your head inclined.
- b) **Insomnia:** Mobile phones emit blue light, disturbing the sleep cycle and making it more difficult for users to fall asleep.
- c) **Increased Risk of Cancer:** Continuous radiation exposure from mobile phones can cause an increased risk of tumors and even brain cancer.
- d) **Trigger Thumb:** The repetitive actions of texting, typing, or clenching your phone in your hand may cause your thumb to get stuck in a bent position.
- e) **Thumb Arthritis:** Frequent pinching movements caused by texting or even holding the phone in your

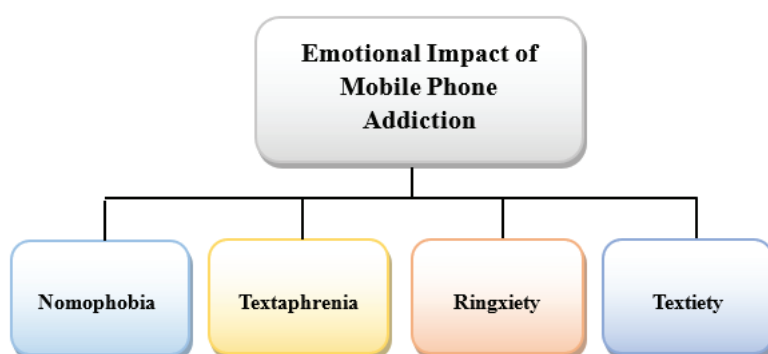


Figure 1. Emotional Impact of Mobile Addiction.

hands may result in pain and tenderness in the area of your thumb joint closest to your wrist.

- f) **Cubital Tunnel Syndrome:** Leaning your elbows on a surface while texting or talking on the phone can lead to numbness and tingling in your ring finger and pinky fingers as well as pain in your elbow joint.
- g) **Vision Issues:** Blue light emitted by mobile phones can strain your eyes and adversely impact your overall vision as well as damage your cornea.
- h) **Male Infertility:** Having a phone close to your body or using it when it is charging can have negative consequences for male fertility due to radiation.
- i) **Hearing Loss:** Exposure to the electromagnetic field produced by mobile phones can lead to hearing impairment.
- j) **Impact on Unborn Child:** Excessive radiation emitted by mobile phones during pregnancy can impair fetal brain development and lead to attention deficit hyperactivity disorder, ADHD.

The above health hazards demonstrate the need to moderate the use of mobile phones and develop healthy habits to mitigate their negative impacts. Mobile phones were invented to make life easier, but an over-reliance on them could undermine one's health.

Predictive Modeling

Machine learning (ML), which is basically an AI discipline [5], helps machines learn like humans through the process of learning from data, without explicitly programming them. Predictive modeling is one type of model construction which focuses on creating computational or mathematical models capable of predicting future occurrences based on the patterns obtained from existing and past data [6]. This usually involves analyzing the dataset by performing statistical analysis or implementing machine learning algorithms to discover correlations among variables. Then comes the process of developing models that will be used for prediction purposes. For instance, predictive modeling can assist in determining a student's performance based on the study patterns, attendance records, and cell phone usage, among others; a somewhat indirect approach to prediction. This entails such concepts

(a). Parametric Models

In parametric machine learning models [7], certain strong assumptions are made regarding the data, making the model simpler and, in some cases, increasing the accuracy of predictions. Parametric methods always maintain a constant number of parameters irrespective of the size of the training set used. Examples [8] include:

- ✓ Logistic Regression
- ✓ Linear Regression
- ✓ Linear Discriminant Analysis (LDA)
- ✓ Naive Bayes
- ✓ Perceptron
- ✓ Simple Neural Networks

(b). Non-Parametric Models

Since non-parametric approaches do not place any stringent assumptions on the underlying structure of the data, they fit well in large data sets even when no prior information about them is available. The fact is that such approaches usually get complicated with larger data sets, and they work very well in constructing mapping functions. Examples of non-parametric approaches are [9, 10]:

- ✓ Support Vector Machines (SVM)
- ✓ K-Nearest Neighbors (KNN)
- ✓ Decision Trees
- ✓ Random forest

(c). Top Predictive Analytics Models

Most predictive modeling techniques are either machine learning or statistical models that can be applied to analyze historical and current data in order to make an inference of what may occur in the future or predict certain types of behavior. In a sense, such models attempt to find out data patterns and then make some sort of educated guess about the future based on those findings. Five most prominent models [11], in fact, do something like that – though, of course, with some slight modifications:

Classification Model: It provides answers to questions that have two possible answers; yes and no. This model also makes decision making easier in various sectors.

Forecast Model: It forecasts numeric [12] values based on past data; this can be helpful for activities such as sales forecasting and demand forecasting.

Anomaly Model: It detects anomalies inside datasets, which is helpful for finding fraud, or other irregularities that do not “fit.”

Clustering Model: It groups data into clusters based on their similarities and dissimilarities for better understanding.

Time Series Model: It analyzes sequential data points over time, then it tries to estimate trends or future values.

The right predictive model is important, because it helps organizations use insights in a useful way and make decisions that are more informed across industries. The top 5 predictive analytics models are shown in Fig.2.

Process of Predictive Modeling

The process of predictive modeling is kind of a step by step process [13], to develop models that help predict what happens next, based on existing data. Most of the time it goes in a sequence like:

Defining the exact outcome which has to be predicted. This particular outcome largely dictates the type of data to be used as well as the modeling technique to be used. Precision forecasting needs quality data. Data should be gathered from reliable sources, then cleansed from inconsistencies, mistakes, and missing values [14]. After that, the data is transformed in order to make everything consistent and improve the quality of data overall. This step consists of identification and description of the features, which are alternatively

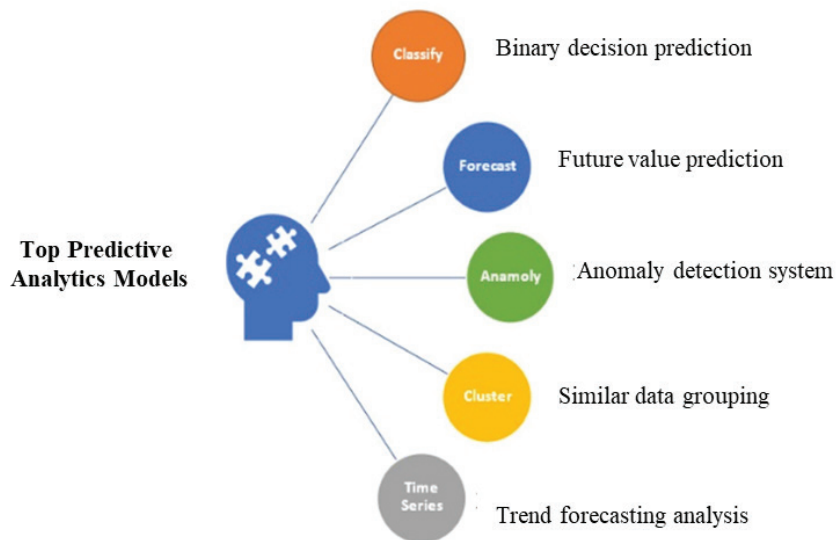


Figure 2. Top 5 predictive analytics models.

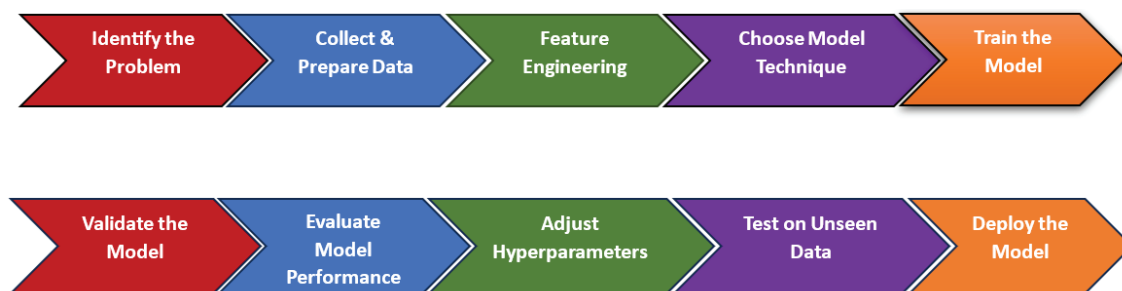


Figure 3. Predictive Modeling Process.

referred to as predictors, in the raw data. This consists of normalization, encoding, dimensionality reduction, and domain-specific transformation in order to find the connections which will be helpful in prediction. This step consists of selection of the appropriate model according to the nature of the data and problem complexity (decision trees, regression and neural networks). This step consists of training the chosen model using the training data set through parameter optimization. This step consists of validation of the model using cross-validation and holdout validation data sets in order to determine the model's performance on new data. This step consists of evaluation of the model's performance through accuracy, precision, recall, F1 Score, AUC-ROC, among others. The outcome of this step is largely used to determine the efficiency of the model. This step consists of tuning of the hyperparameters such as learning rate or tree depth of the model in order to improve the model's performance. This kind of process includes grid searches and many other approaches. This step consists of testing the accuracy of the model using the unseen test split which was not used for training and validation purposes. Once the training process

is completed, the next step would be deployment of the model either into production or application and predictions are made immediately once new data appears.

The flow in Figure 3 kind of makes sure that the whole predictive modeling process stays useful and gives insights you can actually act on, and it also fits across a bunch of separate scenarios, while still maintaining accuracy, and enough robustness.

LITERATURE REVIEW: PREDICTING MOBILE PHONE ADDICTION USING MACHINE LEARNING

Many studies have aimed to predict mobile phone addiction, which is an increasing problem, with implications for mental health, academic performance and social relationships [15], and family life, using machine learning (ML) predictive techniques. This subsection is a literature review of existing research results and prediction models in the literature.

Depression Detection via Mobile Phone Usage

Presented a minimalist ML system for depression detection through app usages over the period of seven days.

With the LGBM, this system achieved an accuracy of 82.4% with no need for sensors or resource-intensive techniques – in turn being both scalable and low-cost [16].

Mobile Phone Addiction and Physical Activity

Study of adolescents showed a negative association of DGA and PA and a positive one with obesity [17] Their findings suggest that increasing physical activity can reduce DGA by 1.51 times.

Clustering Mobile Phone Usage Behaviors

Designed an unsupervised clustering algorithm to identify the presence of any abnormal patterns of mobile phone usage. Daily activity-details made the algorithm more effective in performing the task. K-Means was found to be marginally better than K-Medoids in this regard [18].

Prediction of Problematic Mobile Phone Use during the Pandemic

Used the shrinkage approach of Lasso regression for predicting problematic mobile phone use during the COVID-19 outbreak by producing accurate results with very low error measures [19].

Mobile Phone Dependency Among University Students

Applied the Stratified-K-Fold cross validation and Support Vector Machines (SVM) algorithm for predicting the dependency on mobile phones among university students [20].

Ensemble Methods for Risk Prediction

Compared various ensemble classification techniques for forecasting student's at-risk, using teacher employment status along with student performance. Boosted tree models, however, proved effective in dealing with large data sets, while the Multilayer Perceptron model performed relatively well with small data sets [21].

Factors that Influence Mobile Phone Addiction

Performed a logistic regression analysis on 1981 participants and found that gender and life quality were factors that determined the risk of mobile phone addiction [22].

Gender-Based Usage of Apps

Examined the gender variations in mobile phone addiction and the usage of apps with Machine Learning models like, decision tree and logistic regression [23].

SVM for Mobile Phone Addiction Prediction

Used SVM with an RBF kernel to predict mobile phone addiction based on the features obtained from questionnaires filled by 1143 respondents. The findings appeared convincing and were validated using confusion matrices [24].

Depression Prediction through Changes in Activities

Used machine learning models such as XGBoost and Random Forest for detecting changes in activities to predict depression. The precision obtained by the model XGBoost was highest in all results [25].

Gender-Based Behavioral Insights

Studied the stages of mobile phone addiction in terms of gender, and concluded that females are using mobile phones more than 12 hours per day in comparison to males who used mobile phones for shorter periods [26].

Family Dynamics and Mobile Phone Addiction

Carried out a study on the effect of mobile phones on family relations using Naive Bayes, KNN and Logistic Regression models, of which KNN model was the most precise, which shows about 95% accuracy in predicting worsening of family bond relationship due to increased mobile phone use [27].

The machine learning approach yields useful information for the prediction of mobile phone addiction, considering the behavioral data, demographic characteristics, and app usage of varying populations. These models provide possible targets for early intervention to reduce the negative impact of mobile phone use worldwide.

Appraisal of Literature on Machine Learning Algorithms for Predicting Mobile Phone Addiction

This section reviews past and current studies of machine learning (ML) models that have been applied to predict mobile phone addiction. Even with all the advancements made, there is still room for improvement when it comes to the quality of the data and choice of algorithms used.

SYNTHESIS AND COMPARATIVE ANALYSIS OF RESEARCH ON THE UTILIZATION OF MOBILE PHONES, ADDICTIONS, AND MENTAL HEALTH

This paper is set to conduct a synthesis of studies done regarding mobile phone addictions, depression detection, and behavioral analysis, focusing on the utilization of machine learning technologies.

Use of Machine Learning in Mental Health and Addiction Detection

There have also been several studies that use ML methods to identify mental illnesses and behavior addictions. [16] built Mon Majhi—a light-weight ML driven app-behaviour-based depression detection system [25] utilized ML models like XGB, RF to identify screen status-associated behavioral changes as early descriptors of depression [23- 27] employed ML classifiers namely Decision Trees, SVMs, Logistic Regression, KNN for forecasting mobile phone addiction in most cases, with either gender- or activity-related factors. These research papers indicate a trend toward light-weight, scalable ML tools for behavior and mental health monitoring, using different algorithms but mostly positive results with regards to the accuracy of the outcomes.

Behavioral Patterns and Risk Factors

Behavioural characteristics and demographics were similar among different studies [16] and [27] associated digital overuse with gender, age, and family relationships.

Table 1. Comparative assessment

Paper	Main Focus	Methodology	ML Use	Key Insight
Ahmed et al. [16]	Depression detection	ML (LGBM)	Yes	Lightweight, accurate, scalable
Gülü et al. [17]	DGA, obesity	Cross-sectional	No	DGA linked to less activity, more obesity
NurUzZaman et al. [18]	Smartphone addiction	Clustering (K-Means)	Yes	Activity data improves clustering
Xiao et al. [19]	Smartphone overuse	Shrinkage regression	Yes	FoMO, self-regulation predict overuse
Giraldo-Jiménez et al. [20]	University student dependency	SVM + Risk factors	Yes	Socioeconomic & physical risk factors matter
Naveed Answer et al. [21]	Academic performance prediction	Ensemble classifiers	Yes	Boosted trees best for large datasets
Pradeep et al. [22]	Cell phone addiction	Logistic regression	No	Life skills reduce risk
Aggarwal et al. [23]	Smartphone addiction	Supervised ML	Yes	Usage patterns strongly correlated
Koklu et al. [24]	Smartphone addiction	SVM	Yes	RBF kernel + confusion matrix used
Asare et al. [25]	Depression via phone data	Multiple ML models	Yes	XGB, RF, KNN perform best
Mazumdar et al. [26]	Gender & usage analysis	Correlation study	Partial	Female users show higher addiction
Anjaly et al. [27]	Family impact	Naive Bayes, KNN	Yes	

[22] and [20] identified connections between risk for addiction and social, psychological and life factors [19] considered FoMO as a crucial predictor of problematic mobile phone use and self-regulation as a predictor. This suggests a wide agreement on the importance of personality characteristics and situational factors in digital addiction (DA) and mental distress (MD).

Comparative Algorithm Performance

Several models of ML algorithms were compared in the studies [16] LGBM was identified the best algorithm to achieve high sensitivity to depression detection [19]. Lasso regression was discovered as the top algorithm to predict mobile phone overuse. [24] SVM with RBF helped to achieve best results for mobile phone addiction prediction [25]. XGB, RF algorithms helped to find out depression through phone behavior accurately [23]. Decision Trees, AdaBoost and KNN algorithms were determined as best to classify addiction [27]. KNN reached an accuracy of 95% in family relationship impact. On studying the performance of different ML algorithms, tree-based and ensemble models like LGBM, RF, XGB generally work better than the vanilla classifiers, especially for more difficult prediction problems.

Gender and Demographic Observations

A number of researches such as [17, 22, 26, 27] revealed that females are likely to have higher mobile phone or game addiction levels than males. Age and lifestyle components such as physical activities, peer relations and academic history were also identified as significant factors.

COMPARATIVE EVALUATION

This Table represents the comparative evaluation of various research studies performed for predicting mobile phone addiction.

Altogether, the studies demonstrate an emerging trend towards increasing use of machine learning methods to discover behavioural and psychological states in the context of mobile phone use. Ensemble models are the ones that work best for the prediction of mental health (XGB, LGBM, RF), while best among the behavioral type classification are KNN and SVM.

Based on these studies, it is apparent that psychological variables (FoMO, self-regulation), demographic variables (gender, age) and behavior (screen time, app use) are inter-related. This comparative study also proves that evidence exists for the convergence of mobile data and ML for scalable and efficient health diagnostics, although the extent of cross-cultural generalisation, data privacy and ethical issues need to be investigated in future studies.

DISCUSSION

The effectiveness of a prediction model is more or less, determined by how well it can lay bare relationships, and patterns inside a dataset. Its ability to generalize to data it hasn't seen before is super important, because it helps boost prediction accuracy, and also leads to clearer actionable insights. In other words a kind of comparative reading of different ML algorithms from the literature is wrapped up in Table 2.

Table 2. A comparative analysis of various algorithms to predict mobile phone addiction

Author/ Ref. No	Year of Publication	Methods/Models/ Algorithms used	Best Models/ Methods	Dataset Used	Sample Size	Performance Metrics	Future Work
Ahmed et. al. [16]	2023	1. Decision Tree 2. Information gain (IG) algorithm 3. Random Forest algorithm 4. Gradient Boost 5. LGBM 6. XG Boost 7. K-Nearest Neighbor 8. Logistic Regression 9. ADA Boost 10. CatBoost 11. Naive Bayes	Light Gradient Boosting Machine (LGBM)	Patient Health Questionnaire	100 Students	Accuracy 82.4%	To develop prudent computational models to identify psychological problems in low-resource settings leveraging behavioral data.
Gülü et. al. [17]	2023	Synthetic Minority Over-sampling Technique for Nominal and Continuous (SMOTE-NC)	Synthetic Minority Over-sampling Technique for Nominal and Continuous (SMOTE-NC)	DGA Questionnaire and Physical activity Questionnaire	405 Adolescents	Not Mentioned	1. Future research should include a longitudinal method to better represent the developmental course of this proposed disorder. 2. The effect of digital game addiction can be investigated in more detail by methods that can analyse self-efficacy, mental, and physical health conditions in more detail.
Pradeep et. al. [22]	2022	1. Cross-sectional data analysis 2. Logistic Regression analysis	Univariate and Multivariable Logistic Regression	6-item questionnaire	1981 Participants	Not mentioned	Complexity of associations for below criteria needs to be further analyzed. 1. Quality of life vs risk of cell phone addiction. 2. Number of peers vs risk of cell phone addiction.
Aggarwal et. al. [23]	2022	1. Decision tree 2. AdaBoost 3. Logistic Regression 4. KNNs 5. Naive Bayes with Pearson's coefficient	Decision tree with AdaBoost classification	Mobile Apps developed to collect data	96 Participants	Accuracy 75%	Classification can be narrowed down to include additional features like app-initiated events and the number of notifications each app offers, thus providing a better understanding of the app's usage.
Nigmet Koklu. N et. al. [24]	2021	1. Support Vector Machine 2. Classification Method 3. Radial Basis Function 4. Confusion Matrix	Support Vector Machine	Questionnaire	1143 Individuals	Accuracy 92.4%	Mobile application or software needs to be developed to conduct a comprehensive analysis.

Table 2. A comparative analysis of various algorithms to predict mobile phone addiction (continued)

Author/ Ref. No	Year of Publication	Methods/Models/ Algorithms used	Best Models/ Methods	Dataset Used	Sample Size	Performance Metrics	Future Work
Kennedy Opoku Asare et. al. [25]	2021	1. Random Forest 2. Support Vector Machine 3. Radial Basis function kernel 4. XG Boost 5. K-Nearest Neighbor 6. Logistic Regression 7. Random Weighted Classifier 8. Decision Tree classifier.	XG Boost	Carat app	629 participants from 56 countries	Accuracy 96.44%-98.14%.	Wearable sensor data sets can be used for correlation
Arpita Mazumdar et. al. [26]	2020	1. Unsupervised Machine Learning techniques 2. K-means Clustering	K-means clustering	Questionnaire	115 under graduates participated	Not mentioned	Further refining the model can certainly help to understand phone usage patterns and possibly predict certain threats prevalent among smartphone addicted people.
Anjaly K et. al. [27]	2020	1. Naive Bayes 2. KNN 3. Logistic Regression	KNN algorithm	Questionnaire	280 People	Accuracy 95%	To focus on a wider age group within the family

CONCLUSION

Mobile phone addiction seems to be rising everywhere, especially among students, and also in the wider general population. The problem is becoming more obvious, both in terms of a minor personal matter and a serious hindrance that can ruin daily life. The consequences include strained relations within families, poor academic performance at schools, behavioral changes and even depression. Social networks such as Facebook, WhatsApp and Instagram may contribute greatly to developing such dependency. However, mobile phones are not “evil” in themselves; they provide many benefits including fast access to relevant information, navigational assistance, educational material, e-mail correspondence, assistance in remote working, news services and entertainment. On the other hand, usage patterns vary among individuals depending on their habits and, frankly, self-discipline. In most cases, the issue of mobile phone addiction is closely connected with the user’s level of self-discipline and his or her capability to set priorities concerning maintaining relations with one’s relatives, being present at the moment and engaging in other activities.

Indeed, machine learning algorithms have already proven their effectiveness when it comes to predicting mobile phone addiction with considerable accuracy. Therefore, in future research, it is important not only to rely on symptoms as the definition of mobile phone addiction but rather discover

the root cause, which triggers it. The final aim of such an approach is to examine the impact of mobile phone addiction on academic results, physical and psychological health, and family relations. Such an objective can be achieved via conducting a review study based on existing literature, including the use of machine learning algorithms.

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AUTHORSHIP CONTRIBUTIONS

Authors equally contributed to this work.

DATA AVAILABILITY STATEMENT

The authors confirm that the data that supports the findings of this study are available within the article. Raw data that support the finding of this study are available from the corresponding author, upon reasonable request.

CONFLICT OF INTEREST

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

ETHICS

There are no ethical issues with the publication of this manuscript.

STATEMENT ON THE USE OF ARTIFICIAL INTELLIGENCE

Artificial intelligence was not used in the preparation of the article.

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