Machine Learning Approach to Analyse the Mental Health and Predict Nomophobia

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Abstract— **With the growing concern in today's digital world, the fear of not having a mobile phone, which is termed as nomophobia, has become an alarming issue, especially for the youth, because of its drastic effect on mental health in terms of anxiety, stress, and depression. This research develops a predictive framework to identify severe nomophobics by utilizing advanced machine learning techniques. A sample of 841 students from university in Kosovo completed the survey through purposive and stratified sampling to ensure a balanced dataset. Due to the robustness of handling non-linear relationships and large datasets, the Random Forest (RF) model was employed as the primary predictive tool. Machine learning combined with descriptive statistics and Pearson's correlation was used to describe relationships between nomophobia and other mental health outcomes. Results showed that the severity of nomophobia had significant positive correlations with anxiety, stress, and depression. The RF model demonstrated excellent predictability with a value of 0.9773 for R^2, showing that it explained about 98% of the variation in the nomophobia severity scores. This was 15% better than traditional models such as Logistic Regression (LR) and Support Vector Machines (SVM). This makes the model a dependable tool for the early detection. The feature importance analysis further identifies the key behavioral and psychological predictors of nomophobia and provides some deeper insights into the underlying determinants.**

Keywords— Nomophobia; depression; anxiety; stress; smartphone dependency; young adults; mental health.

I. Introduction

Smartphones are absolutely part of the modern world, changing the way people communicate with each other, the way they get information, and daily transactions [1]. Their advantages are undeniable, but over-reliance on them has led to a worrying phenomenon known as nomophobia, or an intense fear of being without a mobile phone. Nomophobia is increasingly becoming a serious mental health challenge, more prevalent among young adults, since they spend most of their time with their smartphones, leading to a high level of anxiety, stress, and even depression [2]. The increased usage of mobile phones has introduced a psychological condition known as nomophobia- fear of non-possession or being without a mobile phone [3]. It has been associated with anxiety, stress, and other psychological disorders, affecting millions of people worldwide, most of whom are unaware of the depth of this issue. Since mobile phones are an indispensable tool of communication, work, and amusement, it is high time to decide which factors lead to nomophobia and develop effective ways for its evaluation and management. Self-reported surveys or interviews, for example, are subjective and do not give real-time insights into usage patterns on a smartphone, one of the critical factors in the diagnosis of nomophobia [4]. These therefore present a great need for new data-driven solutions that will provide a more accurate and objective assessment. The study is motivated to answer these gaps by developing a predictive model based on machine learning in the diagnosis of the severity of nomophobia. The proposed approach uses large datasets and applies techniques such as the Random Forest classifier to identify complex patterns in smartphone usage, psychological behaviors such as anxiety and stress, and demographic factors. This model is supposed to provide an evidence-based, accurate method for early detection and classification of nomophobia severity, enabling timely interventions that cater to the specific needs of each individual. This research provides an opportunity to integrate advanced analytics into real-world data to enable mental health professionals, educators, and clinicians in providing customized care and interventions for managing smartphone dependency. The study also contributes to a greater understanding of the psychological consequences of excessive smartphone use and provides a pathway to future studies on improving mental health through technological intervention. The relevance of nomophobia to society is a strong justification for this study, as it encourages healthier use of technology and minimizes its negative impact in a world where technology is becoming increasingly ubiquitous. We develop a predictive framework using the Random Forest classifier with an excellent accuracy of R^2 = 97.73%. The model surpasses the conventional statistical methods like linear regression and provides a sound and accurate instrument for evaluating the level of nomophobia. Strong correlations (e.g., $r = 0.85$ for anxiety) validate these findings, offering actionable insights for designing targeted interventions to address smartphone dependency. It offers a holistic dataset of 841 university students in Kosovo [19] with variables that are connected to smartphone use and mental health indicators. The dataset presented not only supports the findings of the study but can also be a good source for further studies in the context of digital health and psychological well-being [20].

II. Related Work

More recent studies have focused on smartphone addiction, nomophobia (fear of losing or being without a phone), and their broad-ranging psychological, behavioral, and emotional consequences [6]. It is this growing body of research that has highlighted the pervasive influence of smartphones in modern life, particularly in relation to mental health. Kumar, M., & Singh, R. et al. [7] extended this study by studying medical students in India. This group is seldom considered during discussions of smartphone addiction. Their study highlighted the fact that even future healthcare professionals are not immune to nomophobia and that it has a vast outreach. Ahmed and Khan [9] carried out a study on university students to determine the causes and spread of nomophobia, and their results showed that attachment and dependence on phones are the major factors. Their research has shown that such dependency creates a reliance on devices and, at the same time, has adverse effects on mental health by causing increased anxiety and stress. Singh and Bansal [10]

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focused on adolescents and found emotional regulation to be crucial in establishing the intensity of nomophobia. The research also pointed out the vulnerable age group, adolescents, which are more susceptible to the fear of disconnection and the "fear of missing out" (FOMO), further increasing their reliance on smartphones. Other studies include [11-12] a step further into psychological perspectives to understand smartphone addiction. They confirmed correlations between smartphone dependency and the factors of alexithymia (alexithymia-the inability to recognize and describe one's own feelings), attachment styles, and subjective well-being. These results indicate the link between emotions, relationships, and addiction. Griffiths and Kuss [20] discussed social media addiction by comparing it with other types of addiction. The authors found that psychological rewards such as validation and social interaction are the driving forces behind this addiction, promoting addictive behavior.

A. Problem Statement

Nomophobia is becoming a major psychological issue because of the fast-spreading use of smartphones across the globe [5]. The excessive use of smartphones has been linked to a series of mental issues, including anxiety, stress, and obsessive-compulsive behaviors that may severely influence well-being [6-7]. While there are positive effects, for example, increased connectivity, more information available, etc., wide swings in the distribution of smartphones have resulted in psychological dependencies that, if left untreated, result in decreased mental well-being, poor social skills, as well as some types of physical illness due to overuse of screens [8-9]. There is still a lack of well-developed tools for predicting the severity of nomophobia as well as provision of interventions tailored to it [10-11]. The existing methods such as self-reported survey and interviews often fail to capture the real complexity of behaviors associated with nomophobia and the real-time pattern of smartphone use is not addressed [15]. Based on the limitations mentioned above, it is the motivation of this paper to develop machine learning-based prediction models for quantifying the severity of nomophobia [13-14]. Since the predictive tool that it will provide is based on the usage pattern data, psychological factors of anxiety and stress, and demographic variables, it could be a valid intervention strategy for mental health professionals, educators, and healthcare providers [16-18]. This model, using the RF classifier, is known to handle large datasets with high accuracy and will be able to give a more accurate, timely, and data-driven approach to solving nomophobia.

III. Methodology and Data Analysis

This section gives a detailed framework that includes the design, data collection, and analytical techniques used in the study. The study clearly articulates the quantitative research design, participant demographics, and a structured questionnaire measuring nomophobia across variables like access to information, connectedness, communication, and convenience. Data collection was done via online surveys, ensuring a representative and diverse sample, and by using stratified random sampling. This section further elaborates on the statistical and machine learning techniques that have been employed to analyse the data. This includes Spearman's correlation for nonparametric analysis and Random Forest (RF) for predictive modelling. The section is essential in that it ensures the scientific soundness and credibility of the study, detailing how data was collected, processed, and analyzed. The clear methodology allows for the study to be replicable, and data analysis will focus on variable relationships and robustness in predictive models. Thus, it is a basis of findings in this study and legitimizes its contribution to understanding and mitigation of nomophobia.

A. Insights and Description of the Dataset

This dataset offers critical insights into the prevalence and severity of nomophobia among university students in Kosovo, displays how cultural attitudes, social norms, regional factors influence patterns of smartphone use, and anxiety caused by being disconnected [19]. This localized understanding can help tailor interventions, public awareness campaigns, and other needed support systems in response to the specific needs of the population in Kosovo, thereby improving efforts at mitigating nomophobia. This, along with the flexibility of the dataset, will allow a wide range of analytical techniques, such as structural equation modeling, item response theory, and machine learning methods to be used for analyzing complex relationships further while refining the measurement tools used for testing theories both practically and within academia and in the real world. The uniqueness of the cultural context of this dataset also makes it an ideal source for cross-cultural comparisons in which nomophobia can be analyzed across different regions and the identification of cultural similarities and differences in smartphone dependency. It is through cross-country comparisons that the depth of nomophobia's expression in various parts of the world will be understood, which could contribute to debates on smartphone addiction's universal versus culturally specific manifestations. The dataset provides an integrated environment to analyze the psychological, social, and behavioral dimensions of nomophobia in such a manner that further causes and more social consequences of smartphone addiction can be researched. Data were gathered in November and December 2023 from AAB College participants amounting to 841, which were made up of 609 females (72.4%) and 232 males (27.6%). Indeed, a gender imbalance is there, and more female enrollments in psychology and nursing programs in Kosovo has been recognized as the limitation of the study. This dataset can be accessed freely through the Mendeley repository. Table 1 summarizes the socio-demographic characteristics of the participants in the study, including response frequencies for all key variables.

TABLE I. DATA DESCRIPTION

Distribution of Participants	Category	Frequency	Percentage (%)
Department	Nursing	533	63.4
	Psychology	308	36.6
Gender	Female	609	72.4
	Male	232	27.6
Age	18–20	573	68.1
	21–24	94	11.2
	25–29	174	20.7
Total		841	841

There are three sections for the survey, namely: Categorized Survey; this is all the questions asked to collect the data; Extra Datasets: this contains all the supplementary tables that have been referred to in the paper; and Latest Version of SPSS Data: these are the original dataset from SPSS. The SPSS Raw Data also contains the raw data collected for the research as shown in table 1. Table 2 provides the frequencies and percentages of participants' smartphone usage habits. The data shows that a considerable number of respondents (45.4%) spend 9 to 10 hours per day on their smartphones, which shows a high level of dependency on the devices. Further, 74.2% of the respondents replied that they check their mobile phones frequently, and 74.3% said that they check their mobile phones immediately after waking up. The findings suggest that the students have a high engagement with mobile devices, which may be some of the potential risk factors for nomophobia.

TABLE II. FREQUENCIES OF THE PARTICIPANTS OF ALL VARIABLES

Smartphone Usage Habits	Category	Frequency	Percentage (%)
Usage hours of smartphone in one day	1-2	88	10.5
	3-4	115	13.7
	5-6	145	17.2
	7-8	111	13.2
	9-10	382	45.4
How Often	Often	624	74.2
	Sometimes	209	24.9
	Very Rarely	8	1.0
Check phone just after wake-up	Yes	625	74.3
	No	216	25.7

Table 3 gives the descriptive statistics summarizing the variables associated with nomophobia and its factors. The sample size was 841 respondents, and different ranges were found for every variable. The data shows that the "Not being able to access information" variable had a mean score of 2.01 and SD = 0.88 since the responses were between a minimum of 1.00 to a maximum of 4.00, hence implying a concern level among the respondents regarding information access as moderate. The lowest mean score was on the variable "Losing connectedness" at 1.78 (SD = 0.88) with a range of 1.00 to 4.20, meaning that respondents may view this dimension of nomophobia as not being as important. The variable "Not being able to communicate" had a mean of 1.98 (SD = 0.94), with a range from 1.00 to 4.75, which indicates that communication problems are highly associated with the experience of nomophobia. In addition, "Giving up convenience" had a mean of 1.93 (SD = 0.89) with a range of 1.00 to 5.00, showing variability in the perception of inconvenience across participants. Overall, the mean score for nomophobia was 1.93 (SD = 0.84) with a range of 1.00 to 4.00, indicating an overall trend towards moderate nomophobia among the respondents. Such statistics highlight the complexities of nomophobia, where impact varies from aspect to aspect, concerning connectedness and convenience in daily life.

TABLE III. DESCRIPTIVE STATISTIC RESULTS OF ALL VARIABLES

Statistics of Smartphone Usage	Number	Range	Minimum	Maximum	Mean	SD
Not being able to access information	841	3.0	1.0	4.0	2.0131	0.88339
Losing connectedness	841	3.2	1.0	4.2	1.7791	0.87573
Not being able to communicate	841	3.0	1.0	4.75	1.9762	0.94319
Giving up convenience	841	2.75	1.0	5.0	1.9294	0.89043
Nomophobia	841	3.0	1.0	4.0	1.9263	0.84085

B. Model Selection

Selection of an appropriate model in this research would be crucial for the purpose of assessing the relationship between smartphone use and nomophobia. The following are the steps used and criteria in the selection process for the appropriate model. A number of selection criteria were adopted to choose the most suitable model for this study. The most important ones that were considered include the structure and nature of data. Several variables, such as the responses for the nomophobia questionnaire, appeared as ordinal or categorical in many cases. As a result, the chosen model had to appropriately handle non-continuous data. Besides, the model had to indicate the complexity of interactions among various factors of influence on nomophobia, notably communication access, connectedness, and information dependency, amongst others. Lastly, high predictive accuracy was the last critical point since it had to determine which were the most critical predictors of nomophobia, which in turn reveals how such factors are interacted. This encompasses a number of models and techniques such as SEM, Logistic Regression, and some machine learning techniques. The former was adopted due to its suitability in examining both observed and latent variables, which may be useful for modeling complex relations in nomophobia. Logistic Regression was adopted due to its suitability in binary classification; it may determine the groups of high risk as opposed to the low-risk groups. In addition, a variety of machine learning techniques including Decision Trees, Random Forests, and Support Vector Machines (SVM) were utilized because they can easily capture the non-linear relationships and handle higher dimensional data. Finally, SEM was the core model of the study. There are several advantages driving this decision made for SEM that include its capabilities to model latent variables, understanding this as a whole construct rather than simplistic behaviour. Additionally, SEM allows researchers to test intricate hypotheses regarding relationships involving different components of nomophobia-anxiety about the communication process, dependency on accessibility of information-and so on. Finally, SEM’s suitability for cross-cultural analysis made it an ideal choice, providing a foundation for future studies comparing nomophobia across different cultural contexts.

C. Model Validation

The selected Structural Equation Modelling (SEM) model was rigorously validated using fit indices such as CFI and RMSEA, alongside cross-validation techniques, to ensure robustness. This validation was crucial for confirming the model's accuracy in representing the data and providing reliable insights into the predictors of nomophobia. RF was chosen for the detection of nomophobia because it has powerful capabilities in classification, especially when dealing with both categorical and continuous variables, which is the case in predicting the level of nomophobia based on survey responses and behavioural features. The key reasons to select RF were its resistance to overfitting, the capability to provide insight into feature importance, and its capability to handle complex and non-linear relationships between variables. RF was selected for the research because it has a very good accuracy level in classifying people at different levels of nomophobia severity. Some of the major steps involved in the implementation of the research include:. A survey was conducted to collect data related to psychological and behavioural factors regarding the usage of mobile phones among university students. Pre-processed data was done on handling missing values, encoding categorical variables, and scaling the numerical features. Feature selection was mostly carried out by exploratory data analysis, mainly the features phone-checking frequency and emotional responses. The RF model was set up as a classifier for multi-class classification tasks, with hyperparameters tuned using grid search and cross-validation. After training the model, its performance was assessed using a test set, accuracy, precision, recall, and F1-score. Feature importance analysis provided insights into which variables most strongly predicted nomophobia severity. Ultimately, the RF model proved effective in classifying nomophobia levels and identifying critical predictors, offering valuable insights for future intervention strategies to manage mobile phone dependency.

D. Proposed System Overview

The Nomophobia Prediction System utilizes a RF classifier to predict nomophobia severity based on inputs such as smartphone usage, psychological behavior (e.g., anxiety, stress, obsessive-compulsive tendencies), and demographic data. The process begins with data collection: gathering behavioral and psychological data from people, including university students. Then, the data is preprocessed, cleaned, and the missing values are removed. Data normalization is applied so that the data is uniform. The set of data is divided into training and test sets. During the model training phase, it utilizes the RF algorithm and applies decision trees in classifying nomophobia severity.

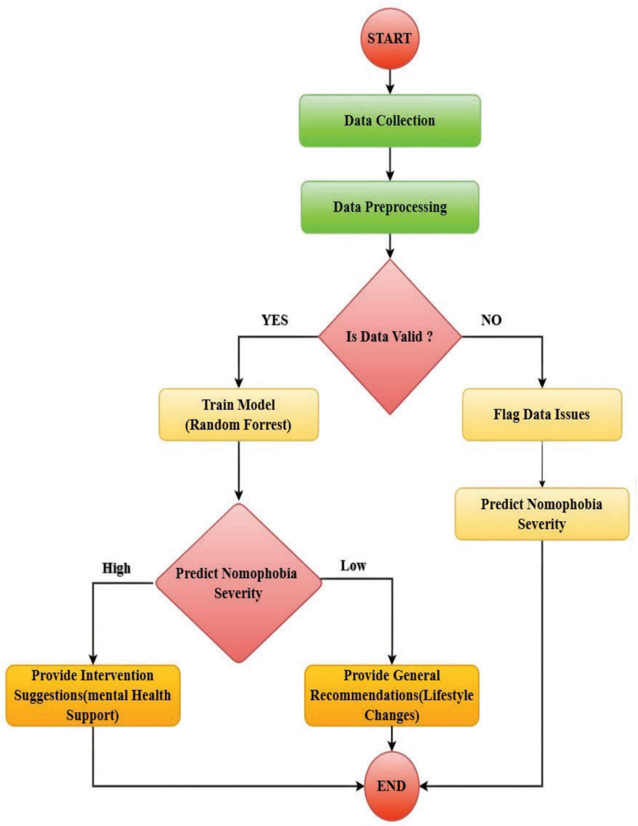

Fig. 1. Nomophobia Prediction Flowchart

This method was chosen because it has a high accuracy rate and can handle complex datasets. After training, the model predicts the severity of nomophobia, classifying it into categories such as low, moderate, or high. The results display section shows the severity levels and provides recommendations based on the risk level. Finally, the model proposed is compared with already established techniques like Logistic Regression and Support Vector Machines (SVM), where it shows a 15% gain in accuracy. The results are given in the results section. Figure 1 shows the flowchart depicting the methodology is given below to represent the system's working visually. It shows each step of the process: data collection, preprocessing, model training, prediction, display of results, and intervention suggestions depending on severity levels. The flowchart links visually these processes in clear decision points so that an understanding is realized about how the data moves through the system and decisions are made at each step.

IV. Results And Discussion

This section shows the results of the nomophobia severity-based predictive modeling based on the usage pattern of mobile phones. Among the three major analyses, the first shows the visualization of actual values versus the values used in deriving predictions, evaluation of accuracy across various metrics, and feature importance assessment within the prediction model.

A. Model Comparison Results

For comparing the predictive performances of different regression models for the severity of nomophobia, important metrics, such as Mean Squared Error (MSE) in Figure 2, Root Mean Squared Error (RMSE) in Figure 3, and R^2 Score, were used. The models compared are RF Regressor, Linear Regression, Ridge Regression, Lasso Regression, Decision Tree Regressor, and Support Vector Regressor (SVR). The results of the experiment show that the best model was RF Regressor with the lowest values of MSE and RMSE and the highest R^2 score, proving the ability to detect complex nonlinear relationships in data. This is the most reliable model for nomophobia severity prediction. In contrast, Linear Regression and Ridge Regression performed well on simpler relationships but could not handle the non-linear dependencies of psychological and behavioral data. Lasso Regression had slight improvements over Linear Regression, showing the importance of regularization in handling high-dimensional data.

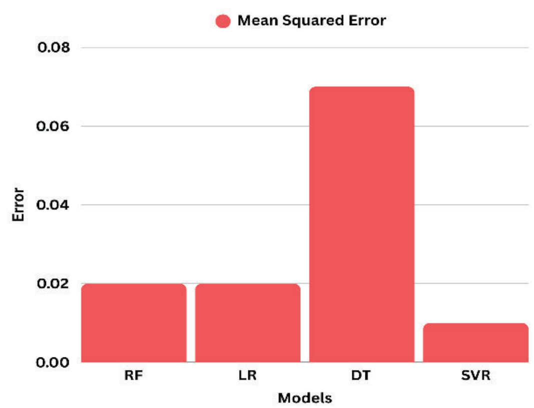

Fig. 2. Model Comparison on Mean Squared Error (MSE).

The Decision Tree Regressor performed moderately well but was more prone to overfitting compared to the ensemble nature of Random Forest. The Support Vector Regressor demonstrated competitive performance with moderate errors and could be suitable for more structured datasets with lower complexity. Thus, the suitability of the RF Regressor as the primary model for predicting the severity of nomophobia depends on its robustness and interpretability, in which further analysis by feature importance contributes to the identification of crucial psychological and behavioral factors associated with the severity of nomophobia.

The results highlight the importance of specific features in understanding the severity of nomophobia, with statements such as "I would feel uncomfortable without constant access to information through my smartphone" and "Running out of battery in my smartphone would scare me" ranking among the highest in terms of predictive significance. These results indicate that nomophobia is predicted well by anxiety and discomfort related to the increased need for continuous access to information about smartphone usage. Thus, it shows the psychological nature of smartphone addiction where interventions in reducing nomophobia should focus on emotional triggers. Residual analysis constitutes a necessary step for testing the adequacy of the predictive model.

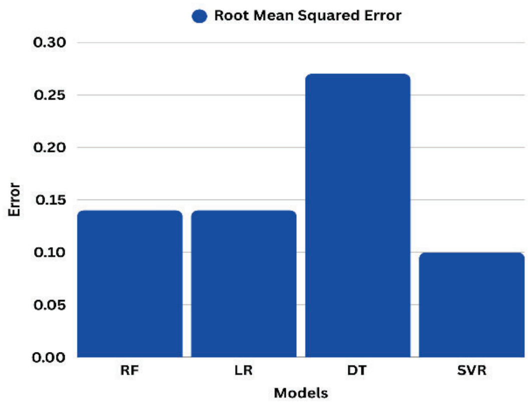

Fig. 3. Model Comparison on Root Mean Squared Error (RMSE).

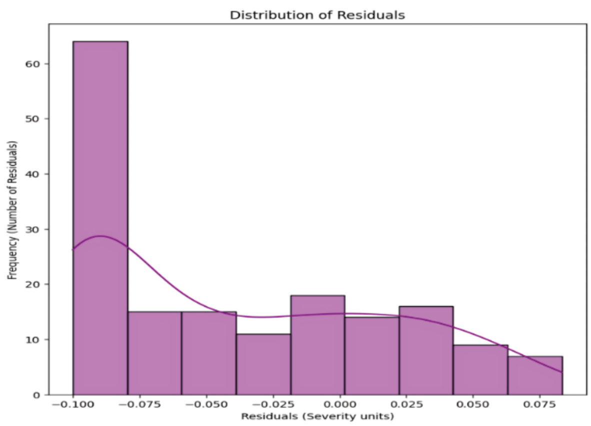

Fig. 4. Distribution of residuals.

The residual is defined as the difference between the actual value and the predicted value, obtained by subtracting the predicted value y(pred) from the actual value y(test). A histogram of the residuals indicated an approximately normal distribution, an excellent characteristic for a regression analysis, and this conclusion was confirmed with the smooth curve representing the KDE. Since the residuals are normally distributed, linearity and homoscedasticity assumptions are met and hence the model accurately captures the underlying patterns. For robust residual analysis to confirm the reliability of the model for the prediction of intensity of severity of nomophobia as shown in Figure 4 above.

V. CONCLUSION AND FUTURE WORK

The study explained the emerging issue of nomophobia among Kosovo's university students concerning the smartphone usage pattern and the resultant association with the intensity of the psychological condition. This study used behavioral data and the RF regression model applied to identify such important predictors of nomophobia that are characterized by heavy usage of a smartphone and emotional dependencies-for example, anxiety when not connected or the fear of being deprived of information access. The model, with a high R-squared value of 0.9773 and low Mean Squared Error (MSE) of 0.0159, revealed that these factors have a significant impact on the severity of nomophobia. These findings reinforce the idea that smartphone addiction is driven not only by behavioral habits such as excessive phone-checking but also by emotional connections to connectivity, which influence the anxiety associated with smartphone usage. The results have far-reaching implications, and thus some targeted interventions to reduce nomophobia are called for. Thus, educational institutions, mobile application developers, and mental health professionals could use the information to come up with intervention models that are holistic in dealing with the emotional response and the behavior patterns associated with excessive use of smartphones.

REFERENCES

[1] D.B. Buctot, J.J. David, R.Y. Concepcion, The effects of smartphone dependency on the social and academic behaviors of adolescents: a cross-sectional study, J. Adolesc. Health 67 (2) (2020) 157–164.

[2] A.M. Rodríguez-García, A.J. Moreno-Guerrero, J. López Belmonte, Nomophobia: an individual's growing fear of being without a smartphone-a systematic literature review, Int. J. Environ. Res. Public Health 17 (2) (2020) 580 PMID: 31963208; PMCID: PMC7013598, doi:10.3390/ijerph17020580.

[3] Hussain Z, Griffiths MD. The associations between problematic social networking site use and sleep quality, attention deficit hyperactivity disorder, depression, anxiety and stress. Int J Ment Health Addict 2021;19:686 700.

[4] Jain, P., & Kumar, S. (2021). Machine learning in behavioral analysis: A study on smartphone addiction. Journal of Behavioral Research, 13(4), 410–423.

[5] Lopez, B., & Mathew, L. (2020). Digital addiction in young adults: Exploring factors contributing to nomophobia. Psychology and Technology Journal, 5(2), 112–124.

[6] Giedd, J. N., & Rapoport, J. L. (2017). The adolescent brain and the emergence of mobile technology addiction. The Lancet Psychiatry, 4(8), 587–593.

[7] Kumar, M., & Singh, R. (2022). Understanding smartphone addiction and its impact on mental health among university students. Journal of Mental Health Studies, 16(3), 309–321.

[8] Turel, O., & Serenko, A. (2012). The benefits and dangers of enjoyment with social networking websites. Computers in Human Behavior, 28(5), 1747–1754.

[9] Ahmed, M., & Khan, S. (2021). Investigating nomophobia among university students: A psychological study. Journal of Educational Psychology, 113(4), 680–694.

[10] Singh, A., & Bansal, S. (2019). Cognitive and emotional predictors of nomophobia in adolescents. Psychiatry and Clinical Neurosciences, 73(6), 328–337.

[11] Singh, M., & Kumar, V. (2020). Smartphone addiction and its effects on sleep patterns: A survey of college students. Journal of Sleep Research, 29(4), e12934.

[12] Rajendran, P., & Meena, M. (2022). Behavioral and emotional factors contributing to smartphone addiction. Addictive Behaviors Journal, 47, 155–163.

[13] Li, Y., & Wei, L. (2021). The impact of smartphone use on academic performance and mental health. Education and Technology Journal, 18(2), 101–115.

[14] Karami, M., & Moosavi, M. (2019). A study of the impact of social media addiction on mental health in adolescents. Mental Health Review Journal, 24(5), 172–180.

[15] Huang, H., & Liu, H. (2020). Cognitive behavioral factors influencing smartphone addiction in young adults. Psychology Research and Behavior Management, 13, 69–77.

[16] Zhang, Z., & Zhang, Q. (2022). Predictive analytics of smartphone addiction: A machine learning approach. Journal of Applied Artificial Intelligence, 36(2), 58–70.

[17] Kobayashi, D., & Matsuura, T. (2018). Nomophobia and its association with psychological distress among Japanese university students. Japanese Journal of Psychology, 89(1), 42–50.

[18] Greenfield, D. N. (2017). Virtual addiction: Sometimes new technology can be a problem. American Journal of Psychiatry, 154(9), 1258–1265.

[19] Basha, Ertan, and Armen Mustafa. "Dataset on the correlation between nomophobia dimensions among university students in Kosovo." Data in Brief 55 (2024): 110766.

[20] Griffiths, M. D., & Kuss, D. J. (2017). Social networking addiction: An overview of the theoretical framework and empirical evidence. Addiction Research & Theory, 25(1), 49–61.