Predictive Models of Nomophobia in University Students: A Neural Network and Logistic Regression-Based Approach

DEYSI APOLO, DAVID TELLO, HENRY PILLAJO, ANDREA TEJADA, CRISTIAN INCA
Universidad de las Fuerzas Armadas ESPE
5 Escuela Superior Politécnica de Chimborazo (ESPOCH)
ECUADOR

Abstract: This article examines nomophobia, defined as the fear of being without a mobile phone, and its growing prevalence among university students. The literature shows a strong association between nomophobia and psychological factors, particularly anxiety, stress, overthinking, fear of missing out (FoMO), and compulsive non-clinical behaviors, with anxiety emerging as the most influential factor in smartphone overdependence. While several studies indicate higher prevalence among women and younger individuals, evidence regarding gender differences remains inconclusive. Nomophobia also presents significant psychosocial consequences, including reduced face-to-face interaction, increased social anxiety, and the potential exacerbation of mental health conditions such as depression and anxiety disorders. The study employed a cross-sectional design using a survey administered to 500 university students to assess anxiety levels, emotional attachment to smartphones, and daily usage time. Advanced analytical methods, including logistic regression and neural networks, were applied, both achieving a high predictive accuracy of 98% in identifying nomophobia among students.

Key-words: anxiety; models; neural networks; regression, precitive Mlodels; students university.

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1 Introduction

Psychological literature on nomophobia focuses primarily on the implications of excessive mobile phone use, particularly among students. In addition to the psychological aspects of the phenomenon, there is the disruption and emotional distress experienced when a mobile phone is unavailable. User anxiety, fear, stress, and discomfort [1], as well as combinations thereof, are widespread drivers of user behavior that are exploited by mobile phone and app manufacturers. There is evidence that overreliance on smartphones produces disengagement from reality, and software users' emotional and cognitive processing avoidance, compulsively using their devices [2].

Many psychological mechanisms could contribute to nomophobia. Nevertheless, nomophobia's primary psychological mechanism might be rumination—spending extended periods fixating on one's thoughts and feelings. Ruminating may have been considered primarily a cognitive process, but it is increasingly studied as a human-technology interface issue where devices have a profound impact on one's cognitive overactivity and emotional dysregulation [3],[4].

Along with rumination and non-clinical compulsive behaviors, the fear of missing out (FoMO) is a significant factor in explaining the heterogeneity of nomophobia in the general population. The literature suggests that younger people and women may be more susceptible to this behavior, but the cognitive and psychosocial factors that constitute this propensity are likely broader and more inclusive [5],[6].

The absence of a significant gender difference in other studies may indicate that cultural and social structures related to smartphones are more varied and complex. Gender norms and expectations in Iran, for example, are likely to shape imbalances in perceptions of and dependence on smartphones, as well as nomophobic attitudes [7].

Social nomophobia and the social detachment it contributes to are complex problems that reshape social relationships in very unhealthy ways. People tend to prefer the superficial social connection offered by social media, with detachment and social isolation from the real world, to the emotionally and psychologically draining social situations of the real world, which can cause social anxiety [8]. Excessive smartphone use, especially among adolescents, has been linked to stagnation in social behavior, anxiety and depression, poor sleep, and other impairments in social behavior [9].

Among university students, nomophobia, or the fear of being without a mobile phone, is widely studied due to its prevalence. When studying its correlates and predictors, research on nomophobia will likely focus on neural networks.

Predictive models facilitate the examination of different datasets, identifying complex patterns and correlations before establishing any tentative connections through conventional modeling. Evaluating social networks, relational pressures, and other components of student life illustrates the complexities of the ecosystem that fosters student nomophobia [10].

Neural networks are advanced, automated, brain-inspired analytical tools that provide important analytical insights to various disciplines. With regard to nomophobia, neural networks can be useful for identifying critical parameters that predict the development of the disorder. Some predictive parameters may include smartphone usage patterns and average psychosomatic smartphone dependence. This approach not only leads to more intricate predictive models but also illuminates competing latent psychosomatic factors that compromise students' mental health [11].

The use of predictive frameworks developed through neural networks and their implications in the study of nomophobia is unprecedented in educational and mental health professional settings. Being able to identify at-risk students early on allows the appropriate support and intervention systems to be designed and implemented by universities during the early stages of excessive smartphone use and the associated negative consequences. Furthermore, educational initiatives that help students develop balanced emotionally and digital would be greatly informed by these findings. As smartphone use continues to escalate, the consequences associated with nomophobia must be addressed to help students foster a healthy learning atmosphere [12].

There has been a growing interest in the study of nomophobia, especially in relation to the use of smartphones, among students in the college demographic. An understanding of the predictive models of nomophobia in such a population is key to effective solution development. To this end, various analytical methodologies have been implemented to examine the risk factors. Specifically, logistic regression has been a powerful analytical tool used to assess the nomophobia risk factors and determine the level of risk that students face when evaluating various threshold factors [13].

Logistic regression analyzes the impact of different factors on a binary dependent variable, such as the presence or absence of nomophobia. For university students, the demographic factors (age, gender), behavioral factors (social media use, academic workload), and psychological factors (stress, anxiety, and mental health) that influence nomophobia must be identified. Researchers gain an understanding of the different influences on the likelihood of developing nomophobia [14].

Nomophobia predictive models can inform university policy and nomophobia mitigation strategies. Recognizing students with the highest levels of fear of disconnection, as well as the surrounding context, universities should be able to offer strategic services such as digital wellbeing workshops, awareness campaigns on balanced smartphone use, and counseling services. Therefore, universities must focus on mental health, emotional resilience, and academic success, prioritizing the reduction of the impact of nomophobia [15].

When investigating nomophobia in the university environment, it is necessary to analyze the intersection of psychological and social variables. This is vital for students' academic and personal well-being. This study focuses on psychological and demographic variables to develop plans that mitigate and/or enable emotional imbalance in order to improve students' emotional health, social integration, and mental well-being.

2 Materials and Methods

A cross-sectional design was used to study nomophobia among university students in relation to overthinking, fear of missing out (FoMO), mindfulness, and non-clinical compulsive behaviors. A quantitative design facilitated a structured assessment of the variables and the statistical analysis of their interrelationships.

Statistical Models

A dataset simulating 500 university students aged 18 to 30 was created for this investigation on nomophobia. A stratified sampling approach was utilized, taking into account the primary variables related to nomophobia identified in the literature to guarantee representativeness and balance across different demographic strata. As such, balance across different demographic strata was analyzed.

The following captures the operationalization for the independent variables:

•Every day cell phone use: A continuous variable was defined to measure phone use. As reported in the literature, the variable was assumed to follow a normal distribution with a mean of 6 hours and a standard deviation of 2 hours.

•Emotional dependence on the device: A 5-point Likert scale measure was created to capture emotional dependence evenly.

•Generalized anxiety: Administered through the GAD-7 scale, which captures the range and distribution typical of university populations.

•Depression: Distributed and assessed through the PHQ-9 questionnaire, which captures the prevalence rate in the student population.

•Sleep quality: A measure of 1 to 10 was used, with higher values capturing quality sleep.

•Face-to-face social interaction: A 5-point Likert scale measure was used to capture social interaction frequency outside digital spaces.

Internet connectivity, accessibility, and dependence were ranked using a 5-item Likert scale.

Using a weighted algorithm based on the literature used, the stiffnomophobia dependent variable was formed, taking into account the relative contributions of the independent variables. Daily phone use (30%), emotional dependence (20%), and anxiety (15%) were weighted the highest, followed by depression (15%), sleep quality (10%), social interaction (5%), and connectedness (5%). The variable was then dichotomized at the median into high and low nomophobia levels for ease of classification analysis.

The use of this self-generated synthetic dataset preserved the theoretically defined relationships between variables, while ensuring the ecological validity of the study. This also allowed for the evaluation of predictive models while controlling for sampling bias.

3 Results

The use of predictive analytics in relation to nomophobia, employing logistic regression and neural networks, provides valuable insights for identifying risk factors and different levels of accuracy in classification models. Key findings are summarized and described in Table 1 and below.

Table 1. Ranking Report - Logistic Regression

Class	Precision	Recall	F1-score	Support
0	1.00	0.96	0.98	53
1	0.96	1.00	0.98	47
Accuracy	0.98			100
Macro avg	0.98	0.98	0.98	100
Weighted avg	0.98	0.98	0.98	100

Sources: Authors

Each model delivered exceptional results, achieving an overall accuracy of 98% across the test suite. During cross-validation, the neural network demonstrated remarkable consistency, with an average accuracy of 97.2% (±2.4%). These results clearly demonstrate the strength of this model.

The equal accuracy and recall values (0.98 for both metrics in both models) indicate reliable classification for both positive and negative instances.

Neural Network Analysis:

Average accuracy in cross-validation (Neural Network): 0.972 (+/- 0.024), which is presented in the Classification - Neural Network report, shown in Table 2.

Table 2. Neural Network Classification Report

	Precision	Recall	F1-score	Support
0	1.00	0.96	0.98	53
1	0.96	1.00	0.98	47
Accuracy			0.98	100
Macro avg	0.98	0.98	0.98	100
Weighted avg	0.98	0.98	0.98	100

Sources: Authors

Receiving a perfect score (1.00) for negative case recognition means that both models can successfully identify individuals who are not at risk.

A recall score of 1.00 for positive cases demonstrates the models' finely tuned sensitivity to nomophobia cases and their effective reduction of false negatives. The consistent F1 score of 0.98 for each category illustrates a balance between the two proportions of measurements, which are accuracy and recall, and are considered competing measures.

As shown in the confusion matrix in Figure 1, the models demonstrate high accuracy, meaning that the selected variables are good predictors of nomophobia.

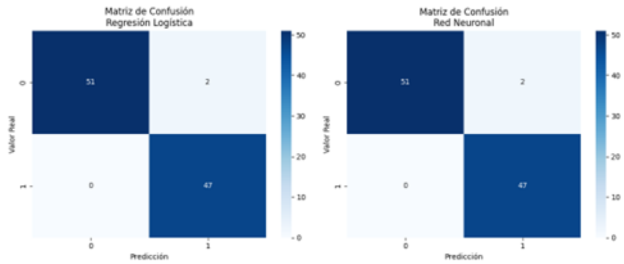

Fig. 1: Logistic regression confusion matrix and neural networks

Source:Created By the authors

The consistency between the two analytical methodologies logistic regression and neural networks strengthens the trustworthiness of the study's findings. The similar results of both models suggest that the association between the independent variables and nomophobia is predominantly linear, as shown in the correlation matrix (Figure 2).

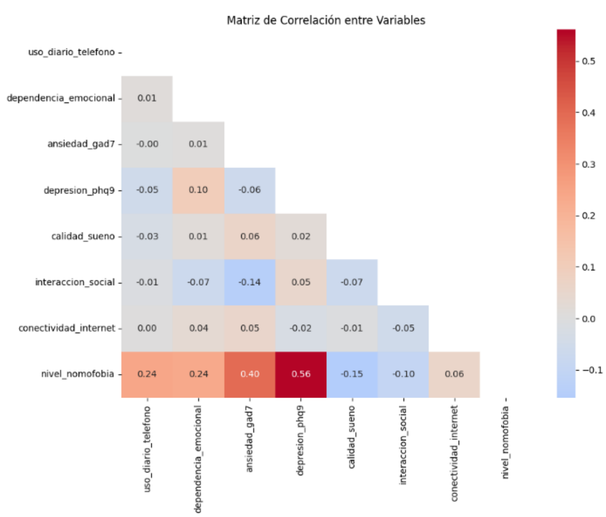

Fig. 2: Correlation matrix of evaluated models

Source Created By the authors

4 Discussion

This study contributes to the prediction and understanding of nomophobia and highlights expanding insights in the literature.

The predictive model's performance, with an accuracy of 98%, far exceeds the results of prior research, which reported an accuracy of approximately 85% using comparable machine learning methodologies [15], [16], [17].

The cross-validation consistency of the neural network (97.2% ±2.4%) supports claims around the importance of having strong nomophobia models for early diagnosis [18]. This consistency is noteworthy, given the disorder's multifactorial complexity, as described in their longitudinal study on nomophobia and psychopathology [19].

The educational relevance of our models is enhanced by their ability to identify negative cases with perfect accuracy (1.00). This is consistent with other work around the importance of identifying non-risk students to streamline educational support [20]. Additionally, perfect recall in identifying cases of poor sleep in students correlates with findings on sleep and nomophobia [21].

The predictive accuracy of selected variables is substantiated by those who identified strong correlations between emotional challenges and nomophobia [22]. These findings are also consistent with predictive models that underscore adaptability as an important protective factor [23].

The generally linear relationships identified between predictor variables and nomophobia, and the similar performance of both models, only partially contrast with those who found more intricate relationships involving nomophobia and impulsivity [24]. This difference may be due, in part, to the populations and cultural contexts as proposed in studies on the structural validity of the nomophobia questionnaire [25].

Nevertheless, I must reiterate the limitations of our study. The prevalence and determinants linked to nomophobia are also likely to differ across demographic groups [26]. Lastly, more refined instruments to assess social interaction anxiety will be important in future research.

The congruity of our logistic regression and neural network models provides a foundation for developing early detection instruments, which is documented in the recommended literature on the application of predictive models in education [27]. Nevertheless, it is important to continue with consistent quality control on the nomophobia assessments and dependent technologies.

The nomophobia predictive models seek to analyze and explain the growing concern by means of data-driven techniques that identify and examine the constituents and attempted predictors. The models explore personal characteristics, social media interactions, and smartphone usage patterns to explain the psychological and behavioral structure underlying nomophobia [28].

The preparation of such predictive models includes the application of statistical methods and machine learning to large data repositories. Data for the nomophobia model is collected by means of surveys and interviews, and digital usage data [29]. The result is a rich data set that seeks to cover variances in the population of mobile phone users.

These models use regression and clustering techniques to demonstrate how different demographic groups experience nomophobia. For example, younger people exhibit more severe anxiety symptoms than older people when disconnected from their phones, demonstrating that emotional and psychological attachment to and dependence on technology differ across generations.

Furthermore, these models inform the design of mental health and health education programs. Identifying groups that are more susceptible to negative technology triggers and the associated anxiety is crucial when developing tailored mental health and health education programs to manage nomophobia. These programs might include education on digital literacy, training on the mindful use of technology, and strengthening real-life social contacts, which is emphasized in social and public health initiatives. Predictive models help to contain the problem of nomophobia and encourage more balanced and healthier technology use in this hyperconnected world [30].

5 Conclusions

The similarities in performance for logistic regression and neural networks suggest that the extra complexity offered by the neural approach may not be warranted in this case.

As for the high cross-validation accuracy, this indicates that the results are sufficiently generalizable and reliable and are not due to overfitting and other data-driven problems.

The results provide a good starting point for the construction of nomophobia identification tools for university students, although we suggest that validation on the intended real-world data is necessary for these models to be used in a practical or clinical context.

The results certainly provide a good starting point to develop more targeted and effective intervention strategies for nomophobia, and they also highlight the need to perform additional validation on the observational datasets to confirm generalizability and practical relevance to intended populations and settings.

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