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A Neural Network Model of Risk and Protective Factors for Poor Sleep Quality in Healthcare Providers: Role of Aggression and Self-regulation

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Abstract

Background: *Although the literature discusses the benefits of good sleep on physiological, psychological, and physical health, poor sleep quality is common among healthcare providers. The present study aimed to predict poor sleep quality among healthcare providers based on multiple risk factors (aggression, gender, and age) and the protective factor of self-regulation using a neural network model.*
Methods: *Using multistage cluster sampling, a group of 400 healthcare workers (70% female, with an age average of 32 years) from Kermanshah city in western Iran were selected for the cross-sectional study. Data were collected using the Pittsburgh Sleep Quality Index (PSQI), the Buss-Perry Aggression Questionnaire (BPAQ), and the Self-Regulation Questionnaire (SRQ). A neural network model and receiver operating characteristic (ROC) curve were used for data analysis.*
Results: *Four hidden units were found in a single hidden layer extracted using the current model. More than 84% of the training and testing models accurately predicted good and poor sleepers. The neural network model's good predictive value was indicated by the Area under the ROC Curve (AUC=0.863). The results imply that self-regulation (0.30), anger (0.20), physical aggression (0.19), verbal aggression (0.11), hostility (0.10), age (0.06), and sex (0.05) have normalized importance values ranging from 18% to 100%, making them significant predictors of both the good and poor sleep subgroups.*
Conclusions: *The present neural network-based algorithm, which considers the risk and protective factors of poor sleep quality, could be effectively used by healthcare providers.*

Keywords: Aggression, Neural network, Protective factor, Risk factor, Self-regulation, Sleep quality.
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Introduction

The term "sleep quality" refers to how satisfied one is with different aspects of the sleep experience, such as wakefulness after sleep onset, latency and duration, and efficiency[1]. Numerous studies in recent years have highlighted the advantages of high-quality sleep on physiological, psychological, and physical health[2,3]. However, between 5 and 88 percent of various populations have been found to have poor sleep quality, according to various studies[4–8]. With prevalence rates ranging from 33 to 61 percent, poor sleep quality is also a common psychiatric condition among medical students and healthcare professionals[9–12]. It is also reported that more than 70% of Iranian medical students and healthcare professionals have poor sleep quality[13–15].

Numerous research endeavors aim to identify the physical and psychological risk factors for poor sleep quality in various populations, as it has been shown that poor sleep quality negatively impacts the psychological well-being of communities and quality of life[1,5,17–23]. Studies[1,5,17–23] emphasized the significance of female sex, aging, smoking, immobility, caffeine consumption three hours before bed, using mobile phones right before bed, spouses' poor sleep quality, somatic symptoms, worry, anxiety, depression, temperament and personality features, and violence and aggression.

Recent research aims to investigate the possible links between violent behavior and poor sleep quality[20,22]. The World Health Organization (WHO) defines violence as "the intentional use of physical force or power, threatened or actual, against oneself, another person, or against a group or community, that either result in or has a high likelihood of resulting in injury, death, psychological harm, mal-development or deprivation. Self-directed violence, collective violence, and interpersonal violence are the three broad categories into which the WHO divides violence[24]. Intimate family and community violence are two subtypes of the latter type, which is defined as violence between individuals[24,25]. Anger, hostility, verbal aggression, and physical aggression are among the main forms of aggression that are indicative of interpersonal violence[26]. According to definitions, aggression is an innate behavior that, depending on the circumstances, can be either disproportionate or proportionate[27].

While disproportionate aggression is maladaptive behavior in the face of real or perceived risk, proportional aggression is an adaptive behavior that adapts to changes in social values[27]. According to recent research, up to 80% of adult populations worldwide report experiencing some form of aggression or violence at some point in their lives[28–30]. Up to 68 percent of Iranian adults also frequently engage in violence and aggression[31-33].

Although most of the previous studies consider sleep problems as the cause of anger and aggressive behaviors[34,35], it seems that there is a two-way interaction between these variables. Aggressive behaviors can be manifested in two forms, state and trait. The state of anger is affected by environmental conditions and stressors and is an unstable behavior, while the trait of anger is rooted in the abnormal personality of the person and appears frequently[36]. However, the trait of anger is influenced by personality rather than sleep problems. Both the state and trait of anger were strongly linked to emotional regulation difficulties[37]. Some studies have reported a relationship between emotional self-regulation and poor sleep quality[38,39]. Therefore, we hypothesize that different forms of aggression such as anger, hostility, verbal aggression, and physical aggression are risk factors for poor sleep quality, while emotional self-regulation is a protective factor. However, the relevance literature is limited in several aspects in evaluating the hypothesis (for example: aggression was predicted by poor sleep quality, the total score of aggression was reported rather than all its forms, self-regulation was not included as a protective factor for poor sleep quality caused by aggression). To our knowledge, no research has utilized neural network models to predict poor sleep quality while taking into account various forms of aggression and self-regulation. In addition to all the variables examined in this study, we expanded the list of predictor variables to include age and sex, which have been identified in the past as risk factors for poor sleep quality. However, there are several benefits to using neural networks: they don't require as much formal statistical training; they can detect all possible interactions between predictor variables; they can implicitly detect complex nonlinear relationships between dependent and independent variables; and there are several training algorithms available[40]. Thus, the present study aimed to predict poor sleep quality in healthcare providers by different forms of aggression including anger, hostility, verbal aggression, and physical aggression as well as self-regulation, sex, and age utilizing a neural network model.

Materials and Methods

All healthcare providers employed from March 2021 to March 2022 in Kermanshah City's four government hospitals made up the statistical population of this cross-sectional study. A multi-stage cluster sampling technique was employed to invite 450 individuals to partake in the research. The formula (N>50+8×independent variables) indicates that 122 subjects is an appropriate sample size for the present study because it includes nine predictor variables[41]. For every predictor variable, five to filthy persons have been mentioned in certain reports[41,42]. Therefore, 450 individuals is a more appropriate sample size. Twenty of the 430 persons we invited, nevertheless, did not return the questionnaires to the study team. Following the removal of 10 subjects with significant missing data, the final sample comprised 400 subjects. We included participants who agreed to participate in the study, spoke Persian fluently, ranged in age from 20 to 60, and had not taken medication or received psychotherapy within the previous four weeks. Samples with physical disabilities and subjects with a high number of missing or incorrect responses were also excluded. The Ethics Committee's code of ethics was received, and then the data collection process got underway.

First, we identified the samples and gave them our word that their information would be kept private. Next, a self-report form was used to gather the sample socio-demographic data, which included gender and age groups, marital status, degree of education, and history of life-threating illness. Subsequently, a skilled clinical psychologist administered three reliable questionnaires to each participant to asses predictor and criterion variables. The Buss-Perry Aggression Questionnaire (BPAQ) and the Self-Regulation Questionnaire (SRQ), which measure various forms of aggression and self-regulation, were used to assess the predictor variables. The predictor variables also included sex and age of the participants. The Pittsburgh Sleep Quality Index (PSQI), which measures sleep quality, served as the criterion variable.

The Pittsburgh Sleep Quality Index (PSQI): The PSQI is a validated self-report measure with seven categories and eighteen items[43]. Questions 1, 3, and 4 deal with the efficiency of sleep; question 9 pertains to subjective sleep quality; item 2 and item 5a score deal with sleep latency; question 4 deals with the duration of sleep; item 5b and item 5j deal with sleep disturbance; item 6 deals with using sleeping pills; and item 7 and 8 deal with daytime dysfunction. Every question has a point value between 0 and 3, with a maximum of 3 points allocated to each category. These seven categories are used to calculate the scale's total score, which goes from 0 to 21. Higher scores denote lower sleep quality and scores above five signify poorer sleep quality. Based on prior research,[44] the PSQI in Persian has been found to be reliable.

The Buss-Perry Aggression Questionnaire (BPAQ): Aggression is measured using the 29-item BPAQ scale[26]. The questions were on a five-point scale from "very uncharacteristic of me" to "very characteristic of me". Anger, hostility, verbal aggression, and physical aggression are the four subscales that make up the BPAQ. Normalized scores range from 0 to 1, where 1 represents the highest degree of aggression. A prior report [45] stated that the Persian version of BPAQ has acceptable reliability.

The Self-Regulation Questionnaire (SRQ): The ability and severity of self-regulation are evaluated using the 31-item SRQ[46]. A Likert scale from one to five is used to rate the questionnaire (strongly disagree or strongly agree). The individual's score falls between 31 and 155; higher scores correspond to higher levels of self-regulation. According to a prior Iranian study[47], this questionnaire's reliability is acceptable. The mean and standard deviation of the scores for each independent variable including age, sex frequency, physical and verbal aggression, hostility, anger, and self-regulation were first presented. Using independent t-test statistics the continuous scores of the aggression subscales, age, and self-regulation were compared between the groups. The Chi-square test was used to compare the sex categories between the good and poor sleepers. Using the aggression subscales, self- regulation, age, and sex, a neural network model was used to predict the good and poor sleepers. This was done because neural networks are useful tools for predictive models that contain nonlinear multiple variables. The purpose of the neural network model was to determine the relationship between linear and nonlinear data using a multilayer perceptron (MLP), which has three different kinds of input, output, and hidden layers. The receiver operating characteristic (ROC) curves were then used to detect sleep disorders in both good and poor sleepers with high sensitivity. The ROC curves' area under the curve (AUC) for each group was also provided. A model with good predictability is indicated by a value of 0.80 or higher[48]. The statistical software version 20 was utilized for all the analyses, and the significance level was set at 0.05.

Results

Table 1 displays the variations in the independent variables between the w good and poor sleepers. According to the results, all forms of aggression including physical aggression, verbal aggression, anger, and hostility are significantly higher among poor sleepers (P-value<0.001). In contrast, poor sleepers have a significantly lower self-regulation score (approximately 104 vs. 122, with P-value<0.001). Men are more common in the poor sleeper group because there is a significant difference in sex between the groups (P-value=0.011). The groups' mean ages did not differ from one another (P-value=0.269).

The neural network model summary, hidden layer statistics, and units for all independent variables are displayed in Table 2 to predict individuals who have poor sleeping. Out of all dataset samples, the predictive model chose 276 (69%) and 124 (31%) individuals to form the training and testing samples, respectively. For every training and testing sample, there were 15% and 16% of incorrect predictions, respectively. This indicates that over 84% of the poor sleepers can be accurately predicted by all independent variables. One hidden layer with four hidden units was found using a neural network model that included two dependent variables and several independent variables. Every group's total bias was the same as 0.81 and 0.64.

The importance and normalized importance of each independent variable in predicting poor sleepers are also displayed in Table 2. The findings show that the normalized importance ranges from 18 to 100% for the following variables: self-regulation (importance=0.30), anger (importance=0.20), physical aggression (importance=0.19), verbal aggression (importance=0.11), hostility (importance=0.10), age (importance=0.06), and sex (importance=0.05). These variables are more strongly predictive of both groups.

The ROC curve for all independent variables, which is highly sensitive to both good and poor sleepers, is displayed in Figure 1. It is evident that the dependent variable's two ROC curves are separated significantly from the diagonal reference line. The AUC for the ROC Curve (=0.863) is perfectly acceptable for both the good and poor sleeper groups. This indicates that the neural network model has a sensitivity of more than 86% when it comes to predicting both good and poor sleepers. Consequently, the ROC curve validates the outcomes that the neural network model produced.

Table 1. The differences in the independent variables between the good and poor sleepers

Independent variables (Mean±SD)	Total sample (N=400)	Good sleeper (N=93, 23%)	Poor sleeper (N=307, 77%)	P-value
Age, years (a)	32.5±8.8	33.4±9.2	32.3±8.6	0.269
Aggression (a)				
Physical aggression	25.7±6.1	21.3±4.6	27.1±5.9	<0.001
Verbal aggression	14.5±3.9	12.0±3.0	15.2±3.8	<0.001
Anger	18.4±5.1	15.1±5.0	19.5±4.7	<0.001
Hostility	22.0±5.6	17.9±5.1	23.2±5.2	<0.001
Self-regulation	108.0±15.7	121.6±13.0	103.9±14.1	<0.001
Sex (%) (b)				0.011
Female	280 (70)	75 (27)	205 (73)	
Male	120 (30)	18 (19)	102 (81)	

Note: a=t-test, b=Chi-square test.
Abbreviation: SD=Standard Deviation.

Table 2. Summary of the neural network model and statistics of the hidden layer and unites

The model summary	Statics
Training	
Number of subjects (%)	276 (69)
Cross entropy error	99.5
Incorrect predictions (%)	15.2
Testing	
Number of subjects (%)	124 (31)
Cross entropy error	47.7
Incorrect predictions (%)	16.1
Number of units	
Independent variable	8
Dependent variable	2
Hidden layer	1
Units in the hidden layer	4
Hidden layer (bias)	
Good sleepers	0.81
Poor sleepers	0.64
Independent variable importance (%)	

Self-regulation	0.30 (100)
Anger	0.20 (68)
Physical aggression	0.19 (64)
Verbal aggression	0.11 (37)
Hostility	0.10 (33)
Age	0.06 (19)
Sex	0.05 (18)

Note: Activation function of hidden layer=Hyperbolic Tangent, Error function=Cross-entropy, Rescaling method for covariates=Standardized.

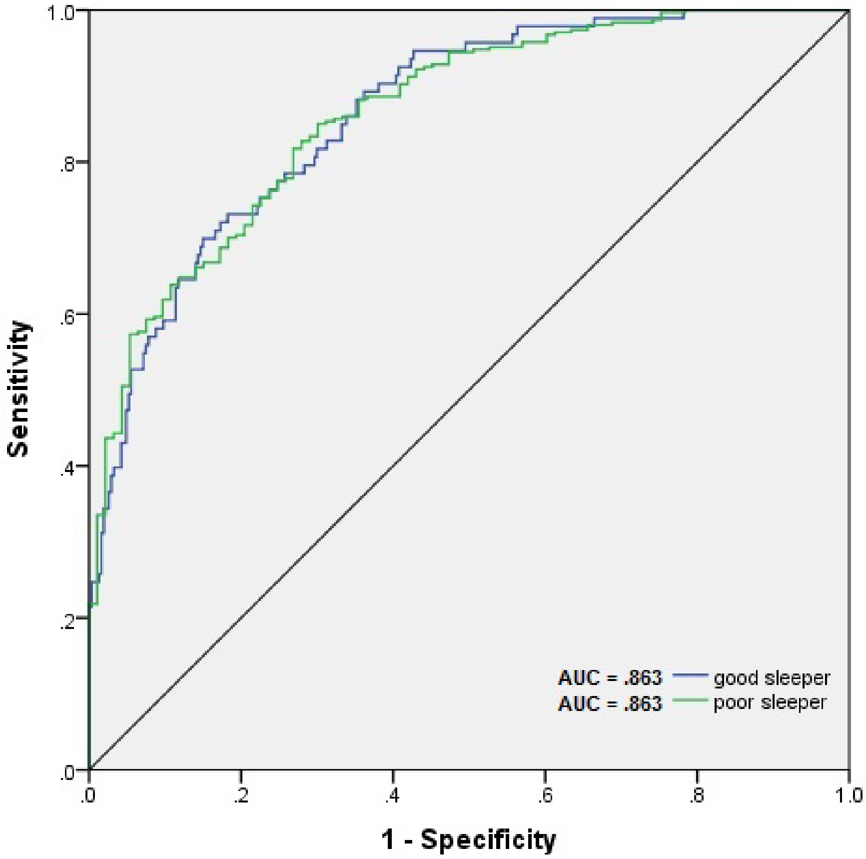

Figure 1. ROC curve of the dependent variables to predict the poor sleepers

Discussion

The present study aimed to predict poor sleep quality among healthcare providers based on various forms of aggression, including anger, hostility, verbal and physical aggression, as well as self-regulation, gender, and age using a neural network model. The present neural network model, which included two dependent variables and a set of independent variables, identified one hidden layer with four hidden units. The model was able to accurately predict over 84% of poor sleepers (i.e., with a low margin of error). The results show that the current neural network model is an approach with excellent predictability[40,48]. We conclude that various forms of aggression and self-regulation contribute to sleep quality in healthcare providers. These results are consistent with the results of previous reports on the associations of aggression and self-regulation with poor sleep quality and sleep problems in adults[34,35,38,39].

The AUC for ROC Curve further supported the results from our neural network model. The receiver operating characteristic curve is a common and effective statistical method in diagnostic test assessment[48,49]. With a sensitivity of 86%, we discovered that the neural network model could accurately predict both good and poor sleepers. As a result, it was once again demonstrated that the neural network approach could predict sleep quality using a variety of risk and protective factors. In previous studies, poor sleep quality is primarily predicted by general linear models[34,35,38,39]. Over the past three decades, there has been discussion about the benefits of using artificial neural networks instead of general linear models such as regressions for predicting medical consequences[40]. Algorithms known as artificial neural networks provide a new alternative to regression techniques by enabling the execution of non-linear statistical modeling. The predictive method has several advantages, including the need for less formal statistical training, the ability to recognize complex non-linear relationships between independent and dependent variables implicitly, the capacity to recognize all possible interactions between predictors, and the availability of several training algorithms[40].

The present findings revealed that all forms of aggression including physical aggression, verbal aggression, anger, and hostility are significantly higher among poor sleepers, while poor sleepers had a significantly lower self-regulation score. The results imply that self-regulation, anger, physical aggression, verbal aggression, hostility, age, and sex have normalized importance values ranging from 18% to 100%, making them significant predictors of both the good and poor sleep subgroups. The trigger of aggression, whether state or trait, is activated by environmental stimuli and stressors. When faced with dysfunctional emotional self-regulation, a person is ready to express exaggerated reactions, mostly disproportionate to the situation. Over time this may lead to interpersonal problems and loss of social support systems. Some studies support the negative impact of both dysfunctional self-regulation and a poor supportive system on the occurrence of sleep problems[37-39,50].

The current research is an advanced study that provides useful data and information for health policymakers and professionals. To our knowledge, no prior research has used a neural network model to examine the complicated relationships between a range of risk and protective factors (age, gender, aggression, and self-regulation) and poor sleep quality. However, the current study has certain shortcomings. Although longitudinal data from subsequent studies could test the stability of associations as well as mediating factors, the cross-sectional design of the current study precludes the reporting of causal relationships between multiple risk/protective factors and poor sleep quality. All of the variables, including aggression, self-regulation, and the quality of sleep, were measured using self-report scales. As self-report instruments have the potential to yield biased data,[51] objective behaviors and more precise measures, like polysomnography, may be used in future research. Lastly, our sample was limited to healthcare providers who, due to their shift work, typically have a higher prevalence of sleep problems. As such, it is crucial to proceed with caution when generalizing this sample's findings to other Iranian populations.

Certain demographic and behavioral factors, as well as emotional mechanisms like sex, age, different forms of aggression, and self-regulation, can be used to predict both good and poor sleep quality among healthcare providers using the neural network algorithm. The emotional mechanism of self-regulation is the most significant factor related to poor sleep quality in people who provide medical care, even though all forms of aggression are important in identifying individuals who have trouble sleeping. Not only is self-regulation the primary predictor variable in the current neural network model, but it also serves as a potent deterrent for aggressive behavior of any kind in the event of poor sleep quality. Subsequent investigations may examine the intricacy of behavioral and affective pathways linked to poor sleep quality that coexist with other sleep issues.

Ethical Considerations

All procedures performed in the study involving human participants were in accordance with the 1964 Helsinki Declaration. The study procedures were approved by the Ethics Committee of Kermanshah University of Medical Sciences (Ethics Code: IR.KUMS.REC.1402.130). Written formed consent was obtained from all individual participants included in the study.

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Conflict of Interest

The authors declare that they have no competing interests.

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