Correlation Analysis Between Insomnia Severity and Depressive Symptoms of College Students Based on Pseudo-Siamese Network

Ya-fei Wang[1], Yan-ling Zhu[1], Peng Wu[1], Meng Liu[1,2,3], and Hui Gao[3](✉)

[1] Department of Nursing, Anhui Medical College, Hefei 230601, Anhui, People's Republic of China
zhuyanling@ahyz.edu.cn

[2] Affiliated Maternal and Child Care Hospital of Nantong University, Nantong 226000, Jiangsu, People's Republic of China

[3] Department of Pediatrics, The First Affiliated Hospital of Anhui Medical University, Hefei 230022, Anhui, China
gh20190130@163.com

Abstract. To explore the correlation between emotional mood and sleep quality in a college student population, we propose a new method based on pseudo-siamese network, which can quickly diagnose the causes of depression. This paper investigated the association between distinct sleep levels and depressive mood, with the aim of enhancing sleep quality and treatment approaches. The meta-test was conducted to examine the influencing factors and the results showed that the *OR* of the association between insomnia severity and depression in university students was 2.128, with a 95% confidence interval of 1.603–2.824 and a Z of 5.23, $P < 0.05$. Students with low sleep levels had a 2.128 times higher risk of experiencing depression compared to those with high sleep quality. Furthermore, a significant correlation was observed between low sleep levels and heightened depressive mood among students. The association model, employing a pseudo-siamese network, was developed by controlling for variables including weight, diet, age, and gender. The independent variable of sleep quality was entered into the model to determine the level of depressed mood among university students. The findings hold significance in analyzing the relationship between insomnia severity and depressed mood among university students, as well as in improving the overall sleep quality among this population.

Keywords: Pseudo-siamese Network · Sleep Quality · Depressed Symptoms

1 Introduction

During their time at university, students undergo rapid psychological development and face many challenges. These include navigating group dynamics, coping with academic responsibilities, managing employment prospects and coping with emotional stress. These factors can contribute to the emergence of detrimental emotions such as anxiety

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and depression, subsequently exerting a negative impact on their sleep quality [1]. On the contrary, insomnia has a propensity to induce or exacerbate symptoms of depression and anxiety [2]. Currently, the mental well-being of university students has become a widespread concern, with depression emerging as a predominant issue among graduates. Depression is characterized by an abnormally low, distressing, and negative emotional state in which individuals experience feelings of self-criticism and self-blame. This can lead to self-harming tendencies and suicidal thoughts, significantly impacting both individuals' daily lives and society as a whole [3]. According to studies conducted in China, a considerable percentage of university students, ranging from 25.7% to 31.2%, are reported to experience depression. Moreover, the detection rate of depression among university students is observed to be progressively increasing year after year [4]. The sleep quality of university pupils is intricately linked to the physical health, as a good quality of sleep plays a vital role in promoting their overall physical and psychological well-being. Notably, a scholarly survey revealed that among high-level university students, approximately 2.13 out of every 10 individuals are at risk of developing depression. Sleep disturbances are a prominent clinical manifestation of depression, and extensive research has demonstrated substantial changes in signaling pathways among individuals with depression [5, 6]. Research has indicated that inadequate sleep can readily shift the central nervous system from an aroused to an inhibited state, resulting in various negative consequences [7].

At present, pseudo-siamese networks has become an important research direction of computer vision and sound. It is a computer-aided algorithm that can assist doctors in quickly diagnosing the causes of depression in university students and it is able to achieve rapid diagnosis by doctors by docking the neural signals in university students' brains to build a pseudo-siamese model. Therefore, the use of pseudo-siamese networks to study the causes of depression and its mechanisms affecting university students can help reduce and prevent its onset and make it better. Computer models and machine algorithms can be employed to analyze the relationship between insomnia severity and depression among university students. This analytical approach can assist healthcare professionals in efficiently identifying and diagnosing depression in university students. Several researchers have utilized data mining algorithms to construct predictive models concerning the link between insomnia severity and stress levels in students. Ultimately, regression prediction analysis is employed to derive the outcomes regarding the relationship between sleep quality and depression in university students [8, 9].

The main contributions of this paper are as follows. Firstly, it employs a pseudo-siamese network model to assess the insomnia severity and levels of depression among college students. Secondly, it investigates the present state of sleep and mode among college pupils, along with associated factors, to establish a correlation between sleep status and depression. Lastly, it proposes a depression intervention as a means to enhance the sleep quality and mental health of college students, thereby addressing the identified issues effectively.

2 Methodology

2.1 Data

In this study, 2050 volunteers were recruited from three universities in Nanjing and Hefei cities between September and December 2022. After the data collection process, 1850 valid responses were obtained, resulting in a return rate of 90.24%. The study employed a school-based survey methodology aimed at assessing behaviors and mental health among Chinese university students. Among the volunteers, 505 were first-year students, 520 were second-year students, 440 were third-year students, and 385 were fourth-year students. All surveys were administered on-site within the schools, where trained investigators provided guidance to the volunteers, facilitating the completion of the written questionnaires.

2.2 Evaluation Methodology

Health Questionnaire-9 (PHQ-9). The PHQ-9 is a self-rating scale consisting of nine items designed to screen for depressive symptoms. It has demonstrated robust psychometric properties in various primary care settings, indicating its effectiveness as a screening tool [10]. As shown in Table 1, it assesses the presence and severity of depressive symptoms experienced within the past two weeks and a higher score on the scale indicates a greater severity of depressive symptoms [11].

Table 1. Contents of PHQ-9 scale.

Answer code	Experience of depressive symptoms	Degree of depression
0	None	without
1	several days	mild
2	More than half the days	moderate
3	Almost every day	serious

Insomnia Severity Index (ISI). The ISI (Insomnia Severity Index) is a tool used to assess the severity of insomnia. It consists of seven items, and volunteers respond to each item using a scale of 0, 1, 2, 3, or 4. These responses correspond to the options "not at all," "mild," "moderate," "severe," and "extremely severe," respectively. The total score on the ISI ranges from 0 to 28. Higher scores indicate more severe insomnia. Cronbach's alpha is 0.873[12].

2.3 Statistical Analysis of Correlation Model Based on Pseudo-Siamese Network

If the confidence interval of a mediating (indirect) effect includes 0, it indicates that the effect is not statistically significant at the 5% significance level. This means that there is no significant evidence to support the presence of a mediating effect. Regarding the algorithm based on a pseudo-siamese network, it has demonstrated favorable performance in image classification tasks. The structural form of the pseudo-siamese network consists of a twin layer, the core part of which is the twin layer, whose main function is the extraction and output of sleep features [13]. The computational process that is referring to involves the utilization of multiple twin kernels in a given scenario. Its objective is to decrease the image size and mitigate overfitting while preserving the original features. The fully connected layer serves to transform the extracted features from the preceding layer into one-dimensional features. Lastly, the attrition layer, which is the final component in the network, enables a comparison between the model's results and the actual data. A well-performing classification model aims to minimize the error in these comparison results. The structure consists of multiple layers of neurons, which are interconnected based on the input and output. These layers include one or more hidden layers positioned between the input and output layers. Within each hidden layer, every neuron is connected to neurons in the previous (m-1st) hidden layer and the subsequent (m+1st) hidden layer. This interconnected structure enables information flow and computation throughout the network. Pseudo-siamesening neural networks have a number of characteristics [14]. Firstly, neural networks possess a remarkable parallel data processing capability. This means that multiple computations can be performed simultaneously, leveraging the power of parallel processing. Additionally, the use of multiple neurons allows for the execution of multiple operations in parallel. Consequently, a neural network can efficiently handle large-scale processing by distributing the workload across multiple neurons. Secondly, neural networks excel in their ability to combine and integrate information. Through neuron-to-neuron associative weighting, the network efficiently processes diverse and uncertain information, enabling effective analysis and decision-making. Thirdly, neural networks possess the capability of self-education. The associative capacity of neurons is determined by their weights, which undergo adjustments during the network's evolution. This dynamic nature allows the system to engage in continuous learning and upgrading. In a neural network, each neuron represents a specific type of information. The collaborative operation of these neurons determines the overall performance of the network in processing information. Consequently, even if a single neuron experiences an error or failure, it does not have a detrimental impact on the network as a whole or its ability to process information effectively. The distributed nature of information processing ensures robustness and fault tolerance within the network. One of the prominent forms of deep learning is the pseudo-siamese network, which leverages twin operations to capture the individual characteristics of neurons. This algorithm belongs to the family of forward neural networks and exhibits a deep neural network structure. It utilizes twin operations to process input data and extract meaningful features for learning and inference tasks. The pseudo-siamese network is widely employed in various domains due to its ability to handle complex patterns and facilitate efficient information processing [14, 15]. The pseudo-siamese network includes a pseudo-siamese layer, a pooling layer and a fully connected layer. The specific operation of the pseudo-siamese layer method involves multiplying each corresponding unit by a circular center using a pseudo-siamese kernel of a specific size (see Fig. 1).

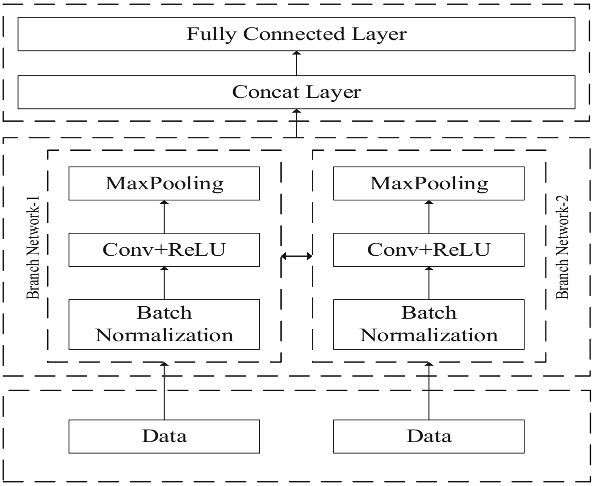

Fig. 1. Structural features of the pseudo-siamese network

2.4 Data Processing

To perform text retrieval, a pseudo-siamese network is utilized after filtering users. The process involves segregating the identified volunteers with depression from those with normal emotions. By logging in with cookies, the original microblogs of the selected volunteers are mined in a specific time sequence. Subsequently, the collected data is filtered and organized. Following the data crawling process, a total of 382 volunteers exhibiting depressive symptoms and 372 normal controls are obtained. The text information from the microblogs is saved on a per-user basis, serving as the fundamental unit for further analysis and processing. This approach allows for the efficient extraction and organization of relevant textual data for subsequent investigations.

$$L_j = \frac{\sum_{i=a} \lambda x^3 e^x}{\sqrt{\eta \ln x^3}} \tag{1}$$

$$L_{\mathrm{i}} = \iint_{i=a} \ln x^a \varepsilon \vec{x} dxdy \tag{2}$$

$$K_a = \overline{\overline{\sin x^2 \cdot \ln x^x}} \tag{3}$$

$$K_b = \coprod_{i=a}^{n} \ln x^a \cdot \sin x^3 \tag{4}$$

$$V = \frac{\left\| \sin x + \cos x^2 \right\|}{2\mu} \tag{5}$$

$$R_a = \begin{vmatrix} 0 & & 1 \\ 1 & x & 0 \\ x & 0 & 0 \end{vmatrix} \tag{6}$$

where L_j denotes the number of iterations, L_i denotes the loss energy, K_a denotes the data similarity, K_b denotes the convolution step, V denotes the random gradient and R_a denotes the output data feature set [15].

2.5 Correlation Model Establishment and Test Plan

This experiment used AMOS17.0 software to construct seven different structural equations. To analyze the factors influencing the quality evaluation score, survey grade, publication time, and sampling method, meta-regression was conducted. The results revealed that these factors collectively explain 88.6% of the observed differences. Notably, the regression coefficient obtained in this analysis was 0.0958 lower compared to the regression coefficient obtained using the random effect model in the meta-analysis. This indicates that research quality, survey grade, publication time, and sampling method significantly contribute to the observed variations in the quality evaluation score. The meta-regression provides valuable insights into the factors influencing the overall quality assessment of the studies analyzed. The Beg rank correlating method was used to test the insomnia situation deviation: $Z = 0.94 < 1.96$, $P > 0.05$, no significant insomnia situation deviation was found. By applying the Rosenthal method, a failure safety degree of 821 is obtained, indicating that it satisfies the specified requirements. This means that among the 821 papers analyzed on the correlation between depression and insomnia, there is substantial evidence supporting the claim that poor sleep quality is indeed a risk factor for depression. The robustness of the findings and the large number of papers supporting this relationship provide strong support for the hypothesis. As shown in Table 2.

Table 2. Test of sleep quality deviation by Beg rank correlation method.

Independent variable	Case	Maximum value	Average value	Deviation
Study load	1850	5	2.56	0.642
Self-assessment of health status	1850	5	2.2	0.790
Self assessment of family economic conditions	1850	1	1.67	0.373
One child	1850	2	1.67	0.486

3 Results

3.1 General Demographic Characteristics

The detection rates of mild, moderate, and severe depressive symptoms among 1850 college students were 25.4%, 5.2%, and 2.5%, respectively. Except for different nationalities, the detection rates of depressive symptoms among medical students with different demographic characteristics, such as gender, education level, family residence, and so on, were statistically significant ($P < 0.05$), as seen in supplementary material.

3.2 Mediation Effect Analysis

In the analysis conducted using a random effects model, the results revealed an odds ratio (*OR*) of 2.128, indicating that 95% of university students experienced sleep disturbances. This finding was statistically significant with a *Z*-score of 5.23 and a *P*-value less than 0.05. Additionally, it was observed that 5% of university students reported poor sleep quality, which had a significant impact on changes in their depressed mood.

To further investigate the data, a subgroup analysis was performed based on different types of research data, publication time, and sampling methods. This analysis revealed significant differences in sleep quality, activity time, survey year, and sampling method, as depicted in Fig. 2. These findings highlight the variations in sleep patterns among university students across different research studies, time periods, and sampling techniques, emphasizing the importance of considering these factors when examining the relationship between sleep quality and depressed mood.

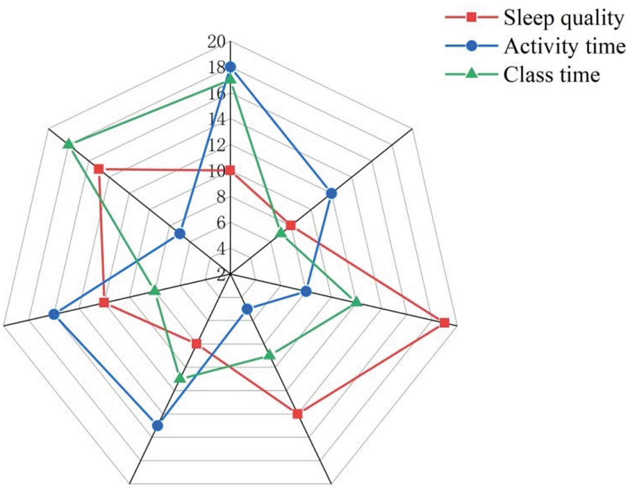

Fig. 2. Data heterogeneity analysis by META

Based on the subgroup meta-analysis results, a significant correlation between poor sleep quality and depression was observed across most subgroups. However, it is worth noting that in the randomly selected classes from the sample of grades 1 to 4, there was no significant difference detected ($Q = 68.39$, $P > 0.05$). This finding suggests that the relationship between insomnia level and depression may not be consistent across all academic years. It is possible that other factors, such as academic workload or social dynamics, may play a more influential role in these specific grade levels, masking the direct association between poor sleep quality and depression. Meta-regression analysis was calculated as follows.

$$Z_1 = \sum_{a=1} \ln x^2 \beta \sin y^3 \tag{7}$$

$$Z_2 = \frac{\sqrt{V(x)\sum_{i=a}\ln x^a}}{2\varepsilon} \tag{8}$$

$$Y_1 = \eta \sin x^2 \iint_{a=1} \ln x^a dxdy \tag{9}$$

$$Y_2 = [Z_1(x) + \sum \ln x^{2y} V(x)] \tag{10}$$

$$U = \sum_{i=a}^{n} \begin{vmatrix} x & 1 & 1 \\ 0 & x & 0 \\ 0 & 1 & 1 \end{vmatrix} \tag{11}$$

$$I = \int_{\mathrm{i}=a} \sum_{n=1} \sin x^2 \prod_{i=a} \eta \tan x^a \tag{12}$$

where Z_1 denotes regression coefficient, Z_2 denotes reliability coefficient, Y_1denotes validity coefficient, Y_2 denotes sleep score, U denotes ISI score and I denotes significance.

The model used in this study demonstrated a good fit, as indicated by the fit indices: CFI (Comparative Fit Index) of 0.950, TLI (Tucker-Lewis Index) of 0.988, RMSEA (Root Mean Square Error of Approximation) of 0.007, and SRMR (Standardized Root Mean Square Residual) of 0.004. These values suggest that the model adequately represents the data and fits the observed relationships well, as depicted in Fig. 3. The pseudo-siamese network regression analysis conducted on the relationship between T1 sleep levels and T2 sleep duration revealed a significant effect of T1 depression on T2 sleep ($Beta = 0.18, P < 0.01$). This finding suggests that initial levels of depression have an impact on subsequent sleep quality. However, when T1 depression was controlled for, the expected effect of T1 sleep levels on T2 depression was not significant ($P > 0.05$), indicating that sleep levels alone may not have a direct influence on subsequent depression levels.

3.3 Physical Activity Impact

This study provides evidence for the presence of a mediating factor in the relationship between subjective sleep levels and depression among university students. The findings indicate that subjective insomnia level scores have a positive effect on depression ($P < 0.001$), implying that poorer sleep level is associated with higher levels of depression. Additionally, subjective insomnia level scores are positively correlated with negative values ($P < 0.001$), indicating that lower subjective sleep quality is associated with a more negative emotional state. Moreover, when considering the prediction of depression, the use of subjective sleep quality scores with the awareness reassessment method has a greater impact on depression ($P < 0.001$). This suggests that cognitive reassessment plays a moderating role in the relationship between subjective insomnia and depression in university students. In the pseudo-siamese network model, the maximum effect size

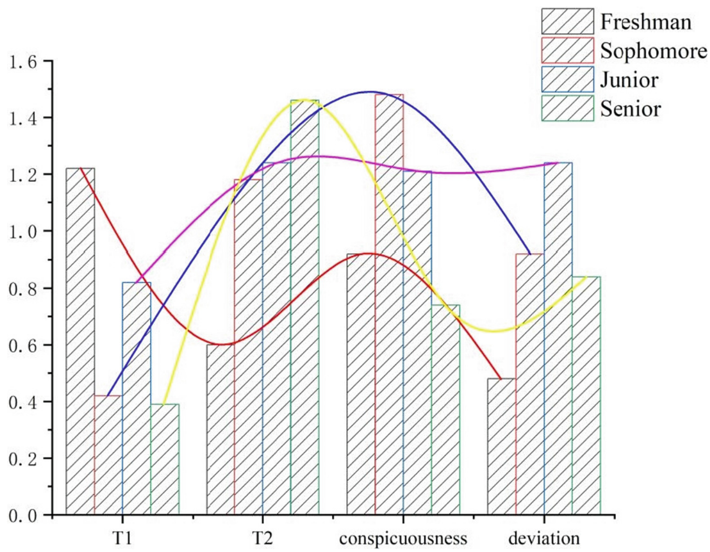

Fig. 3. Pseudo-siamese Network regression analysis

with cognitive reassessment is calculated as −0.21 * 0.29 = 0.0609, while subjective sleep level has a maximum effect size of 0.33, corresponding to a coefficient of 0.391 and an intermediate effect size of 16.38%. These findings highlight the significant association between sleep quality and depressed mood in university students, as indicated by the neural data established by the neurons in the pseudo-siamese network model. Furthermore, the time spent in physical activity is identified as a significant mediating variable.

4 Discussion

Among university students, anxiety and depression are the main mental health issues. Senior students show a higher tendency towards insomnia, and there is a higher proportion of university students who habitually stay up late, have poor academic performance, irregular breakfast habits, and engage in late-night snacking. The detection rates of mild, moderate, and severe depressive symptoms among 1850 college students were 25.4%, 5.2%, and 2.5%, respectively. A study carried out showed that depression amongst medical students is a global issue [16]. Generally speaking, sleep problems may be a predictive factor for depression, as the authors of studies found: students reported somatic symptoms rather than psychological problems [17]. Additionally, low family income, the habit of staying up late, poor academic performance, irregular breakfast habits, and lack of exercise were identified as significant influencing factors for depression among university students. There is also a significant association between sleep patterns and depressive symptoms, which is consistent with previous results [6, 18].

To investigate the correlation between college students' insomnia situation and depressive mood, this study establishes a pseudo-siamese network model space and conducts correlation analyses using meta-neural data nodes. In the diagnosis and identification of depression, a classification model is typically constructed, and relevant rules are extracted to facilitate screening, identification, and diagnosis of depression. Hence, it is crucial to assess the accuracy of the depression classification model in order to make correct predictions and diagnoses, ultimately improving clinical outcomes. Given that the collected information often contains redundant data that can hinder prediction accuracy, it becomes essential to extract relevant information that aids in prediction through feature information processing and feature selection. Feature extraction and engineering play a significant role in accurately forecasting pseudo-siamese network models. With the abundance of collected information, it becomes necessary to extract meaningful features that contribute to the prediction task. This involves processing the information to identify and select the most relevant features for accurate forecasting. The success of the pseudo-siamese network model relies heavily on the effective extraction and matching of features, as they directly impact the model's predictive capabilities in the context of depression diagnosis and prognosis [14]. On this basis, the machine learning method based on neural network will be used to construct depression risk factors, biomarkers, and so on. Standardized data will be obtained through pre-processing, and divided into different training sets and test sets. After training the training sets, the model will be finally evaluated, and it will be continuously improved at the evaluation stage. Based on the prediction of depression, machine learning can reflect the factors of depression and various disease indicators, such as influencing factors, symptoms and physiological characteristics.

The results demonstrate that college students with insufficient sleep time and poor insomnia situation exhibit greater fluctuations in the twin space model of mental mood, whereas those with sufficient sleep time and higher sleep quality display fewer fluctuations in their mental mood test. These findings indicate that college students with poor sleep quality are more likely to experience depressive symptoms compared to those with better sleep habits. This study found the relationships between insomnia situation, depression, cognitive reassessment, and physical activity time. Overall, this study emphasizes the importance of considering subjective sleep and its impact on mental health outcomes, particularly in the context of university students. The findings provide insights into potential intervention strategies that target sleep quality and cognitive reassessment to improve mental well-being in this population. A meta-analysis on sleep quality showed that insomnia situation affected 65% of pupils in Europe [19]. Poor sleep quality is associated with lower academic performance. It is also correlated with the onset of depression and stress [20]. This study found the relationships between sleep quality, depression, cognitive reassessment, and physical activity time. Overall, this study emphasizes the importance of considering subjective sleep quality and its impact on mental health outcomes, particularly in the context of university students. The findings provide insights into potential intervention strategies that target sleep quality and cognitive reassessment to improve mental well-being in this population.

In future meta-analyses, it is recommended to incorporate prospective findings such as cohort studies to further explore the association between insomnia levels and depression among university students. Additionally, efforts should be made to include subjects with high-quality sleep scores in meta-analyses to further examine the relationship with depression. The results underscore the connection between college students' sleep quality and their risk of depression, emphasizing that those with poor sleep quality are at higher risk.

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