# Integrating Multi-modal Features for Evaluating and Predicting Sleep Status

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**Abstract.** This study investigates the link between depression, rumination, and sleep among Uyghur high school students in Kashgar, Xinjiang. Utilizing data from 680 students across three randomly selected high schools, it finds significant correlations: depression positively correlates with both sleep issues and rumination, while rumination also positively correlates with sleep problems. Mediation analysis reveals that rumination partially mediates the relationship between depression and sleep. Furthermore, a novel multi-modal deep learning model, integrating self-reported data and numerical evaluations, effectively predicts students' sleep status. These findings underscore the importance of addressing depression and rumination to enhance students' sleep quality and propose innovative approaches for student health management and education.

**Keywords:** depression levels; ruminative thinking; sleep status prediction; multi-modal; mediating effects.

## 1 Introduction

With the rapid development of science and information technology in recent years and changes in social patterns, life and learning communication styles, depressive symptoms and depressed mood have become more common among adolescents[1-2]; High school students are at an age when depression is at a high risk, so it is important to conduct targeted research on sleep and depression among high school students from different regions and ethnicities, to explore the factors behind it, and to provide practical strategies to help high school students grow up physically and mentally[3].The Blue Book of Chinese National Mental Health (2020) states that 84.1% to 90.8% of adolescents suffer from sleep deprivation[4]; Yu et al. conducted a meta-analysis of the detection rates of mental health problems among high school students in mainland China over the ten-year period from 2010 to 2020, stating that the detection rates of sleep problems and depression among high school students in mainland China were 23.0% and 28.0%, respectively[5]. However, it is unclear


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whether depression in high school students affects sleep status directly or indirectly through certain mediating factors.

Many factors influence sleep status, and it has been demonstrated that depression levels and ruminant thinking levels are two important factors affecting sleep status [6-8].Patten et al. study of depressive symptoms and sleep problems in adolescents aged 14 - 18 years showed that depressive symptoms significantly predicted sleep status, and those with higher levels of depression typically had poorer sleep status compared to the average[9]. Adolescents with depressive symptoms were more likely to respond to excessive negative emotional responses to perceived threats, and the reactivation of these ruminative thoughts before bedtime may enhance these responses, leading to further sleep disturbances[10]. Rumination is a persistent cognitive process and a risk factor for sleep status, and of the three factors Carney found in clinical insomnia patients, only rumination was associated with sleep status[11].

Currently, however, only a limited number of studies have examined the mediating role of ruminative thinking between depression levels and sleep status[6-8]. Studies have shown that ruminant thinking mediates between depression levels and sleep status in healthy youth[6, 7]and adolescents[8]. The purpose of this study was to investigate ruminant thinking as a mediator of the relationship between depression level and sleep status. At present, there is no mediation analysis on the relationship between depression and sleep among high school students from ethnic minorities in border areas of China. In this study, we constructed a relational model of the relationship between depression-rumination-sleep with depression as the independent variable, sleep status as the dependent variable, and rumination as the mediating variable, and our results are expected to provide support for the mediating role of rumination in this relational model and provide a theoretical basis for improving the sleep status of Uyghur high school students.

How students sleep is critical to their physical and mental health, academic performance, and overall quality of life. However, traditional sleep assessment methods usually rely on questionnaires or sleep monitoring equipment, and these methods have certain limitations in reflecting students' sleep status. Therefore, developing a deep learning model based on multi-modal data that can more accurately predict students' sleep status is crucial and of great significance to improving their quality of life and health.

## 2 Methods

1.1 The questionnaires were distributed in the class, and before administering the test, the test leader explained to the students the purpose of the test, the way of answering, the principle of confidentiality, the freedom to choose whether to withdraw from the test, and other principles of administration. Students were required to complete the test continuously and all questionnaires were collected on the spot. After eliminating invalid questionnaires, the valid data of this test were constituted.

1.2 The Center for Epidemiologic Studies Depression Scale (CES-D), a questionnaire to assess individual depressive status, was developed by Radloff et al.

In 2010, Zhang Jie et al.did the creation of a Chinese national urban normative scale for this scale.A total score of ≤15 was considered as no depressive symptoms, 16-19 as possible depressive symptoms, ≥20 as definite depressive symptoms, and ≥28 as the cut-off score for depression screening[12]. In this study, a total score of ≥20 was used as the cut-off score for the presence or absence of depressive symptoms. The internal consistency coefficient in the present study was 0.89.

1.3 Ruminative Responses Scale (RRS), the RRS scale was developed by Nolen-Hoeksema in 1991 to describe concerns about individual depressive symptoms; Yiqun Gan and Xiuqiong Shen first introduced a scale related to ruminant thinking into China in 2005, revising the Nolen-Hoeksema's response style questionnaire, and developed a normative model of the Chinese RRS questionnaire. The Chinese version was later revised by Han Xiu and Yang Hongfei, and the findings indicated the applicability of the scale in measuring ruminant emotions among Chinese undergraduates; in the same year, Yang Juan et al. used a group of high school students aged 14-16 as subjects , providing a basis for the application of the scale among adolescents in China. The scale consists of 22 items and is scored on a 4-point scale, with higher scores indicating higher levels of individual reflection. The internal consistency coefficient in this study was 0.95.

1.4 Pittsburgh sleep quality index scale (PSQI), this scale was developed by Buysse et al. in 1989 as a self-assessment scale of sleep quality. The scale was revised by Liu Xianchenin 1999 according to the actual situation in China to measure the sleep quality index in the last 1 month . The higher the score on the Pittsburgh Sleep Quality Index (PSQI), the worse the quality of sleep. Globally, a total score of 6 or more is defined as the threshold for determining poor sleep quality, and 7 is used as the threshold in China. In this study, poor sleep quality was defined by a PSQI score of ≧7; sleep time of less than 30 minutes and sleep efficiency of more than 85% were used as criteria for better sleep quality. The internal consistency coefficient in this study was 0.89.

1.5 Study procedures and data analysis

Structural analysis of structural equations (AMOS, version 24.0) and SPSS 26.0 software were used to analyze the data. Independent samples t-test was used to analyze differences in each variable and its dimensions, Pearson correlation was used to correlate each variable and its dimensions, and stepwise multiple regression analysis was used to explore the predictive effects of depression on rumination, and depression and rumination on sleep status. The mediating effect was tested using a bias-corrected Bootstrap method with parameters set at 5000 times. Indirect effects were considered significant at the $p < 0.05$ level when the confidence interval did not contain 0. In structural equation modeling (SEM), The chi-square ($\chi^2$) statistic is not significant in the model, but it is strongly influenced by the sample size[13].Values of RMSEA ≤ 0.08 and RMR ≤ 0.05 were considered as sufficient model fit values. The remaining indices (e.g., GFI, TLI, and CFI) ≥ 0.90 indicated an adequate model fit[14].

1.6 Prediction of Student Sleep State Based on Multimodal Feature Fusion

Students' sleep status has an important impact on their health, academic performance and quality of life. Traditional sleep assessment methods often rely on questionnaires or sleep monitoring equipment, and these methods have certain limitations. Therefore, it is of great significance to develop a deep learning model based on multi-modal data that can more accurately predict students' sleep status.

The Transformer model can capture semantic information in text sequences and has the advantage of parallel computing. We use the Transformer model to convert students' sleep self-reports into the Transformer's hidden representation. During the feature extraction stage, pre-trained Transformer models are utilized for encoding. The Transformer model is pre-trained via unsupervised learning of large-scale corpora, yielding rich semantic information. An encoder is defined for processing the input sequence, comprising multiple stacked encoder layers. Each encoder layer consists of two sub-layers: a multi-head self-attention sub-layer and a feed-forward neural network sub-layer.

The self-attention mechanism enables the model to attend to other positions in the input sequence during processing, assigning varying semantic information to different attention heads. The calculation involves:

$$\mathrm{MHA}\ (Q, K, V) = \mathrm{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right) V \tag{1}$$

where Q, K, and V are the query, key, and value matrices obtained by a linear transformation of the input sequence, $d_k$is the dimension of each attention head.

A feed-forward neural network processes the output of the encoder layer via two linear transformations and an activation function, typically ReLU. This is computed as:

$$\mathrm{FFN}\ (x) = \mathrm{ReLU}\ (xW_1 + b_1)\, W_2 + b_2 \tag{2}$$

where $W_1$, $b_1$, $W_2$ and $b_2$ are learnable parameters.

The encoder layer combines the outputs of the multi-head self-attention sublayer and the feedforward neural network sublayer using residual connections and layer normalization:

$$\begin{aligned} EL(x) &= LN(x + MHA(x)) \\ EL(x) &= \mathrm{LN}\ (x + \mathrm{FFN}\ (x)) \end{aligned} \tag{3}$$

where $LN()$ is the layer normalization operation. The whole encoder is stacked by multiple encoder layers. Just like the encoder, the decoder is tasked with producing the output sequence of the target language and is also composed of multiple stacked decoder layers.

We use the weight vector obtained by the attention mechanism to perform a weighted summation of the hidden representation of the Transformer and the normalized depression evaluation and rumination evaluation to obtain an integrated representation. We then take the integrated representation as input through an MLP model to predict the classification probability of sleep states.

$$X_{\mathrm{int}} = W_{\mathrm{att}} \cdot [\ \mathrm{Transformer\_output}\ ; \alpha_{\mathrm{d}}\ ; \alpha_{\mathrm{r}}\ ] + b_{\mathrm{att}} \tag{4}$$

$$\hat{\mathbf{y}} = \sigma(\mathbf{W} X_{\mathrm{int}} + \mathbf{c}) \tag{5}$$

where $X_{\text{int}} \in \mathbb{R}^{T\times(3E+2)}$ represents the hidden state after fusion, $W_{\text{att}} \in \mathbb{R}^{(3E+2)\times E}$ and $b_{\text{att}}$ represent the parameters of the attention layer, and $\hat{\mathbf{y}}$ represents the predicted sleep state probability distribution. Finally, we update all parameters via the cross-entropy loss:

$$Loss = -\sum_{i=1}^{n} \boldsymbol{y}_i \log(\hat{\boldsymbol{y}}) \tag{6}$$

# 3 Research Results

## 3.1 Correlation Analysis of Depression Level, Ruminative Thinking, and Sleep Status of High School Students

To investigate whether there is a significant correlation between the level of depression, ruminative thinking and sleep status in high school students, Pearson correlation analysis was used to examine the correlation between the overall level of depression and its four dimensions of symptoms negative mood, positive mood,, somatic symptoms and activity retardation, and interpersonal score, the ruminative thinking and its three dimensions of reflection, brooding, and repression, and the overall level of sleep status and its seven factors of sleep quality, sleep time, sleep duration, sleep efficiency, sleep disorder, sleep medication, and daytime dysfunction. After that,combined with the regression analysis, Pearson correlation analysis was used to test the correlation between the overall level of depression and its two dimensions of negative mood, somatic symptoms and activity retardation, ruminant thinking and its repression dimension and the overall level of sleep status in high school students, and the following correlation matrix was obtained for the level of depression, ruminant thinking and sleep status in high school students. All variables were significantly positively correlated ($p<0.01$); the correlation results are shown in Table 1.

**Table 1.** Correlation matrix of depression level, ruminative thinking and sleep status of high school students (N=519)

| | Depression level | Ruminant Thinking | Sleep status | Depressed mood | Somatic symptoms and activity retardation | Repression |
|---|---|---|---|---|---|---|
| Depression level | 1 | | | | | |
| Ruminant Thinking | .739** | 1 | | | | |
| Sleep status | .637** | .631** | 1 | | | |
| Depressed mood | .902** | .751** | .662** | 1 | | |

| | | | | | | |
|---|---|---|---|---|---|---|
| Somatic symptoms and activity retardation | .910** | .721** | .656** | .832** | 1 | |
| Repression | .740** | .975** | .645** | .765** | .736** | 1 |

Note: * $p < 0.05$; * * $p < 0.01$; *** $p < 0.001$, same as below.

### 3.2 Regression Analysis of Depression Level, Ruminative Thinking, and Sleep Status of High School Students

***Regression Analysis of Depression Level and Sleep Status Among High School Students***

The correlation analysis indicated that the four dimensions of depression level of senior high school students, including negative emotion, positive emotion, physical symptoms and activity retardation, and interpersonal score, were significantly related to the overall level of sleep status.Therefore, in order to further explore the influence of the four dimensions of negative mood, positive mood, somatic symptoms and activity delay, and interpersonal score on the overall level of sleep status based on the correlation, the four dimensions of negative mood, positive mood, somatic symptoms and activity delay, and interpersonal score of depression level were used as independent variables and sleep status as dependent variable . In order to avoid the collinearity among the four dimensions of negative mood, positive mood, somatic symptoms and activity delay, and interpersonal score of depression level, regression analysis was also performed by stepwise multiple regression method , and the results are shown in Table 2.

The coefficients of the depressed mood and somatic symptoms and activity delay dimensions on the overall level of the dependent variable sleep status were 0.377 and 0.342, respectively, which were greater than 0. That is, both the depressed mood and somatic symptoms and activity delay dimensions of the depression level had a positive effect on the overall level of sleep quality, which showed that the more pronounced the tendency of high school students to have depressed mood and somatic symptoms and activity delay, the higher the Pittsburgh Sleep Index, the greater the likelihood of poorer sleep status occurring. The coefficient of determination of the regression model of high school students' depression level on sleep status, $R^2$ , was 0.472, indicating that the independent variables depressed mood and somatic symptoms and activity retardation together explained 47.2% of the total variation in the overall level of sleep status. The fitted F-value of 232.214 for the regression model of the overall level of sleep status for high school students' depressed mood and somatic symptoms and activity delay reached the 0.001 significant probability level, indicating that the regression model of the overall level of sleep status was significantly explained by both high school students' depressed mood and somatic symptoms and activity delay.

**Table 2.** Regression analysis of depression level and sleep status of high school students

| | B | Standard error | β | t | P | Adjusted $R^2$ | F |
|---|---|---|---|---|---|---|---|
| (Constant) | 2.128 | 0.171 | | 12.480 | 0.000 | 0.472 | 232.214 |
| Depressed mood | 0.220 | 0.034 | 0.377 | 6.543 | 0.000 | | |
| Somatic symptoms and activity retardation | 0.299 | 0.050 | 0.342 | 5.943 | 0.000 | | |

***Regression Analysis of Ruminant Thinking and Sleep Status Among High School Students***

The correlation analysis showed that the three dimensions of ruminant ： repression, brooding and reflection were significantly correlated with the overall level of sleep status in high school students. Therefore, in order to further explore the degree of influence of the three dimensions of ruminant： repression, brooding and reflection on the overall level of sleep status based on the correlation, the three dimensions of ruminant ： repression, brooding and reflection were used as independent variables and the sleep status was used as the dependent variable to avoid the collinearity among the three dimensions of repression, brooding and reflection of ruminative thinking, the same stepwise multiple regression method was used for regression analysis, and the results are shown in Table 3.

The coefficient of influence of the repression dimension on the overall level of sleep status of the dependent variable was 0.645, which was greater than 0. That is, the repression dimension of ruminant thinking had a positive influence on the overall level of sleep quality in all cases, showing that the more pronounced the repression tendency of ruminant thinking in high school students, the higher the Pittsburgh Sleep Index, and the greater the likelihood of poorer sleep status occurring. Also the coefficient of determination $R^2$ of the regression model of high school students' ruminative thinking on sleep status was 0.415, indicating that the independent variable repression explained 41.5% of the total variation in the overall level of sleep status. The fitted F-value for the regression model of high school students' repression dimension on the overall level of sleep status was 368.938, which reached a significant probability level of 0.001, indicating that the repression dimension of high school students significantly explained the regression model of the overall level of sleep status.

**Table 3.** Regression analysis of ruminative thinking and sleep status of high school students

| | B | Standard error | β | t | P | Adjusted $R^2$ | F |
|---|---|---|---|---|---|---|---|
| (Constant) | -1.742 | 0.362 | | -4.811 | 0.000 | 0.415 | 368.938 |
| Repression | 0.292 | 0.015 | 0.645 | 19.208 | 0.000 | | |

### 3.3 The Mediating Role of Ruminative Thinking in the Relationship Between the Effect of Depression Level on Sleep Status in High School Students

The mediating model was tested using structural equation modeling. Depression, rumination and sleep were modeled according to latent variables to examine the predictive effect of rumination on sleep and its plausibility. Combined with the results of univariate correlation analysis, depressed mood,somatic symptoms and activity delay, and interpersonal score were selected as three observed variables of depression level into the model, repression, brooding and reflection as three observed variables of ruminative thinking, and sleep duration, subjective sleep quality, time to fall asleep, sleep disturbance and daytime dysfunction as five observed variables of sleep status, according to the structural equation modeling requirements, according to the above variables were used to establish the mediating model. Among them, the index of the predictive effect was mainly the path coefficient of depression on sleep quality, and the index of reasonableness was the main fitting index of the path analysis model. In the model of the predictive effect of depression on sleep quality, the exogenous variables included 1, i.e., ruminative thinking, and the observed indicators of ruminative thinking included repression, brooding and reflectin. The results showed a good fit of the model, as detailed in Table 4, and the specific path coefficients are shown in Table 5.

**Table 4.** Model fit indices

| Statistical test volume | X2 degrees of freedom ratio | RMSEA | RMR | GFI | AGFI | CFI | NFI | TLI | IFI |
|---|---|---|---|---|---|---|---|---|---|
| Threshold | < 3.00 | < 0.08 | < 0.05 | > 0.90 | > 0.90 | > 0.90 | > 0.90 | > 0.90 | > 0.90 |
| Value | 2.23 | 0.05 | 0.03 | 0.97 | 0.95 | 0.99 | 0.98 | 0.98 | 0.99 |

From the above intermediary model fit index results, it can be seen that the RMSEA value is 0.05, which is less than 0.08, and the RMR value is 0.03, which is less than 0.05; it indicates that the model fit is reasonable, and the GFI,AGFI, CFI, and NFI are all greater than 0.90, which can indicate that the constructed model can be accepted and the model fit is good, and the model can be used for mediated effects analysis.

**Table 5.** Standardized path coefficients

| Paths | Estimate | Standardized Estimate | S.E. | C.R. | P-value |
|---|---|---|---|---|---|
| Total ruminant score <-- total depression score | 1.127 | 0.83 | 0.044 | 25.864 | *** |
| Total sleep score <-- total ruminant score | 0.021 | 0.28 | 0.005 | 3.941 | *** |

| | | | | | |
|---|---|---|---|---|---|
| Total sleep score <-- total depression score | 0.058 | 0.58 | 0.008 | 7.261 | *** |

From the results of the standardized path coefficients, there was a significant positive correlation between depression and sleep scores, a significant positive correlation between depression and rumination, and a significant positive correlation between rumination and sleep quality scores, that is, the higher the depression and rumination scores, the higher the sleep scale scores, and the poorer the sleep quality; this can indicate that rumination partially mediates the effect between depression and sleep. The mediation effect of the model was tested for significance using the bootstrap method, and the mediation effect of the model in this study did not contain 0 at the 95% confidence interval (BootLLCI=0.058, BootULCI=0.104), so the mediation effect was significant. The results of the mediation model analysis were that the total effect c = 0.81, the direct effect c' = 0.58, and the indirect effect a*b = 0.23, so the indirect effect accounted for a*b/c * 100% = 28.40% of the total effect, indicating that rumination partially mediates the pathway of depression to sleep, with a mediating effect of 28.40%, as shown in Figure 1.

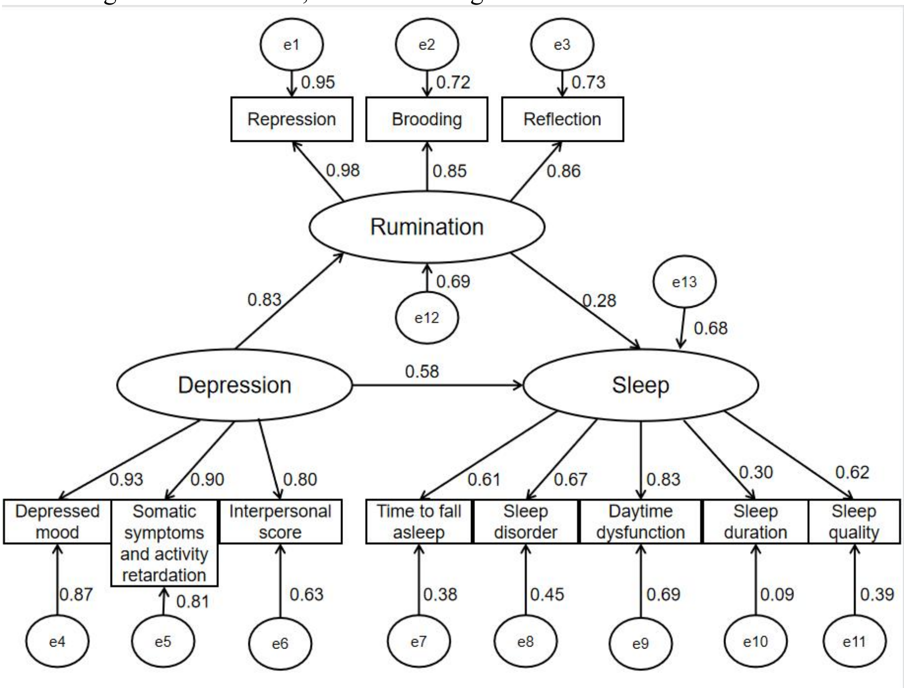


**Fig. 1.** The mediating effect model of rumination on depression levels and sleep status

### 3.4 Student Sleep State Prediction Results

We selected five baselines for comparison with our proposed sleep state prediction method based on multi-modal feature fusion. Bi-RNN (Bidirectional Recurrent

Neural Network) is a neural network model commonly used for modeling sequence data. Bi-LSTM (Bidirectional Long Short-Term Memory Network) is an improved recurrent neural network structure with better long-term dependency modeling capabilities. Seq2seq (sequence-to-sequence model) is a neural network structure used for sequence generation tasks, usually consisting of an encoder and a decoder. Attention is a mechanism for dynamically focusing on different parts of an input sequence when processing sequence data. Avg (average pooling) is a simple feature extraction method that averages all vectors in the input sequence to obtain a fixed-length vector representation.

**Table 6.** Performance comparison of all models

| Model | Accuracy | Precision | Recall | F1 Score |
|---|---|---|---|---|
| Bi-RNN | 0.803 | 0.785 | 0.840 | 0.811 |
| Bi-LSTM | 0.822 | 0.803 | 0.862 | 0.834 |
| Seq2seq | 0.788 | 0.762 | 0.825 | 0.796 |
| Attention | 0.817 | 0.797 | 0.854 | 0.823 |
| Avg | 0.795 | 0.774 | 0.839 | 0.806 |
| **Our** | **0.852** | **0.824** | **0.883** | **0.851** |

As shown in Table 6, we list the performance of our model with several baseline models (Bi-RNN, Bi-LSTM, Seq2seq, Attention, Avg) on indicators such as accuracy, precision, recall, and F1 Score . Our model has better performance relative to other baseline models because it combines Transformer and attention mechanisms and is better able to capture semantic information in text sequences. Bi-RNN, Bi-LSTM and Seq2seq models have certain advantages in processing sequence data, but they may encounter the problem of vanishing or exploding gradients when processing long sequences. The Attention and Avg models may not be as good as sequence-based models in capturing global semantic information, but may be more suitable for processing shorter text sequences.

## 4 Conclusion

The above findings illustrate the two-by-two correlation between depression level, ruminant thinking, and sleep status, and also reflect the mediating role of the trait of ruminant in the relationship between depression and sleep in high school students. Overall, this paper conducted an empirical study on the role of rumination and clarified that rumination can play a mediating role in depression and sleep status of high school students. This study can provide some ideas for counseling to prevent and address sleep problems in high school students. It is suggested that schools should conduct more outdoor activities with various themes, guide students to focus on their studies while conducting timely psychological counseling activities , cultivate a positive and optimistic mindset, improve students' sleep status, and help them to be more comfortable in arranging and dealing with their studies and life and other aspects. This study contributes to the ultimate goal of improving sleep quality by improving ruminative thinking, which in turn relieves depression in high school students. In addition, we propose a multi-modal deep learning model based on Transformer and attention mechanism, aiming to predict students' sleep status. This model has the ability to comprehensively consider various information such as students' self-reports of sleep status, depression evaluation, and rumination evaluation, so as to effectively predict students' sleep status. This research provides a new perspective and solution for students' health management and education.

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