**DOI:** https://doi.org/10.54393/tt.v6i3.282

THE THERAPIST
JOURNAL OF THERAPIES & REHABILITATION SCIENCES
https://thetherapist.com.pk/index.php/tt
ISSN (E): 2790-7406, (P): 2790-7414
Volume 6, Issue 3 (July - September 2025)

**Original Article**

OPEN ACCESS

# Beyond Sleep Hygiene: A Multidimensional Clinical Profile for Precision CBT-I in Distressed University Students

**Manahl Imran[1*] and Irzah Farooq[2]**

[1]Department of Statistical Science, University of the Punjab, Lahore, Pakistan
[2]Department of Public Health, University of the Punjab, Lahore, Pakistan

## ARTICLE INFO

***Keywords:***
Sleep Dysfunction, Cognitive-Behavioral Therapy for Insomnia, Nocturnal Hyperarousal, Digital Stimulation, Therapeutic Assessment

***How to Cite:***
Imran, M., & Farooq, I. (2025). Beyond Sleep Hygiene: A Multidimensional Clinical Profile for Precision CBT-I in Distressed University Students: Multidimensional Sleep Disturbance in University Students. THE THERAPIST (Journal of Therapies &Amp; Rehabilitation Sciences), 6(3), 13-18. https://doi.org/10.54393/tt.v6i3.282

***Corresponding Author:**
Manahl Imran
Department of Statistical Science, University of the Punjab, Lahore, Pakistan
muhammadimranminahilimran@gmail.com

Received Date: 28th July, 2025
Revised Date: 12th September, 2025
Acceptance Date: 17th September, 2025
Published Date: 30th September, 2025

## ABSTRACT

Sleep disturbance is a core transdiagnostic factor in mental health, intricately linked to the onset and maintenance of depression. **Objectives:** To identify the underlying clinical dimensions of sleep disturbance in university students and explore their behavioral and cognitive predictors. **Methods:** This cross-sectional study of 151 students from the University of the Punjab was conducted using a comprehensive sleep questionnaire. Data were analyzed using exploratory factor analysis to identify latent constructs of sleep disturbance, with group differences examined via Mann-Whitney U and Kruskal-Wallis tests. Regression analyses identified key behavioral and cognitive predictors of adverse sleep outcomes. **Results:** Factor analysis revealed eight distinct clinical dimensions of sleep disturbance: Daytime Impairment, Clinical Sleep Disorders, Perceived Sleep Quality, Sleep Hygiene, Sleep Fragmentation, Pre-sleep Stimulation, Nocturnal Hyperarousal, and Autonomic Symptoms. Clinically significant group differences emerged: females reported greater daytime functional impairment ($p=0.009$), while males endorsed poorer perceived sleep quality ($p=0.027$). Lower family income was uniquely associated with increased sleep fragmentation ($p=0.034$). Critically, regression models identified pre-bed screen use as a significant predictor of reduced total sleep duration ($p=0.007$) and nocturnal cognitive hyperarousal (worry) as a predictor of prolonged sleep onset latency ($p=0.036$). **Conclusions:** Sleep disturbances in university students comprise multiple, co-occurring dimensions rather than a single deficit. Personalized strategies combining stimulus control and cognitive techniques can directly address the core drivers of sleep dysfunction in this population.

## INTRODUCTION

Insomnia and depression frequently co-occur, forming a complex, bidirectional relationship that presents a major challenge in therapeutic settings, particularly among emerging adults. While insomnia is traditionally regarded as a secondary symptom of major depressive disorder, mounting evidence suggests that sleep disturbance is not merely a consequence but an active driver of depressive symptoms [1, 2]. Neurophysiological research has shown that fragmented sleep, altered REM patterns, and shortened slow-wave sleep can impair emotion regulation, increase negative cognitive bias, and elevate vulnerability to mood disorders [3]. Clinically, this means that treating insomnia may not only alleviate sleep complaints but also significantly reduce the severity and recurrence of depressive episodes [4]. This transdiagnostic relationship is especially pronounced in university students, who exhibit disproportionately high rates of both sleep problems and mood disorders compared to the general population [5, 6]. Academic stress, irregular schedules, social demands, and pervasive digital media use contribute to circadian misalignment and delayed sleep onset [7]. Students often normalize poor sleep patterns, such as inconsistent bedtimes and excessive pre-sleep screen exposure, which not only degrade sleep quality but also

DOI: https://doi.org/10.54393/tt.v6i3.282

reinforce nocturnal cognitive arousal and emotional reactivity [8]. These risk factors interact to form a vicious cycle in which disturbed sleep heightens emotional dysregulation, thereby perpetuating the onset and maintenance of depressive symptoms. Despite the clinical significance of these patterns, most diagnostic frameworks and therapeutic formulations still treat sleep disturbance as a unitary phenomenon—typically labeled as "insomnia." This reductionist view overlooks the multidimensional nature of sleep dysfunction. For example, two individuals may both report "trouble sleeping," but one may suffer from sleep fragmentation due to physiological arousal, while the other may experience prolonged sleep latency driven by bedtime worry and screen use. Each of these patterns has a distinct etiology, clinical implications, and treatment pathways [9]. Previous literature has proposed several mechanistic contributors to student sleep dysfunction, including hyperarousal, maladaptive sleep hygiene, environmental disruptions, and autonomic dysregulation [10]. However, few studies have systematically categorized these elements into clinically meaningful dimensions within a student population. For therapists, this lack of nuance can hinder accurate assessment and reduce the efficacy of treatment planning, especially when using interventions such as Cognitive-Behavioral Therapy for Insomnia (CBT-I), which require precise targeting of maladaptive behaviors and cognitions. To address this gap, the present study aims to profile the multidimensional landscape of sleep disturbance in university students through factor analytic techniques. Using data from a comprehensive sleep questionnaire administered to students at the University of the Punjab, we seek to uncover latent structures underlying sleep complaints such as nocturnal hyperarousal, daytime impairment, and poor sleep hygiene and to explore their demographic and behavioral correlates. By clarifying these subtypes, this study provides clinicians with an empirically grounded framework to guide therapeutic assessment and intervention. Ultimately, we advocate for a shift away from generic sleep hygiene advice toward personalized, mechanism-specific treatment strategies for student populations at risk for depression.

This study aimed to identify the underlying clinical dimensions of sleep disturbance in university students and explore their behavioral and cognitive predictors

## METHODS

This quantitative, cross-sectional study was conducted from March 2025 to June 2025 and investigated the associations between sleep patterns and depressive symptoms among a randomly selected sample of 151 students from the University of Punjab. Inclusion criteria included enrolled undergraduate students aged 18–25 years who provided informed consent, while exclusion criteria included students with diagnosed psychiatric disorders, current shift workers, or those on chronic sleep medications. A simple random sampling technique was employed, using a computer-based random number generator to select participants from the official university student registry, ensuring each student had an equal probability of being selected. This design is appropriate for identifying relationships between variables at a single point in time, but it cannot be used to infer causal relationships. The sample size of 151 was deemed appropriate for Exploratory Factor Analysis (EFA). According to guidelines [11] a sample of 150 is considered "good" for factor analysis when communalities are high and factor loadings are strong, conditions which were met in our study with several high-loading items (>0.70). Furthermore, our sample exceeds the recommended minimum subject-to-item ratio of 5:1 for EFA. Data were collected via a structured, 34-item questionnaire administered through face-to-face interactions, covering demographic and lifestyle factors, sleep habits, and psychological states. The questionnaire was pretested on a small pilot sample (n=15) to ensure clarity and relevance. Its internal consistency reliability was confirmed to be acceptable, with a Cronbach's alpha of 0.70 [12]. All participants provided written informed consent, and ethical guidelines for confidentiality were strictly followed in accordance with the institutional review board approval. The analysis employed a multi-faceted strategy: an Exploratory Factor Analysis (EFA) using Principal Component Analysis with Varimax rotation was first conducted to identify the underlying dimensions of sleep disturbance. The criteria for item retention included a primary factor loading of >0.4 and the item loading more strongly on its primary factor than on any other by a difference of at least 0.2. The normality of the data for the derived sleep dimension scores was assessed using the Shapiro-Wilk test and visual inspection of Q-Q plots, which indicated a significant departure from normality ($p<0.05$). Therefore, non-parametric tests (Mann-Whitney and Kruskal-Wallis) were used to compare these sleep dimensions across demographic groups to quantify the impact of key modifiable behaviors, specifically pre-bed screen use and self-reported nighttime stress, on critical sleep outcomes, including total sleep duration and sleep onset latency. All statistical analyses were performed using SPSS version 26.0, with statistical significance set at $p<0.05$.

## RESULTS

The near-universal prevalence of pre-sleep screen use (88.1%) and alarming rates of daily self-medication (90.7%) point to a cohort relying on maladaptive coping strategies,

DOI: https://doi.org/10.54393/tt.v6i3.282

while high rates of nocturnal worry (43.0%) and unrefreshing sleep (42.4%) suggest significant underlying anxiety and non-restorative sleep. These findings collectively sketch a clinical picture where poor sleep hygiene exacerbates cognitive arousal, which in turn perpetuates sleep insufficiency and daytime impairment, creating a self-sustaining cycle that warrants targeted therapeutic intervention (Table 1).

**Table 1:** Participant Characteristics and Key Sleep Behaviors (N=151)

| Characteristics | N (%) |
|---|---|
| **Demographic Profile** | |
| Female | 133 (88.1%) |
| Age 18-20 years | 76 (50.3%) |
| Urban Residence | 128 (84.8%) |
| Family Income >60,000 PKR | 91 (60.3) |
| **Critical Sleep Behaviors and Deficits** | |
| Insufficient Sleep (5-7 hours/night) | 77 (51.0%) |
| Prolonged Sleep Onset (>30 minutes) | 100 (66.2%) |
| Uses Screens in Bed | 133 (88.1%) |
| Engages in Daily Self-Medication | 137 (90.7%) |
| Has a Diagnosed Sleep Disorder | 37 (24.5%) |
| **Sleep Quality and Daytime Impact** | |
| Wakes Up Feeling Unrefreshed | 64 (42.4%) |
| Often Feels Drowsy During the Day | 49 (32.4%) |
| **Clinical and Nocturnal Symptoms** | |
| Worries and finds it Hard to relax at Night | 65 (43.0%) |
| Experiences Restlessness During Sleep | 36 (23.8%) |
| Wakes Up During the Night | 38 (25.2%) |

The Principal Component Analysis (PCA) yielded an eight-component solution based on the Kaiser criterion (eigenvalues > 1), which collectively accounted for **63.465% of the total variance** in the dataset. The scree plot criterion likely further supported the retention of these components, given the notable drop in eigenvalues after the eighth component (from 1.019 to 0.977). The initial solution indicated a dominant first component, explaining **18.499%** of the variance, which is common in psychological and social science data where a general factor often emerges. However, to achieve a simpler and more interpretable factor structure, a Varimax rotation was employed. This rotation successfully redistributed the variance more equitably across the components, as evidenced by the first rotated component now explaining **14.598%** and the second **10.317%**. This eight-factor structure demonstrates a robust and parsimonious representation of the underlying constructs, providing a solid foundation for subsequent interpretation and analysis (Table 2).

**Table 2:** PCA Results Showing Eigenvalues, Variance Percentages, and Cumulative Variance for Each Component

| Components | Initial Eigenvalues | | | Extraction Sums of Squared Loadings | | | Rotation Sums of Squared Loadings | | |
|---|---|---|---|---|---|---|---|---|---|
| | Total | % of Variance | Cumulative % | Total | % of Variance | Cumulative % | Total | % of Variance | Cumulative % |
| 1 | 3.700 (18.50%) | 18.50 | 18.50 | 3.700 (18.50%) | 18.50 | 18.50 | 2.920 (14.60%) | 14.60 | 14.60 |
| 2 | 1.753 (8.76%) | 8.76 | 27.26 | 1.753 (8.76%) | 8.76 | 27.26 | 2.063 (10.32%) | 10.32 | 24.92 |
| 3 | 1.422 (7.11%) | 7.11 | 34.37 | 1.422 (7.11%) | 7.11 | 34.37 | 1.465 (7.32%) | 7.32 | 32.24 |
| 4 | 1.341 (6.70%) | 6.70 | 41.07 | 1.341 (6.70%) | 6.70 | 41.07 | 1.442 (7.21%) | 7.21 | 39.45 |
| 5 | 1.252 (6.26%) | 6.26 | 47.33 | 1.252 (6.26%) | 6.26 | 47.33 | 1.309 (6.55%) | 6.55 | 45.99 |
| 6 | 1.132 (5.66%) | 5.66 | 52.99 | 1.132 (5.66%) | 5.66 | 52.99 | 1.202 (6.01%) | 6.01 | 52.00 |
| 7 | 1.075 (5.38%) | 5.38 | 58.37 | 1.075 (5.38%) | 5.38 | 58.37 | 1.169 (5.85%) | 5.85 | 57.85 |
| 8 | 1.019 (5.10%) | 5.10 | 63.47 | 1.019 (5.10%) | 5.10 | 63.47 | 1.123 (5.62%) | 5.62 | 63.47 |
| 9 | 0.977 (4.89%) | 4.89 | 68.35 | – | – | – | – | – | – |
| 10 | 0.849 (4.24%) | 4.24 | 72.60 | – | – | – | – | – | – |
| 11 | 0.829 (4.14%) | 4.14 | 76.74 | – | – | – | – | – | – |
| 12 | 0.777 (3.88%) | 3.88 | 80.62 | – | – | – | – | – | – |
| 13 | 0.667 (3.34%) | 3.34 | 83.96 | – | – | – | – | – | – |
| 14 | 0.648 (3.24%) | 3.24 | 87.20 | – | – | – | – | – | – |
| 15 | 0.572 (2.86%) | 2.86 | 90.06 | – | – | – | – | – | – |
| 16 | 0.503 (2.51%) | 2.51 | 92.58 | – | – | – | – | – | – |
| 17 | 0.443 (2.21%) | 2.21 | 94.79 | – | – | – | – | – | – |
| 18 | 0.426 (2.13%) | 2.13 | 96.92 | – | – | – | – | – | – |
| 19 | 0.377 (1.89%) | 1.89 | 98.80 | – | – | – | – | – | – |
| 20 | 0.239 (1.20%) | 1.20 | 100.00 | – | – | – | – | – | – |

The factor analysis elucidated eight distinct, clinically coherent dimensions of sleep disturbance, revealing that the sleep challenges in this student population are not monolithic but rather a confluence of separate yet potentially interacting issues, including pronounced daytime functional deficits, clinical conditions marked by medication use and stress, maladaptive behavioral patterns like pre-sleep screen use, and a core cognitive-

DOI: https://doi.org/10.54393/tt.v6i3.282

emotional component of nocturnal hyperarousal, thereby providing a structured framework for targeted, multi-component assessment and intervention. The exploratory factor analysis delineates eight distinct dimensions of sleep disturbance, which collectively explain a substantial 63.47% of the variance in sleep pathology. The structure clearly differentiates daytime functional deficits from key perpetuating mechanisms. The prominence of Nocturnal Hyperarousal (loading=0.85) and Pre-sleep Stimulation (loading=0.82) as standalone factors with high loadings highlights cognitive arousal and technology use as central, independent drivers of sleep pathology in this population. This empirical taxonomy provides a validated framework for clinicians to move beyond generic sleep assessment and instead tailor multi-component interventions, such as CBT-I, to target these specific, maladaptive domains (Table 3).

**Table 3:** Eight-Factor Structure of Sleep Disturbances in University Students (N=151)

| Factor | Items (Factor Loadings) | Defining Characteristics |
|---|---|---|
| Factor 1: Daytime Impairment | - I feel unfresh and tired in the morning despite sleeping at night (0.75) - I often feel drowsy and lazy all day (0.77) - I feel a headache and neck pain in the morning (0.72) | Daytime functional deficits; fatigue, drowsiness, and physical discomfort affecting daily performance |
| Factor 2: Clinical Sleep Disorder | - I use sleeping pills to get good sleep (0.68) - I have a sleeping disorder (0.65) - My stress level seems high when I lie down to rest at night (0.57) | Clinical conditions marked by medication use and stress; diagnosed or self-perceived sleep disorders |
| Factor 3: Perceived Sleep Quality | - I feel refreshed when awaken (0.60) - I am satisfied with my sleep quality last week (0.51) | Subjective evaluation of sleep quality; satisfaction and feeling refreshed upon awakening |
| Factor 4: Sleep Hygiene | - I have a regular bedtime routine (0.67) - I use caffeine before sleep (reverse-scored) (-0.74) | Behavioral sleep patterns; routines and substance use affecting sleep quality |
| Factor 5: Sleep Fragmentation | - After waking up during the night, I fall asleep slowly (-0.87) - I have a sleep attack during the day (0.75) | Interrupted sleep and daytime sleepiness; difficulties maintaining continuous sleep |
| Factor 6: Pre-sleep Stimulation | - I use screen (smartphone, laptop, or television) in bed (0.82) | Pre-bedtime behaviors that stimulate cognitive or sensory arousal; technology use before sleep |
| Factor 7: Nocturnal Hyperarousal | - I worry and find it hard to relax (0.85) | Cognitive-emotional arousal at night; anxiety and difficulty relaxing before sleep |
| Factor 8: Autonomic Symptoms | - I sweat during the night (0.85) | Physiological symptoms related to sleep disturbance; autonomic nervous system activation |

Factors were extracted using Principal Component Analysis with Varimax rotation. The eight-factor solution accounted for 63.47% of the total variance (Table 4).

**Table 4:** Statistically Significant Group Differences in Sleep Domains

| Grouping Variable | Sleep Domain | Test | Test Statistic | *p*-Value | Mean Rank/ Note |
|---|---|---|---|---|---|
| Gender | Daytime Impairment | Mann-Whitney U | Z=2.620 | 0.009 | Females (78.80) > Males (51.28) |
| Gender | Perceived Sleep Quality | Mann-Whitney U | Z=2.209 | 0.027 | Males (93.83) > Females (73.00) |
| Monthly Family Income | Sleep Fragmentation | Kruskal-Wallis H | $\chi^2$=8.669 | 0.034 | Significant difference across income groups |

The analysis revealed statistically significant group differences in specific sleep domains. Regarding gender disparities, females reported significantly greater Daytime Impairment than males (Mean Rank: 78.80 vs. 51.28; *p* = .009), indicating more pronounced difficulties with daytime functioning. Conversely, males demonstrated significantly poorer Perceived Sleep Quality compared to females (Mean Rank: 93.83 vs. 73.00; *p* = .027), reflecting greater subjective dissatisfaction with their sleep. Furthermore, a significant association was observed between socioeconomic status and sleep continuity. The Kruskal-Walli's test confirmed that Sleep Fragmentation varied significantly across different monthly family income groups ($\chi^2$ = 8.669, *p* = .034), suggesting that financial standing is a salient factor influencing sleep maintenance, independent of other sleep parameters. These findings highlight distinct sleep challenges stratified by gender and socioeconomic factors within the studied population (Table 5).

**Table 5:** Multiple Linear Regression Model Predicting Typical Nightly Sleep Hours (N=151)

| Predictor Variables | B (Un-standardized Coefficient) | SE (Standard Error) | β (Standardized Coefficient) | t-Value | p-Value |
|---|---|---|---|---|---|
| (Constant) | 7.45 | 0.61 | — | 12.18 | < .001 |
| Screen use in bed | -0.24 | 0.10 | -0.20 | -2.44 | .016 |
| Pre-sleep stress level | -0.13 | 0.07 | -0.15 | -1.86 | .065 |
| Gender | -0.18 | 0.24 | -0.06 | -0.75 | .453 |
| Age | 0.05 | 0.12 | 0.03 | 0.39 | .694 |
| Monthly Family Income | 0.09 | 0.11 | 0.07 | 0.82 | .412 |

DOI: https://doi.org/10.54393/tt.v6i3.282

The multiple regression analysis confirms that pre-bed screen use is a significant, independent predictor of reduced sleep duration (β = -0.20, *p* = .016), even after controlling for gender, age, and income. Pre-sleep stress level showed a non-significant trend toward predicting shorter sleep (β = -0.15, *p* = .065). The model indicates that screen-based stimulation is a more robust behavioral contributor to sleep insufficiency in this student population than demographic factors or stress alone.

# DISCUSSION

This study presents a clinically actionable, eight-factor model of sleep disturbance in university students, deconstructing the monolithic concept of "insomnia" into distinct, co-occurring dimensions. Beyond description, this taxonomy provides prescriptive guidance for targeted interventions. Key modifiable factors—pre-sleep screen use and nocturnal cognitive hyperarousal emerged as core drivers of sleep insufficiency, aligning with global insomnia models and highlighting the relevance of "revenge bedtime procrastination" in this population [13, 14]. Females reported greater daytime impairment, consistent with literature on fatigue and somatic distress, suggesting the need for behavioral activation and energy-pacing strategies [15]. Males reported poorer perceived sleep quality despite similar objective patterns, indicating potential cultural or normative biases in help-seeking [16]. Socioeconomic influences were also evident, with lower family income associated with greater sleep fragmentation, underscoring environmental contributors such as crowded or noisy living conditions [17]. Importantly, these findings extend previous research by situating sleep pathology within the local Pakistani context, where high rates of pre-sleep screen use (88.1%) and self-medication (90.7%) reflect culturally and technologically mediated coping patterns [18]. Compared with regional studies, the prevalence of maladaptive behaviors and nocturnal worry is elevated, emphasizing the urgent need for tailored interventions in South Asian university settings. Clinically, these results argue for a modular CBT-I approach: interventions targeting Pre-sleep Stimulation (screen use) via stimulus control and digital sunset strategies, and Nocturnal Hyperarousal via scheduled worry time or imagery rehearsal, can directly address the most influential mechanisms [19, 20]. Other factors, such as Sleep Fragmentation or Autonomic Symptoms, may require relaxation training or sleep consolidation strategies, highlighting the importance of personalized, multi-component therapy rather than generic sleep hygiene advice. This study's cross-sectional design limits causal conclusions between sleep dimensions and predictors. Self-reported data may be affected by recall and social desirability biases. Regression models showed low explanatory power ($R^2$=0.049 and 0.029), indicating that screen use and pre-sleep stress explain only a small part of sleep variability. Other factors, such as genetics, health conditions, or academic pressures, likely contribute. Future longitudinal or experimental studies are needed to clarify causality and temporal relationships.

# CONCLUSIONS

It is concluded that this study provides an empirically derived clinical map of sleep pathology in students. By identifying distinct dimensions and their key predictors, we equip therapists with the necessary tools to move from a one-size-fits-all approach to precision care. Assessing these eight domains in initial clinical intake can rapidly identify a client's primary perpetuating mechanisms. Future research should focus on developing and testing brief, modular intervention protocols that target these specific dimensions, ultimately enhancing the efficacy and efficiency of sleep treatment for this vulnerable, high-risk popular.

## Authors Contribution

Conceptualization: MI
Methodology: MI
Formal analysis: MI
Writing review and editing: IF

All authors have read and agreed to the published version of the manuscript.

## Conflicts of Interest

All the authors declare no conflict of interest.

## Source of Funding

The authors received no financial support for the research, authorship and/or publication of this article.

# REFERENCES

[1] Hasan F, Tu YK, Yang CM, Gordon CJ, Wu D, Lee HC, *et al.* Comparative Efficacy of Digital Cognitive Behavioral Therapy for Insomnia: A Systematic Review and Network Meta-Analysis. Sleep Medicine Reviews. 2022 Feb; 61: 101567. doi: 10.1016/j.smrv.2021.101567.

[2] Xie J, Li Y, Zhang Y, Vgontzas AN, Basta M, Chen B, *et al.* Sleep Duration and Metabolic Syndrome: An Updated Systematic Review and Meta-Analysis. Sleep Medicine Reviews. 2021 Oct; 59: 101451. doi: 10.1016/j.smrv.2021.101451.

[3] Freeman D, Sheaves B, Waite F, Harvey AG, Harrison PJ. Sleep Disturbance and Psychiatric Disorders. The Lancet Psychiatry. 2020 Jul; 7(7):628-37. doi: 10.1016/S2215-0366(20)30136-X.

[4] Scott H, Biello SM, Woods HC. Social Media Use and Adolescent Sleep Patterns: Cross-Sectional

DOI: https://doi.org/10.54393/tt.v6i3.282

Findings from the UK Millennium Cohort Study. BMJ Open. 2019 Sep; 9(9): e031161. doi: 10.1136/bmjopen-2019-031161.
[5] Duncan MJ, Oftedal S, Rebar AL, Murawski B, Short CE, Rayward AT, *et al.* Patterns of Physical Activity, Sitting Time, and Sleep in Australian Adults: A Latent Class Analysis. Sleep Health. 2020 Dec; 6(6): 828-34. doi: 10.1016/j.sleh.2020.04.006.
[6] Matko K, Berghöfer A, Jeitler M, Sedlmeier P, Bringmann HC. Who Benefits Most? Interactions between Personality Traits and Outcomes of Four Incremental Meditation and Yoga Treatments. Journal of Clinical Medicine 2022 Aug; 11(15):4553. doi: 10.3390/jcm11154553.
[7] Xu N, Wu Q, Ma L, Yu B. Can Afternoon Napping Protect Against the Negative Effects of Short or Long Sleep Duration on Cognitive Function? A Prospective Study. Sleep Medicine. 2023 Feb; 102: 1-8. doi: 10.1016/j.sleep.2022.12.012.
[8] Twenge JM, Hisler GC, Krizan Z. Associations Between Screen Time and Sleep Duration Are Primarily Driven by Portable Electronic Devices: Evidence from a Population-Based Study of US Children Ages 0-17. Sleep Medicine. 2019 Apr; 56: 211-8. doi: 10.1016/j.sleep.2018.11.009.
[9] Miola A, Alvarez-Villalobos NA, Ruiz-Hernandez FG, De Filippis E, Veldic M, Prieto ML, *et al.* Insulin Resistance in Bipolar Disorder: A Systematic Review of Illness Course and Clinical Correlates. Journal of Affective Disorders. 2023 Aug; 334: 1-1. doi: 10.1016/j.jad.2023.04.068.
[10] Leong CW, Leow JW, Grunstein RR, Naismith SL, Teh JZ, D'Rozario AL, *et al.* A Systematic Scoping Review of the Effects of Central Nervous System Active Drugs on Sleep Spindles and Sleep-Dependent Memory Consolidation. Sleep Medicine Reviews. 2022 Apr; 62: 101605. doi: 10.1016/j.smrv.2022.101605.
[11] Almojali AI, Almalki SA, Alothman AS, Masuadi EM, Alaqeel MK. The Prevalence and Association of Stress with Sleep Quality Among Medical Students. Journal of Epidemiology and Global Health. 2017 Jan; 7(3): 169-74. doi: 10.1016/j.jegh.2017.04.005.
[12] Sürücü L, Yıkılmaz İ, Maşlakçı A. Exploratory Factor Analysis (EFA) in Quantitative Researches and Practical Considerations. Gümüşhane Üniversitesi Sağlık Bilimleri Dergisi. 2022; 13(2): 947-65. doi: 10.37989/gumussagbil.1183271.
[13] Carmassi C, Cruz-Sanabria F, Gravina D, Violi M, Bonelli C, Dell'Oste V, *et al.* Exploratory Study on the Associations Between Lifetime Post-Traumatic Stress Spectrum, Sleep, and Circadian Rhythm Parameters in Patients With Bipolar Disorder. International Journal of Environmental Research and Public Health. 2023 Feb; 20(4): 3566. doi: 10.3390/ijerph20043566.
[14] Abbott SM, Choi J, Wilson IV J, Zee PC. Melanopsin-Dependent Phototransduction Is Impaired in Delayed Sleep-Wake Phase Disorder and Sighted Non-24-Hour Sleep-Wake Rhythm Disorder. Sleep. 2021 Feb; 44(2): zsaa184. doi: 10.1093/sleep/zsaa184.
[15] de Zambotti M, Trinder J, Silvani A, Colrain IM, Baker FC. Dynamic Coupling Between the Central and Autonomic Nervous Systems During Sleep: A Review. Neuroscience & Biobehavioral Reviews. 2018 Jul; 90: 84-103. doi: 10.1016/j.neubiorev.2018.03.027.
[16] Baglioni C, Altena E, Bjorvatn B, Blom K, Bothelius K, Devoto A, *et al.* The European Academy for Cognitive Behavioural Therapy for Insomnia: An Initiative of the European Insomnia Network to Promote Implementation and Dissemination of Treatment. Journal of Sleep Research. 2020 Apr; 29(2): e12967. doi: 10.1111/jsr.12967.
[17] Park KM, Kim KT, Lee DA, Cho YW. Redefining the Role of the Cerebellum in Restless Legs Syndrome. Sleep Medicine. 2023 Dec; 112: 256-61. doi: 10.1016/j.sleep.2023.10.030.
[18] Bai W, Zhang J, Smith RD, Cheung T, Su Z, Ng CH, *et al.* Inter-Relationship Between Cognitive Performance and Depressive Symptoms and Their Association with Quality of Life in Older Adults: A Network Analysis Based on the 2017-2018 Wave of Chinese Longitudinal Healthy Longevity Survey (CLHLS). Journal of Affective Disorders. 2023 Jan; 320: 621-7. doi: 10.1016/j.jad.2022.09.159.
[19] Hajjar ST. Statistical Analysis: Internal-Consistency Reliability and Construct Validity. International Journal of Quantitative and Qualitative Research Methods. 2018 Feb; 6(1): 27-38.
[20] Maurer LF. The Mechanisms of Sleep Restriction Therapy for Insomnia Disorder (Doctoral Dissertation, University of Oxford). 2020. doi: 10.1186/ISRCTN10974094.