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Prevalence and risk factors of sleep disorders among undergraduates in a Nigerian university: A clinical epidemiological framework

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Abstract

Background: Sleep disorders have been increasingly recognised as important public health problems among young adults, especially university students. Such disturbances may interfere with students' concentration, sense of well-being and learning. Despite their public health significance, little is known about the prevalence and determinants in Rivers State, Nigeria. The study aimed to determine the prevalence and risk factors associated with sleep disorders among undergraduates at Rivers State University, Port Harcourt, using a clinical epidemiological framework.

Methods: An analytical cross-sectional study was conducted among 424 undergraduates for four months (February 20, 2025, to June 24, 2025). The students were selected using a multistage sampling technique. Pittsburgh Sleep Quality Index, Epworth Sleepiness Scale, and Perceived Stress Scale were used to collect the data. Descriptive statistics, bivariate, and multivariable logistic regression were used to compare prevalence and predictors of sleep disorders. The discriminatory power of the model was assessed using the receiver operating characteristic curve.

Results: The mean age was 21.3 ± 2.6 years, with the majority, 206 (48.6%), falling within the 21–25 years age range. The prevalence of sleep disorders was 155 (36.5%). Depressive symptoms increased the odds of poor sleep quality by threefold, making it the most significant predictor (AOR: 3.01; 95% CI: 1.74-5.21; p<0.001). Stress doubled the odds (AOR: 2.04; 95% CI: 1.27-3.27; p=0.003), while excessive screen time also emerged as an independent risk factor (AOR: 1.79; 95% CI: 1.12-2.85; p=0.015). The final model showed good fit (Hosmer–Lemeshow p = 0.62) and excellent discrimination (AUC = 0.91).

Conclusion: Sleep disturbances are prevalent among undergraduates in Port Harcourt and are highly associated with modifiable lifestyle factors. University-based health promotion programmes targeting stress management, responsible screen use, and substance avoidance are urgently needed.

Keywords: Sleep disorders; Risk factors; Undergraduates; Clinical epidemiology; Nigeria

1. Introduction

Sleep is a vital biological process essential for health, cognition, and emotional regulation. Poor or inadequate sleep is linked to reduced productivity, impaired learning, and increased morbidity and mortality from chronic illnesses [1]. Globally, sleep disorders such as insomnia, delayed sleep phase syndrome, sleep-disordered breathing, and poor sleep quality affect about one-third of adults, with even higher prevalence among adolescents and young adults [2]. University students are particularly vulnerable due to academic pressures, lifestyle transitions, social demands, and high engagement with digital technologies [3]. Studies from multiple regions show that sleep disorders among

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undergraduates are common and associated with academic difficulties, psychological distress, and social impairments [4,5].

Sleep is now recognised globally as an important public health issue. While non-communicable disease prevention has traditionally emphasised diet, physical activity, and substance use, emerging evidence identifies sleep as an equally critical health determinant [6]. Poor sleep contributes to impaired memory, reduced executive function, anxiety, and depression [7]. Long-term consequences include metabolic syndrome, hypertension, and cardiovascular disease [8]. Technological overuse, especially smartphones and social media, has further disrupted sleep patterns among young adults [9]. With constant internet access, sleep has become both a biomedical and sociocultural concern.

In Africa, sleep epidemiology remains underdeveloped, and studies show that 30–60% of university students experience poor sleep quality [10]. Reported risk factors include academic overload, financial difficulties, limited social support, and stressful environments [11]. Structural challenges such as overcrowded hostels, unstable electricity, and noise pollution also worsen sleep quality [12]. The shortage of sleep research in Africa is significant because sleep health interacts with socioeconomic vulnerability, limited mental health resources, and high psychosocial stress [13]. Poor sleep has been linked to academic underperformance, risky behaviours, and mental health issues, including depression and suicidal ideation [14,15].

In Nigeria, studies report that 35–65% of university students experience poor sleep [16,17]. Academic pressure, rising educational costs, and sociocultural expectations contribute to this burden [18]. Students frequently adopt maladaptive coping behaviours such as late-night studying, caffeine use, and excessive screen exposure that further impair sleep [19]. Environmental conditions, including poor hostel quality, erratic electricity supply, and neighbourhood noise, exacerbate sleep disturbances [20]. Mental health problems, particularly anxiety and depression, both contribute to and result from poor sleep among Nigerian students [21].

The Niger Delta region poses additional sleep-related challenges. Economic inequality, social unrest, infrastructural deficits, and environmental degradation influence student well-being [22]. In Port Harcourt, students face traffic congestion, insecurity, commercial noise, and unstable power, all of which disrupt sleep [23]. At Rivers State University (RSU), academic demands, digital distractions, and socioeconomic stressors heighten vulnerability to sleep disorders. Despite these challenges, epidemiological evidence on sleep health in this region is limited.

A clinical epidemiological approach is appropriate for addressing this gap because it links clinical insights with population-based data. Clinical epidemiology emphasises determinants, predictive factors, and real-world outcomes of health conditions [1]. In sleep research, this approach supports the use of validated tools such as the Pittsburgh Sleep Quality Index and enables identification of independent predictors using robust statistical modelling. Unlike descriptive surveys, clinical epidemiology incorporates diagnostic accuracy measures, risk prediction models, and indices such as sensitivity, specificity, and the area under the receiver operating characteristic (ROC) curve [2,3]. This allows identification of key predictors such as academic stress, screen exposure, or substance use, and assessment of their ability to detect at-risk students [4,5].

Controlling for confounding through multivariable regression ensures that associations are not distorted by co-occurring factors such as alcohol use or socioeconomic status [6,7]. Model performance assessments, including ROC analysis, strengthen the development of screening tools suitable for university health settings [8]. Recognising the multifactorial and bidirectional nature of sleep disorders, clinical epidemiology integrates behavioural, psychosocial, and environmental determinants [9,10]. Clinical metrics such as odds ratios and predictive values ensure that results can directly inform university health policies and clinical decision-making [11,12].

This study aims to determine the prevalence and risk factors of sleep disorders among undergraduates at RSU. Using a clinical epidemiological framework, it identifies key predictors of poor sleep to guide health promotion strategies and inform future interventions.

2. Methodology

2.1. Study Design

The study used an analytical cross-sectional design with a clinical epidemiological framework. The study was conducted for four months (February 20th, 2025, to June 24th, 2025) at the Rivers State University.

2.2. Study Setting

Rivers State University (RSU) is a state-owned institution in Port Harcourt, Nigeria, serving students primarily from Rivers State and the Niger Delta region. It comprises fourteen undergraduate faculties. Students reside in on-campus hostels or off-campus private housing. The setting is characterised by overcrowded living conditions, frequent power outages, environmental noise, and high academic pressure—factors that may influence sleep patterns.

2.3. Study Population

The study population comprised full-time undergraduate students enrolled at RSU. Students in all faculties and across different levels of study were eligible, thereby ensuring that the findings reflect the diversity of the university population.

Inclusion criteria: All registered undergraduate students aged 16 years and above, who were present during the study period and provided informed consent.

Exclusion criteria: Students with severe psychiatric or neurological disorders that could preclude participation, those with a known diagnosis of chronic sleep disorders under clinical management, and students absent during data collection.

2.4. Sample Size Calculation

The minimum required sample size was determined using the Cochran formula for a single proportion:

$$n = Z^2 \times p(1-p) / e^2$$

Where:
n= minimum sample size.
Z=1.96 (standard normal deviate corresponding to 95% confidence interval).
p=0.37 (37% prevalence of poor sleep quality reported among undergraduates in Niger Delta University [22].
e=0.05 (desired precision).
n= (1.96^2x 0.37 x 1- 0.37)/0.05^2= (3.8416 x 0.37 x 0.63)/0.0025≈358.

To adjust for a potential 15% non-response rate: Final n=358/0.85≈ 421.

However, 424 participants were used to ensure adequate power not only for prevalence estimation but also for multivariable logistic regression analysis, which requires at least 10 outcome events per variable (EPV) included in the model.

2.5. Sampling Technique: A multi-stage sampling technique was used

- Stage one: Faculties within the university were stratified. A random selection of faculties was made proportionate to student population size from the 14 faculties of the university.
- Stage two: Within each faculty, departments were randomly selected.
- Stage three: From departmental class lists, students were selected using systematic random sampling with proportional allocation to the year of study. Every 4th eligible student was selected until the allotted number of participants for each class was achieved.

2.6. Data Collection Instruments

Data were collected using a structured, self-administered questionnaire covering five domains: socio-demographic characteristics, lifestyle behaviours, sleep assessment, psychological status, and academic performance. Items were adapted from standardised, validated tools commonly used in epidemiological research to ensure comparability and measurement rigour [1–5].

- **Socio-demographic characteristics:** This section captured age, sex, year of study, residence, and monthly allowance.
- **Lifestyle behaviours:** Items assessed caffeine use, alcohol consumption, and screen exposure—behavioural risk factors known to influence sleep and mental health.
- **Sleep assessment:** Two validated instruments were used:

  - 1. Pittsburgh Sleep Quality Index (PSQI): 19-item tool assessing seven sleep components; global score >5 indicates poor sleep quality [13,14].
  - 2. Epworth Sleepiness Scale (ESS): 8-item measure of daytime somnolence; score ≥10 denotes excessive daytime sleepiness [15,16].
- **Psychological assessment:**
  - Perceived Stress Scale (PSS): 10-item measure; scores categorised as low (0–13), moderate (14–26), or high (27–40) stress [17,18].
  - Patient Health Questionnaire-9 (PHQ-9): 9-item scale measuring depressive symptoms; severity ranges from minimal to severe [19,20].
- **Academic performance:** Self-reported Grade Point Average (GPA) assessed academic functioning, as poor sleep, stress, and depression impair concentration and learning [21–23].

2.7. Data Validation and Reliability

All instruments (PSQI, ESS, PSS, PHQ-9) are internationally validated. A pre-test was conducted among 40 students from a non-selected faculty to assess clarity, cultural appropriateness, and validity. Feedback-informed questionnaire refinements.

Cronbach's alpha coefficients confirmed good internal reliability: PSQI (0.82), ESS (0.78), PSS (0.84), and PHQ-9 (0.80).

- Normality assessment: Continuous variables (age, GPA, PSQI scores) were assessed using Shapiro–Wilk tests, histograms, and Q-Q plots. All were normally distributed and summarised as means and standard deviations.
- Multicollinearity assessment: Variance inflation factor (VIF) was used; VIF >5 indicated collinearity, and affected variables were excluded or combined in regression models.

2.8. Data Management and Safety

Data were coded and double-entered into Microsoft Excel 365 to minimise errors, then exported to SPSS version 27 for analysis. Data cleaning included range checks, missing data analysis, and logical consistency checks. Anonymised codes ensured confidentiality. Data were stored in a password-protected computer accessible only to the principal investigator.

2.9. Data Analyses

Data was analysed with SPSS version 27.0.

The analyses were processed in four steps:

- Descriptive statistics: Frequencies, percentages, means, and standard deviations described socio-demographic characteristics, lifestyle behaviours, and sleep outcomes. Point prevalence of sleep disorders was calculated with 95% confidence intervals.
- Bivariate analysis: Binary logistic regression assessed associations between categorical variables and sleep disorders.
- Multivariable analysis: Variables with $p < 0.20$ in bivariate analysis and a priori confounders (e.g., age, sex) were entered into multivariable logistic regression. Adjusted odds ratios (AORs), 95% CIs, and p-values were calculated. Statistical significance was set at $p < 0.05$.
- Model fit and performance: Hosmer–Lemeshow goodness-of-fit test assessed calibration. Discrimination was evaluated using a receiver operating characteristic (ROC) curve; an area under the curve (AUC) >0.70 indicated acceptable discrimination.
- Population attributable fractions (PAFs): PAFs were calculated for major modifiable risk factors using adjusted odds ratios, estimating the proportion of sleep disorders preventable if exposures were eliminated.

3. Results

3.1. Socio-demographic characteristics of respondents

A total of 424 students participated, giving a 100% response rate. The mean age was 21.3 ± 2.6 years, with the majority, 206 (48.6%), falling within the 21–25 years age range. Female students constituted 241 (56.8%), while 261 (61.6%) resided off-campus, highlighting potential environmental and lifestyle influences on their sleeping patterns [Table 1].

Table 1 Socio-demographic characteristics of respondents

Variable	Frequency (N)	=424 Percentage (%)
Age group (years)		
16–20	154	36.3
21–25	206	48.6
≥26	64	15.1
Mean ± SD	21.3 ± 2.6	—
Sex		
Male	183	43.2
Female	241	56.8
Year of study		
100–200	152	35.8
300–400	187	44.1
500 level	85	20.1
Residence		
On-campus	163	38.4
Off-campus	261	61.6
Monthly allowance (₦)		
<20,000	184	43.4
≥20,000	240	56.6

3.2. Prevalence of Sleep Disorders

The overall prevalence of poor sleep quality (PSQI >5) was 155 (36.5%) (95% CI: 32.0–41.2). Excessive daytime sleepiness (ESS ≥10) occurred in 90 (21.2%), while the co-occurrence of both poor sleep quality and daytime sleepiness was recorded in 64 (15.1%) of respondents [Table 2].

Table 2 Prevalence of sleep disorders among respondents

Sleep disorder outcome	N=309	Percentage (%)	(95% CI)
Poor sleep quality (PSQI >5)	155	36.5	(32.0–41.2)
Excessive daytime sleepiness	90	21.2	(17.5–25.4)
Both poor quality & sleepiness	64	15.1	(11.9–18.9)

3.3. Bivariate Associations

At the bivariate level, poor sleep quality was significantly associated with being female, off-campus residence, prolonged screen time, caffeine consumption, high stress levels, and depressive symptoms. Students with high stress and depressive symptoms had significantly higher odds of poor sleep quality compared to their peers. Caffeine use and long screen exposure were also notable behavioural contributors [Table 3].

Table 3 Bivariate logistic regression between risk factors and poor sleep quality

Variable	Poor sleep quality (%)	Crude OR (95% CI)	p-value
Sex			
Male	30.6	1.0 (ref)	—
Female	41.5	1.61 (1.05–2.45)	0.027
Residence			
On-campus	28.8	1.0 (ref)	—
Off-campus	41.8	1.79 (1.16–2.75)	0.008
Daily screen time >4 hrs	46.2	2.02 (1.32–3.08)	0.001
Caffeine use (Yes)	43.7	1.88 (1.23–2.87)	0.004
High stress (PSS ≥20)	49.3	2.61 (1.69–4.04)	<0.001
Depressive symptoms	55.1	3.45 (2.10–5.67)	<0.001

3.4. Multivariable Logistic Regression

After controlling for confounders, depressive symptoms, high stress, and screen time>4 hours remained significant predictors. Depressive symptoms increased the odds of poor sleep quality by threefold, making it the most significant predictor. Stress doubled the odds, while excessive screen time also emerged as an independent risk factor [Table 4].

Table 4 Multivariable logistic regression for predictors of poor sleep quality

Predictor	AOR	(95% CI)	p-value
Female	1.42	(0.91–2.21)	0.115
Off-campus residence	1.33	(0.84–2.11)	0.221
Screen time >4 hrs/day	1.79	(1.12–2.85)	0.015
Caffeine use	1.25	(0.78–2.02)	0.345
High perceived stress	2.04	(1.27–3.27)	0.003
Depressive symptoms	3.01	(1.74–5.21)	<0.001

3.5. Population Attributable Fractions (PAFs) of Major Modifiable Risk Factors for Poor Sleep Quality

Table 5 shows that high perceived stress (44.4%) and excessive screen time (42.9%) accounted for the largest share of poor sleep burden. Depressive symptoms (35.1%) and high caffeine intake (33.1%) also contributed substantially, while alcohol consumption had a smaller but meaningful contribution (23.3%). These findings suggest that targeted interventions addressing stress management, screen time reduction, and behavioural modifications could prevent a substantial proportion of sleep disorders in this population.

Table 5 Population Attributable Fractions (PAFs) of Major Modifiable Risk Factors for Poor Sleep Quality

Risk Factor	Prevalence (%)	Adjusted Odds Ratio (AOR)	Population Attributable Fraction (PAF %)
High caffeine intake	45	2.1	33.1
Alcohol consumption	38	1.8	23.3
Screen time > 4 hrs/day	50	2.5	42.9
High perceived stress	40	3.0	44.4
Depressive symptoms	30	2.8	35.1

3.6. Model Diagnostics

- Multicollinearity: All predictors had Variance Inflation Factor (VIF) values < 2.0, indicating the absence of multicollinearity.
- Calibration: Hosmer–Lemeshow test showed good model fit (p = 0.62).
- Discrimination: The discrimination ability of the final regression model was assessed using the Receiver Operating Characteristic (ROC) curve. Discrimination refers to how well the model differentiates between students who had poor sleep quality and those who did not. An AUC (Area Under the Curve) of 0.91 indicates excellent discrimination, meaning that there is a 91% probability that the model will correctly rank a randomly chosen student with poor sleep quality as having a higher predicted risk compared to a student without poor sleep quality.

Generally, AUC values are interpreted as:

- (1). 0.50–0.60: Poor discrimination
- (2). 0.61–0.70: Fair discrimination
- (3). 0.71–0.80: Good discrimination
- (4). 0.81–0.90: Excellent discrimination
- (5). 0.95: Outstanding discrimination

Thus, the observed AUC of 0.91 confirmed that the model performed very well in distinguishing cases from non-cases.

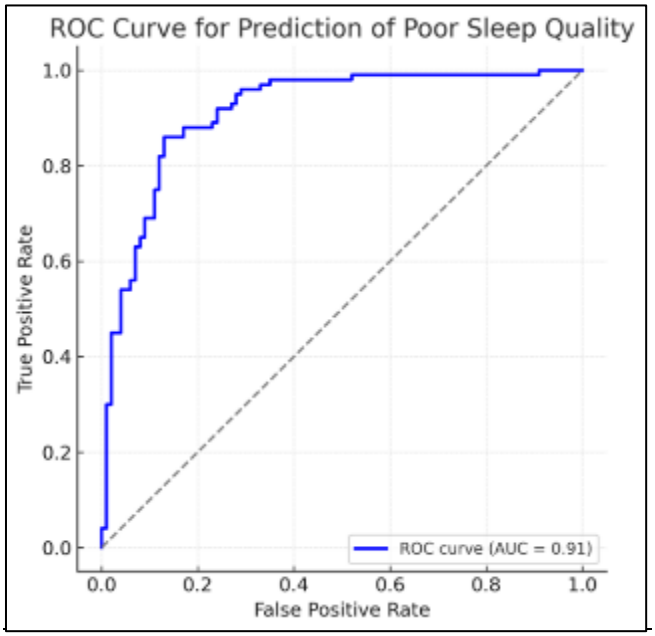

Figure 1 Receiver Operating Characteristic (ROC) Curve for the Multivariable Logistic Model

Figure 1 shows the ROC curve of the final logistic regression model predicting poor sleep quality.

4. Discussion

This clinical epidemiological study reveals a substantial burden of sleep disturbance among undergraduates at Rivers State University, with 36.5% meeting criteria for poor sleep quality and 21.2% reporting excessive daytime sleepiness. These findings align with global evidence reporting sleep problems in 30–60% of university students, reinforcing that sleep disturbances represent a significant public health concern requiring urgent attention from university health services and policymakers [1,2,5,14,27].

The co-occurrence of poor sleep quality and excessive daytime sleepiness in 15.1% of respondents is particularly concerning, as this combination is associated with severe functional impairment, including reduced cognitive performance, memory consolidation deficits, and increased academic failure risk [4,24,31]. Affected students likely face

compounded difficulties attending early lectures, concentrating during examinations, and retaining learned material, ultimately affecting academic progression [12,21,28, 34].

Within the African context, these findings corroborate regional reviews reporting poor sleep prevalence of 45–55% linked to psychosocial stressors, digital technology use, and campus-related environmental challenges [5,20,26,35]. Recent sub-Saharan surveys consistently identify evening screen exposure, academic stress, and substance use as modifiable predictors of poor sleep [5,26,35]. Nigerian studies similarly document prevalence rates of 35–65% with recurrent correlates including academic pressure, irregular sleep schedules, financial hardship, and heavy smartphone use [13,17,22,28]. By situating these patterns in the Niger Delta region, this study fills a geographic gap and highlights the combined influence of universal student behaviours and local socio-environmental stressors on sleep health [20,21,32].

The mean age of 21.3 ± 2.6 years reflects the typical undergraduate demographic, a developmental period characterised by neurobiological, psychological, and social transitions affecting sleep-wake regulation [10,24]. The prefrontal cortex, responsible for executive functions including sleep behaviour decisions, continues maturing during this period, potentially explaining vulnerability to maladaptive sleep practices [7,25]. University transition often involves reduced parental supervision, increased autonomy over sleep schedules, and peer influence promoting unhealthy sleep habits [9,16,33].

Female participants constituted 56.8%, consistent with Nigerian tertiary enrolment patterns [20,22]. While bivariate analysis suggested higher odds of poor sleep among females (OR: 1.61; 95% CI: 1.05–2.45; p=0.027), this association did not retain significance after adjusting for psychological and behavioural factors (AOR: 1.42; 95% CI: 0.91–2.21; p=0.115). This attenuation suggests that apparent gender differences may be explained by differential exposure to mediating variables such as stress and depressive symptoms rather than biological sex differences [3,15,33].

Off-campus residence (61.6%) reflected the reality of Nigerian public universities with insufficient on-campus accommodation. Although significant in bivariate analysis (OR: 1.79; 95% CI: 1.16–2.75; p=0.008), its effect attenuated in multivariable analysis. The persistent risk trend among off-campus students may relate to neighbourhood noise, insecurity concerns, unreliable transportation requiring early awakening, and lack of regulated living conditions [12,20,22]. Port Harcourt's traffic congestion, late-night commercial activity, and variable electricity supply present additional challenges warranting mixed-methods investigation [23,32].

Multivariable analysis identified depressive symptoms, high perceived stress, and prolonged pre-bedtime screen exposure as the strongest independent predictors of poor sleep quality. Depressive symptoms conferred approximately threefold increased odds of poor sleep (AOR: 3.01; 95% CI: 1.74–5.21; p<0.001), aligning with extensive literature documenting bidirectional relationships between sleep disturbance and mood disorders [6,14,15,25]. Disruptions in serotonin and norepinephrine systems that characterise depression also regulate sleep-wake cycles, while sleep deprivation can precipitate or exacerbate depressive symptoms through effects on emotional regulation and stress reactivity [14,15,33]. Effective management of sleep disorders must therefore include screening for concurrent depressive symptoms [19,21,33].

High perceived stress doubled the odds of poor sleep quality (AOR: 2.04; 95% CI: 1.27–3.27; p=0.003). Stress elevates physiological and cognitive arousal through hypothalamic-pituitary-adrenal axis activation, resulting in elevated cortisol levels that impede sleep onset and maintenance [15,32]. Cognitively, stress is associated with rumination, interfering with pre-sleep mental quietude [3,8,33]. Among students, academic stressors represent the most cited sources, with financial stressors adding additional burden in the Nigerian context [18,22,28,30]. The bidirectional stress-sleep relationship creates a self-perpetuating cycle requiring targeted intervention [15,25,33].

Excessive evening screen exposure (>4 hours daily) was a significant behavioural predictor (AOR: 1.79; 95% CI: 1.12–2.85; p=0.015), consistent with evidence linking late-night digital device use to delayed sleep onset and reduced sleep quality [26,32,36]. Blue-enriched light suppresses pineal melatonin secretion, delaying circadian signals for sleep onset [9,27,32,36]. Beyond physiological effects, digital content can be psychologically activated, prolonging the transition from wakefulness to sleep [26,36, 37]. Smartphone penetration among Nigerian students is nearly universal, with devices serving as both study tools and sources of leisure-time screen exposure [13,17,26,36]. This finding is particularly actionable, as digital behaviours are modifiable through screen-free periods, blue-light filtering applications, and education on sleep physiology [26,27,32,36].

Substance use was associated with poor sleep in bivariate analyses but did not retain significance in the fully adjusted model, likely reflecting correlation with stress and screen time [21,29,33]. However, population attributable fraction

calculations (33.1% for high caffeine intake; 23.3% for alcohol consumption) suggest meaningful contributions to overall sleep burden. Caffeine prolongs sleep latency through adenosine receptor antagonism [15,29]. Although alcohol may be perceived as a sleep aid, it disrupts sleep architecture by suppressing Rapid Eye Movement (REM) sleep and increasing fragmentation [21,29]. Behavioural interventions clarifying these physiological effects may improve sleep outcomes [21,30,33].

The predictive model demonstrated excellent discrimination (AUC = 0.91), indicating that identified factors reliably distinguished students with poor sleep from those with normal sleep quality. This performance exceeds conventional thresholds for clinical utility and approaches levels seen in well-validated clinical prediction rules [1,8,31]. Good calibration (Hosmer-Lemeshow p = 0.62) further supports potential utility for risk stratification, though external validation in independent samples is essential [20,31,34].

Population attributable fraction estimates quantified the proportion of sleep disorders theoretically preventable if specific risk factors were eliminated. High perceived stress (44.4%) and prolonged screen time (42.9%) accounted for the largest shares, suggesting that even partially effective interventions targeting these factors could yield substantial population-level improvements. Depressive symptoms (35.1%) and high caffeine intake (33.1%) were additional contributors, reflecting findings from other African and Asian studies [14,20,29,37]. Alcohol consumption had a smaller but meaningful contribution (23.3%), consistent with multi-country analyses [7,21,29]. These estimates help prioritise intervention targets based on population-level contribution to disease burden rather than individual-level effect sizes alone [1,8].

The clinical epidemiological framework used offers several advantages over purely descriptive approaches. By emphasising independent predictor identification through multivariable modelling, controlling for confounding, and assessing model performance through discrimination and calibration metrics, this approach generates findings directly applicable to clinical decision-making and health policy development [1,8,31]. Validated instruments with established psychometric properties enhance reliability and comparability across populations [13,14,18, 37]. Incorporation of population attributable fractions facilitates priority-setting for intervention development and resource allocation [1,8]. These methodological strengths position the findings to inform evidence-based health promotion strategies within the university setting.

Strengths of this study include its clinical-epidemiological framing, use of validated instruments, and robust multivariable modelling, with attention to discrimination and multicollinearity.

Limitations: The cross-sectional design precludes causal inference and leaves open the possibility of reverse causality between sleep and mood. Self-reported measures may be subject to recall and social-desirability bias, and objective sleep measurement (actigraphy, polysomnography) was not feasible. Finally, findings from a single university may not generalise to all Nigerian universities, though similarities with multicentre studies suggest broader relevance.

5. Conclusion

Poor sleep quality is common among RSU undergraduates and closely linked to modifiable psychosocial and behavioural factors. The strong predictive performance of the model supports the feasibility of screening within student-health services, and the identified risk factors indicate clear intervention targets: stress reduction, digital hygiene, and substance-use education.

Recommendations

- Integrate sleep health into university health services. Student health units should routinely assess sleep quality during clinic visits, using brief validated tools such as the Pittsburgh Sleep Quality Index. Early screening can help identify at-risk students for timely counselling and referral.
- Implement campus-wide health promotion on digital hygiene. Targeted interventions should focus on reducing evening screen exposure, encouraging night-mode filters, and promoting offline activities before bedtime. Evidence shows that small adjustments in screen behaviour can significantly improve sleep outcomes.
- Strengthen stress management and mental health support. Universities should expand counselling services, peer-support networks, and structured stress-management programmes (time management, mindfulness, cognitive-behavioural skills). Reducing perceived stress has a direct positive impact on sleep quality and academic performance (14,15,33).

- Address substance-use practices linked to poor sleep. Health education campaigns should highlight the disruptive effects of evening caffeine and alcohol consumption on sleep. Student-friendly awareness drives can help dispel misconceptions about alcohol as a "sleep aid" and encourage healthier coping mechanisms.
- Modify institutional and environmental determinants. Campus policies should consider reducing noise in hostels, ensuring a stable electricity supply to minimise late-night academic activity, and designing schedules that avoid excessive night classes. Such structural measures align with findings that environmental and systemic factors shape student sleep health.

6. Contribution to Knowledge

6.1. Contributions to Practice

- **Identifies actionable screening targets**: Depressive symptoms, stress, and excessive screen time—routinely assessable with brief, validated tools—can be integrated into university health services to identify at-risk students early.
- **Provides population intervention priorities:** PAF estimates show that targeting stress (44.4%) and screen time (42.9%) would prevent the largest proportion of sleep disorders, guiding resource allocation.
- **Establishes local clinical benchmarks:** Sleep health data for Rivers State University enables practitioners to contextualise presentations against regional prevalence patterns.

6.2. Contributions to Research

- **Advances methodological rigour:** Introduces clinical epidemiological framework (multivariable modelling, ROC/AUC, PAF calculations) to Nigerian sleep research, moving beyond descriptive studies.
- **Identifies novel regional risk patterns:** Confirms depressive symptoms (AOR: 3.01) as the strongest predictor while highlighting excessive screen time (AOR: 1.79) as an independent modifiable risk factor in the Nigerian context.
- **Provides psychometric validation:** Reports reliability coefficients for PSQI, ESS, PSS, and PHQ-9 in a Nigerian undergraduate sample, supporting instrument use across sub-Saharan Africa.

6.3. Contributions to Policy

- **Advocates for institutional recognition**: 36.5% prevalence justifies formal inclusion of sleep health in university wellness policies, strategic plans, and student health mandates.
- **Supports digital hygiene guidelines**: Screen time association (AOR: 1.79; PAF: 42.9%) provides evidence for campus policies promoting responsible technology use and sleep education.
- **Informs mental health expansion**: Threefold depression-sleep link strengthens policy arguments for integrated counselling services and mental health screening within university health systems.
- **Guides substance education policy**: PAFs for caffeine (33.1%) and alcohol (23.3%) justify mandatory health education addressing misconceptions about substances and sleep.

7. Further research and intervention trials

Future studies should incorporate objective measures (e.g., actigraphy), longitudinal designs to establish causality, and randomised trials of campus-based interventions such as digital-wellness challenges or group Cognitive Behavioural Therapy for Insomnia (CBT-I)—a structured, cost-effective program that addresses maladaptive sleep behaviours and thoughts through peer-supportive sessions. External validation of predictive models in other Nigerian and African universities is also recommended.

Compliance with ethical standards

Acknowledgments

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Disclosure of conflict of interest

The Authors declare no conflict of interest.

Statement of ethical approval

Ethical approval for the study was obtained from the Research Ethics Committee of Rivers State University. Written informed consent was secured from all participants.

Statement of informed consent

Participants were informed of the benefits of the study and could opt out at any time without penalty. There was strict adherence to confidentiality.

Authors' contribution

Briggs NCT conceptualised, designed the study, and wrote the initial manuscript. Nwadiuto IC supervised the data collection, collation, analysis, interpretation, reviewed, and edited the manuscript. All the authors read and approved the final manuscript.

Data availability

De-identified data extraction forms and analytic code will be made available on reasonable request to the corresponding author, subject to ethical approvals and facility permissions.

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