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Autonomic function classification and sleep quality among young adults in Central Java, Indonesia: A cluster analysis

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ABSTRACT

Objective: Sleep regulation is linked to autonomic function, with sleep disruptions often indicating dysregulation in the autonomic nervous system (ANS). This study conducted a cluster to identify the autonomic function profiles associated with sleep quality.
Methods: This cross-sectional study was conducted in Banyumas Regency, Central Java, Indonesia, in February to April 2023, and recruited 437 individuals aged 18–26 years. Autonomic function was evaluated using heart rate variability parameters, including low-frequency, very-low-frequency, and high-frequency bands. Sleep quality was evaluated using the Pittsburgh Sleep Quality Index. A *k*-means cluster analysis was conducted to identify patterns in ANS activity across various clusters, and the optimal number of clusters was determined using the silhouette method.
Results: Three clusters of participants with poor sleep quality ($n = 381$) were identified. Cluster 1 ($n = 95$) exhibited normal overall activity, with low sympathetic nervous system (SNS) activity and high parasympathetic nervous system (PNS) activity; Cluster 2 ($n = 81$) exhibited high ANS and SNS activity and normal PNS activity; and Cluster 3 ($n = 205$) exhibited low PNS and ANS activity and normal PNS activity. Two clusters of participants with good sleep quality ($n = 56$) were identified. Cluster 1 ($n = 11$) exhibited high ANS and PNS activity and low SNS activity, and Cluster 2 ($n = 45$) exhibited low ANS and PNS activity and normal SNS activity.
Conclusion: Understanding autonomic function clusters is essential for developing techniques for measuring sleep quality in young adults and establishing effective health promotion programs.

1. Introduction

The autonomic nervous system (ANS) regulates various body functions, including blood pressure, body temperature, gastrointestinal motility, pupillary response, sexual function, and reflex action (Gibbons, 2019). This regulatory function is achieved through autonomic reflexes, which transmit afferent signals to reflex pathways located in control centers such as the hypothalamus and brainstem (McCorry, 2007). The ANS comprises two discrete systems: the sympathetic nervous system (SNS) and the parasympathetic nervous system (PNS). These two systems continually provide neural input to tissues to maintain the stability of autonomic processes and overall physiological activity (McCorry, 2007).

Heart rate variability (HRV) is an indicator of cardiac autonomic function that can be noninvasively measured. Measurement of HRV involves analyzing fluctuations in the R-R interval, which reflect the combined effect of SNS and PNS activity on heart function (Lahiri et al., 2008). The PNS can reduce heart rate, sometimes slowing it to as low as 20–30 beats per minute or even temporarily stopping the heart altogether (Marie, 2010). Both the PNS and SNS contribute to low-frequency components, particularly affecting blood pressure regulation at baroreceptors (Shaffer & Ginsberg, 2017), with the PNS having a greater effect (Reyes del Paso et al., 2013). The high-frequency band, also referred to as the respiratory band, primarily reflects PNS activity and is correlated with heart rate variations during the respiratory cycle (Grossman & Taylor, 2007). In addition, very-low-frequency rhythms originate from

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spontaneous oscillations of the heart and are modulated by sympathetic nerve endings (McCraty & Shaffer, 2015).

The ANS plays a crucial role in regulating various body functions, including sleep (Miglis, 2016). During rapid eye movement (REM) sleep, sympathetically driven phasic sleep is often accompanied by REMs and fluctuations in the cardiorespiratory rate. By contrast, tonic REM sleep is accompanied by an overall low muscular tone observed throughout the body. As sleep progresses from non-REM stage N1 to deeper stages, sympathetic activity decreases and parasympathetic activity increases (Miglis, 2016). This shift leads to reductions in heart rate, arterial blood pressure, and peripheral vascular resistance. Consequently, cardiac output becomes less strained, promoting autonomic stability (Van de Borne et al., 1994). During REM sleep, autonomic balance shifts from parasympathetic to sympathetic dominance, leading to a sudden increase in heart rate and blood pressure (Kim et al., 2022).

Transitioning from adolescence to adulthood is a key developmental phase. In addition to age-related hormonal fluctuations (Coupal et al., 2019), alterations in brain connections associated with ANS function may contribute to individual differences in ANS activity (Gao et al., 2007). Neurogenesis plays a crucial role in maintaining homeostasis in adulthood (Harteveld et al., 2021), with ANS activity typically increasing and reaching its peak during adolescence (Lefcort, 2020). Poor sleep quality in young adults can lead to chronic sleep problems that may persist throughout adulthood, with sleep difficulties during adolescence serving as a predictor of adult sleep disruptions (Bruce et al., 2017). Understanding the function of the ANS and its relationship with sleep quality across different developmental stages, particularly in young adults, is essential.

Few studies have explored the autonomic functions that affect sleep quality. The majority of studies have focused on the relationship between sleep and ANS function (Castro-Diehl et al., 2016; Oliver et al., 2020). Only one study investigated autonomic temporal networks in participants experiencing distress (Fisher et al., 2022). In the present study, a cluster analysis was performed to determine the autonomic function profiles associated with sleep quality, including good and poor sleep quality in healthy young adults.

2. Methods

2.1. Participants and design

This cross-sectional study was conducted from February to April 2023 in Banyumas Regency, Central Java, Indonesia, on young adults aged 18–26 years. Individuals who were on sleep medications or antidepressants, who engaged in illicit drug or alcohol consumption, or who had a history of mental health disorders, neurological conditions, or cardiac diseases were excluded from the study. A total of 437 participants were included for analysis. The study protocol was approved by the Institutional Review Board of Universitas Muhammadiyah Purwokerto, Indonesia (approval no. KEPK.UMP/59/I/2023). Written informed consent was obtained from all participants.

2.2. Measurement

2.2.1. Demographic characteristics

A biopsychosocial framework was used to explore biological, psychological, and social factors (Wright et al., 2019). Biological factors were age, sex, residence type (urban or rural), body mass index (BMI), and smoking status. BMI was calculated as weight (kg) divided by height squared (m^2). Psychological factors were feelings of sadness, demotivation, loneliness, and anxiety, evaluated through “Yes” or “No” questions. Social factors were the degree of family support and the quality of family relationships, evaluated through questions such as “How is your relationship with your family?” and “How much support do you receive from your family?” Responses were categorized as either “Good” or “Bad.” All data were collected using a self-reported questionnaire.

2.2.2. Sleep quality

Sleep quality was evaluated using the pittsburgh sleep quality index (PSQI). This index has seven dimensions: sleep latency, sleep duration, sleep efficiency, medication use, daytime dysfunction, sleep disturbance, and subjective sleep quality (Buysse et al., 1989). Each dimension is scored from 0 to 3, and total scores range from 0 to 21. A total score of <5 indicates good sleep quality. In another study, the PSQI was reported to have high internal consistency, with a Cronbach’s alpha coefficient of 0.73 (Buysse et al., 1989). In the present study, the PSQI had a Cronbach’s alpha coefficient of 0.79.

2.2.3. Heart Rate Variability (HRV)

HRV was examined using a Gordon GSH751 heart rate monitor. This device is certified by the National Communications Commission (CCAF15LP0280T1), Ministry of Health and Welfare (006983), and Taiwan Food and Drug Administration (11001002) (“GSH751 Gordon heart rate monitor”).

To generate HRV parameters, the process began with calculating time-domain measures, specifically the standard deviation of normal-to-normal intervals. These measures were subsequently transformed into the frequency domain by using a fast Fourier transform algorithm to derive the power spectrum components of the very-low-frequency, low-frequency, and high-frequency bands. Fast Fourier transform is a widely used technique for HRV spectral analysis because of its simplicity and low computational cost (Singhand & Bharti, 2015). A frequency-domain analysis was conducted to identify the power spectrum components for the following bands: very-low-frequency (0.0033–0.04 Hz), low-frequency (0.04–0.15 Hz), and high-frequency (0.15–0.4 Hz). The low-frequency band reflects ANS activity (Lehrer et al., 2020; Shaffer & Ginsberg, 2017). The very-low-frequency band reflects SNS activity (McCraty & Shaffer, 2015). The high-frequency band reflects PNS activity (Grossman & Taylor, 2007). The epoch size for HRV parameter calculations was averaged over 1-min intervals to enhance temporal precision and ensure consistency across measurements. A 1-min epoch size is considered sufficient for accurately representing HRV indices (Melo et al., 2021) and is commonly used in sleep research (Radha et al., 2019).

To ensure data quality, artifacts and ectopic beats were excluded from sinus intervals, an an R-R interval variation threshold of 30 % was applied (Huikuri et al., 1999). During time-domain analysis, R-R intervals differing by 20 % to 30 % from the preceding ones were excluded (Huikuri et al., 1999). These steps were automatically performed using the GSH751 Gordon heart rate monitor. For very-low-frequency, low-frequency, and high-frequency measurements, normal ranges were defined as within $\pm$10 % of the mean value (Wang, 2021).

2.3. Data collection

Each participant underwent a 5-min HRV measurement conducted within a controlled, soundproofed environment at a constant temperature of 21–25 °C. To maintain uniformity, all participants were instructed to refrain from consuming alcohol or caffeine for 24 h prior to the measurement because these substances can influence HRV outcomes (Karpyak et al., 2014). Additionally, smokers were instructed to abstain from smoking for 1 h prior to the measurement (Sajjadieh et al., 2020). Data were collected for each participant between 8:00 and 12:00 am (Sajjadieh et al., 2020), with detailed instructions provided throughout the procedure. All participants were instructed to remain at rest without closing their eyes or falling asleep, to refrain from engaging in conversation, and to breathe naturally during the measurement.

2.4. Statistical analysis

Participant characteristics were described using the descriptive statistics of frequencies, percentages, means, and standard deviations. Chi-square tests were used to analyze categorical variables and *t*-tests were

used to analyze continuous variables in comparisons of poor versus good sleep quality. Pearson's correlation analysis was used to examine the correlation between HRV parameters and the seven dimensions of sleep quality. Logistic regression was used to identify additional associations between HRV and sleep quality.

A *k*-means cluster analysis was conducted to identify patterns in ANS condition across different clusters. This condition was defined by integrating scores derived from HRV parameters such as low-frequency, very-low-frequency, and high-frequency. The optimal number of clusters was determined using the silhouette method. This method evaluates how well an object fits within its cluster. The average silhouette score indicates the optimal number of clusters, with a higher score indicating a better fit (Salihoun, 2020). In cases with high silhouette scores, the textual corpus should be divided into *k* clusters (Boulaajoul & Aknin, 2019).

The R packages *NbClust* and *optCluster* were used to validate and visualize individual placements within specific clusters. The parameters for each cluster are visualized in boxplots. Comparisons between clusters were performed using chi-square tests for categorical variables and one-way ANOVA for continuous variables. Data were analyzed using R software (version 4.3.2), and *p*-values of <0.05 were considered significant.

3. Results

3.1. Participant characteristics

Table 1 presents an overview of the participants' biopsychosocial factors and HRV parameters. A total of 437 participants were included in this study, and the average age of the participants was 20.87 years. Among the participants, 381 had poor sleep quality and 56 had good sleep quality.

Supplementary Table S1 presents the correlations between PSQI dimensions and HRV parameters. PSQI dimensions that were significantly correlated with the low-frequency band were PSQI global score, sleep disturbance, and daytime dysfunction. Only daytime dysfunction was correlated with very-low-frequency. Global score and sleep latency were correlated with high-frequency ($p < 0.05$). None of the HRV parameters exhibited a significant association with the risk of poor sleep quality, either before or after adjustment (Supplementary Table S2).

3.2. Cluster analysis of all participants

The optimal number of clusters for HRV parameters identified using the silhouette method was three (Fig. 1A, B). Supplementary Fig. S1 depicts the central value of each cluster for comparison. (See Fig. 1B.)

For all participants, Cluster 1 ($n = 104$) had a mean low-frequency value of 342.4 ms^2 (SD = 187.1 ms^2), a mean very-low-frequency value of 28.5 ms^2 (SD = 9.8 ms^2), and a mean high-frequency value of 739.42 ms^2 (SD = 195.5 ms^2, Table 2). This cluster was characterized by normal ANS, low SNS, and high PNS activity (Table 3). Cluster 2 ($n = 93$) had a mean low-frequency value of 625.25 ms^2 (SD = 192.3 ms^2), a mean very-low-frequency value of 61.5 ms^2 (SD = 11.7 ms^2), and a mean high-frequency value of 331.7 ms^2 (SD = 164.2 ms^2, Table 2). Notably, no significant differences in biopsychosocial factors were observed between these two clusters ($p > 0.05$, Table 2). Cluster 2 was characterized by high ANS, high SNS, and normal PNS activity (Table 3). Cluster 3 ($n = 240$) had a mean low-frequency value of 200.3 ms^2 (SD = 103.7 ms^2), a mean very-low-frequency value of 47.9 ms^2 (SD = 17.4 ms^2), and a mean high-frequency value of 201.1 ms^2 (SD = 119.4 ms^2, Table 2). This cluster was characterized by low ANS, normal SNS, and low PNS activity (Table 3).

3.3. Cluster analysis of participants with poor sleep quality

For poor sleep quality, the optimal number of clusters for HRV parameters identified using the silhouette method was three (Fig. 2A, B). Supplementary Fig. S2 depicts the central value of each cluster for comparison. (See Fig. 2B.)

For participants with poor sleep quality, Cluster 1 ($n = 95$) had a mean low-frequency value of 329.8 ms^2 (SD = 181.6 ms^2), a mean very-low-frequency value of 28.3 ms^2 (SD = 9.9 ms^2), and a mean high-frequency value of 729.9 ms^2 (SD = 173.3 ms^2, Table 2). This cluster was characterized by normal ANS, low SNS, and high PNS activity (Table 3). Cluster 2 ($n = 81$) had a mean low-frequency value of 629.1 ms^2 (SD = 198.7 ms^2), a mean very-low-frequency value of 61.1 ms^2 (SD = 11.7 ms^2), and a mean high-frequency value of 338.1 ms^2 (SD = 168.4 ms^2). Notably, no significant differences in biopsychosocial factors were observed between these two clusters ($p > 0.05$, Table 2). Cluster 2 was characterized by high ANS, high SNS, and normal PNS activity (Table 3). Cluster 3 ($n = 205$) had a mean low-frequency value of 195.8 ms^2 (SD =

Table 1
Characteristics of young adults with poor and good sleep quality in Banyumas Regency, Central Java, Indonesia, examined from February to April 2023 (n = 437).

Characteristics	All participant (n = 437) n (%)	Poor sleep quality (n = 381) n (%)	Good sleep quality (n = 56) n (%)	*p*-value
Biological factors				
Age (mean ± SD) (year)	20.8 ± 1.6	20.8 ± 1.6	20.9 ± 3.2	0.794
Gender				0.339
Female	363 (83.1)	318 (83.5)	45 (80.4)	
Male	74 (16.9)	63 (16.5)	11 (19.6)	
Place of living				0.077
Rural	253 (57.9)	226 (59.3)	27 (48.4)	
Urban	184 (42.1)	155 (40.7)	29 (51.6)	
BMI (mean ± SD) (kg/m^2)	21.2 ± 3.8	21.3 ± 3.9	20.8 ± 3.2	0.032
Smoking				0.493
Yes	44 (10.1)	39 (10.2)	5 (8.9)	
No	393 (89.9)	342 (89.8)	51 (91.1)	
Psychological factors				
Feeling sad				0.009
Yes	255 (58.4)	231 (60.6)	24 (42.9)	
No	182 (41.6)	150 (39.4)	32 (57.1)	
No motivation				0.006
Yes	135 (30.9)	126 (33.1)	9 (16.1)	
No	302 (69.1)	255 (66.9)	47 (83.9)	
Feeling alone				<0.001
Yes	168 (38.4)	157 (41.2)	11 (19.6)	
No	269 (61.6)	224 (58.8)	45 (80.4)	
Feeling worry				<0.001
Yes	216 (49.4)	201 (52.8)	15 (26.8)	
No	221 (50.6)	180 (47.2)	41 (73.2)	
Social factors				
Relation to family				0.167
Good	425 (97.3)	289 (75.9)	46 (82.1)	
Bad	12 (2.7)	92 (24.1)	10 (17.9)	
Support from family				0.039
Good	421 (96.3)	284 (74.5)	48 (85.7)	
Bad	16 (3.7)	97 (25.5)	8 (14.3)	
HRV parameters				
Low-frequency (mean ± SD) (ms^2)	324.6 ± 223.2	321.3 ± 225.4	346.5 ± 208.4	0.668
Very-low-frequency (mean ± SD) (ms^2)	46.2 ± 18.5	45.9 ± 18.8	48.1 ± 16.9	0.181
High-frequency (mean ± SD) (ms^2)	357.0 ± 266.4	357.4 ± 260.7	354.6 ± 304.8	0.770

Abbreviations: SD, standard deviation; BMI, body mass index; HRV, heart rate variability. Significance was determined at $p < 0.05$ using the following tests: Chi-square test for gender, residence type, smoking habits, sadness, demotivation, loneliness, anxiety, family relationships, and family support; an independent t-test was used for age, BMI, low-frequency band, very-low-frequency band, and high-frequency band.

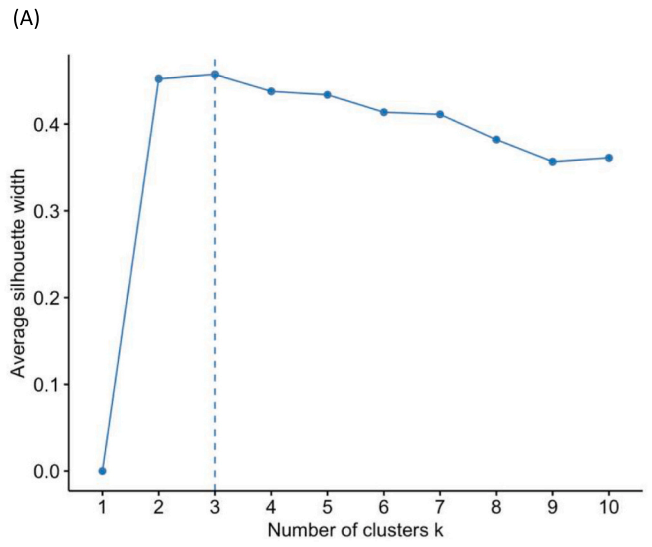

Fig. 1A. The optimal number of clusters determined by the silhouette method of young adults with poor and good sleep quality in Banyumas Regency, Central Java, Indonesia, examined from February to April 2023 (n = 437).

Fig. 1B. K-means clustering identified three distinct clusters based on heart rate variability parameters of young adults with poor and good sleep quality in Banyumas Regency, Central Java, Indonesia, examined from February to April 2023 (n = 437).

102.4 ms^2), a mean very-low-frequency value of 48.1 ms^2 (SD = 17.8 ms^2), and a mean high-frequency value of 196.1 ms^2 (SD = 116.1 ms^2). This cluster was characterized by low ANS, normal SNS, and low PNS activity (Table 3).

3.4. Cluster analysis of participants with good sleep quality

For good sleep quality, the optimal number of clusters for HRV parameters identified using the silhouette method was two (Fig. 3A, B). Supplementary Fig. S3 depicts the central value of each cluster for comparison. (See Fig. 3B.)

For participants with good sleep quality, Cluster 1 (n = 11) had a mean low-frequency value of 571.4 ms^2 (SD = 105.2 ms^2), a mean very-low-frequency value of 35.2 ms^2 (SD = 6.4 ms^2), and a mean high-frequency value of 982.8 ms^2 (SD = 351.8 ms^2, Table 2). Individuals in this cluster significantly differed in terms of age, degree of sadness, and level of anxiety ($p < 0.05$, Table 2). Cluster 1 was characterized by high ANS, low SNS, and high PNS activity. Cluster 2 (n = 45) had a mean low-frequency value of 314.3 ms^2 (SD = 199.9 ms^2), a mean very-low-frequency value of 49.9 ms^2 (SD = 17.2 ms^2), and a mean high-frequency value of 164.8 ms^2 (SD = 158.7 ms^2, Table 2). This cluster was characterized by low ANS, normal SNS, and low PNS activity (Table 3).

4. Discussion

Of a total of 437 individuals who participated in the study, 381 reported poor sleep quality and 56 reported good sleep quality. Autonomic functions were classified by analyzing HRV data through a clustering technique. This analysis revealed three clusters comprising all participants, including those with poor sleep quality. Participants with good sleep quality were divided into two groups on the basis of their autonomic function.

4.1. All participants

Cluster 1 comprised individuals with a typical ANS profile characterized by low SNS and high PNS activity (Table 3). With the development of the ANS, parasympathetic function increases, which in turn increases the high-frequency band (Fyfe et al., 2014). During fight-or-flight responses, the SNS assumes control and prepares the body for intense physical activity. Its primary role is to enhance the flow of nutrient-rich blood to vital tissues, particularly to actively engaged skeletal muscles (McCorry, 2007). During rest, the PNS assumes control (McCorry, 2007). Its primary role is to conserve and store energy and to monitor fundamental bodily processes such as digestion and urination (McCorry, 2007).

Cluster 2 comprised individuals with high ANS, high SNS, and normal PNS activity (Table 3). Sympathetic predominance is an indicator of increased stress sensitivity and adaptive stress response activation (Fisher et al., 2021). These responses are crucial for using energy resources to meet environmental demands, including the release of proinflammatory cytokines (Irwin & Cole, 2011). This phenomenon increases cardiovascular tone, vasoconstriction, heart rate, and contractility (Berntson et al., 2007). Sympathetic dominance is typically observed 2–4 weeks after myocardial infarction (Malliani, 2005). During this period, attempts to augment the low-frequency component through a tilting maneuver are usually ineffective (Malliani, 2005). This cluster highlights cardiovascular and stress responses with increased sympathetic activity, particularly in the context of chronic stress and cardiovascular disease progression.

Cluster 3 comprised individuals with low ANS, normal SNS, and low PNS activity (Table 3). This cluster had the most participants (n = 240, Table 2). Studies on ANS regulation deficits have supported a model reflecting the contribution of ANS dysmaturation to neuropsychiatric disorders (Mulkey & du Plessis, 2019). Low HRV serves as a marker of major depressive disorders (Sun et al., 2016). Disruptions in vagal balance, presenting as reduced vagal tone or increased vagal reactivity, can influence various neuropsychiatric disorders (Beauchaine et al., 2007). Reductions in parasympathetic tone are associated with anxiety, depression, posttraumatic stress disorder, and schizophrenia (Thayer & Brosschot, 2005). Overall, this cluster represents a key topic for future research, particularly in the context of clinical implications and neuropsychiatric associations with diminished parasympathetic activity and autonomic dysregulation.

4.2. Poor sleep quality

Cluster 1 of participants with poor sleep quality demonstrated a normal ANS profile characterized by low SNS and high PNS activity (Table 3). During non-REM sleep, a decrease in cardiac sympathetic

Table 2
Cluster characteristics of young adults with poor and good sleep quality in Banyumas Regency, Central Java, Indonesia, examined from February to April 2023 (n = 437).

	All participants (n = 437)				Participants with poor sleep quality (n = 381)				Participants with good sleep quality (n = 56)		
Variable	Cluster 1 n (%)	Cluster 2 n (%)	Cluster 3 n (%)	*p*-value	Cluster 1 n (%)	Cluster 2 n (%)	Cluster 3 n (%)	*p*-value	Cluster 1 n (%)	Cluster 2 n (%)	*p*-value
n	104	93	240		95	81	205		11	45	
Biological factors											
Age (mean ± SD) (year)	20.8 ± 1.6	20.7 (1.6)	20.9 (1.6)	0.488	20.9 ± 1.6	20.7 ± 1.6	20.8 ± 1.6	0.705	19.9 ± 0.9	21.2 ± 1.7	0.002
Gender				0.859				0.832			0.673
Female	88 (84.6)	76 (81.7)	199 (82.9)		80 (84.2)	69 (85.2)	169 (82.4)		8 (72.7)	37 (82.2)	
Male	16 (15.4)	17 (18.3)	41 (17.1)		15 (15.8)	12 (14.8)	36 (17.6)		3 (27.3)	8 (17.8)	
Place of living				0.367				0.199			1
Urban	50 (48.1)	38 (40.9)	96 (40)		46 (48.4)	32 (39.5)	77 (37.6)		6 (54.4)	23 (51.1)	
Rural	54 (51.9)	55 (59.1)	144 (60)		49 (51.6)	49 (60.5)	128 (62.4)		5 (45.5)	22 (39.3)	
BMI (mean ± SD) (kg/m^2)	21.25 (3.8)	20.68	21.48 (4.0)	0.238	21.3 ± 3.9	20.7 ± 3.1	21.5 ± 4.1	0.321	21.1 ± 3.1	20.8 ± 3.3	0.705
Smoking				0.758				0.737			1
Yes	11 (10.6)	11 (11.8)	22 (9.2)		10 (10.5)	10 (12.3)	19 (9.3)		1 (9.1)	4 (80)	
No	93 (89.4)	82 (88.2)	218 (90.8)		85 (89.5)	71 (87.7)	186 (90.7)		10 (90.9)	41 (20)	
Psychological factors											
Feeling sad				0.690				0.839			0.041
Yes	58 (55.7)	55 (59.1)	148 (61.7)		60 (63.2)	48 (59.3)	123 (60)		8 (72.7)	16 (35.6)	
No	46 (44.3)	38 (40.9)	92 (38.3)		35 (36.8)	33 (40.7)	82 (40)		3 (27.3)	29 (64.4)	
Feeling alone				0.640				0.591			0.637
Yes	40 (38.5)	32 (34.4)	96 (40)		38 (40)	30 (37)	89 (43.4)		3 (27.3)	8 (17.8)	
No	64 (61.5)	61 (65.6)	144 (60)		57 (60)	51 (63)	116 (56.6)		8 (72.7)	37 (82.2)	
Feeling worry				0.730				0.841			0.03
Yes	52 (50)	49 (52.7)	115 (47.9)		50 (52.6)	45 (55.6)	106 (51.7)		6 (54.5)	9 (20)	
No	52 (50)	44 (47.3)	125 (52.1)		45 (47.4)	36 (44.4)	99 (48.3)		5 (45.5)	36 (80)	
Social factors											
Relation to family				0.933				0.680			1
Good	101 (97.1)	90 (96.8)	234 (97.5)		91 (95.8)	78 (96.3)	200 (97.6)		11 (100)	45 (100)	
Bad	3 (2.9)	3 (3.2)	6 (2.5)		4 (4.2)	3 (3.7)	5 (2.4)		0	0	
Support from family				0.786							1
Good	99 (95.2)	90 (96.8)	232 (96.7)		89 (93.7)	78 (96.3)	198 (96.6)		11 (100)	45 (100)	
Bad	5 (4.8)	3 (3.2)	8 (3.3)		6 (6.3)	3 (3.7)	7 (3.4)		0	0	
HRV parameters											
Low-frequency (mean ± SD)	342.4 ± 187.1	625.2 ± 192.3	200.3 ± 103.7	<0.001	329.8 ± 181.6	629.1 ± 198.7	195.8 ± 102.4	<0.001	571.5 ± 105.2	314.3 ± 199.9	0.002
Very-low-frequency (mean ± SD)	28.5 ± 9.8	61.5 ± 11.7	47.9 ± 17.4	<0.001	28.3 ± 9.9	61.1 ± 11.7	48.1 ± 17.8	<0.001	35.2 ± 6.4	49.9 ± 17.2	0.03
High-frequency (mean ± SD)	739.4 ± 195.9	331.7 ± 164.2	201.1 ± 119.4	<0.001	721.9 ± 173.3	338.1 ± 168.4	196.1 ± 116.1	<0.001	982.8 ± 351.8	264.8 ± 158.7	<0.001

Abbreviations: SD, standard deviation; BMI, body mass index; HRV, heart rate variability. Significance was determined at $p < 0.05$ using the following tests: the Chi-square test for sex, residence type, smoking habits, sadness, loneliness, and anxiety; Fisher's exact test for family relationships and family support; and ANOVA for age, BMI, low-frequency band, very-low-frequency band, and high-frequency band.

Table 3
Clinical characteristics of heart rate variability stratified by clusters of young adults with poor and good sleep quality in Banyumas Regency, Central Java, Indonesia, examined from February to April 2023 (n = 437).

	All participant (n = 437)			Participant with poor sleep quality (n = 381)			Participant with good sleep quality (n = 56)	
	Cluster 1 (n = 104)	Cluster 2 (n = 93)	Cluster 3 (n = 240)	Cluster 1 (n = 95)	Cluster 2 (n = 81)	Cluster 3 (n = 205)	Cluster 1 (n = 11)	Cluster 2 (n = 45)
Overall activity (low-frequency)	Normal	High	Low	Normal	High	Low	High	Low
Sympathetic activity (very-low-frequency)	Low	High	Normal	Low	High	Normal	Low	Normal
Parasympathetic activity (high-frequency)	High	Normal	Low	High	Normal	Low	High	Low

Note: to define the normal value for each heart rate variability parameter, ±10 % of the mean value was used. For all participants, the normal values for low-frequency, very-low-frequency, and high-frequency ranged between 292.149 and 357.071 ms^2, between 41.598 and 50.842 ms^2, and between 321.345 and 392.755 ms^2, respectively. For participants with poor sleep quality, the normal values for low-frequency, very-low-frequency, and high-frequency ranged between 289.242 and 353.518 ms^2, between 41.346 and 50.534 ms^2, and between 321.669 and 393.151 ms^2, respectively. For participants with good sleep quality, the normal values for low-frequency, very-low-frequency, and high-frequency ranged between 311.886 and 381.194 ms^2, between 43.299 and 52.921 ms^2, and between 319.14 and 390.06 ms^2, respectively. Values below the specified range were categorized as low, whereas values above the specified range were categorized as high.

activity and an increase in parasympathetic activity are observed (Jafari, 2017). Dipping is a phenomenon characterized by a 10 % reduction in mean arterial pressure relative to wakefulness, attributable to a decline in sympathetic drive (Silvani & Dampney, 2013). Deviations from normal dipping patterns are associated with cardiovascular risks (Silvani & Dampney, 2013). Reduced respiratory rate and muscle tone

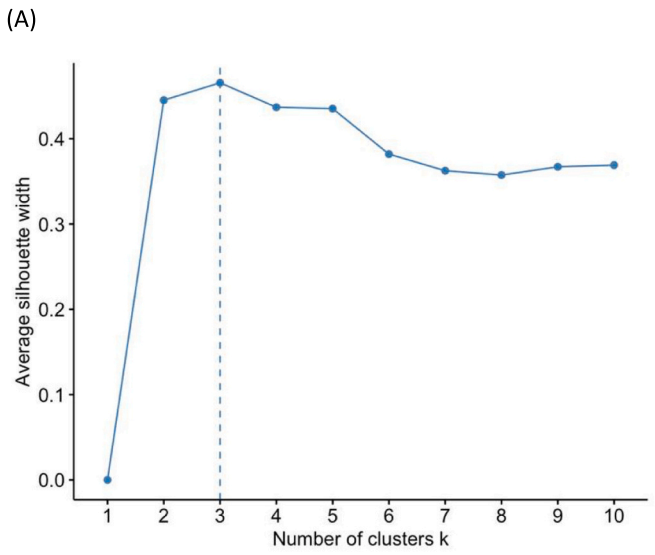

Fig. 2A. The optimal number of clusters determined by the silhouette method of young adults with poor sleep quality in Banyumas Regency, Central Java, Indonesia, examined from February to April 2023 (n = 381).

Fig. 2B. K-means clustering revealed three distinct clusters based on heart rate variability parameters of young adults with poor sleep quality in Banyumas Regency, Central Java, Indonesia, examined from February to April 2023 (*n* = 381).

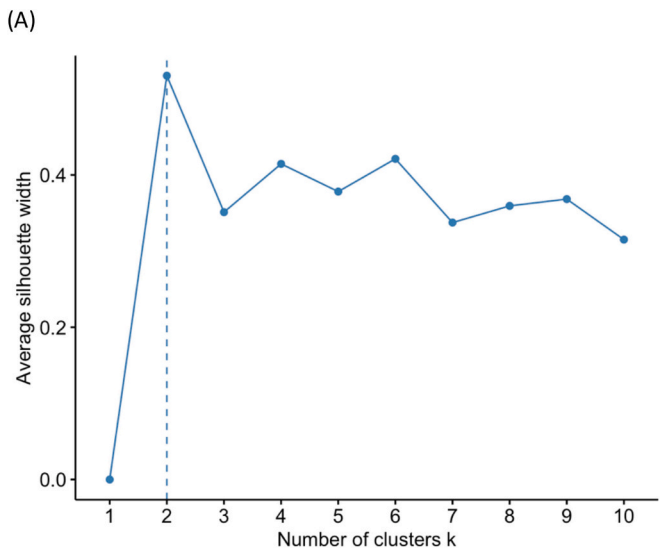

Fig. 3A. The optimal number of clusters determined by the silhouette method of young adults with good sleep quality in Banyumas Regency, Central Java, Indonesia, examined from February to April 2023 (n = 56).

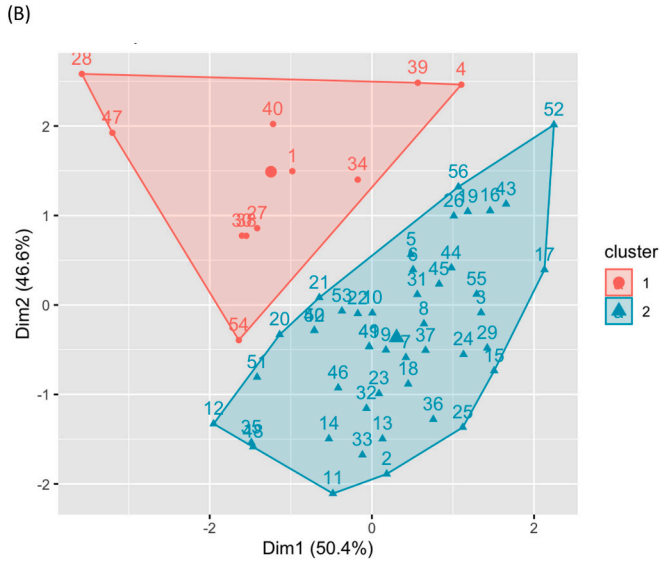

Fig. 3B. K-means clustering revealed two distinct clusters based on heart rate variability parameters of young adults with good sleep quality in Banyumas Regency, Central Java, Indonesia, examined from February to April 2023 (*n* = 56).

during non-REM sleep emphasize the influence of autonomic shifts occurring during sleep (Miglis, 2016; Sowho et al., 2014).

Cluster 2 of participants with poor sleep quality demonstrated high ANS, high SNS, and normal PNS activity (Table 3). This classification was absent in participants with good sleep quality (Table 3) because the traits associated with this cluster are generally linked to various sleep disorders (Kim et al., 2022; Miglis, 2016). Microneurography measures sympathetic nerve activity and catecholamine levels, revealing high values in patients with obstructive sleep apnea (Narkiewicz & Somers, 2003). Regardless of its underlying cause, sleep deprivation can increase sympathetic drive (Miglis, 2016). Individuals in this cluster typically exhibit high low-frequency components and increased urinary norepinephrine excretion (Kim et al., 2022). Conditions such as periodic limb movement disorder, restless legs syndrome (Kim et al., 2022), narcolepsy (Fronczek et al., 2008), and insomnia (Miglis, 2016) emphasize the relationship between abnormal movements and autonomic profiles in the context of increased SNS activity.

Cluster 3 of participants with poor sleep quality demonstrated low ANS, low PNS, and normal SNS activity (Table 3). During phasic REM sleep, which is marked by vivid dreaming, sympathetic tone increases, whereas parasympathetic tone decreases (Miglis, 2016). During this phase, blood pressure and heart rate may considerably fluctuate, often reaching levels substantially higher than those observed during wakefulness (Miglis, 2016). Compared with the general population, individuals who sleep for less than 6 h are more likely to exhibit reduced PNS activity (Kim et al., 2022).

4.3. Good sleep quality

Cluster 1 of participants with good sleep quality demonstrated high

ANS, low SNS, and high PNS activity (Table 3). This profile corresponds to the transition from the non-REM N1 sleep stage to deeper stages, marking a shift from light to deep sleep (Miglis, 2016). During this transition, sympathetic tone decreases and parasympathetic tone increases (Miglis, 2016). These changes reduce heart rate, arterial blood pressure, and peripheral vascular resistance, which in turn reduce cardiac output and promote autonomic stability (Van de Borne et al., 1994).

Cluster 2 of participants with good sleep quality demonstrated low ANS, normal SNS, and normal PNS activity (Table 3). This cluster had the same characteristics as those of Cluster 3 across all participants, including those with poor sleep quality. Similar traits can be observed in both waking and REM phases, indicating a decline in parasympathetic activity (Miglis, 2016).

Cluster analysis revealed distinct patterns in autonomic regulation, providing valuable insights for the development of health promotion strategies. Developing an integrated approach incorporating HRV parameters is crucial for understanding the diverse forms of autonomic regulation, particularly in individuals with varying sleep quality.

This study has several limitations. First, the study included a larger proportion of participants experiencing poor sleep quality compared with those reporting good sleep quality. Nonetheless, our study provided mechanistic insights into autonomic regulation, paving the way for future research endeavors. Second, short-term HRV measurements (5 min) were conducted instead of the standard 24-h measurements. This limitation can be overlooked because short-term measurements have been widely employed and studied for many years, serving as the predominant source of published HRV data (Shaffer & Ginsberg, 2017). Last, this study did not evaluate other sleep disturbances. Research has indicated that HRV is influenced by various sleep-related conditions, including sleep apnea, sleep-disordered breathing (Wang et al., 2008), insomnia, and sleep deprivation (Sauvet et al., 2010; Stein & Pu, 2012).

5. Future directions

Using cluster analysis, this study demonstrated that variations in sleep quality are associated with different autonomic function profiles in young adults. Understanding these cluster patterns is pivotal for both determining the status of autonomic regulation in this demographic and obtaining valuable insights that can guide the development of health promotion strategies. Future studies should explore conditions that influence autonomic regulation, such as cardiovascular disease and mental health conditions, while incorporating additional sleep-related variables.

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CRediT authorship contribution statement

Vivi Leona Amelia: Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Chia-Hui Wang:** Validation, Software, Formal analysis. **Nurina Jihan Yulianti:** Writing – original draft, Visualization, Resources, Project administration. **Jebul Suroso:** Investigation, Formal analysis, Data curation. **Min-Huey Chung:** Writing – original draft, Supervision, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Min-Huey Chung reports article publishing charges was provided by National Health Research Institutes Research Program, Taiwan. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.pmedr.2025.103029.

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