

Health Informatics Analysis of Self-Regulation, Sleep, and Perceived Immune Health

Qurratul Aini¹, Titik Muti'ah², and Usman Agus Dwiyanto¹

¹ Master of Hospital Administration, Universitas Muhammadiyah Yogyakarta, Yogyakarta, Indonesia

² Faculty of Psychology, Universitas Sarjanawiyata Tamansiswa, Yogyakarta, Indonesia

Corresponding author: Qurratul Aini (e-mail: qurrotul_aini@umy.ac.id), **Author(s) Email:** Titik Muti'ah (e-mail: titik@ustjogja.ac.id), Usman Agus Dwiyanto (e-mail: usman.agus.psc22@mail.umy.ac.id)

Abstract Electronic medical records increasingly support structured clinical data, but psychological and behavioural indicators relevant to student health remain rarely integrated into health-information workflows. Among medical students, self-regulation, sleep, and risk-taking may shape perceived health resilience, yet their relative contributions remain unclear. This study examined associations between self-leadership (as a self-regulation indicator), risk-taking behaviour, and sleep quality and perceived immune health, and identified which indicators retained unique associations in a multivariable model. A cross-sectional study included 92 medical students at a private university in Yogyakarta, Indonesia. Data were analysed using Pearson correlations, hierarchical and multiple regression, 95% confidence intervals, collinearity and residual diagnostics, Harman's single-factor test, and covariate sensitivity analysis. Self-leadership ($r = .840$) and sleep quality ($r = .801$) correlated positively with perceived immune health, whereas risk-taking behaviour correlated negatively ($r = -.701$), all $p < .001$. The final regression model explained 77.6% of outcome variance ($R^2 = .776$; adjusted $R^2 = .768$). Self-leadership ($\beta = .479$, $p < .001$) and sleep quality ($\beta = .374$, $p < .001$) remained significant, whereas risk-taking behaviour did not ($\beta = -.106$, $p = .175$). Covariate adjustment produced minimal change. These findings identify self-regulatory capacity and restorative sleep as the strongest independent self-report correlates of perceived immune health in this sample. They support prospective evaluation of these indicators as low-burden structured data elements for digital health screening, while longitudinal validation, threshold development, and governance safeguards are required before implementation.

Keyword: Health informatics; Self-regulation; Sleep quality; Perceived immune health; Medical students

1. Introduction

Medical students form the future clinical workforce and are themselves a group at elevated health risk. Prolonged academic workloads, irregular routines, and high performance expectations place sustained demands on self-regulation during early adulthood [1], [2]. Poor sleep, psychological distress, and reduced health functioning are common in this group [3]. How students appraise their own health under these conditions therefore matters for both education and preventive care. Indonesia has also moved towards a fully digital model of clinical record-keeping, since the Ministry of Health mandated electronic medical record adoption through Regulation No. 24 of 2022, with national data exchange routed through the SATUSEHAT platform [4]. Adoption has expanded quickly, although readiness still varies with infrastructure, staff digital skills, and recordkeeping culture [5], [6]. That national context frames why low-burden self-report indicators of student health are worth identifying, but it is background to the present study rather than its subject.

Records of this kind hold clinical and biomedical variables such as diagnoses, laboratory values, and medication histories [7], [8], while psychological and behavioural determinants of health are rarely captured as structured data [9]. This omission matters for preventive health, where self-regulation and lifestyle shape outcomes long before clinical signs appear. Capturing

these vulnerabilities through digital screening would allow earlier and more targeted support. Sleep quality is one of the strongest determinants of physical and psychological functioning among university students. Sleep regulates both innate and adaptive immune activity, and disrupted sleep promotes inflammatory dysregulation [13]. Sleep and inflammation work together in sickness and health, linking restorative sleep directly to perceived health resilience [14]. Both short and prolonged sleep disruption carry measurable health consequences [15]. Among medical students, poor sleep quality is associated with stress, anxiety, and depressive symptoms [16], and with reduced wellbeing during clinical training [17]. Sleep therefore offers a behavioural indicator that is clinically meaningful and easy to self-report.

Self-leadership describes a process of self-influence through which individuals regulate their thoughts, motivation, and behaviour to reach personal goals. Stronger self-leadership has been linked to resilience, adaptive coping, and proactive health behaviour [18]. Among nurses, self-leadership supports professional functioning and self-regulation in demanding clinical settings [19], [20]. Individuals with stronger self-leadership tend to organise routines, manage stress, and preserve restorative habits such as sleep. These qualities make self-leadership a plausible correlate of perceived immune health. Throughout this paper, self-leadership serves as the self-regulation indicator, and both terms

refer to the same measured construct. Risk-taking behaviour follows a different developmental pattern. Reward sensitivity and impulsive tendencies remain heightened during emerging adulthood because self-regulatory systems are still maturing [21]. Adolescents and young adults often weigh immediate rewards against longer-term costs in ways that favour risk [22], and both positive and negative forms of risk-taking shift across this period [23]. Short sleep can further raise risk-taking, which signals overlap among sleep, regulation, and risky behaviour [24]. Excessive risk-taking can harm health through unhealthy lifestyle choices, irregular sleep, and stress-related dysregulation. Whether risk-taking relates to perceived immune health independently of self-regulation and sleep remains unclear.

Previous studies have examined sleep quality, self-leadership, and risk-taking behaviour largely in isolation. Few have modelled these self-report indicators together in relation to perceived immune health, and even fewer have asked which retains a unique association once the others are present. This study addresses that gap with a cross-sectional correlational design. The analysis proceeds from composite scoring and reliability estimation to Pearson correlation, hierarchical entry of the three predictors, multiple regression with 95% confidence intervals, collinearity and influence diagnostics, a test for common-method variance, and a covariate sensitivity model. Section II-E states this framework formally in 35 numbered equations, and [Algorithm 1](#) sets out the procedure step by step. The study makes three distinct contributions. The statistical contribution is a fully specified and diagnostically verified regression framework, reported with confidence intervals, incremental variance, collinearity indices, influence measures, and a common-method test, so that every estimate can be reproduced and audited. The behavioural contribution is evidence on which self-regulatory and restorative indicators carry a unique association with perceived immune health when modelled jointly rather than separately, which reframes risk-taking as a correlate of weaker self-regulation rather than an independent correlate of health appraisal. The prospective digital-health contribution is deliberately limited and stated as future work, since the study identifies a compact self-report set that could later be evaluated for digital screening but develops no system, derives no thresholds, and validates no algorithm. The following hypotheses were tested:

- H1: Self-leadership is positively associated with perceived immune health.
- H2: Risk-taking behaviour is negatively associated with perceived immune health.
- H3: Sleep quality is positively associated with perceived immune health.
- H4: Self-leadership, risk-taking behaviour, and sleep quality jointly account for variance in perceived immune health.

II. Materials and Method

A. Research Design and Data Set

This study applied a quantitative cross-sectional design and is reported in line with the STROBE guideline for cross-sectional studies. The data set consisted of self-report responses from 92 early adulthood medical students enrolled at a private university in Yogyakarta, Indonesia. To preserve institutional confidentiality and comply with ethical requirements, the university name is not disclosed. Four constructs were measured: self-leadership, risk-taking behaviour, sleep quality, and perceived immune health. Each construct was measured as a structured variable. In principle, these variables could be mapped to discrete fields within an electronic medical record or a student health information system, an application treated here as future work rather than a feature of the present study.

B. Participants and Sampling

Participants were 92 medical students aged 18 to 24 years ($M = 20.40$, $SD = 1.71$). Female students made up 56.5% of the sample ($n = 52$) and male students 43.5% ($n = 40$). Participants were distributed across academic years one to six, and academic year was retained as a covariate in the sensitivity model reported in Section III-F. Students were eligible if they were actively enrolled in the medical programme, were aged 18 years or older, and gave informed consent. Responses were excluded if consent was withheld or enrolment was inactive at the time of data collection. Recruitment used convenience sampling. Data were collected during March-May 2026. The questionnaire was distributed to 100 students, and 92 returned complete responses (92% participation). Because the digital form required an answer to every item, the data set contained no missing values, and no cases were excluded after screening. The study was not preregistered. The descriptive, correlational, and multiple regression analyses were planned before the data were examined. The hierarchical regression, the test for common-method variance, the diagnostic tests, and the covariate sensitivity analysis were added during revision in response to peer review. An a priori power analysis guided the sample size. For a multiple regression with three predictors, a conventional medium effect (Cohen $f^2 = 0.15$), and $\alpha = .05$, 77 participants provide about .80 power. The achieved sample of 92 provides about .88 power for the same effect. Convenience sampling from a single site limits external validity, so the results describe this student population rather than medical students in general.

C. Instruments

Four self-report instruments were administered through the digital questionnaire. Self-leadership was measured with the Revised Self-Leadership Questionnaire (RSLQ) [25], which contains 35 items rated from 1 to 5, giving a composite range of 1 to 5 after item averaging, with higher values indicating stronger self-leadership. Risk-taking

behaviour was measured with the Domain-Specific Risk-Taking (DOSPERT) scale [26], rated on the same five-point metric, with higher values indicating greater risky tendencies. Sleep quality was measured with the Pittsburgh Sleep Quality Index (PSQI) [27], which yields seven component scores from 0 to 3 that sum to a global score from 0 to 21, where higher raw scores indicate poorer sleep. Because this direction is opposite the other three measures, the global score was reversed and linearly rescaled to a 1 to 5 metric using Eq. (4), so that higher values indicate better sleep quality. No individual PSQI item was recoded; the reversal was applied once, at the level of the global score, and every mean, correlation, and coefficient reported here uses the reversed metric under the label sleep quality. Perceived immune health was measured with the Immune Status Questionnaire (ISQ) [10], [28], a seven-item measure scored so that higher values indicate more favourable perceived immune health. The composite score for each construct was the mean of its items, as defined in Eq. (2). Internal consistency in the present sample was acceptable to good and was computed with Eq. (5) (self-leadership $\alpha = .89$; risk-taking behaviour $\alpha = .81$; sleep quality $\alpha = .86$; perceived immune health $\alpha = .84$).

D. Data Collection

Data were collected using a secure Google Form. Before completing the questionnaire, participants received information about the study objectives and confidentiality procedures, and participation was voluntary and anonymous. Digital administration allowed responses to be exported directly into a structured data file, which mirrors how patient-reported indicators can be captured and stored within an electronic medical record.

E. Mathematical Formulation

This section states the analytical framework formally so that every reported value can be reproduced. Throughout, N denotes the number of participants, p the number of items in an instrument, k the number of predictors, X the design matrix with a leading column of ones, y the vector of observed outcomes, and X' the transpose of X . SL, RT, and SQ denote self-leadership, risk-taking behaviour, and sleep quality, and Y denotes perceived immune health.

1. Case screening, composite scoring, and reliability

A case entered the analysis only when every item carried a response. The valid sample size N_{valid} , Eq. (1), counts complete records, where c_i is the number of items participant i completed and $I(\cdot)$ equals 1 when $c_i = p$. Construct score X_{ij} , Eq. (2), is the mean of its p_j items, where x_{ijm} is participant i 's response to item m . The PSQI global score $PSQI_i$, Eq. (3) [27], sums its seven component scores C_{ic} . Eq. (4) rescales PSQI to give S_i , used as SQ_i below. Coefficient alpha, Eqs. (5)-(6) [29], used sm^2 , the variance of item m , and sT^2 , the total score variance.

$$N_{\text{valid}} = \sum_{i=1}^N I(c_i = p) \quad (1)$$

$$X_{ij} = \frac{1}{p_j} \sum_{m=1}^{p_j} x_{ijm} \quad (2)$$

$$PSQI_i = \sum_{c=1}^7 C_{ic}, \quad C_{ic} \in \{0,1,2,3\} \quad (3)$$

$$S_i = 1 + 4 \left(\frac{21 - PSQI_i}{21} \right) \quad (4)$$

$$\alpha = \frac{p}{p-1} \left(1 - \frac{\sum_{m=1}^p s_m^2}{s_T^2} \right) \quad (5)$$

$$s_T^2 = \text{Var}(\sum_{m=1}^p x_m) \quad (6)$$

2. Descriptive and correlational statistics

Central tendency and dispersion follow Eqs. (7)-(8), where M is the sample mean, SD is the sample standard deviation, and x_i is the value for participant i . The correlation r between x and y , Eq. (9), used M_x and M_y . The t statistic, Eq. (10), tested r on $N - 2$ degrees of freedom [30].

$$M = \frac{1}{N} \sum_{i=1}^N x_i \quad (7)$$

$$SD = \sqrt{\frac{1}{N-1} \sum_{i=1}^N (x_i - M)^2} \quad (8)$$

$$r = \frac{\sum_{i=1}^N (x_i - M_x)(y_i - M_y)}{\sqrt{\sum_{i=1}^N (x_i - M_x)^2 \sum_{i=1}^N (y_i - M_y)^2}} \quad (9)$$

$$t = \frac{r\sqrt{N-2}}{\sqrt{1-r^2}}, \quad df = N - 2 \quad (10)$$

3. Multiple regression

The population model, Eq. (11), has intercept β_0 , coefficients β_1 to β_3 for SL, RT, and SQ, and error term ε_i . Eq. (12) gives b , the OLS coefficient vector [31]. Fitted values $\hat{Y}_i$, Eq. (13), use b_0 to b_3 from b . Eq. (14) gives standardised weight β_k from b_k , and the SDs of predictor k and Y . Eq. (15) gives $SE(b_k)$, where σ^2 is the residual variance, and kk is the diagonal element of $(X'X)^{-1}$. Eqs. (16)-(17) [31], [30] give t_k and the 95% CI, using the critical value $t(0.975, N-k-1)$.

$$Y_i = \beta_0 + \beta_1 SL_i + \beta_2 RT_i + \beta_3 SQ_i + \varepsilon_i \quad (11)$$

$$b = (X'X)^{-1} X'y \quad (12)$$

$$\hat{Y}_i = b_0 + b_1 SL_i + b_2 RT_i + b_3 SQ_i \quad (13)$$

$$\beta_k = b_k \frac{SD_{xk}}{SD_y} \quad (14)$$

$$SE(b_k) = \sqrt{\sigma^2 [(X'X)^{-1}]_{kk}} \quad (15)$$

$$t_k = \frac{b_k}{SE(b_k)}, \quad df = N - k - 1 \quad (16)$$

$$CI_{95} = b_k \pm t_{(0.975, N-k-1)} SE(b_k) \quad (17)$$

4. Model fit, incremental variance, and effect size

R^2 and R^2_{adj} , Eqs. (18)-(19), use SS_{res} and SS_{tot} , the residual and total sums of squares. Eq. (20) [31] is the omnibus F test. Hierarchical entry use the increment ΔR^2 's, Eq. (21), where s is the entry step, and R^2 's is R^2 after step s . Its test F_{change} , Eq. (22) [30], uses q , predictors added at step s , and ks , cumulative predictors through step s . Cohen's f^2 , Eq. (23), sets the sample size via G^* Power [32], [33].

$$R^2 = 1 - \frac{SS_{\text{res}}}{SS_{\text{tot}}} \quad (18)$$

$$R^2_{\text{adj}} = 1 - \frac{(1-R^2)(N-1)}{N-k-1} \quad (19)$$

$$F = \frac{R^2/k}{(1-R^2)/(N-k-1)} \quad (20)$$

$$\Delta R_s^2 = R_s^2 - R_{s-1}^2 \quad (21)$$

$$F_{change} = \frac{\Delta R_s^2/q}{(1-R_s^2)/(N-k_s-1)} \quad (22)$$

$$f^2 = \frac{R^2}{1-R^2} \quad (23)$$

5. Collinearity

Tolerance in Eq. (24) uses R^2_k from the regression of predictor k on the remaining predictors, and the variance inflation factor in Eq. (25) is its reciprocal [31].

$$Tol_k = 1 - R_k^2 \quad (24)$$

$$VIF_k = \frac{1}{Tol_k} \quad (25)$$

6. Residual and influence diagnostics

Residuals e_i follow Eq. (26). Leverage h_{ii} , the diagonal of the hat matrix, follows in Eq. (27), where x_i is participant i 's row of X , including the leading 1. The standardised residual e_i^* , Eq. (28) [34], uses σ , the residual standard deviation estimated by RMSE in Eq. (30). Cook's distance D_i , Eq. (29) [35], quantifies influence. The Durbin-Watson statistic DW , Eq. (31) [36], tests independence. The Breusch-Pagan statistic LM , Eq. (32) [37], tested heteroscedasticity, where R^2_{aux} comes from regressing the squared residuals on the predictors. The Shapiro-Wilk statistic W , Eq. (33) [38], tests normality, where $a(i)$ are tabulated weights for the ordered sample $x(i)$.

$$e_i = y_i - \hat{Y}_i \quad (26)$$

$$h_{ii} = x_i'(X'X)^{-1}x_i \quad (27)$$

$$e_i^* = \frac{e_i}{\sigma\sqrt{1-h_{ii}}} \quad (28)$$

$$D_i = \frac{e_i^2}{(k+1)\sigma^2} \cdot \frac{h_{ii}}{(1-h_{ii})^2} \quad (29)$$

$$RMSE = \sqrt{\frac{1}{N-k-1} \sum_{i=1}^N e_i^2} \quad (30)$$

$$DW = \frac{\sum_{i=2}^N (e_i - e_{i-1})^2}{\sum_{i=1}^N e_i^2} \quad (31)$$

$$LM = N R_{aux}^2 \sim \chi^2(k) \quad (32)$$

$$W = \frac{(\sum_{i=1}^N a(i)x_{(i)})^2}{\sum_{i=1}^N (x_{(i)} - M)^2} \quad (33)$$

7. Common-method variance and covariate sensitivity

Because every measure shared one self-report source, the variance share of the first unrotated factor, V_1 , was computed with Eq. (34), where λ_1 and λ_m are the largest and m -th eigenvalues, and M is the total number of eigenvalues extracted, that is, items entered into the factor analysis. Below 0.50 indicates no dominant method factor [39]. The sensitivity model, Eq. (35), adds covariates Age_i, Sex_i, and Year_i, with coefficients β_4 to β_6 : age in years, academic year from one to six, and sex coded female = 1, male = 0. Its increment over Eq. (11) was tested with Eqs. (21)-(22).

$$V_1 = \frac{\lambda_1}{\sum_{m=1}^M \lambda_m} \quad (34)$$

$$Y_i = \beta_0 + \beta_1 SL_i + \beta_2 RT_i + \beta_3 SQ_i + \beta_4 Age_i + \beta_5 Sex_i + \beta_6 Year_i + \varepsilon_i \quad (35)$$

Algorithm 1. Statistical analysis procedure applied to the study data

```

(1) Input: item response matrix  $R$  ( $N \times P$ ), covariate set  $Z$  (age, sex, academic year)
(2) Output: coefficient, increment, and diagnostic tables
(3) FOR each participant  $i$ 
(4) IF any administered item of  $i$  is unanswered THEN drop  $i$  // Eq. (1)
(5) END FOR
(6) FOR each construct  $j$ 
(7)  $X_{ij} \leftarrow$  mean of the  $p_j$  items of construct  $j$  // Eq. (2)
(8) END FOR
(9)  $PSQI\_i \leftarrow$  sum of the seven component scores // Eq. (3)
(10)  $SQ\_i \leftarrow$  reverse and rescale  $PSQI\_i$  onto the 1 to 5 metric // Eq. (4)
(11) FOR each instrument,  $\alpha \leftarrow$  internal consistency // Eqs. (5)-(6)
(12) Compute  $M$ ,  $SD$ , median,  $IQR$ , and range for every variable // Eqs. (7)-(8)
(13) FOR each variable pair, compute  $r$ ,  $t$ , and  $p$  // Eqs. (9)-(10)
(14) Model 1  $\leftarrow$  regress  $Y$  on  $SL$  // Eqs. (11)-(13)
(15) Model 2  $\leftarrow$  Model 1 +  $SQ$ 
(16) Model 3  $\leftarrow$  Model 2 +  $RT$ 
(17) FOR  $s = 1$  TO 3, compute  $R^2$ ,  $R^2_{adj}$ ,  $dR^2$ , and  $F$  change // Eqs. (18)-(22)
(18) FOR each predictor  $k$  in Model 3, compute  $\beta$ ,  $SE$ ,  $t$ , and 95% CI // Eqs. (14)-(17)
(19) FOR each predictor  $k$  in Model 3, compute tolerance and VIF // Eqs. (24)-(25)
(20) Compute  $e_i$ ,  $h_{ii}$ ,  $e_i^*$ ,  $D_i$ , and  $RMSE$  // Eqs. (26)-(30)
(21) Test independence, homoscedasticity, and normality // Eqs. (31)-(33)
(22)  $V_1 \leftarrow$  variance share of the first unrotated factor // Eq. (34)
(23) IF  $V_1 < 0.50$  THEN method bias is not dominant
(24) Model 4  $\leftarrow$  Model 3 + age + sex + academic year // Eq. (35)
(25) Compute  $dR^2$  and  $F$  change of Model 4 over Model 3 // Eqs. (21)-(22)
(26) Evaluate  $H_1$  to  $H_4$  at  $\alpha = .05$  using  $t_k$  and  $CI_{95}$ 
    
```

Algorithm 1 mirrors the block diagram in Fig. 1 and fixes the order in which the analyses were run, so that the

reported estimates can be regenerated from the raw item responses without further discretionary choices.

F. Data Processing and Statistical Analysis

Responses were screened for completeness before analysis. Because the digital form required an answer to every item, the data set contained no missing values, and composite scores were computed as item means. Descriptive statistics summarised each variable, including the median and interquartile range alongside the mean and standard deviation. Pearson product-moment correlations examined the bivariate relationships. Hierarchical regression then entered self-leadership first, sleep quality second, and risk-taking behaviour third, recording the change in R^2 and the associated F test at each step. The order follows the theoretical proposition that self-influence processes govern the routines through which restorative behaviour is maintained, so self-regulatory capacity is entered before the behaviour it is held to organise [18], [20]. Sleep quality follows as the

contributes anything beyond the two preceding blocks. Entering predictors in a sequence set by theory, and judging each block by its increment in explained variance, follows standard practice for hierarchical model building [30]. A final multiple regression estimated the unique contribution of each predictor, with 95% confidence intervals for the unstandardised coefficients. Assumptions were examined numerically rather than assumed. Multicollinearity was assessed with tolerance and the variance inflation factor. Residual normality was assessed with the Shapiro-Wilk test together with skewness and kurtosis, homoscedasticity with the Breusch-Pagan test, and independence with the Durbin-Watson statistic. Influence was assessed with Cook's distance, leverage values, and standardised residuals. Because all measures were self-reported, common-method variance

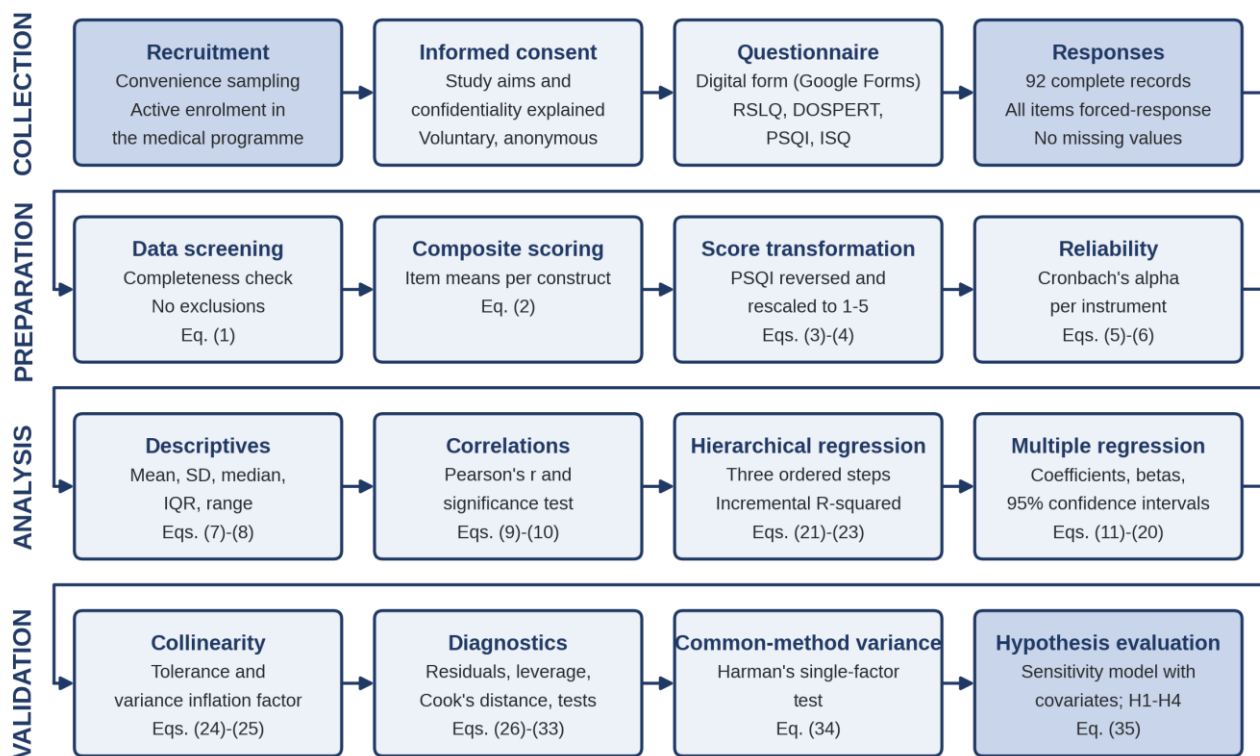


Fig. 1. Block diagram of the research procedure. The four phases run from data collection through data preparation, statistical analysis, and validation. Each block names the operation performed and, where applicable, the numbered equation that defines it. Phase 1 covers recruitment, informed consent, questionnaire administration, and response collection, carried out under the ethical approval described in Section II-G. Phase 2 covers completeness screening (Eq. 1), composite scoring (Eq. 2), the PSQI reversal and rescaling (Eq. 3 and Eq. 4), and reliability estimation (Eq. 5 and Eq. 6). Phase 3 covers descriptive statistics (Eq. 7 and Eq. 8), Pearson correlation (Eq. 9 and Eq. 10), multiple and hierarchical regression (Eq. 11 to Eq. 23), and collinearity assessment (Eq. 24 and Eq. 25). Phase 4 covers residual and influence diagnostics (Eq. 26 to Eq. 33), the common-method variance test (Eq. 34), the covariate sensitivity model (Eq. 35), and hypothesis evaluation. Algorithm 1 states the same procedure as numbered pseudocode.

proximal restorative mechanism linking self-regulation to perceived health [13], [14]. Risk-taking is entered last because the developmental literature treats it as an outcome of incomplete self-regulation rather than as a prior cause [21], [23], so its increment tests whether it

was examined with Harman's single-factor test. A sensitivity model added age, sex, and academic year as covariates to test whether the focal associations were confounded. Analyses were conducted in IBM SPSS Statistics 26, with significance set at $p < .05$.

G. Ethical Considerations

The study followed the principles of the Declaration of Helsinki, and all participants provided informed consent before participation. Ethical approval was granted by **RSUD DR. TJITROWARDOJO No. 060/KEPK/07/2023**

III. Results

A. Descriptive Statistics and Correlations

Table 1 presents descriptive statistics for the four study variables as means, standard deviations, medians, interquartile ranges, and observed ranges. No subjective severity labels are applied because validated cut-off values are not established for the transformed composite scores; the distributional statistics are reported directly.

Table 1. Descriptive statistics of the four study variables among the medical students (N = 92).

Variable	Mean	SD	Median	IQR	Range
Self-leadership	3.54	0.57	3.59	3.14–4.03	1.81–4.49
Risk-taking behaviour	1.78	0.52	1.74	1.37–2.13	0.82–3.25
Sleep quality	3.21	0.58	3.28	2.80–3.66	1.92–4.33
Perceived immune health	3.63	0.64	3.67	3.20–4.05	1.27–4.94

Note. N = 92.

Table 2 reports the Pearson correlations among the variables. Self-leadership correlated strongly and positively with perceived immune health ($r = .840$, $p < .001$). Sleep quality also correlated strongly and positively

with perceived immune health ($r = .801$, $p < .001$). Risk-taking behaviour correlated strongly and negatively with perceived immune health ($r = -.701$, $p < .001$). The predictors were intercorrelated, which signalled the need to test their unique contributions in a regression model.

Table 2. Pearson product-moment correlations among self-leadership, risk-taking behaviour, sleep quality, and perceived immune health.

Variable	1	2	3	4
1. Self-leadership	—			
2. Risk-taking behaviour	-.752***	—		
3. Sleep quality	.754***	-.630***	—	
4. Perceived immune health	.840***	-.701***	.801***	—

Note. N = 92. *** $p < .001$.

B. Multiple Regression

Table 3 presents the multiple linear regression results. The model was significant, $F(3, 88) = 101.62$, $p < .001$, and was associated with 77.6% of the variance in perceived immune health ($R^2 = .776$, adjusted $R^2 = .768$). Self-leadership carried the largest standardised weight ($\beta = .479$, 95% CI for B [0.337, 0.751], $p < .001$), followed by sleep quality ($\beta = .374$, 95% CI [0.244, 0.586], $p < .001$).

Risk-taking behaviour showed no unique association once the other variables were included ($\beta = -.106$, 95% CI [-0.319, 0.059], $p = .175$), and its interval includes zero. Collinearity stayed within accepted limits (tolerance .30 to .43; variance inflation factor 2.35 to 3.29), although the predictors were substantially intercorrelated, so the individual weights should be read as partial associations rather than separable causal contributions.

Table 3. Multiple linear regression predicting perceived immune health from the three self-report indicators.

Predictor	B	SE B	β	t	p	95% CI for B
Constant	0.60	0.46	—	1.31	.193	[-0.31, 1.52]
Self-leadership	0.544	0.104	.479	5.23	< .001	[0.337, 0.751]
Risk-taking behaviour	-0.130	0.095	-.106	-1.37	.175	[-0.319, 0.059]
Sleep quality	0.415	0.086	.374	4.81	< .001	[0.244, 0.586]

Note. N = 92. $R^2 = .776$; adjusted $R^2 = .768$; $F(3, 88) = 101.62$, $p < .001$.

C. Hierarchical Regression

Table 4 reports the hierarchical regression. Self-leadership alone accounted for 70.6% of the variance in perceived immune health, $F(1, 90) = 216.00$, $p < .001$. Adding sleep quality raised the explained variance to 77.1%, a significant increment of 6.5 percentage points,

$F(1, 89) = 25.43$, $p < .001$. Adding risk-taking behaviour raised it only to 77.6%, a non-significant increment of 0.5 percentage points, $F(1, 88) = 1.87$, $p = .175$. The pattern shows that self-leadership and sleep quality carry almost all of the shared association with perceived immune health, and that risk-taking behaviour adds little once they are present.

Table 4. Hierarchical regression showing the incremental contribution of each predictor to perceived immune health.

Model	Predictors entered	R ²	Adj. R ²	ΔR ²	F change	df	p
odel 1	Self-leadership	.706	.703	.706	216.00	(1, 90)	< .001
odel 2	+ Sleep quality	.771	.766	.065	25.43	(1, 89)	< .001
odel 3	+ Risk-taking behaviour	.776	.768	.005	1.87	(1, 88)	.175

Note. N = 92. Predictors were entered in the order self-leadership, sleep quality, risk-taking behaviour. ΔR² is the change in R² at each step.

D. Common-Method Variance

Because all measures came from the same self-report source, common-method variance was examined with Harman's single-factor test. A single unrotated factor accounted for 38.7% of the total item variance, below the 50% threshold indicating a dominant method factor. Common-method bias is therefore unlikely to account for the observed associations on its own. Shared method and conceptual overlap among self-regulatory constructs may still inflate correlations to some degree, so the strength of the associations should be read with this in mind.

E. Regression Diagnostics

Regression assumptions were examined numerically, and Table 5 summarises the results. Residuals were approximately normal, with a Shapiro-Wilk statistic of .99 ($p = .51$), skewness of -0.17 , and excess kurtosis of -0.24 . The Breusch-Pagan test supported homoscedasticity ($p = .16$), and a Durbin-Watson statistic of 1.75 indicated no meaningful residual autocorrelation. No case exceeded a Cook's distance of 1.00, with a maximum of 0.24. Maximum leverage was 0.13, and standardised residuals ranged from -2.60 to 2.29 , within the expected band of ± 3 . The residual standard error was 0.31. The diagnostics support the linear model, with no

sign of serious assumption violation or undue influence from single cases.

F. Sensitivity Analysis with Covariates

To test whether demographic factors confounded the associations, a sensitivity model added age, sex, and academic year to the three focal predictors. Age was entered as completed years, and academic year as an ordinal value from one to six, both treated as continuous covariates. Sex was entered as a single dummy variable coded female = 1 and male = 0, so its coefficient represents the adjusted mean difference for female relative to male students. Confidence intervals are reported for every coefficient in the model. Table 6 reports the results. The three covariates were jointly non-significant, and adding them raised the explained variance by less than one percentage point, $\Delta R^2 = .009$, $F(3, 85) = 1.19$, $p = .32$. Self-leadership ($\beta = .459$, $p < .001$) and sleep quality ($\beta = .390$, $p < .001$) remained significant, and risk-taking behaviour remained non-significant ($\beta = -.109$, $p = .19$). None of age, sex, or academic year reached significance. The focal associations were therefore stable after adjustment for these variables, although unmeasured factors such as physical activity, perceived stress, chronic illness, or recent infection were not available and may still contribute.

Table 5. Regression diagnostic results for the model of perceived immune health.

Diagnostic	Value	Reference	Conclusion
Shapiro-Wilk (residuals)	W = .99, $p = .51$	$p > .05$	Normal residuals
Residual skewness	-0.17	-1 to $+1$	Acceptable
Residual excess kurtosis	-0.24	-1 to $+1$	Acceptable
Breusch-Pagan test	LM = 5.20, $p = .16$	$p > .05$	Homoscedastic
Durbin-Watson	1.75	near 2	Independent residuals
Maximum Cook's distance	0.24	< 1.00	No influential case
Maximum leverage	0.13	$2(k+1)/N = 0.09$	Few high-leverage cases
Standardised residual range	-2.60 to 2.29	within ± 3	Acceptable
Residual standard error	0.31	—	—

Note. N = 92. k is the number of predictors. LM is the Lagrange multiplier statistic.

Table 6. Sensitivity analysis adding age, sex, and academic year as covariates.

Predictor	B	SE B	β	t	p
Self-leadership	0.522	0.107	.459	4.87	< .001
Risk-taking behaviour	-0.134	0.100	-.109	-1.33	.187
Sleep quality	0.433	0.087	.390	5.00	< .001
Age	-0.016	0.042	-.042	-0.38	.707
Sex (female)	-0.063	0.067	-.097	-0.94	.352
Academic year	-0.018	0.045	-.045	-0.39	.695

Note. $N = 92$. Sex coded female = 1, male = 0. $R^2 = .785$; adjusted $R^2 = .770$; $F(6, 85) = 51.73$, $p < .001$.

G. Hypothesis Testing

Table 7 summarises the hypothesis testing. H1, H3, and H4 were supported, while H2 received only partial

support. Risk-taking behaviour showed a strong negative bivariate association with perceived immune health, but its unique association fell away once self-leadership and sleep quality were accounted for.

Table 7. Summary of hypothesis testing for the correlates of perceived immune health.

Hypothesis	Association	Result	Decision
H1	Self-leadership → perceived immune health	Significant positive	Supported
H2	Risk-taking behaviour → perceived immune health	Bivariate only	Partially supported
H3	Sleep quality → perceived immune health	Significant positive	Supported
H4	Joint model	Significant	Supported

Note. $N = 92$.

IV. Discussion

A. Interpretation of the Findings

Self-leadership and sleep quality were associated with perceived immune health among early adulthood medical students, while risk-taking behaviour showed no independent association. Self-leadership showed the strongest association, followed by sleep quality. These results suggest that self-regulatory capacity and restorative functioning relate to how students appraise their health resilience more than risky behaviour does. Students who manage their thoughts, routines, and stress responses tend to appraise themselves as healthier and more resilient. The combined model accounted for a large share of the variance. This high proportion should be read with caution because all measures shared a single self-report method, the constructs overlap conceptually, and the sample was homogeneous; each of these factors tends to inflate observed associations beyond what fully independent measurement would yield.

The strong role of self-leadership fits its definition as a process of self-management, self-observation, and goal-directed regulation [18]. In demanding educational settings, students with stronger self-leadership maintain healthier routines and regulate stress more effectively [20]. This regulatory capacity plausibly supports restorative habits, including sleep, which in turn supports perceived immune health. Sleep quality was also associated with perceived immune health, which reinforces evidence that sleep regulates immune and inflammatory processes [13], [14]. Students who sleep well experience better recovery, emotional stability, and subjective vitality [15]. Because medical students often report irregular schedules and insufficient rest, restorative

sleep stands out as a practical target for screening and intervention. Risk-taking behaviour behaved differently. It correlated strongly with perceived immune health at the bivariate level, yet lost significance in the regression model. This pattern suggests that risk-taking overlaps with broader self-regulatory and lifestyle processes already captured by self-leadership and sleep quality. Risk-taking may therefore act as a secondary marker of weaker self-regulation rather than an independent correlate of perceived immune health.

B. Comparison with Previous Studies

These findings align with research linking poor sleep to distress, fatigue, and reduced wellbeing among medical students [16], [17]. They are consistent with multicentre evidence on the determinants of sleep quality in this population [40] and with work showing that sleep quality moderates the link between coping and distress [41]. Cross-cultural studies that connect resilience, sleep, and sleepiness in medical students point in the same direction [42], as does evidence linking stress to sleep quality among medical students in other settings [43]. The findings also extend work connecting self-leadership to resilience and proactive health behaviour [18], [19] by showing that self-leadership is specifically associated with perceived immune health. The non-significant unique effect of risk-taking differs from studies that treat risky behaviour as a direct predictor of poorer health [44]. The difference likely reflects modelling choices, since earlier work often examined risk-taking in isolation rather than alongside self-regulation and sleep [45]. Cultural and educational factors in the Indonesian context, including strong academic and family expectations, may also strengthen behavioural self-regulation among these students. In the present sample, the bivariate association

between sleep quality and perceived immune health was strong ($r = .801$), and self-leadership showed an even stronger association ($r = .840$). These values sit above the small-to-moderate correlations usually reported when sleep or self-regulation is related to health outcomes in student samples, which reflects the shared self-report method, the conceptual overlap among the constructs, and the homogeneity of the sample rather than a uniquely strong effect. Published work in comparable populations reports weaker associations. Among 504 Egyptian medical students, sleep hygiene practices correlated with sleep quality at $r = .366$ [46]. A national Vietnamese survey of 1,284 medical students found that depressive symptoms raised the PSQI global score by 0.54 points (95% CI 0.17 to 0.91) and increased the odds of poor sleep quality by half (OR = 1.50, 95% CI 1.13 to 1.99) [40]. A further Vietnamese study of 577 students reported poor sleep quality in 45.8% of the sample, a mean PSQI of 5.4 (SD = 2.3), and a difference between clinical and preclinical students of 51.8% against 40.0% [17]. Multicentre studies in Croatia [3] and Peru [42] examine sleep quality alongside mental health and resilience in the same population, and studies of perceived stress and sleep quality among medical students report associations of similar magnitude [16], [41], [43]. Across this literature the bivariate associations between sleep and psychological outcomes fall largely in the small to moderate range, well below the values obtained here. Three features account for the difference. All four measures shared a single self-report method. Self-leadership, sleep appraisal, and perceived immune health overlap conceptually, because each draws on a general sense of how well the person is functioning. The sample was also homogeneous in age, institution, and programme, which narrows the variation that would otherwise attenuate the correlations.

C. Possible Future Applications in Digital Screening

The practical relevance of these findings is prospective rather than immediate. Indonesia now requires electronic medical record adoption across health facilities [4], and embedded predictive models are becoming standard components of clinical decision support [8], including systems built to improve medication safety in Indonesian outpatient care [47]. In principle, a future screening module could capture self-leadership and sleep quality as two structured, low-burden indicators and store them as discrete fields within an electronic medical record or a student health information system. Because these two indicators carried most of the explained variance in this model, a short self-report set might approximate a longer assessment while reducing response burden. Standardised data elements would allow such indicators to travel through interoperability standards such as Health Level Seven Fast Healthcare Interoperability Resources [4], [5]. Any routing of low scores to student health services would require validated thresholds, and no such

thresholds exist yet, so the workflow in Fig. 1 is a design proposal rather than a validated pathway. The present study measured associations in a single cross-sectional sample. It did not build a screening instrument, derive cut-off values, or test decision-support rules. Whether student wellness screening should flow through routine clinical data-exchange platforms such as SATUSEHAT is a separate governance question, because wellness data differ from routine clinical records in purpose and sensitivity [48], [49].

D. Ethical and Governance Considerations for Future Screening

Any future screening use of these indicators would raise ethical and governance requirements that go beyond the present analysis. Informed consent would need to cover secondary use of self-report data within an electronic medical record, not only participation in a single survey. Access to the data would need role-based controls, and the stored fields would need data minimisation and a defined retention period. The scoring logic would need to be transparent to students and staff, because opaque risk flags can undermine trust. False positives carry real costs, since a student wrongly flagged as at risk may face stigma or unnecessary scrutiny, while false negatives may create false reassurance. Screening within an educational institution also involves unequal power between students and the institution, so results must not influence academic evaluation, progression, or standing. Participation in wellness screening would need to remain voluntary, with a clear separation between supportive health services and academic assessment. These safeguards are preconditions for any deployment and were outside the scope of this study.

E. Limitations

Several limitations apply and directly affect how far the estimates travel. The cross-sectional design rules out causal or temporal inference among self-leadership, sleep quality, and perceived immune health, so the reported weights are partial associations measured at one moment. Recruitment used convenience sampling at a single private university in Yogyakarta, so the sample was not randomly drawn and may overrepresent students willing to complete a health survey; the findings describe this population rather than Indonesian medical students generally. Every variable came from the same self-report instrument completed in one sitting, so common-source measurement remains a concern even though a single unrotated factor accounted for only 38.7% of item variance. Sleep was captured by self-report rather than actigraphy or polysomnography, and daytime sleepiness in student populations tracks academic schedules that a single questionnaire does not record [50]. The constructs also overlap conceptually, because self-leadership, sleep appraisal, and perceived immune health each draw on a general sense of how well the person is functioning, and the strong intercorrelations (tolerance .30 to .43) mean

their unique contributions cannot be cleanly separated. The sleep variable was a reversed and linearly rescaled PSQI global score rather than the raw clinical metric, which preserves rank order and direction but discards the conventional cut-off of five and prevents comparison with prevalence-based studies. Several health-relevant confounders were not measured, including physical activity, perceived stress, depressive symptoms, chronic illness, medication use, smoking, caffeine intake, and recent infection, and the covariate model adjusted only for age, sex, and academic year. Finally, the outcome was perceived immune health. No biomarkers, infection records, leukocyte profiles, or clinical diagnoses were collected, so nothing in these data speaks to physiological immune function [10].

F. Practical Implications and Future Research

The findings point to two directions. First, programmes that strengthen self-leadership and sleep hygiene may support student health resilience, and both are modifiable targets. Second, after prospective validation, the same indicators could anchor a future digital screening module [46]. Longitudinal designs are needed to clarify temporal order. Studies that add objective markers, such as actigraphy for sleep or inflammatory measures for immune function, would test whether perceived immune health tracks physiological status. A prospective study would also need to derive and calibrate thresholds and to report sensitivity and specificity before any screening claim is justified. Comparative studies across universities and countries would test whether the indicator set transfers to other student populations. Any move towards an operational electronic medical record module would require the governance safeguards described above.

V. Conclusion

This study examined how self-leadership, risk-taking behaviour, and sleep quality relate to perceived immune health among early adulthood medical students. Together, the three predictors explained 77.6% of the variance in perceived immune health ($R^2 = .776$; adjusted $R^2 = .768$; $F(3, 88) = 101.62$, $p < .001$). Self-leadership held the largest standardised weight ($\beta = .479$, 95% CI for B [0.337, 0.751], $p < .001$), followed by sleep quality ($\beta = .374$, 95% CI [0.244, 0.586], $p < .001$). Risk-taking behaviour showed no unique association ($\beta = -.106$, 95% CI [-0.319, 0.059], $p = .175$) and added $\Delta R^2 = .005$ ($p = .175$) on hierarchical entry, despite a strong negative bivariate correlation ($r = -.701$). Adjusting for age, sex, and academic year left the pattern unchanged ($\Delta R^2 = .009$, $p = .32$). Among these students, self-regulatory capacity and restorative sleep were therefore more closely associated with perceived health resilience than risk-taking behaviour was. The outcome reflects perceived rather than biologically measured immune function, so these results describe health appraisal and not immune status. Self-leadership and sleep quality form

a compact, low-burden self-report set. Whether that set can support digital screening remains an open question that longitudinal validation, threshold derivation, and governance safeguards would have to settle before any deployment.

Author Contributions

Qurratul Aini contributed to the conceptualisation, research design, data collection, statistical analysis, interpretation, and preparation of the original draft. Titik Muti'ah contributed to the theoretical framework, supervision, critical review, and interpretation of the psychological findings. Usman Agus Dwiyanto contributed to methodological evaluation, academic editing, interpretation of results, and final revision. All authors read and approved the final version of the manuscript.

Conflicts of Interest

The authors declare no conflicts of interest related to this study.

Declaration of Generative Ai and Ai-Assisted Technologies

During the preparation of this manuscript, the authors used generative artificial intelligence and AI-assisted technologies solely for language refinement, grammar correction, and structural organisation. The authors independently conducted and critically reviewed all scientific interpretations, conceptual development, data analysis, and conclusions, and take full responsibility for the accuracy, integrity, and originality of the final content.

Source of Funding

This research received no specific grant from funding agencies in the public, commercial, or non-profit sectors.

Acknowledgements

The authors thank all medical students who participated voluntarily in this study, and acknowledge the academic support provided by Universitas Muhammadiyah Yogyakarta and Universitas Sarjanawiyata Tamansiswa.

References

- [1] S. M. Sawyer, P. S. Azzopardi, D. Wickremarathne, and G. C. Patton, "The age of adolescence," *Lancet Child Adolesc. Health*, vol. 2, no. 3, pp. 223–228, 2018, doi: 10.1016/S2352-4642(18)30022-1.
- [2] D.-S. Tran, D.-T. Nguyen, T.-H. Nguyen, C.-T.-P. Tran, S. Duong-Quy, and T.-H. Nguyen, "Stress and sleep quality in medical students: a cross-sectional study from Vietnam," *Front. Psychiatry*, vol. 14, art. no. 1297605, 2023, doi: 10.3389/fpsyt.2023.1297605.
- [3] S. Vidović et al., "Sleep quality and mental health among medical students: a cross-sectional study," *J. Clin. Med.*, vol. 14, no. 7, art. no. 2274, 2025, doi: 10.3390/jcm14072274.

- [4] Ministry of Health of the Republic of Indonesia, "Regulation of the Minister of Health No. 24 of 2022 concerning medical records (Permenkes No. 24/2022)," Jakarta, Indonesia, 2022.
- [5] M. K. Hossain, J. Sutanto, P. W. Handayani, A. A. Haryanto, J. Bhowmik, and V. Frings-Hessami, "An exploratory study of electronic medical record implementation and recordkeeping culture: the case of hospitals in Indonesia," *BMC Health Serv. Res.*, vol. 25, art. no. 245, 2025, doi: 10.1186/s12913-025-12399-0.
- [6] B. Al Bahrani and I. Yunus, "Technology acceptance model to implementation of electronic medical record (EMR's) at Clinic of Rumah Sehat Keluarga Jember," *J. Aisyah J. Ilmu Kesehat.*, vol. 7, no. 4, 2022, doi: 10.30604/jika.v7i4.1370.
- [7] H.-L. Lin, D.-C. Wu, S.-M. Cheng, C.-J. Chen, M.-C. Wang, and C.-A. Cheng, "Association between electronic medical records and healthcare quality," *Medicine (Baltimore)*, vol. 99, no. 31, art. no. e21182, 2020, doi: 10.1097/MD.00000000000021182.
- [8] T. C. Lee, N. U. Shah, A. Haack, and S. L. Baxter, "Clinical implementation of predictive models embedded within electronic health record systems: a systematic review," *Informatics*, vol. 7, no. 3, art. no. 25, 2020, doi: 10.3390/informatics7030025.
- [9] L. Dornan, K. Pinyopornpanish, W. Jiraporncharoen, A. Hashmi, N. Dejkriengkraikul, and C. Angkurawaranon, "Utilisation of electronic health records for public health in Asia: a review of success factors and potential challenges," *BioMed Res. Int.*, vol. 2019, art. no. 7341841, 2019, doi: 10.1155/2019/7341841.
- [10] L. J. F. Wilod Versprille et al., "Development and validation of the Immune Status Questionnaire (ISQ)," *Int. J. Environ. Res. Public Health*, vol. 16, no. 23, art. no. 4743, 2019, doi: 10.3390/ijerph16234743.
- [11] M. V. S. Lantman, M. Mackus, L. S. Otten, A. J. A. E. van de Loo, A. D. Kraneveld, J. Garssen, and J. C. Verster, "Mental resilience, perceived immune functioning, and health," *J. Multidiscip. Healthc.*, vol. 10, pp. 107–112, 2017, doi: 10.2147/JMDH.S130432.
- [12] N. A. Lueke and A. Assar, "Poor sleep quality and reduced immune function among college students: perceived stress and depression as mediators," *J. Am. Coll. Health*, vol. 72, no. 7, pp. 2146–2154, 2024, doi: 10.1080/07448481.2022.2068350.
- [13] L. Besedovsky, T. Lange, and M. Haack, "The sleep-immune crosstalk in health and disease," *Physiol. Rev.*, vol. 99, no. 3, pp. 1325–1380, 2019, doi: 10.1152/physrev.00010.2018.
- [14] M. R. Irwin, "Sleep and inflammation: partners in sickness and in health," *Nat. Rev. Immunol.*, vol. 19, no. 11, pp. 702–715, 2019, doi: 10.1038/s41577-019-0190-z.
- [15] G. Medic, M. Wille, and M. E. H. Hemels, "Short- and long-term health consequences of sleep disruption," *Nat. Sci. Sleep*, vol. 9, pp. 151–161, 2017, doi: 10.2147/NSS.S134864.
- [16] W. Huang, Y. Li, X. Zhang, J. Chen, and Z. Liu, "Association of perceived stress and sleep quality among medical students: the mediating role of anxiety and depression symptoms during COVID-19," *Front. Psychiatry*, vol. 15, art. no. 1272486, 2024, doi: 10.3389/fpsyt.2024.1272486.
- [17] N. Truong, L. Bui, H. Nguyen, T. Pham, and D. Chu, "Sleep quality by clinical training status among medical students and its associated factors: a cross-sectional study in Da Nang, Vietnam," *Sci. Rep.*, vol. 15, art. no. 33671, 2025, doi: 10.1038/s41598-025-18256-8.
- [18] R. Bjerke, A. Mikkelsen, and M. Mikkelsen, "The role of health-promoting self-leadership among business students and managers," *Adm. Sci.*, vol. 14, no. 9, art. no. 211, 2024, doi: 10.3390/admsci14090211.
- [19] S. Kim and Y. Kim, "Factors associated with nurse self-leadership: a cross-sectional study of nurses working at public health centers and primary healthcare posts," *Res. Community Public Health Nurs.*, vol. 35, no. 3, pp. 195–206, 2024, doi: 10.12799/rcphn.2024.00493.
- [20] K. Pursio, T. Kvist, P. Kankkunen, and L. A. Fennimore, "Self-leadership and why it matters to nurses: a scoping review," *Int. Nurs. Rev.*, vol. 72, no. 1, art. no. e70014, 2025, doi: 10.1111/inr.70014.
- [21] A. C. K. van Duijvenvoorde, J. van Hoorn, and N. E. Blankenstein, "Risks and rewards in adolescent decision-making," *Curr. Opin. Psychol.*, vol. 48, art. no. 101457, 2022, doi: 10.1016/j.copsyc.2022.101457.
- [22] N. Duell, "Positive risk taking in adolescence," *Child Dev. Perspect.*, vol. 13, no. 1, pp. 48–52, 2019, doi: 10.1111/cdep.12310.
- [23] N. Duell and L. Steinberg, "Positive and negative risk taking in adolescence," *Curr. Dir. Psychol. Sci.*, vol. 30, no. 5, pp. 364–371, 2021, doi: 10.1177/09637214211031356.
- [24] D. L. Dickinson, J. Brookes, C. Ferguson, and S. P. A. Drummond, "The impact of self-selected short sleep on monetary risk taking," *J. Sleep Res.*, vol. 31, no. 3, art. no. e13529, 2022, doi: 10.1111/jsr.13529.
- [25] J. D. Houghton and C. P. Neck, "The revised self-leadership questionnaire: testing a hierarchical factor structure for self-leadership," *J. Manag. Psychol.*, vol. 17, no. 8, pp. 672–691, 2002, doi: 10.1108/02683940210450484.
- [26] E. U. Weber, A.-R. Blais, and N. E. Betz, "A domain-specific risk-attitude scale: measuring risk

- perceptions and risk behaviors," *J. Behav. Decis. Mak.*, vol. 15, no. 4, pp. 263–290, 2002, doi: 10.1002/bdm.414.
- [27] D. J. Buysse, C. F. Reynolds III, T. H. Monk, S. R. Berman, and D. J. Kupfer, "The Pittsburgh Sleep Quality Index: a new instrument for psychiatric practice and research," *Psychiatry Res.*, vol. 28, no. 2, pp. 193–213, 1989, doi: 10.1016/0165-1781(89)90047-4.
- [28] E. Išerić, J. C. Verster, and J. Garssen, "The Immune Status Questionnaire: a critical review," *J. Clin. Basic Psychobehav. Res.*, vol. 4, no. 1, 2025, doi: 10.36922/JCBP025150030.
- [29] L. J. Cronbach, "Coefficient alpha and the internal structure of tests," *Psychometrika*, vol. 16, no. 3, pp. 297–334, 1951, doi: 10.1007/BF02310555.
- [30] J. Cohen, P. Cohen, S. G. West, and L. S. Aiken, *Applied Multiple Regression/Correlation Analysis for the Behavioral Sciences*, 3rd ed. Mahwah, NJ, USA: Lawrence Erlbaum Associates, 2003, ISBN 978-0-8058-2223-6.
- [31] M. H. Kutner, C. J. Nachtsheim, J. Neter, and W. Li, *Applied Linear Statistical Models*, 5th ed. New York, NY, USA: McGraw-Hill/Irwin, 2005, ISBN 978-0-07-310874-2.
- [32] J. Cohen, *Statistical Power Analysis for the Behavioral Sciences*, 2nd ed. Hillsdale, NJ, USA: Lawrence Erlbaum Associates, 1988, ISBN 978-0-8058-0283-2.
- [33] F. Faul, E. Erdfelder, A.-G. Lang, and A. Buchner, "G*Power 3: a flexible statistical power analysis program for the social, behavioral, and biomedical sciences," *Behav. Res. Methods*, vol. 39, no. 2, pp. 175–191, 2007, doi: 10.3758/BF03193146.
- [34] D. A. Belsley, E. Kuh, and R. E. Welsch, *Regression Diagnostics: Identifying Influential Data and Sources of Collinearity*. New York, NY, USA: Wiley, 1980, doi: 10.1002/0471725153.
- [35] R. D. Cook, "Detection of influential observation in linear regression," *Technometrics*, vol. 19, no. 1, pp. 15–18, 1977, doi: 10.1080/00401706.1977.10489493.
- [36] J. Durbin and G. S. Watson, "Testing for serial correlation in least squares regression. II," *Biometrika*, vol. 38, no. 1–2, pp. 159–178, 1951, doi: 10.1093/biomet/38.1-2.159.
- [37] T. S. Breusch and A. R. Pagan, "A simple test for heteroscedasticity and random coefficient variation," *Econometrica*, vol. 47, no. 5, pp. 1287–1294, 1979, doi: 10.2307/1911963.
- [38] S. S. Shapiro and M. B. Wilk, "An analysis of variance test for normality (complete samples)," *Biometrika*, vol. 52, no. 3–4, pp. 591–611, 1965, doi: 10.2307/2333709.
- [39] P. M. Podsakoff, S. B. MacKenzie, J.-Y. Lee, and N. P. Podsakoff, "Common method biases in behavioral research: a critical review of the literature and recommended remedies," *J. Appl. Psychol.*, vol. 88, no. 5, pp. 879–903, 2003, doi: 10.1037/0021-9010.88.5.879.
- [40] D. Phung, L. H. Nguyen, C. Latkin, H. P. Do, C. T. Nguyen, R. C. M. Ho, T. M. T. Vu, V. A. T. Dam, T. S. Vu, and C. S. H. Ho, "Factors associated with sleep quality among medical students in Vietnam: a national cross-sectional study," *BMJ Open*, vol. 15, no. 3, art. no. e083168, 2025, doi: 10.1136/bmjopen-2023-083168.
- [41] S. Perveen, N. Imran, and S. Batool, "Moderating effect of sleep quality in the relationship between coping and distress among medical college students," *Front. Psychiatry*, vol. 15, art. no. 1259842, 2024, doi: 10.3389/fpsyt.2024.1259842.
- [42] J. P. Zila-Velasque, P. Grados-Espinoza, B. S. Caira Chuquineyra, M. Diaz-Vargas, G. S. Sierra Calderón, S. Choquegonza, M. S. Temoche-Rivas, K. Siguan Peixoto, M. J. Valladares-Garrido, and V. E. Failoc-Rojas, "Resilience, sleep quality and sleepiness in Peruvian medical students: a multicenter study," *Front. Psychiatry*, vol. 15, art. no. 1284716, 2024, doi: 10.3389/fpsyt.2024.1284716.
- [43] M. A. Safhi et al., "The association of stress with sleep quality among medical students at King Abdulaziz University," *J. Family Med. Prim. Care*, vol. 9, no. 3, pp. 1662–1667, 2020, doi: 10.4103/jfmpc.jfmpc_745_19.
- [44] J. Salas-Rodríguez, L. Gómez-Jacinto, I. Hombrados-Mendieta, and N. del Pino-Brunet, "Applying an evolutionary approach of risk-taking behaviors in
- [45] M. A. Short and N. Weber, "Sleep duration and risk-taking in adolescents: a systematic review and meta-analysis," *Sleep Med. Rev.*, vol. 41, pp. 185–196, 2018, doi: 10.1016/j.smrv.2018.03.006.
- [46] A. Talaia, A. Sowidan, A. Fahim, A. Elzohery, A. Hammada, and I. Kabbash, "Sleep hygiene practices and sleep quality among medical students in Egypt: a cross-sectional study," *Sleep Sci. Pract.*, vol. 9, art. no. 6, 2025, doi: 10.1186/s41606-025-00125-y.
- [47] F. Erawantini, S. Farlinda, and A. L. Suryana, "Design electronic medical records with clinical decision support system (CDSS) to prevent interaction of drug content in outpatient department," *Bali Med. J.*, vol. 11, no. 2, pp. 651–659, 2022, doi: 10.15562/bmj.v11i2.3117.
- [48] B. Al-Sahab, A. Leviton, T. Loddenkemper, N. Paneth, and B. Zhang, "Biases in electronic health records data for generating real-world evidence: an overview," *J. Healthc. Inform. Res.*, vol. 8, no. 1, pp. 121–139, 2024, doi: 10.1007/s41666-023-00153-2.

- [49] D. F. Prabhu, V. Gurupur, A. Stone, and E. Trader, "Integrating artificial intelligence, electronic health records, and wearables for predictive, patient-centered decision support in healthcare," *Healthcare*, vol. 13, no. 21, art. no. 2753, 2025, doi: 10.3390/healthcare13212753.
- [50] S. D. Hershner and R. D. Chervin, "Causes and consequences of sleepiness among college students," *Nat. Sci. Sleep*, vol. 7, pp. 73–84, 2015, doi: 10.2147/NSS.S62907.

Author Biography



Qurrotul Aini is a lecturer and researcher in the Master of Hospital Administration programme at Universitas Muhammadiyah Yogyakarta, Indonesia. She teaches hospital management, organisational behaviour, and health promotion at the postgraduate level. Her research examines healthcare quality improvement, hospital service performance, healthcare leadership, and the behavioural determinants of health among students and health workers. She has published in national and international journals on hospital administration, Islamic healthcare services, and health promotion, and she supervises postgraduate theses in these fields. She also leads community engagement projects that connect universities with hospitals and primary care providers in Yogyakarta. Her current work applies structured self-report indicators and electronic health records to preventive health screening. She can be contacted at email: qurrotul_aini@umy.ac.id

Titik Muti'ah is a senior lecturer at the Faculty of Psychology, Universitas Sarjanawiyata Tamansiswa, Yogyakarta, Indonesia. She teaches developmental



psychology, health psychology, and psychological assessment. Her research covers mental health, psychological resilience, behavioural determinants of wellbeing, and human development across the lifespan. She has published on psychological wellbeing, coping, and behavioural intervention in Indonesian and international outlets. She supervises undergraduate and postgraduate research, and she coordinates practicum programmes that train students in standardised assessment instruments. She also reviews for psychology journals and contributes to community mental health programmes in Yogyakarta. Her present work examines self-regulation and sleep as correlates of perceived health among young adults. She can be contacted at email: titik@ustjogja.ac.id



Usman Agus Dwiyanto is a graduate of the Master of Hospital Administration programme at Universitas Muhammadiyah Yogyakarta, Indonesia. His academic interests cover healthcare management, hospital service quality, organisational development, and educational research in the health sector. He works on studies that combine management theory with quantitative methods, including survey design, reliability testing, and regression modelling. He contributes to interdisciplinary projects that link health services research with the social sciences, and he has supported data collection and analysis for several collaborative studies. He also supports academic editing and manuscript preparation for research groups in hospital administration. His current interest lies in applying structured health data to service improvement. He can be contacted at email: usman.agus.psc22@mail.umy.ac.id