The relationship between sleep hours and exam scores in MATH001

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***Abstract*— This study examines the relationship between academic performance and sleep quality among Undergraduate Informatics students from the 2022 class. Examining math001 scores and Pittsburgh Sleep Quality Index (PSQI) data, the analysis reveals a diverse range of performance in math001, with a notable concentration of students reporting good sleep quality. Covariance and correlation matrices suggest an inverse relationship between PSQI scores and exam performance, indicating that better sleep quality may be associated with higher exam scores. Shape measure analysis further emphasizes the prevalence of good sleep quality among students. However, residual tests unveil challenges such as heteroscedasticity and autocorrelation, cautioning against overinterpretation of the regression model. The GLS model reveals a significant negative correlation between PSQI scores and exam performance, offering valuable insights into the potential impact of sleep quality on academic outcomes. This study contributes to understanding the complex dynamics between sleep quality and academic achievement, acknowledging the need for nuanced interpretation and consideration of underlying statistical assumptions.**

***Index Terms*— PSQI ; sleep quality; math001 ; exam score, academic performance.**

I. Introduction

Quality sleep is crucial for human health, impacting learning, physical, and mental well-being. [1]. The recommended sleep duration for teenagers and adults is 7 to 9 hours.[2] Sleep benefits neural processing, influencing insight, motor skills, perception, and visualization.[2]. It also preserves emotional well-being and cognitive functions. [3]; [4].

Sleep quality is the individual's satisfaction with aspects like efficiency, latency, duration, and waking conditions. [5]. Influenced by lifestyle, environment, work, health, social life, economy, and stress [6]It's also affected by diet, physical activity, and genetics. [7].

Optimal sleep positively impacts students' neurocognitive abilities, enhancing memory and problem-solving [8]. Sufficient sleep correlates with innovative problem-solving, leading to better academic performance. [9]. Good sleep quality, indicated by PSQI > 5, is linked to positive TEOG exam results in medical students. [10]. Research reveals no significant difference in sleep quality between students with varying academic performance levels. [6]. Similarly, poor sleep behavior doesn't correlate with academic success. [11].

This study aims to prove the following hypothesis: Students with better sleep quality will have higher math001 exam scores than students with poor sleep quality. In other words, sleep quality is directly proportional to math001 exam scores.

Mayor hypothesis

H0: Students' sleep quality does not affect their math001 exam scores.
H1: Students' sleep quality affects their math001 exam scores.

Minor hypothesis 1

H0: Students' average PSQI score is less than 5.
H1: Students' average PSQI score is equal to or greater than 5.

Minor hypothesis 2

H0: Students' average aggregate math001 exam score is less than 55.
H1: Students' average aggregate math001 exam score is greater than or equal to 55.

II. Methodology

A. Sleep Quality

Sleep quality, measured by variables like sleep efficiency, latency, and wakefulness after sleep onset, is vital for overall health and well-being [5]. In the realm of neurophysiological states, sleep plays a critical role in learning, memory, and cognitive processing. Studies on sleep deprivation highlight substantial impairments in cognitive processing, impacting the acquisition and integration of information in the brain [12]. Sleep deprivation not only leads to decreased performance in thinking and behavior but also poses health risks, increasing the likelihood of traffic accidents. Furthermore, it diminishes the positive effects of sleep on cognitive processes such as learning and creativity [13].

B. Exam Scores as a Measure of Performance

Exams are one of the most commonly used performance measurement methods in education. Exams objectively assess students' understanding, mastery of subject matter, and cognitive abilities [14]. In addition, exams can reflect the extent to which students have understood and mastered the material. This allows instructors and educational institutions to evaluate the effectiveness of teaching methods and curricula. [15].

C. Relationship between Sleep Quality and Academic Performance

Several studies emphasize the crucial role of sleep quality in shaping academic and work performance. Poor sleep quality is often linked to subpar academic performance, while good sleep quality, coupled with sufficient duration and consistency, tends to correlate with improved academic outcomes. [6];[16].

Academic performance, measured by grades obtained in lectures, is considered a reflection of sleep quality. Studies propose a direct proportionality between sleep quality and student grades. [16]; [17].

Research on college students consistently shows that better sleep quality, longer duration, and greater consistency contribute to enhanced academic performance. A study at MIT by Okano and colleagues (2019) revealed a positive correlation between improved sleep factors and better grades. Similarly, research conducted at NUS College in Singapore by [18] Demonstrated a significant association between poor sleep quality, insufficient sleep, and lower academic performance.

D. Pittsburgh Sleep Quality Index

The Pittsburgh Sleep Quality Index (PSQI) is a self-reported questionnaire that assesses sleep quality and disturbances over time. PSQI is designed to evaluate the overall sleep quality of the subject. Each of the questionnaire's 19 self-reported items is divided into one of seven categories: subjective sleep quality, sleep latency, sleep duration, habitual sleep efficiency, sleep disturbances, use of medications, and daytime dysfunction.

The possible total sum of PSQI is 21, with higher results meaning worse sleep quality and vice versa. In other words, better sleep quality is indicated by lower PSQI scores. The general guidelines for PSQI index scores are as follows:

0–4 = Good sleep quality
5–10 = Poor sleep quality

With values over 10 indicating worse sleep quality.

This research utilizes quantitative methods through questionnaires, which will be distributed to the Undergraduate Informatics students, class of 2022. Who are enrolled in a Math001 course during the even semester of 2023

E. Research Participants

The participants of this study are limited to the Undergraduate Informatics students class of 2022 who have taken Math001 in their second semester (even semester of 2023). Participation in this study will be conducted through publicly accessible questionnaires, which will be provided in the form of Google Forms and distributed accordingly. The UMN Informatics students' class of 2022 is chosen as the object of this study as they are within close reach of the researchers, thus making it easier to collect data. The population of this research is limited to the Undergraduate Informatics students, class of 2022, which consists of 300 students. In order to satisfy the minimum percentage of samples (30% of the population), researchers must obtain at least 90 responses from the questionnaire.

The data acquired from the questionnaires amounts to 100 respondents, with 94 out of the 100 being valid, processable responses. The number of valid data is sufficient to satisfy the 30% minimum sample requirement, as 94 results in 31,33% sample percentage.

F. Research Procedure

Before analyzing the collected data, researchers must perform residual tests using a normality test, a homoscedasticity test, and autocorrelation tests. The normality test uses the Shapiro-Wilk Test. [19]The homoscedasticity test is used for the Constant-error variance test using the Breusch-Pagan Test. [20] , and the autocorrelation test uses the Durbin-Watson Test [21]. All three residual tests will be done in R using the related functions. All residual test results need to show acceptance of H0

The following hypotheses are set for the residual test:

NormalityTest

- H0: Data is distributed normally.
- H1: Data is not distributed normally.

Homoscedasticity Test

- H0: Data is Homoscedastic.
- H1: Data is Heteroscedastic

Autocorrelation test

- H0: Sleep quality and math001 exam scores are not autocorrelated.
- H1: Sleep quality and math001 exam scores are autocorrelated.

The math001 exam scores acquired from the questionnaires are then aggregated into a single numeric index using the following equation:

$$\text{math001 score index} = (\text{mid exam score}) * 0.43 + (\text{final exam score}) * 0.57 \quad (1)$$

This equation is by the scoring guidelines of UMN, modified to disregard students' assignment scores

G. Data Collection

The sampling technique researchers use in this research is Simple Random Sampling, which is a method of drawing samples from a population or universe in a particular way so that each member of the population has an equal chance of being selected or taken (Kerlinger, 2006). To implement this technique, the researcher created a survey in the form of a questionnaire using Google Forms, which consists of questions related to the hypothesis that the researchers have set, then distributed the questionnaire to Undergraduate Informatics student class of 2022 through online chat applications, social media, and manually by asking people to scan the QR code that will lead to a google form to fill out the same questionnaire.

H. Data Analysis and Equations

In this research, the mean is used to provide a central measure of UMN Informatics students' math001 exam scores, offering an average performance that reflects the typical score in the class of 2022. The median is employed as a less sensitive measure of central tendency, particularly useful in handling outliers or skewed data. Variance and standard deviation are analyzed to understand the spread and consistency of math001 exam scores, while quartiles help explore the distribution among different levels of academic achievement.

Skewness and kurtosis assess the asymmetry and shape of the exam score distribution, providing insights into systematic biases and concentration around the mean. Covariance and Pearson correlation examine the relationship between sleep quality and exam scores, indicating whether changes in one variable correspond to consistent changes in the other. The Shapiro-Wilk test assesses the normality of sleep quality and exam score distributions, ensuring the validity of subsequent analyses.

The Breusch-Pagan test investigates heteroscedasticity in exam scores based on varying levels of sleep quality, crucial for robust regression analysis. The Durbin-Watson test explores potential autocorrelation in residuals, maintaining the independence assumption of the regression model. T-tests evaluate the significance of differences in mean exam scores between groups with different sleep quality levels.

For the study's regression model, the Generalized Least Squares (GLS) model is chosen due to its suitability in handling heteroscedasticity and correlated errors, accommodating weighted observations, and considering potential correlations between sleep quality and other factors. This makes GLS well-suited for capturing the intricate dynamics influencing academic performance among Undergraduate Informatics students in the class of 2022

I. PSQI

The Pittsburgh Sleep Quality Index (PSQI) is the chosen tool for assessing the sleep quality of Undergraduate Informatics students from the class of 2022. Recognized for its reliability, the PSQI captures various dimensions of sleep patterns through components like subjective sleep quality, sleep latency, sleep duration, habitual sleep efficiency, sleep disturbances, and daytime dysfunction, offering a comprehensive overview of sleep quality. Lower PSQI scores indicate better sleep quality. Before the primary data collection, a pre-test of the adapted PSQI questionnaire will be conducted with a small sample of informatics students. This pre-test aims to identify and address any potential clarity, wording, or comprehension issues. Feedback from the pre-test participants will inform refinements to the questionnaire, ensuring its effectiveness and reliability in capturing relevant data. Once finalized, the questionnaire will be uploaded to Google Forms for distribution to the target population

J. Research Limitations

This research may be limited by the self-reported nature of the sleep quality data. Additionally, this research may be limited by the fact that it only includes Undergraduate Informatics students from the class of

2022, who are enrolled in a Math 001 course during the even semester of 2023. This research may also be limited by the fact that the timeframe of this research is limited to 6 weeks, from October and November 2023

K. Research Tools

In this research, researchers used several applications to facilitate the process of collecting, processing, and analyzing sample data, including RStudio, Google Forms, and Microsoft Excel. A questionnaire is created using Google Form and distributed it to obtain data from the respondents, the data is then downloaded in spreadsheet format so that it can be accessed using the Microsoft Excel software to make it easier for the researchers to process the data, and grouped the data to facilitate the data analysis process in the RStudio application.

Microsoft Excel is a software program that allows users to process and calculate numerical data. After the data was collected, processed, and processed, the researchers analyzed the data to obtain the desired statistical results using the RStudio application. RStudio is a software program used to statistically analyze and display data in the form desired by the user.

III. Result and Discussion

A. Central Tendency and Spread Analysis

The following images are the results of the syntax run in RStudio to calculate central tendency and spread measures for the exam scores.

```
> mean_nilai <- mean(nilai)
> mean_nilai
[1] 65.02333
> median_nilai <- median(nilai)
> median_nilai
[1] 66.705
> getmode <- function(v) {
+   uniqv <- unique(v)
+   uniqv[which.max(tabulate(match(v, uniqv)))]
+ }
> mode_nilai <- getmode(nilai)
> mode_nilai
[1] 62.29
> variance_nilai <- var(nilai)
> variance_nilai
[1] 290.9151
> sd_nilai <- sd(nilai)
> sd_nilai
[1] 17.05623
> quantile_25 <- quantile(nilai, 0.25)
> quantile_25
    25%
54.7725
> quantile_75 <- quantile(nilai, 0.75)
> quantile_75
   75%
78.635
> iqr_nilai <- IQR(nilai)
> iqr_nilai
[1] 23.8625
```

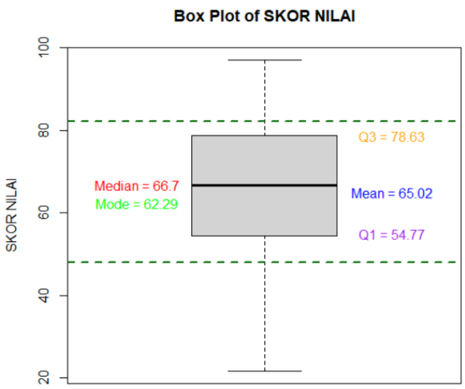

Fig. 1. Central Tendency, Spread, and Boxplot of Math01 Exam Score using R-studio

Undergraduate Informatics students from the class of 2022 had a mean math001 exam score of 65.02, with a slightly higher median of 66.705, indicating a potential negative skewness in the score distribution. The mode was 62.29, suggesting a significant number of students achieved this score. The variance and standard deviation were relatively high at 290.9151 and 17.05623, respectively, indicating notable variability in scores. Examining quartiles revealed a 25% quantile (Q1) of 54.7725, a 75% quantile (Q3) of 78.653, and an interquartile range (IQR) of 23.8625, highlighting a substantial range in students' performance within the middle 50% of the distribution.

```
> mean_psqi <- mean(psqi)
> mean_psqi
[1] 6.478723
> median_psqi <- median(psqi)
> median_psqi
[1] 6
> getmode <- function(v) {
+   uniqv <- unique(v)
+   uniqv[which.max(tabulate(match(v, uniqv)))]
+ }
> mode_psqi <- getmode(psqi)
> mode_psqi
[1] 5
> variance_psqi <- var(psqi)
> variance_psqi
[1] 9.004919
> sd_psqi <- sd(psqi)
> sd_psqi
[1] 3.00082
> quantile_25 <- quantile(psqi, 0.25)
> quantile_25
25%
  4
> quantile_75 <- quantile(psqi, 0.75)
> quantile_75
75%
  8
> iqr_psqi <- IQR(psqi)
> iqr_psqi
[1] 4
```

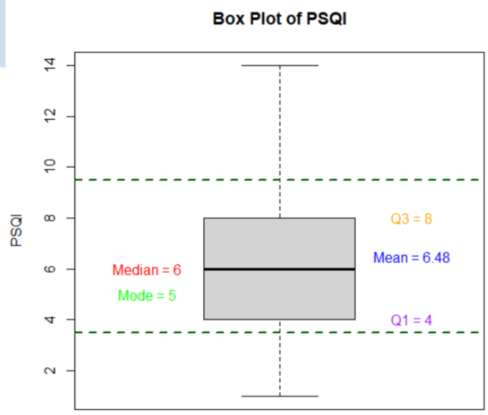

Fig. 2. Central Tendency, Spread, and Boxplot of Math01 PSQI Score using R-studio

The undergraduate Informatics Students class of 2022 had an average Pittsburgh Sleep Quality Index (PSQI) score of approximately 6.48, with a median of 6, suggesting a centered distribution of sleep quality.

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The most frequently reported score was 5, indicating a concentration of students at this level. The variance and standard deviation were 9.004919 and 3.00082, respectively, indicating notable variability in sleep quality scores. Quartile analysis revealed a 25% quantile (Q1) of 4 and a 75% quantile (Q3) of 8, with an interquartile range (IQR) of 4, depicting the spread of sleep quality within the central 50% of the distribution.

B. Covariance and Correlation

The presented image displays the covariance matrix and Pearson's correlation coefficient matrix between PSQI scores and students' exam scores. The covariance matrix indicates a high variance in exam scores (approximately 290.9) and moderate variance in PSQI scores (approximately 9.00).

```
Covariance Matrix:
> print(covariance)
                 FINAL PSQI SCORE SKOR NILAI
FINAL PSQI SCORE         9.004919  -16.51296
SKOR NILAI             -16.512961  290.91507
> cat("\nPearson's Correlation Coefficient Matrix:\n")

Pearson's Correlation Coefficient Matrix:
> print(correlation)
                 FINAL PSQI SCORE SKOR NILAI
FINAL PSQI SCORE        1.0000000 -0.3226279
SKOR NILAI             -0.3226279  1.0000000
```

Fig. 3. Covariance and Correlation

The covariance between the two variables is approximately -16.51, suggesting an inverse relationship: lower PSQI scores tend to correspond with higher exam scores. The correlation coefficient matrix reveals a Pearson's correlation coefficient of approximately -0.323, indicating a weak negative linear correlation between sleep quality and exam scores. This implies that as sleep quality improves (lower PSQI), there is a tendency for exam scores to increase

C. Shape Measure Analysis

The following are the results of shape measure analysis, PSQI Histogram, and Overall Score Histogram.

```
> library(moments)
> skewness(data$`FINAL PSQI SCORE`)
[1] 0.7568865
> kurtosis(data$`FINAL PSQI SCORE`)
[1] 3.347485
> skewness(data$`SKOR NILAI`)
[1] -0.3684753
> kurtosis(data$`SKOR NILAI`)
[1] 2.524035
```

Fig. 4. Shape measure analysis using R programming

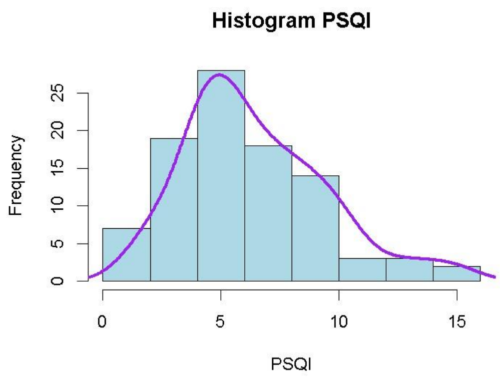

Fig. 5. Histogram PSQI of Math001 Exam Scores

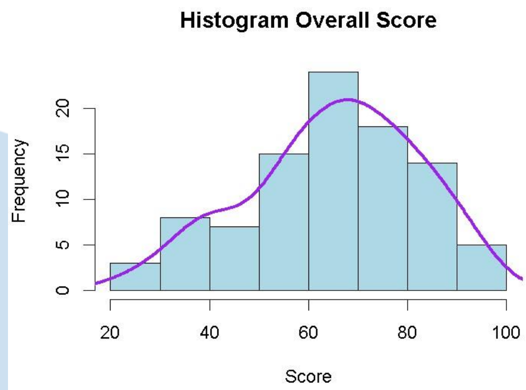

Fig. 6. Histogram of Math001 Exam Overall Score

The PSQI score data shows positive skewness (0.7568865) and high kurtosis (3.347485), indicating a left-leaning distribution and a concentration of scores below 5. This suggests that Undergraduate students generally have good sleep quality. The overall score data for math001 subjects exhibits negative skewness (-0.3684753) and platykurtic kurtosis (2.524035), indicating a right-leaning distribution with scores tending to be above 50. This implies that Undergraduate Informatics students from the class of 2022 have a diverse range of scores.

D. Residual Analysis

The following are the results of the residual test in the form of a normality test, Generalized Least Model (GLM), and Partial Regression Plot Analysis.

1) Normality Test

```
> data_nilai <- as.numeric(dataset$'SKOR NILAI')
> shapiro.test(data_nilai)

        Shapiro-Wilk normality test

data:  data_nilai
W = 0.97866, p-value = 0.1274
```

Fig. 7. Normality test of Math001 Exam Scores

The Shapiro-Wilk Normality Test in Figure 7 was conducted on Undergraduate Informatics Students' Math001 exam grades Class of 2022 with a resulting W-statistic of 0.97866 and a p-value of 0.1274. Given a significance level (alpha) of 0.05, the p-value exceeded this threshold. Consequently, the null hypothesis indicating a normal distribution of exam grades was accepted. This suggests that there is insufficient evidence to claim a significant departure from normality, and researchers can reasonably assume that the data is approximately normally distributed.

```
> data_psqi <- as.numeric(dataset$'FINAL PSQI SCORE')
> shapiro.test(data_psqi)

        Shapiro-Wilk normality test

data:  data_psqi
W = 0.94478, p-value = 0.0005975
```

Fig. 8. Normality Test of PSQI Scores

The Shapiro-Wilk test on PSQI scores for Undergraduate Informatics students (Class of 2022) yielded a W statistic of 0.94478 and a p-value of 0.0005975, indicating a significant departure from normality. However, considering the sample size, if it exceeds 30, the study may proceed with parametric statistical methods. The larger sample size mitigates the impact of minor deviations from normality, aligning with the Central Limit Theorem, and allows for reasonable use of parametric analyses despite the departure indicated by the test.

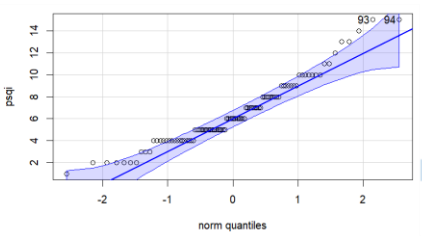

Fig. 9. Q-Q Plot of PSQI with Normal Area Highlighted in Blue

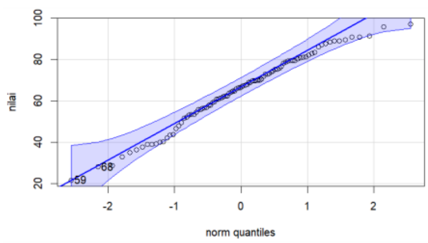

Fig. 10. Q-Q Plot of Math001 Exam Scores with Normal Area Highlighted in Blue

The plots above illustrate the distribution of PSQI and exam scores. The PSQI plot suggests some data points outside the normal zone, indicating a departure from normality. However, given a sample size exceeding 30, it is assumed the data approximates a normal distribution, allowing for subsequent tests. In contrast, the exam scores q-q plot shows all data within the normal zone, confirming a normal distribution.

2) Homoscedasticity Test

The Breusch-Pagan test is used to check for heteroscedasticity, which means the variability of the residuals is not constant across all levels of the independent variable(s).

Figure 11. shows the results of a Breusch-Pagan test done to test for homoscedasticity. The value of the BP is 9.611, with a degree of freedom of 1, and yielding a p-value of 0.001934.

```
> # Homoscedasticity Test (Breusch-Pagan)
> bptest(model)

        studentized Breusch-Pagan test

data:  model
BP = 9.611, df = 1, p-value = 0.001934
```

Fig. 11. Homoscedasticity Test for Constant-error variance

The small p-value suggests evidence against homoscedasticity in the residuals. Therefore, the null hypothesis of homoscedasticity is rejected, and the residuals of the data are indicated to be heteroscedastic

3) Autocorrelation Test

The Durbin-Watson test is used to check for autocorrelation in the residuals, which is a violation of the assumption of independence of residuals.

```
> # Autocorrelation Test (Durbin-Watson)
> dwtest(model)

        Durbin-Watson test

data:  model
DW = 1.2908, p-value = 0.0001202
alternative hypothesis: true autocorrelation is greater than 0
```

Fig. 12. Autocorrelation Test results

Figure 12 shows the results of a Durbin-Watson test done to test for autocorrelation in the residuals. The value of the DW is 1.2908, with a p-value of 0.0001202. The results indicate that the residuals sit against the null hypothesis of non-autocorrelation. Therefore, the residuals of the variables are autocorrelated.

E. T-test

A t-test is a statistical hypothesis test used to determine if there is a significant difference between the means of two groups. It's particularly useful when dealing with small sample sizes or when the population variances are unknown. A one-sample t-test is a statistical hypothesis test used to determine if the mean of a single sample is significantly different from a known or hypothesized population mean [22].

```
> #T-Test
> t_test_result <- t.test(psqi, mu = 5, alternative = "greater")
> print(t_test_result)

        One Sample t-test

data:  psqi
t = 4.7776, df = 93, p-value = 3.302e-06
alternative hypothesis: true mean is greater than 5
95 percent confidence interval:
 5.964501      Inf
sample estimates:
mean of x
 6.478723

> t_test_result <- t.test(nilai, mu = 55, alternative = "greater")
> print(t_test_result)

        One Sample t-test

data:  nilai
t = 5.6976, df = 93, p-value = 7.085e-08
alternative hypothesis: true mean is greater than 55
95 percent confidence interval:
 62.10056      Inf
sample estimates:
mean of x
 65.02333
```

Fig. 13. T-test Results

The t-value indicated in the t-table for alpha = 0.05 and df = 93 is 1.6614. This means that t-values greater than 1.6614 or less than -1.6614 suggest strong evidence against the null hypothesis, thus allowing for the null hypothesis to be rejected. In the t-test above, both PSQI and exam score t-tests result in t-values greater than 1.6614, with the t-value for the PSQI t-test sitting at 4.7776 and the t-value for the exam score t-test sitting at 5.6976.

Based on the t-test above, it can be concluded that the mean PSQI score data is 6.48, showing that UMN Informatics students enrolled in math001 courses on average have poor sleep quality. The mean of the math001 overall score is 65, showing that Undergraduate Informatics students enrolled in math001 courses on average have passed the math001 subject.

The t-test results for PSQI indicate that the null hypothesis, which states students' average PSQI score is less than 5, can be rejected, meaning that students' average PSQI is above 5, indicating poor sleep quality.

The t-test results for exam scores indicate that the null hypothesis, which states students' average aggregate math001 exam score is less than 55, can be rejected, meaning that on average, students' average aggregate math001 exam scores are greater than 55, thus, on average, students pass the math001 course.

F. *Regression Model*

A regression model is a statistical tool used to establish and analyze the relationship between a dependent variable (also known as the outcome, response, or target variable) and one or more independent variables (also called predictors or explanatory variables). Regression analysis is the statistical method used to determine the structure of a relationship between two variables (single linear regression) or three or more variables (multiple regression). The simple regression model for the data is as follows.

```
lm(formula = nilai ~ psqi, data = data)

Residuals:
    Min      1Q  Median      3Q     Max
-42.327 -10.874   0.268  10.673  30.310

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  76.9038     4.0010  19.221  < 2e-16 ***
psqi         -1.8338     0.5609  -3.269  0.00152 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 16.23 on 92 degrees of freedom
Multiple R-squared:  0.1041,    Adjusted R-squared:  0.09435
F-statistic: 10.69 on 1 and 92 DF,  p-value: 0.001517
```

Fig. 14. Simple Regression Model Summary

Figure 14 shows the coefficient of determination for the data, which is at 10.41%, with the adjusted coefficient of determination being at 9,435%. This value indicates that 10% of the variance in the dependent variable is explained by the independent variable in the model. The low percentage also indicates that this regression model may not have a good fit for the data; therefore, other regression models may be used for the data.

G. *The Generalized Least Squares (GLS) model*

The Generalized Least Squares (GLS) model is an advanced regression technique used when the assumptions of Ordinary Least Squares (OLS) regarding the error terms are violated, specifically when errors exhibit heteroscedasticity (unequal variances across observations) or autocorrelation (errors are correlated with each other over time or space) [23].

```
> gls_model <- gls(nilai ~ psqi, data = data, correlation = corAR1())
>
> # Print model summary
> summary(gls_model)
Generalized least squares fit by REML
  Model: nilai ~ psqi
  Data: data
       AIC      BIC    logLik
  779.7439 789.831 -385.8719

Correlation Structure: AR(1)
 Formula: ~1
 Parameter estimate(s):
      Phi
0.3773654

Coefficients:
               Value Std.Error   t-value p-value
(Intercept) 78.08829  5.824803 13.406169  0.0000
psqi        -2.00378  0.809180 -2.476311  0.0151

 Correlation:
     (Intr)
psqi -0.903

Standardized residuals:
        Min          Q1         Med          Q3         Max
-2.57413862 -0.67133286 -0.01234902  0.62754174  1.86457389

Residual standard error: 16.44116
Degrees of freedom: 94 total; 92 residual
```

Fig. 15. GLS (Generalized Least Squares) Summary

The GLS model, considering heteroskedasticity and autocorrelation, investigated the relationship between math001 exam scores ("nilai") and PSQI scores. The AIC and BIC values (779.74 and 789.83) indicate a reasonable fit, with a specified AR (1) correlation structure. The autocorrelation parameter

(Phi) was approximately 0.377. The intercept (78.09) is significantly different from zero (t-value = 13.41, p-value = 0.0000). The coefficient for PSQI scores (-2.00) is statistically significant (t-value = -2.48, p-value = 0.0151), suggesting a negative relationship: as PSQI scores increase, exam scores tend to decrease. The linear regression function is y =78.08829 - 2.00378*psqi. The correlation between the intercept and PSQI score is -0.903. Standardized residuals range from -2.57 to 1.86, indicating how well the model explains variability. The residual standard error is 16.44, suggesting the typical magnitude of residuals around fitted values. With 92 residual degrees of freedom from 94 observations, the model implies a significant negative relationship between exam scores and PSQI, associating higher PSQI values with lower exam scores.

The following figure shows a partial regression scatterplot for a regression model, showing the trendline, individual data points, and a normal line with a normal zone.

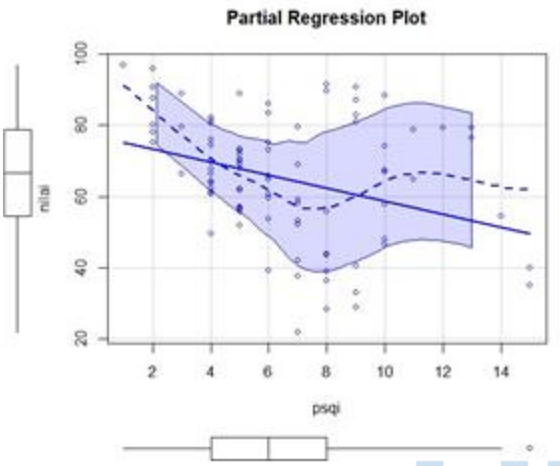

Fig. 16. Partial Regression Plot

Outliers, represented by points outside the normal zone, are visible. The trendline shows a negative linear relationship between "value" (test score) and "psqi" (PSQI score). The data points are evenly distributed, with concentrations near the trendline and within the normal zone, indicating variability in the values of "value" for different values of "psqi." This variability could be due to a variety of influencing factors. The concentration of data points near the trendline implies a systematic change in "value" with changes in "psqi," which is consistent with expectations in a normal distribution. The plot reflects a linear relationship between "psqi" and "value," indicating that changes in "psqi" correspond to changes in "value."

IV. Conclusions

The math001 exam scores exhibit a slightly negatively skewed distribution with a mean of 65.02, indicating average performance. PSQI scores have a mean of 6.48, reflecting average sleep quality. Covariance and correlation matrices reveal an inverse relationship between PSQI and exam scores, suggesting that better sleep quality correlates with higher academic performance. However, the weak correlation coefficient (-0.323) implies a modest linear relationship. Normality tests indicate PSQI scores deviate significantly, but given the sample size, parametric analyses may be reasonable. Regression analyses reveal a significant negative relationship between PSQI and exam scores, with outliers indicating variability. Sleep quality has a moderate effect on exam scores, rejecting the null hypothesis. However, it is not the sole determinant of academic performance, with other external factors playing a role.

The data analysis results show that the first null hypothesis of "Students' sleep quality does not affect their math001 exam scores" can be rejected. The second null hypothesis of "Students' average PSQI score is less than 5" can be rejected, indicating that the average sleep quality of students enrolled in Math001 is poor but not significantly. The third null hypothesis of "Students' average aggregate math001 exam score is less than 55" can be rejected, indicating that, on average, students pass the math001 course.

Moving forward, it is recommended to broaden the scope of research by incorporating additional quantitative variables beyond sleep quality. Factors such as study habits, stress levels, and prior academic achievement could provide a more comprehensive understanding of the determinants of math001 exam scores. Longitudinal studies tracking changes in sleep quality over time and exploring their correlation with academic performance could offer valuable insights. Moreover, considering external influences such as lifestyle and health in future quantitative analyses may contribute to a more holistic perspective on the complex interplay of factors influencing student success.

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