Analysis of Student Performance Differences in Computer Network Courses with Learning Modes in Multimedia Nusantara University

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***Abstract*— Global academic environments have been significantly impacted by the change in educational delivery techniques brought about by the COVID-19 pandemic. This study examines the variations in student performance in Multimedia Nusantara University's Computer Network course across on-site, hybrid, and online learning modes. 526 students data (2019–2022) were evaluated using a variety of statistical techniques, such as the Kruskal-Wallis test, tests for homoscedasticity and normality, pairwise comparison, and post-hoc Dunn's analysis. By taking into consideration the various circumstances and difficulties presented by each learning mode, these techniques guaranteed a thorough assessment of performance variances. The findings indicate that online learning yielded the highest average scores (80.1), demonstrating better performance consistency compared to on-site (75.8) and hybrid modes (72.2), the latter of which showed the widest score dispersion. Statistical evidence revealed significant performance differences between online and other learning modes, whereas no notable differences were observed between hybrid and on-site modalities. These results highlight the effectiveness of online learning in delivering technical courses like Computer Networks, particularly when supported by reliable infrastructure and engaging content design. Nevertheless, improvements in hybrid learning are crucial to reduce performance variability and maximize its potential as a balanced approach to education. This research advocates for future research to explore additional influencing factors, such as teaching strategies, learner engagement, and the role of emotional aspects, in optimizing educational outcomes across various delivery methods.**

***Index Terms*— academic performance; computer network course; online; hybrid; on-site**

I. Introduction

The introduction of technology has had a profound impact on education around the world, particularly during the COVID-19 epidemic, which forced a switch from offline to online schooling. Since research shows that online and offline learning modes differ in content understanding and academic outcomes, this shift had an impact on academic performance [4][19]. In contrast to regulated offline learning, Zimmerman emphasizes the importance of self-regulation in online learning, where a lack of it can impair performance. But online education also gives students the flexibility to use technology and manage their time. In assessing the efficacy of online learning [20], stress the significance of technological infrastructure, lecturer proficiency, and course quality [13][2].

Computer networks play a pivotal role in enabling online learning. A computer network is a system of interconnected devices facilitating data sharing. Stable internet access allows seamless participation in online learning, while technical issues like unstable connections hinder performance [16][7]. Research suggests that computer-based technology enhances student engagement and academic outcomes [14]. Bernard et al. argue that blended learning and technology use in education significantly boost academic performance [3], aligning with Mayer's multimedia learning theory, which posits that multimedia resources improve comprehension and retention [10].

The COVID-19 pandemic expedited the integration of computer networks in education, ensuring learning continuity despite restrictions [5]. This study examines differences in academic performance in online, hybrid, and on-site learning modes among students from three majors Computer Engineering, Informatics Engineering, and Information Systems at Multimedia Nusantara University. Using a statistical test, it seeks to determine the impact of these modes on academic outcomes during and after the pandemic.

Several previous research have addressed topics similar to this research. For instance, Akpen et al. [1] conducted a systematic review analysing the effects of online learning on student performance and engagement. Their study revealed that online learning offers flexibility and accessibility, which can enhance academic performance. However, it also highlighted challenges such as reduced engagement, feelings of isolation, and diminished interaction with lecturers and peers. Trask et al. [17] explored performance predictions in online courses using heterogeneous knowledge graphs. Their research developed a model to identify at- risk students, achieving 70–90% accuracy by analysing factors like consumed content, the institution, and learning modes.

Additionally, Bowers and Kumar found that technology integration in education significantly influences learning outcomes, emphasizing the necessity for robust digital tools [4]. Bernard et al. discussed the impact of blended learning in higher education, concluding that combining online and traditional methods enhances academic performance [3]. Mayer provided insights into multimedia learning, underscoring how technology aids in knowledge retention and comprehension [10]. Meanwhile, Prabowo et al. [12] identified that course quality, lecturer competence, and infrastructure are pivotal for successful online education. These research collectively highlight the opportunities and challenges of online learning and underscore the importance of technological and pedagogic improvements.

This research aims to identify and analyze whether there are differences in the academic performance of Informatics students in the Computer Network course across full online, hybrid, and full on-site learning modes at Multimedia Nusantara University. The findings are expected to provide insights into significant variations in exam results under these different learning conditions.

H_0: There is no significant difference in student performance across the three learning modes (online, hybrid, and on-site) for the Computer Network course.

H_1: There is a significant difference in student performance across at least two of the learning modes (online, hybrid, and on-site) for the Computer Network course.

II. Theoretical Basis

A. Final Exam Scores as a Measure of Performance

Final exam scores serve as an objective measure of students' academic achievements, reflecting their understanding of theoretical concepts and practical skills. Cognitive processes such as remembering, understanding, and applying are critical in assessing student performance In Computer Network courses, final exams evaluate students' mastery of networking theory and technical problem-solving[18].

B. The Impact of Learning Modes on Student Performance

The choice of learning mode online, hybrid, or on-site significantly influences student outcomes, particularly in practice-intensive courses like Computer Network.

1. Online Learning

Software simulations like Cisco Packet Tracer are among the digital tools used in online learning to replace in-person encounters. Nonetheless, studies indicate that experiential learning using actual hardware is more successful in promoting profound comprehension and skill recall [11].

2. Hybrid Learning

Balanced approach to theory and practice is provided by hybrid learning, which blends in-person practical sessions with virtual lectures. Research shows that by combining the advantages of both approaches, it can improve learning results and student engagement [8].

3. On-site Learning

In a completely immersive setting, on-site learning allows students to interact with real hardware, like switches and routers. According to experiential learning theories, the real-world learning opportunities provided by this method have been demonstrated to improve situational awareness and practical abilities[9].

Several research have explored the impact of online learning on student performance. For instance, Akpen et al. [1] conducted a systematic review highlighting both the benefits and challenges of online learning. While flexibility and accessibility can enhance academic performance, issues like reduced engagement and isolation remain significant concerns. Similarly, Trask et al. [17] analyzed student performance predictions in online courses using heterogeneous knowledge graphs, achieving a 70-90% accuracy rate in identifying at-risk students based on factors like learning mode and consumed content.

III. Methodology

A. Research Participants

The participants in this study were undergraduate Informatics students from Multimedia Nusantara University (2019–2022) who had completed at least four semesters, including the Computer Network course. Data were collected from lecturers teaching this course across online, hybrid, and on-site modalities during and after the COVID-19 pandemic. A total of 526 data points were analyzed, comprising 221 from online, 197 from hybrid, and 108 from on-site modes. This selection ensured academic homogeneity while enabling an effective comparison of learning outcomes across different teaching methods.

B. Research Procedure

Prior to analyzing the collected data, researchers must perform residual tests using normality test, homoscedasticity test, and autocorrelation tests. The normality test uses the Shapiro-Wilk Test, the homoscedasticity test uses the Levene Test, and the autocorrelation test uses the Durbin-Watson Test. All three residual tests will be done in R using the related functions. The following hypotheses are set for the residual test:

Normality test:

H_0: Data is distributed normally.

H_1: Data is not distributed normally.

Homoscedasticity test:

H_0: Data is homoscedastic.

H_1: Data is not homoscedastic.

Autocorrelation test:

H_0 : Final score and mode are not autocorrelated.

H_1 : Final score and mode are autocorrelated.

The computer network score index is calculated using the following equations:

Online mode with lab components:

$$0.67 \times ((Mid\ exam\ theory \times 0.3) + (Final\ exam\ theory \times 0.4) + (Theory\ Activities \times 0.3)) + 0.33 * ((Mid\ exam\ practicum * 0.3) + (Final\ exam\ practicum \times 0.4) + (Practicum\ Activities \times 0.3))$$

Hybrid & On-site mode:

$$= ((Mid\ exam \times 0.3) + (Final\ exam \times 0.4) + (Activities \times 0.3))$$

This equation is in accordance with the scoring guidelines of UMN.

C. Data collection

Data was obtained directly from lecturers who taught the Computer Network course in different year of study. The lecturer provided performance records and academic assessments of students across the three learning modalities. This data is considered primary data because it was sourced directly from individuals with firsthand knowledge of the participants' academic performance. Such direct access enhances data validity, as the information originates from trusted academic professionals. The approach aligns with the methodologies discussed by Creswell (2014) for collecting valid, primary data in educational research.

D. Data Analysis and Equations

In this research, the mean is used to provide a central measure of UMN Informatics students performance in the Computer Network course, offering an average score that reflects the typical achievement across online, hybrid, and on-site learning modes. The median serves as a robust central tendency measure, particularly valuable for handling skewed distributions or outliers, while the mode highlights the most frequently occurring scores. Variance and standard deviation are analysed to understand the spread and consistency of scores across the different modalities[6].

Skewness assesses the asymmetry of the score distribution, offering insights into biases and whether performance leans toward higher or lower scores. A distribution table and normality tests, such as the Shapiro-Wilk test, verify the data's conformity to a normal distribution, ensuring the validity of subsequent analyses. The Levene test evaluates homogeneity of variances across the learning modes, while the Durbin-Watson test examines potential autocorrelation in residuals, preserving the regression model's assumptions[12].

The Kruskal-Wallis test is used to detect significant differences in median performance across the three learning modes. When significant differences are found, the Dunn test is applied for pairwise comparisons, revealing specific differences between learning modes. Additionally, a pairwise Wilcoxon test is conducted to further confirm and explore the pairwise differences, providing more robust insights into the performance variability among the groups. This combination of tests ensures a thorough analysis of performance trends and the factors influencing academic achievement in the Computer Network course across online, hybrid, and on- site settings at Multimedia Nusantara University[15].

IV. RESULTS AND ANALYSIS

A. Central Tendency and spread analysis

```
> descriptive_stats <- data %>%
+     group_by(Mode) %>%
+     summarise(
+         Mean = mean(Final_Score),
+         Median = median(Final_Score),
+         Mode = names(sort(table(Final_Score), decreasing = TRUE))[1],
+         Variance = var(Final_Score))
> print(descriptive_stats)
# A tibble: 3 x 4
  Mode      Mean Median Variance
  <chr>    <dbl>  <dbl>    <dbl>
1 80.7      72.2   75.5     269.
2 4.09959   80.1   82.5     200.
3 0         75.8   76.7     186.
```

Fig 1 Results of mean, median, mode, and variance of hybrid, online, and on-site modes

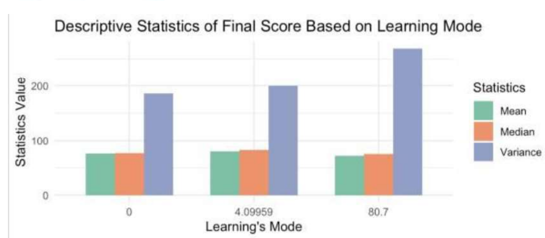

Fig 2 Histogram of central tendency

Descriptive statistics summarize the central tendency and variability in student performance across the three learning modes (Hybrid, Online, and On-site). Hybrid learning has the lowest mean score (72.2), followed by On-site (75.8), and Online with the highest mean (80.1), indicating that students in Online mode tend to perform better. However, variability differs significantly across modes, with Hybrid showing the highest variance (269), indicating greater score dispersion, followed by Online (200) and On-site with the lowest variance (186). The mode for Hybrid is 80.7, appearing five times, suggesting optimal performance, while Online and On-site show no repeated scores. The medians for all modes slightly exceed the means, reflecting left-skewed (negatively skewed) distributions.

B. Shape measure Analysis

```
> skew_online <- skewness(data$Final_Score[data$Mode == "Online"], na.rm = TRUE)
> skew_hybrid <- skewness(data$Final_Score[data$Mode == "Hybrid"], na.rm = TRUE)
> skew_onsite <- skewness(data$Final_Score[data$Mode == "Onsite"], na.rm = TRUE)
> skew_online
[1] -3.051532
> skew_hybrid
[1] -2.37345
> skew_onsite
[1] -2.233519
```

Fig 3 Shape measure result

The skewness analysis of the final score distributions across the three learning modes Online, Hybrid, and On-site indicates that all distributions are left-skewed, as evidenced by negative skewness values (-3.072 for Online, -2.391 for Hybrid, and -2.265 for On-site). This left-skewness implies that the majority of students achieved higher scores, with fewer occurrences of extremely low scores. Among the three modes, the Online mode exhibits the strongest left-skewness, suggesting that students in this mode generally performed better, with a tighter concentration of high scores and minimal extreme low values. The Hybrid and On-site modes, while also showing a tendency for higher scores, display slightly less pronounced skewness, indicating a relatively more balanced score distribution compared to the Online mode. These patterns may reflect differences in the learning environment's influence on student performance, with the Online mode potentially fostering conditions conducive to achieving higher overall scores.

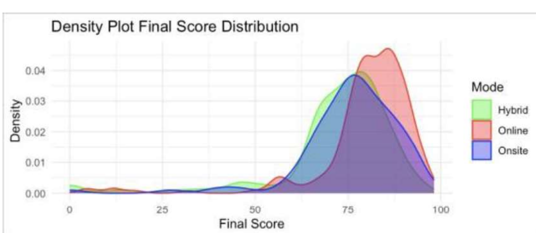

Fig 4 Density plot for skewness distribution of final score

The distribution of Final Scores among UMN students in the Computer Network course reveals that the On-site mode demonstrates the most stable and high performance, with scores concentrated in the 70–90 range and a density peak around 75–80, indicating consistent achievement. The Hybrid mode shows a wider spread, with a density peak around 65–75, reflecting greater variability. Meanwhile, the Online mode exhibits a more asymmetric distribution, with most scores falling in the 70–80 range. Overall, the On-site mode excels in score stability compared to Hybrid and Online modes.

C. Residual Test

Normality Test

```
> shapiro_results <- data %>%
+     group_by(Mode) %>%
+     summarise(p_value = shapiro.test(Final_Score)$p.value)
> print(shapiro_results)
# A tibble: 3 × 2
  Mode   p_value
  <chr>    <dbl>
1 Hybrid 2.33e-16
2 Online 1.68e-19
3 Onsite 7.55e-10
```

Fig 5 Normality test result

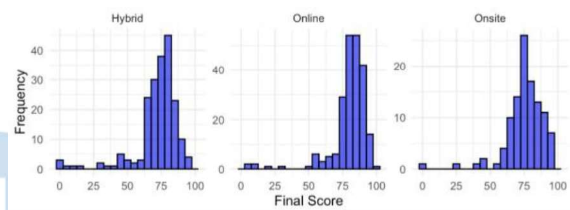

Fig 6 Histogram of final score distribution

The Shapiro-Wilk test was conducted to evaluate the normality of scores across learning modalities. The null hypothesis (H_0) assumes a normal distribution, while the alternative (H_1) indicates non-normality. The p-values for Online $(1.68e^{\wedge} - 19)$, Hybrid $(2.33e^{\wedge} - 16)$, and On-site $(7.55e^{\wedge} - 10)$ were all significantly below 0.05, leading to the rejection of H_0. These results confirm that none of the distributions are normal.

Homoscedasticity Test

```
> leveneTest(Final_Score ~ Mode, data = data)
Levene's Test for Homogeneity of Variance (center = median)
       Df F value Pr(>F)
group   2   1.196 0.3032
      523
```

Fig 7 Homoscedasticity Test result

The Levene's test was conducted to assess the equality of variances across the three learning modes (online, hybrid, and full onsite), a critical assumption for tests such as the Kruskal-Wallis test. The null hypothesis (H_0) posits that the variances are equal across the groups, while the alternative hypothesis (H_1) suggests that the variances differ. The test produced a p-value of 0.3032, which is greater than the significance threshold of 0.05. Consequently, the null hypothesis cannot be rejected, indicating that there is no statistically significant evidence to suggest unequal variances among the three groups. This result confirms that the variances are homogeneous, supporting the assumption of equal variances and ensuring the validity of subsequent statistical analyses.

Autocorrelation Test

```
> model <- lm(Final_Score ~ Mode, data = data)
> dwtest(model)

        Durbin-Watson test

data:  model
DW = 1.7295, p-value = 0.0006993
alternative hypothesis: true autocorrelation is greater than 0
```

Fig 8 Autocorrelation test results

The Durbin-Watson test was conducted to assess the presence of autocorrelation in the residuals of the regression model. The test produced a Durbin-Watson (DW) statistic of 1.7295 and a p-value of 0.0006993. Since the p-value is significantly smaller than the conventional threshold of 0.05, we reject the null hypothesis, which assumes that there is no autocorrelation in the residuals of the model. The results indicate that there is positive autocorrelation present. This suggests that the residuals of the model are not independent and exhibit a pattern where successive residuals are correlated. Positive autocorrelation can impact the validity of standard statistical inferences, such as confidence intervals and hypothesis tests, necessitating further investigation or adjustments to the model to address this issue.

D. Regression Model

```
> model <- lm(Final_Score ~ Mode, data = data)
> summary(model)

Call:
lm(formula = Final_Score ~ Mode, data = data)

Residuals:
    Min      1Q  Median      3Q     Max
-75.956  -3.950   2.536   8.530  23.430

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   72.170      1.063  67.893  < 2e-16 ***
ModeOnline     7.886      1.462   5.395 1.04e-07 ***
ModeOnsite     3.602      1.786   2.017   0.0443 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 14.92 on 523 degrees of freedom
Multiple R-squared:  0.05292,	Adjusted R-squared:  0.0493
F-statistic: 14.61 on 2 and 523 DF,  p-value: 6.677e-07
```

Fig 9 Multiple linear regression model summary

The linear regression model analyses the effect of learning modes (Hybrid, Online, and On-site) on final scores in the Computer Network course. The intercept, representing the Hybrid mode as the baseline, indicates an average score of 72.17 for this mode. Compared to Hybrid, the Online mode significantly improves scores by an average of 7.287 points (p-value < 0.0001), suggesting a strong positive effect on student performance. Similarly, the On-site mode adds an average of 3.602 points (p-value = 0.0443), but its impact is smaller and less statistically significant than the Online mode. These findings indicate that both Online and On- site modalities positively influence performance, with Online showing the strongest effect.

Despite these significant results, the model's adjusted R-squared value of 0.0493 reveals that only 4.93% of the variability in final scores is explained by the learning mode. This indicates that other factors, such as individual effort, instructor quality, or course design, likely play a significant role in performance. The F-statistic (14.61, p-value < 0.0001) confirms the model's overall significance, validating that learning mode impacts scores. However, the residual standard error (14.92) reflects considerable unexplained variability, highlighting the need for further research into additional determinants of academic achievement.

E. Kruskal-Wallis Test

```
> kruskal.test(Final_Score ~ Mode, data = data)

        Kruskal-Wallis rank sum test

data:  Final_Score by Mode
Kruskal-Wallis chi-squared = 57.24, df = 2, p-value = 3.719e-13
```

Fig 10 Statistical test result using Kruskal-Wallis

The Kruskal-Wallis test was employed to examine whether there were statistically significant differences in student performance among the three learning modalities (online, hybrid, and full onsite). This non-parametric test is particularly suitable for comparing groups when the assumption of normality may not be met. The null hypothesis (H_0) of the Kruskal-Wallis test posits that there are no significant differences in performance between the groups, meaning the distributions of scores are similar across the three modalities. Conversely, the alternative hypothesis (H_1) suggests that at least one group differs significantly from the others. The test produced a chi-square statistic, with degrees of freedom equal to 2, and a p-value of 3.719×10^{-13}. Since the p- value is far smaller than the standard significance threshold of 0.05, the null hypothesis is decisively rejected. This result provides strong evidence that there are statistically significant differences in student performance between at least two of the learning modalities. These findings highlight variations in how different teaching modes impact student outcomes, warranting further investigation into which specific modalities contribute to these differences.

F. Pairwise Comparison Test

```
> pairwise.wilcox.test(data$Final_Score, data$Mode, p.adjust.method = "bonferroni")

        Pairwise comparisons using Wilcoxon rank sum test with continuity correction

data:  data$Final_Score and data$Mode

       Hybrid  Online
Online 3.4e-13 -
Onsite 0.13    8.0e-05

P value adjustment method: bonferroni
```

Fig 11 Pairwise comparisons result

The results of the pairwise Wilcoxon rank sum test show comparisons of Final Score across different Mode categories (Hybrid, Online, and Onsite), with the Bonferroni adjustment method used to reduce the risk of errors caused by testing multiple comparisons. This test checks if the distributions of final scores between each pair of modes are similar or not. For the comparison between Online and Hybrid, the p-value is 3.4e-13, which is very small and indicates a significant difference in final scores between these two modes. This means that the mode of delivery has a major effect on the final scores, and Online and Hybrid modes are quite different.

On the other hand, the comparison between Hybrid and Onsite gives a p-value of 0.13, which is not statistically significant at the common threshold of 0.05. This suggests that there is no meaningful difference in final scores between these two modes. Similarly, the comparison between Online and Onsite shows a p-value of 8.0e-05, which is statistically significant, indicating a significant difference between the two modes. The Bonferroni correction helps ensure that the results are accurate by adjusting for the multiple comparisons, reducing the chances of finding false positives.

G. Post-Hoc Test

```
> data$Mode <- as.factor(data$Mode)
> dunnTest(Final_Score ~ Mode, data = data, method = "bonferroni")
Dunn (1964) Kruskal-Wallis multiple comparison
  p-values adjusted with the Bonferroni method.

      Comparison         Z      P.unadj        P.adj
1 Hybrid - Online -7.441764 9.934986e-14 2.980496e-13
2 Hybrid - Onsite -1.990254 4.656293e-02 1.396888e-01
3 Online - Onsite  4.181100 2.901024e-05 8.703071e-05
```

Fig 12 Post-Hoc test results

The Dunn test was employed as a post-hoc analysis following the Kruskal-Wallis test to identify specific differences in student performance between the three learning modes: Hybrid, Online, and On-site. This method allows for pairwise comparisons to determine which learning modes have statistically significant differences in final scores. The results indicate that Online learning significantly outperforms Hybrid learning, with a Z-value of -7.441764 and an adjusted p- value of 2.98×10^{-13}. The extremely low p-value (less than 0.05) provides strong evidence of a substantial advantage for students in the Online mode compared to those in the Hybrid mode. Similarly, Online learning also outperforms On-site learning, as demonstrated by a Z- value of 4.181100 and an adjusted p-value of 8.70×10^{-5}. These findings highlight that Online learning yields the highest overall performance among the three modalities. In contrast, the comparison between Hybrid and On-site learning did not reveal a statistically significant difference in final scores. The Z-value of -1.990254 and the adjusted p-value of 0.1397 (greater than 0.05) suggest that the observed performance differences between these two modes are not significant. This implies that while Online learning stands out as the most effective mode in improving student outcomes, Hybrid and On-site modes perform similarly, with neither showing a clear advantage over the other.

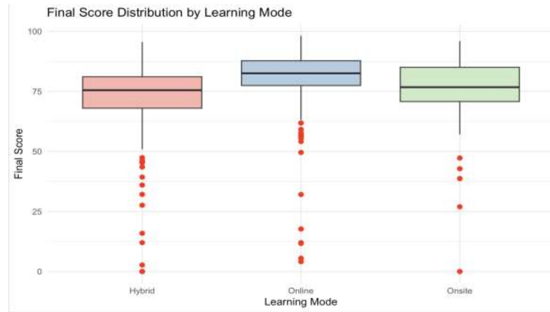

Fig 13 Box plot of final score distribution

The boxplot further supports these findings by visually illustrating the distribution of final scores across the three learning modes. Online learning exhibits a higher median and less variability in scores compared to Hybrid and On-site modes. Both Hybrid and On-site learning display broader score distributions, with overlapping interquartile ranges, which corroborates the statistical analysis indicating no significant difference between these two modes. Collectively, the results emphasize the effectiveness of Online learning in enhancing student performance while suggesting that Hybrid and On-site modes are comparable in their outcomes.

V. CONCLUSION

The research aimed to identify and analyse differences in academic performance among Informatics students in the Computer Network course across Online, Hybrid, and On-site learning conditions. The study revealed significant differences, with Online learning showing the highest mean performance (80.1), followed by On-site (75.8) and Hybrid (72.2). Online learning also demonstrated greater consistency with lower variance, while Hybrid learning exhibited the widest score dispersion, reflecting varied student experiences. Statistical analyses, including the Kruskal-Wallis test, pairwise comparison and post-hoc Dunn's test, confirmed significant performance differences between Online learning and the other modes, though no significant distinction was found between Hybrid and On-site learning.

In technical courses like computer networks, these results demonstrate the relative efficacy of online learning while highlighting areas where hybrid learning needs to be improved to provide more reliable results. Further studies are encouraged to investigate how instructional design, assessment types, and interaction levels contribute to student performance across various learning modes, particularly in practice-intensive courses like Computer Networks. In addition to offering deeper insights into how learning preferences and adaptability vary over time, longitudinal research that monitor changes over several semesters may also assist educators in creating inclusive and fair teaching methods.

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