Analysis of Study Results for “Applied Computer Networking” Course Before and During the COVID-19 Pandemic

Agnes Devita Widjaja1, a), Henry Salim1, b), and Fransiscus Ati Halim2, c)

1Department of Informatics, Universitas Multimedia Nusantara, Tangerang, Indonesia

2Department of Information System, Universitas Multimedia Nusantara, Tangerang, Indonesia

*a) Corresponding author: agnes.devita@student.umn.ac.id*

b)henry.salim@student.umn.ac.id

c)fransiscus.ati@lecturer.umn.ac.id

**Abstract.** The outbreak of the COVID-19 pandemic has remarkably changed the world educational scene and forced universities to move from face-to-face to online teaching. This research examines the results of learning the “Applied Computer Networking” course at Multimedia Nusantara University of students when presented before the pandemic and during it, to determine if the pandemic had a significant effect. The analysis used the assignment data, in the UTS and UAS by 20 odd semester students and 20 even semester students during the pandemic. Applying statistical methodologies, including Shapiro-Wilk, Welch’s t and linear regression, this study tests for theoretical-learning and practical-learning outcomes between two academic years. The study found a significant correlation between the transition to online learning as a result of the pandemic and student achievement, and the hierarchical analysis presented 100% of the R2 value, results showed substantial improvement during the pandemic period (p ¡ 0.0001813). Further testing such as the Welch Two-Sample T- test supported the findings revealing that mean scores during the pandemic were significantly higher than the pre-pandemic scores (p ¡ 0.01'). These results illustrate the potential of digital adaptation strategies to preserve and even augment learning performance in adverse situations. The research highlights the value of blended learning approaches that combine both online and hands-on experiences to support practical learning.

# INTRODUCTION

The COVID-19 pandemic brought huge changes and new challenges in many aspects, especially in academics. Both teachers and students now face new difficulties as a result of the adjustments. COVID-19 has had an impact on every facet of human activity worldwide throughout the pandemic, including education, research, sports, entertainment, transportation, social interactions, the economy, commerce, and politics [1]. COVID-19 has caused problems for the entire world, but the education sector has been particularly hard hit. Governments from many countries have had to adopt new technologies and strategies that enable distance education, provide information access digitally, and encourage society to adapt to the digital era [2].

First discovered in Wuhan, China in 2019, coronavirus disease was later dubbed COVID-19 by the World Health Organization (WHO). The SARS-CoV-2 virus was the origin of the disease, which spread globally and turned into a pandemic with severe health effects [3]. At that time, more than 100 countries implemented a lockdown policy, including school and education institutions closure, affecting more than half of the student population around the world. In Indonesia, this policy led to the adoption of distance learning [4].

However, the implementation of distance learning in Indonesia faces major challenges, especially due to the lack of technology infrastructure and limited supporting resources. Students who need onsite learning are facing significant difficulties. School closure led to several effects:

* Disruption of the learning process: Schools provide essential learning, and when they are closed, students lose the opportunity to develop.
* Unequal access to the online learning system: Many students face difficulties in accessing adequate technology or internet access [2]. This challenge is reinforced by a literature review showing that during the pandemic, most students in Indonesia faced significant barriers, such as limited access to essential devices like laptops, as well as difficulties in accessing stable and affordable internet connections[5].

On the other hand, the pandemic also created new opportunities through the use of online education platforms. With internet penetration and advanced mobile technology, online education platforms could bridge gaps in education and reduce global illiteracy rates [2]. Online education utilizes digital technology to deliver lectures, virtual class sessions, learning materials, and activities efficiently.

In terms of the Applied Computer Networking course at Multimedia Nusantara University, the COVID-19 pandemic presented specific challenges. This course focuses on computer network and communication technology, including internet architecture, routing, network management, and local wired or wireless network aspects [6]. It involves practical sessions to provide hands-on experience through the use of services and internet protocols such as IP, TCP, UDP, and ICMP [6]. At UMN, this course has separate lectures and laboratory sessions. During the pandemic, the laboratory sessions were hindered by limited direct interaction with tutors, even though most activities used digital devices. The characteristics of computer science, which places a strong emphasis on practical activities, such as those found in system and network configuration activities in the Applied Computer Networks course, add an additional layer of complexity to the transition to a fully online learning model [7]. A study of computer science students in physical learning environments shows that factors affecting material accessibility and interaction quality, as well as social aspects in the selection of learning environments, contribute to their academic achievement. This suggests that in the context of online learning for courses rich in practical components, special attention to the design of digital material delivery, facilitating effective two-way interaction, and providing support for student collaboration becomes increasingly crucial [8]. This situation highlights the urgency of developing and utilizing effective and accessible online learning content systems to support student learning independence [9], especially for courses that have significant practical components such as Applied Computer Networks.

This research aims to analyze the differences in learning outcomes in the Applied Computer Networking course at Multimedia Nusantara University before and during the COVID19 pandemic, focusing on lecture and laboratory scores. Key issue to be discussed is whether the pandemic resulted in significantly reduced effectiveness of practice-based learning. The findings from this study are meant to inform stakeholders in the education sector, it will also guide the design of adaptive learning strategies in educational institutions, especially for courses which involves intensive practical sessions. This study is limited to student grade data for the course at Multimedia Nusantara University over two time periods, before and during the pandemic, without considering external factors such as individual student conditions or online learning infrastructure [10].

## Hypothesis Testing

* H0: The study results have no differences while it was held before and during the pandemic era.
* Ha: The study results have differences while it was held during the pandemic era rather than being held before the pandemic era.

# LITERATURE REVIEWS

## COVID-19 Pandemic and Distance Learning

COVID-19 was a watershed moment for the world of education, sending many schools racing toward blending programs and e-learning solutions. This shift is not only a temporary one, but may in fact influence the post-pandemic education system, making it the subject of many studies. The COVID19 pandemic has a huge impact on higher education, which lead universities to switching to online learning with the use of learning management software’s and free digital tools for the continuity of studies [11]. The fate of the higher education sector, which is a gateway to the future of the economy, also seemed to be at stake as it witnessed a drop in interest among Indian students to apply for foreign universities, which was mainly because of worldwide shut down of educational institutions.

COVID-19 pandemic pushed many schools worldwide to adopt a hybrid learning model that combines online and face-to-face education, using various platforms such as Google Classroom, Microsoft Teams, Zoom, and internal e-learning systems [12]. E-learning offers many advantages, such as flexibility, the removal of time and location constraints, and the availability of learning resources in various formats that support self-directed learning. This significant change was not just a temporary solution during the pandemic but also has the potential to shape the global education system in the post-pandemic era.

Distance learning, often considered a form of self-directed learning (SDL), requires students to identify learning needs, design strategies, and evaluate outcomes independently [13]. While this method enhances independence and time management, challenges such as social isolation and mental health issues become major concerns. Social isolation during the pandemic worsened feelings of loneliness and anxiety, particularly for students without family or friends’ support, while students with strong social networks showed better psychological resilience.

The system of higher education learning was dramatically altered during the COVID-19 pandemic. In pre-pandemic days, work was largely face-to-face, allowing professors and students to interact, engage in dialogue and focus on individual teaching. But learning has suddenly moved online due to the pandemic, giving many learners and instructors technical headaches and new challenges to adjust. Lots of lecturers and students were not ready to embrace e-learning platforms; disrupting productivity and learning impact [14]. The stress was further escalated, too not just for the academics, but for the students, by the expectation to acclimatize to new routines. Although online learning provides the convenience of timing, the shortage of internet access, access to devices, and self-control of study time and the coefficient of play time brought down the quality of learning, as compared to a classroom setting [15]. Tahis research is relevant to the Applied Computer Networking course, as ACN covers three main aspects [6]:

* Knowledge: Students understand network concepts, including architecture, routing (OSPF, BGP), network management, and wireless technologies such as WiFi, 4G, and 5G.
* Skills: Students can think creatively, communicate effectively, and use basic tools and protocols to manage computer networks.
* General Competence: Students can apply communication and networking principles responsibly, both independently and in teams.

## Statistical Methods

The following are some statistical tests and formulas used in this research:

1. Shapiro-Wilk Normality Test: One hypothesis test for figuring out if a dataset is normally distributed is the Shapiro-Wilk test [16]. The null hypothesis of this test is that the data is normally distributed; a large p-value suggests that the data is normally distributed, whereas a small p-value suggests that it is not. The formula is shown in equation (1):

(1)

1. Breusch-Pagan Test: The BP test is used to check the homoscedasticity assumption in a regression model. It has been widely applied across different fields, including finance, economics, and social sciences [17]. The formula is shown in equation (2) and (3):

(2)

(3)

where is the number of observations, and is the coefficient of determination from the regression of on the independent variables.

1. Durbin-Watson Test: The Durbin-Watson (DW) test detects the presence of first-order autocorrelation in the residuals of a regression analysis [18], [19]. The formula is shown in equation (4):

(4)

where represents the residuals from the regression model at time , and is the total number of observations [20].

1. Linear Regression: A fundamental statistical technique for simulating the relationship between a dependent variable and one or more independent variables is linear regression [21], [22]. The formula used is shown in equation (5):

(5)

1. Chi Square Test: Chi-Square Test is used to determine whether there is a significant association between categorical variables [23], [24], [25]. The formula is shown in Equation (6):

(6)

1. Welch Two-Sample T-Test: Welch T-test is a statistical test for comparing two means from two independent populations with potentially unequal variances [22]. The formula is shown in equation (7):

(7)

# RESEARCH METHOD

The main subject of this research is Multimedia Nusantara University students’ scores, obtained from one lecturer’s dataset. The dataset covers task scores, mid-term exam (UTS) scores, and final-term exam (UAS) scores in the odd semester of the 2019–2020 academic year (before the COVID-19 pandemic) and the even semester of the 2019–2020 academic year (during the COVID-19 pandemic) for the “Applied Computer Networking” course. Using inferential statistics for two populations, this research explores whether there are differences in study results before and during the COVID-19 pandemic era.

The R programming language and RStudio IDE were used for data analysis. R is widely used for statistical computing and graphics, while RStudio provides an integrated development environment for seamless execution and processing of R scripts.

## Variables and Calculation

The dataset contains:

* Last Name, First Name, Student ID
* UTS-T, UAS-T, UTS-P, UAS-P, TUGAS-T, TUGAS-P

Then, three additional variables were created:

* FINAL-T = 0.30 × TUGAS-T + 0.30 × UTS-T + 0.40 × UAS-T
* FINAL-P = 0.30 × TUGAS-P + 0.30 × UTS-P + 0.40 × UAS-P
* FINAL =0.67 × FINAL-T + 0.33 × FINAL-P

## Result and Analysis

Table 1 summarizes the central tendency measures (mean, median, mode, and interquartile range) for the students’ final scores before and during the COVID-19 pandemic.

The median is higher than the mean for both groups, indicating a left-skewed distribution where lower scores pull down the mean. The mode is 70.006 (before COVID-19) and 79.339 (during COVID-19); in R, if no definitive mode is found, the minimum value may be reported. The interquartile range (IQR) is 5.696 for the pre-pandemic data and 6.004 for the pandemic data, indicating that most data points are relatively close to the median but show a slightly broader spread during the pandemic. Figure 1 illustrates the distributions via histograms.

|  |  |  |
| --- | --- | --- |
| **TABLE 1.** Central tendency for students’ final score (before vs. during COVID-19) | | |
|  | **Before COVID-19** | **During COVID-19** |
| Mean | 82.5499 | 88.8448 |
| Median | 83.409 | 90.563 |
| Mode | 70.006 | 79.339 |
| IQR | 5.696 | 6.004 |

|  |  |
| --- | --- |
| Sebuah gambar berisi diagram, teks, cuplikan layar, Plot  Konten yang dihasilkan AI mungkin salah. | Sebuah gambar berisi teks, diagram, cuplikan layar, Plot  Konten yang dihasilkan AI mungkin salah. |
| (a) | (b) |

**Figure 1.** (a) Distribution of final scores prior to COVID-19 exhibits a symmetrical pattern, with the highest concentration of scores in the 75–85 range. (b) Distribution of final scores during COVID-19 shifts toward higher ranges (80–90), indicating an increased frequency of Grade A scores

## Normality Test (Shapiro-Wilk)

Next, both datasets were tested for normality using the Shapiro-Wilk test. The resulting W statistics are close to 1, and the p-values are well above the conventional alpha level (0.01), indicating that the null hypothesis (that the data are normally distributed) cannot be rejected. Hence, both datasets (before and during COVID-19) can be assumed to follow a normal distribution.

## Residual Tests

Table 2 shows the p-values of the residual diagnostic tests (Normality, Homoscedasticity via Breusch-Pagan, and Independence via Durbin-Watson).

|  |  |  |
| --- | --- | --- |
| **TABLE 2.** Residual tests result | | |
| **Residuals Test** | **P-value** | **Result** |
| Normality Test Before COVID-19 (Shapiro-Wilk) | 0.6101 | Accept H0 |
| Normality Test During COVID-19 (Shapiro-Wilk) | 0.06575 | Accept H0 |
| Homoscedasticity Test (Breusch-Pagan) | 0.7358 | Accept H0 |
| Non-autocorrelation Test (Durbin-Watson) | 0.918 | Accept H0 |

From Table 2, we see that both datasets pass the normality test, meet the homoscedasticity assumption, and do not exhibit autocorrelation.

## Multiple Linear Regression

For the association between the predictor variables (UTS-T, UAS-T, UTS-P, and UAS-P) and the final score (FINAL), a multiple linear regression was performed. The model is statistically significant, as the overall F-statistic is 18.91 with a p value of 1.005e05. The adjusted R2 is approximately 79.03%, which means that these predictors jointly account for a considerable proportion of the variance in the ultimate score.

* UTS-T : β = 0.17026
* UAS-T : β = 0.28735
* UTS-P : β = 0.12911
* UAS-P : β = 0.22534

All predictors have positive relationships with the final score. UAS-T exhibits the largest impact on the final score, followed by UAS-P.

## Welch Two-Sample T-test

Figure 2 shows the results of the Welch Two-Sample T-test comparing the final scores before and during COVID-19. The t-statistic is -4.1513, meaning the mean score before COVID19 is significantly lower than the mean score during COVID19. With a 99% confidence level, the p-value is 0.0001813, which is far less than α = 0.01. The 99% confidence interval is between -10.408027 and -2.181773, indicating that the null hypothesis of no difference is rejected. Thus, the alternative hypothesis holds: “*The study results have differences while it was held during the pandemic era rather than being held before the pandemic era.*”

Sebuah gambar berisi teks, struk, Font, aljabar

Konten yang dihasilkan AI mungkin salah.

**Figure 2.** Welch Two-Sample T-test for students’ final scores before and during COVID-19.

## Chi-Square Test

Additionally, a Chi-Square Test, as shown in Figure 3, was performed to examine the relationship between students’ final scores before and during COVID-19, resulting in a p-value of 0.2058. Since this value is above 0.05, we cannot reject the null hypothesis, suggesting no statistically significant association between the two sets of scores. While the mean scores differ significantly (as shown by the T-test), the Chi-Square result implies there is no strong dependency of one score set on the other. External factors such as grading policy changes or adaptation in teaching approaches might have contributed to this observed increase during the pandemic without being linearly related to the pre-pandemic scores.

Sebuah gambar berisi teks, Font, cuplikan layar, putih

Konten yang dihasilkan AI mungkin salah.

**Figure 3.** Chi-square test for students’ final scores before and during COVID-19

# CONCLUSION

According to the findings of this research, students during the COVID-19 pandemic statistically achieved better results compared to those before the pandemic. The Welch Two Sample T-test showed a significant difference, with the mean score of the pre-pandemic group being lower. At a 99% confidence interval, the null hypothesis was rejected and concluded that COVID-19 pandemic had the effect to learning achievement development to UMN students in Applied Computer Networking subject. Further development of evidence should be conducted with larger and more diverse samples ensure generalizability. Future research studies can also explore the impact of quality of digital infrastructure, nature of instructor-student interactions and the durability of knowledge retention in online learning platforms. Further evaluations of the hybrid learning approach might yield insights into how effective the practical sessions were in encouraging independent learning and how inclusive and robust educational approaches could be developed in technology-based courses.

# ACKNOWLEDGMENTS

We would like to express our sincere gratitude to the course lecturer of Applied Computer Networking at Multimedia Nusantara University for kindly providing the student score data that was invaluable to this research. We also extend our appreciation to Multimedia Nusantara University for the support and for providing the facilities that made this study possible.

# References

1. P. Rani, B. B. Acharya, and K. Trehan, *Digital Inequalities in Media Education in South Asia - Context and Consequences of the Covid-19 Pandemic*. Routledge, 2025.
2. E. M. Onyema *et al.*, “Impact of coronavirus pandemic on education,” *Journal of Education and Practice*, vol. 11, no. 13, pp. 108–121, 2020, [Online]. Available: https://www.iiste.org
3. V. Zoumpourlis, M. Goulielmaki, M. Papadaki, E. Rizos, S. Baliou, and D. A. Spandidos, “The COVID-19 pandemic as a scientific and social challenge in the 21st century,” *Mol Med Rep*, vol. 22, no. 5, pp. 3520–3526, 2020, doi: 10.3892/mmr.2020.11393.
4. UNESCO, “290 Million Students Stay Home due to Coronavirus,” Mar. 2020. [Online]. Available: https://learningenglish.voanews.com/
5. G. James, D. Witten, T. Hastie, and R. Tibshirani, *An Introduction to Statistical Learning: With Applications in R*. Springer, 2013.
6. Norwegian University of Science and Technology, “Applied Computer Networking (TTM4180),” 2024. [Online]. Available: https://www.ntnu.edu/studies/courses/TTM4180#tab=omEmnet
7. G. Kurniawati, O. Karnalim, and S. Budi, “Student Seating Position and Their Academic Performance in Computer Science Major: Observational Study and Student Perspective,” *International Journal of New Media Technology*, vol. 8, no. 1, pp. 16–26, Jun. 2021, doi: 10.31937/ijnmt.v8i1.1741.
8. Z. Bobbitt, “Welch’s t-test: When to use it + examples,” May 2019. [Online]. Available: https://www.statology.org/welchs-t-test/
9. D. H. Fudholi, I. Hanifuddin, and S. Mulyati, “Sistem Konten Pembelajaran di Indonesia : Systematic Literature Review,” *Ultimatics*, vol. 13, no. 1, pp. 26–32, Jun. 2021, doi: 10.31937/ti.v13i1.1948.
10. T. A. Browne, “The Impact of COVID-19 on Student Achievement in Texas: Deepening Disparities,” Western Illinois University, 2023.
11. P. Tarkar, “Impact of COVID-19 pandemic on education system,” *International Journal of Advanced Science and Technology*, vol. 29, no. 9s, pp. 3812–3814, 2020.
12. Y.-M. Wang, Y.-C. Chen, and Y.-S. Wang, “Revisiting the e-learning systems success model in the post-COVID-19 age: The role of monitoring quality,” *Int J Hum Comput Interact*, vol. 40, no. 18, pp. 5087–5102, 2024, doi: 10.1080/10447318.2023.2231278.
13. Q. Liu and D. Lin, “The impact of distance education on the socialization of college students in the COVID-19 era: Problems in communication and impact on mental health,” *BMC Med Educ*, vol. 24, p. 575, 2024, doi: 10.1186/s12909-024-05551-7.
14. A. Mare, E. Woyo, and E. M. Amadhila, *Teaching and Learning with Digital Technologies in Higher Education Institutions in Africa - Case Studies from a Pandemic Context*. Routledge, 2022.
15. Z. Ghali-Zinoubi, M. Al-Absi, and O. Khasawneh, “E-learning in the era of COVID-19 pandemic: Impact of flexible working arrangements on work pressure, work–life conflict and academics’ satisfaction,” *Vision*, vol. 28, no. 5, pp. 621–632, 2024, doi: 10.1177/09722629211054238.
16. G. Malato, “An introduction to the Shapiro-Wilk test for normality,” May 2023. [Online]. Available: https://builtin.com/data-science/shapiro-wilk-test
17. W. H. Greene, *Econometric Analysis*, 7th ed. Pearson, 2012.
18. J. Durbin and G. S. Watson, “Testing for serial correlation in least squares regression,” *Biometrika*, vol. 37, pp. 409–428, 1950, doi: 10.2307/2332391.
19. J. M. Wooldridge, *Introductory Econometrics: A Modern Approach*, 5th ed. South-Western College Publishing, 2015.
20. D. C. Montgomery, E. A. Peck, and G. G. Vining, *Introduction to Linear Regression Analysis*, 5th ed. Wiley, 2012.
21. G. James, D. Witten, T. Hastie, and R. Tibshirani, *An Introduction to Statistical Learning: With Applications in R*. Springer, 2013.
22. Z. Bobbitt, “Welch’s t-test: When to use it + examples,” May 2019. [Online]. Available: https://www.statology.org/welchs-t-test/
23. J. H. McDonald, *Handbook of Biological Statistics*, 3rd ed. Sparky House Publishing, 2014.
24. A. Agresti, *Statistical Methods for the Social Sciences*, 5th ed. Pearson, 2018.
25. A. Field, *Discovering Statistics Using IBM SPSS Statistics*, 5th ed. Sage Publications, 2017