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Factor Influencing Academic Performance During Online Distance Learning: A Case Study at UiTM Arau

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ABSTRACT

According to "COVID-19 Malaysia Updates' (2021), the first COVID-19 case in Malaysia was reported on January 25, 2020, involving a passenger from China. Since then, people's lifestyles, habits, beliefs, feelings, and behaviors have changed, with working individuals adopting Working From Home (WFH) and students transitioning to Online Distance Learning (ODL). Students need to adapt to a new type of learning from home. Undoubtedly, every student will achieve a different level of academic performance. However, The COVID-19 outbreak has undoubtedly affected the educational context, including the students themselves. Universities have had to face these challenges, and some continue to do so. Therefore, this study aims to identify the main factors influencing a students' academic performance and how the pandemic affects their learning behavior. In this study, Multiple Linear Regression was used to find the most significant factors affected students' academic performance during Online Distance Learning (ODL). This study was conducted at UiTM Arau Branch, Perlis Campus, involving students' part five Diploma in Mathematical Sciences and Bachelor of Science Management Mathematics. Sleeping hours, study hours, number of subjects taken, residential area and gender were the factors included in this study. The results indicate that the residential area is the most influential factor, having a statistically significant impact on students' Grade Point Average (GPA).

1. INTRODUCTION

In the era of globalization, social media is one of the essential things. Technological development is advancing day by day. People all over the world are mainly addicted to the use of social media. In 2018, the internet users worldwide were about 4.021 billion, and 3.196 billion people use social networks regularly worldwide (Azizi et al., 2019). Online distance learning was introduced because of the COVID-

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19 pandemic. All students must adapt to a new way of knowledge: Online Distance Learning (ODL). According to Price Banks and Vergez (2022), they discovered that the majority of students preferred in-person courses. Connectivity problems and uneven learning structures served as the foundation for this. The main challenge or issue for most students in online learning is internet connectivity and lack of concentration and focus in class (Pazil et al., 2022). Students are also physically separated from teachers and the school and are primarily in charge of their education (Bagriacik Yilmaz, 2019). However, some students adapt quickly and maintain their learning methods even during ODL. Thus, one of ODL's main goals is to make the student-teacher relationship more convenient and adaptable (Bandara & Kanchana Wijekularathna, 2017).

Classes are methodically planned and held simultaneously at a convenient time for both professors and students after extensive negotiation with both parties. They are recorded and made accessible so that students may if required, revisit them afterward (Fish & Snodgrass, 2019). It is also fascinating to note that some students claim they put more time and effort into their online assignments; even then, it's reasonable to believe that they will be performing better academically (Cerezo et al., 2016; Conijn et al., 2017; Joksimović et al., 2015; Motz et al., 2019). But Motz et al. (2021) find the opposite. Students who put more effort into their assignments felt more accomplished when studying under normal conditions. However, they also received lower grades. It is unquestionably crucial to examine the issues of workload and access to digital resources.

Academic performance is the measurement of student achievement across various academic subjects. Teachers, lecturers, and education officials frequently use high school graduation rates, annual standardized examinations, and college admission exams, including Grade Point Average (GPA), to gauge student achievement. GPA is a student's mark and grade for each semester. It is calculated based on grades for each subject taken for a semester. Grades from each subject will be multiplied and divided by the number of credit hours taken. Other than that, the Cumulative Grade Point Average (CGPA) is a mechanism to evaluate a university graduate's knowledge in Malaysia. Marks from each subject will be multiplied and divided by the number of credit hours taken. Improving their GPAs for every semester can also help students increase their CGPA.

An excellent academic performance does need a lot of effort and hard work. It does depend on the students themselves. Undoubtedly, every student will achieve a different level of academic performance. Besides, the changes related to the COVID-19 outbreak have also affected the educational system. All universities have faced and are still facing many challenges. There is always a chance for a student to miss a lecture due to problems such as internet connection, devices to attend online classes, and two-way communication between lecturer and students. However, some students might have problem with their time management. This problem causes the students failed to manage their time to do some revision after online classes end, sleeping hours, and other daily activities at home.

Many factors can influence students' academic performance. Based on the previous studies, students' performance is indicated by the students' capability to establish the required skills and knowledge expected by future employers and to fulfill the public expectation (Shaffee et al., 2019). Students successfully understand and improve their current knowledge and can decide when facing the subject's difficulties (Sardauna & Yusof, 2018). The studies have been done among Nigerian students found that academic assessment, parent or family background, and teaching methods have a more significant impact on student's academic performance than the school's conductivity and general educational environment (Ayodele et al., 2016).

Moreover, studies have been done by Mahmud et al. (2022) to determine the factor that affect students' academic performance in during ODL class. Throughout the analysis, gender, hours students spent in online learning, hours students spent on preparation before class, number of subjects taken, credit hours, hometown areas and internet connection, act as independent variables. It has been discovered that hometown areas and hours students spent preparing before class are significant to the model. Therefore, it

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has been demonstrated that students who live in rural areas perform significantly better academically than students who live in cities, and the more time students spend preparing for class, the lower their CGPA.

Another factor affecting academic performance is sleeping hours. Sleep is a crucial component of learning and practice, as well as physical and mental wellness, and is an essential component of human health and life (Jalali et al., 2020). Facilities are the other factor that affects student learning achievement. Akomolafe and Adesua (2016) said that adequate learning facilities would encourage and stimulate students to be more active in learning. Teachers mainly need good learning facilities to create the ideal working environment. The same happens to the students; if the learning facilities are sufficient, there will be good motivation to learn, which can increase learning achievement. Regarding Mushtaq and Khan (2012), the students actively engaged in the learning process are observed to have a positive correlation with the CGP.

Academic performance might be influenced by gender. A survey had been conducted by Wrigley-Asante et al. (2023) to compare academic performance of males and females studying Science Technology Engineering and Mathematics (STEM) subjects. The results obtained showed that those males performed better academically than females at the senior high school level, however females looked to perform better academically at higher education.

Previously, Multiple Linear Regression (MLR) has been successfully employed in educational research. For example, Jiménez et al. (2020) examine the impact of academic performance variables by using multiple linear regression. It was found that the variables that affect students in achieving higher academic performances were age, scholarship access, student salary (part-time jobs), and availability of professors that use digital platforms while the variables that having a full-time job, having a tech device for gaming, failing a class, and failing a semester showed a negative impact on student academic performance.

Meanwhile, Ibrahim et al. (2024) studied multiple linear regression in determining the factor that contribute to students' failure such as test score, absentee, gender, and repetition. Based on the finding, attendance and test score have significantly affect to the student's final examination score.

Hence, the main objective of this study is to perform multiple linear regression in order to know the main factor that affects students' academic performance during ODL classes among Diploma in Mathematical Sciences and Bachelor of Science Management Mathematics students in semester five at UiTM Arau Branch, Perlis Campus.

2. METHODOLOGY

This data was collected after the announcement of the final exam results, July 2022 - February 2023 by using an online questionnaire via Google form to 52 students' part five Diploma in Mathematical Sciences and Bachelor of Science Management Mathematics. In Section A, respondents needed to fill in their demographic profile, such as gender and GPA in semester 4. In Section B, the respondents answered a few questions about factors influencing students' academic performance during ODL. The questions included in Section B are "How many subjects are you taking?", "How many hours do you sleep?" and "How many hours you do you spend on revision including weekends?

Multiple Linear Regression was used to find the most significant factors affected students' academic performance during ODL by formulating the problem which is set of variables, validating assumptions and evaluating the fitted model. During the validating assumptions stage, five assumptions must be met or the process must be redone from the beginning (Montgomery et al., 2021). Throughout evaluating the fitted model, the estimated model was tested with three tests before it could be claimed as the best model and could subsequently be used to forecast values. Data was analyzed using R-studio.

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3. FINDING AND DISCUSSION

3.1 Set of Variables

The study analyzed the factors influencing on students' performance in subjects by measuring students' GPA on five factors which are sleeping hours, study hours, number of subjects taken, residential area and gender as shown in Table 1. The objective was to identify which factors significantly impact academic performance during ODL.

Table 1. Set of variables

Variable	Type of variable	Variable Code
Grade Point Average (GPA) Semester 4	Quantitative continuous	GPA
Sleeping hours	Quantitative continuous	Sleep
Study hours	Quantitative continuous	Study
Number of subjects taken	Quantitative discrete	Subject
Residential Area	Qualitative	Area
Gender	Qualitative	Gender

3.2 Forming the Model

The Specific from of the multiple regression with the five variables is given below:

$$y_i = B_0 + B_1X_{i1} + B_2X_{i2} + B_3X_{i3} + B_4X_{i4} + B_5X_{i5} + e_i \quad (1)$$

where

y_i : Grade Point Average (GPA)
B_0 : the intercept
$B_1 ...... B_5$: The regression coefficient for independent variables
X_{i1} : Sleeping hours
X_{i2} : Study hours
X_{i3} : Number of subjects taken
X_{i4} : Residential Area
X_{i5} : Gender
e_i : Model's error term or residuals

3.3 Validating Assumption

In regression analysis, many assumptions about the model and the Multiple Linear Regression (MLR) model are one of the fussier of the statistical techniques as it makes several assumptions about the data. If one or more assumptions are violated, then the model in hand is no longer reliable and not acceptable in estimating the population parameters (Daoud, 2018). In this study, four assumptions were discussed.

3.3.1 The relationship between independent variables and dependent variables is linear

The Pearson correlation analysis was done to determine the strength of the relationship between the dependent variable which is students' academic performance (GPA) and independent variables are sleeping hours, study hours, number of subjects taken, residential area and gender. From the result in Table 2, it was found that all correlation values are in between $\pm 0 < r < \pm 0.5$. Pearson Correlation was identified 0.053 and 0.339 for sleeping hours and study hours respectively with GPA semester 4. It shows that exists weak

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positive relationship between sleeping hours and study hours with GPA in semester 4. In contrast, there is a negative relationship for number of subjects taken residential area and gender with Pearson Correlation values -0.165, -0.455 and -0.028. There is no control or constant component, as evidenced by the connection between the two variables.

Table 2. Parameter estimates

Model	Beta	Std. Error	Std. Beta	t	sig	Correlations	VIF
(intercept)	4.030	0.716		5.625	0.000		
Gender	-0.023	0.099	-0.034	-0.235	0.816	-0.028	1.133
Study	0.173	0.124	0.205	1.399	0.170	0.339	1.177
Sleep	0.212	0.649	0.049	0.327	0.745	0.053	1.202
Subject	-0.720	0.644	-0.154	-1.118	0.271	-0.165	1.039
Area	-0.233	0.080	-0.411	-2.897	0.006	-0.455	1.068

3.3.2 The value of Residuals is Independent

The Durbin-Watson is used to detect autocorrelation in the residuals of the regression model, with values close to 2 indicating no significant autocorrelation. This assumption had been met, as the value obtained 2.0601.

Table 3. Model summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	0.5343	0.2855	0.1939	0.2383	2.0601

3.3.3 Homoscedasticity

Homoscedasticity, also referred to as homogeneity of variances. It shows the consistency in the dispersion of differences between predicted and observed values for any given random variable within an experiment. Based on Fig. 1, it reveals that the spread of residual remains roughly constant across all levels. Therefore, the homoscedasticity assumption had been met.

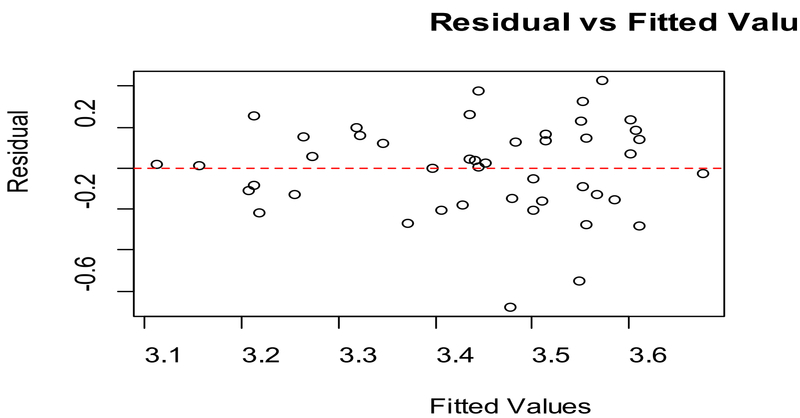

Fig 1. Residual Plot

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3.3.4 The Residuals follow a Normal Distribution

The Q-Q plot in Fig. 2 shows the residuals fall along a roughly straight line at a 45-degree angle. Since the data falls perfectly on the line, it indicates that the data follows the theoretical distribution. The data are normally distributed.

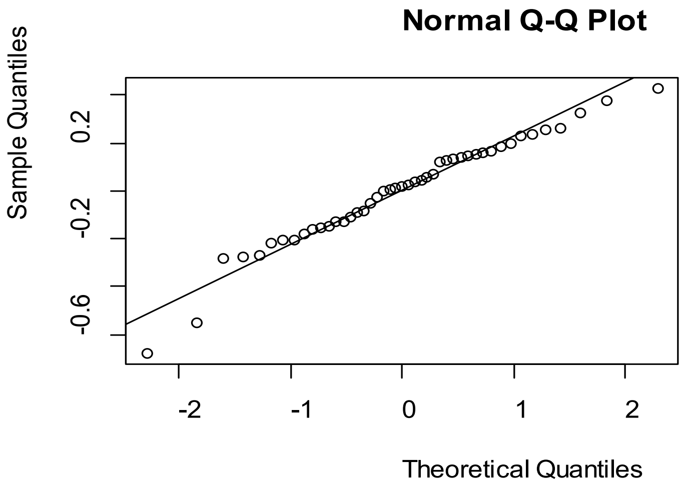

Fig 2. Q-Q plot

3.3.5 Checking Multicollinearity

Multicollinearity is when there is a correlation between independent variables in a model. Based on Table 2, the VIF values for the predictor variables in the model are close to 1, multicollinearity is not a problem in the model. Therefore, there is no absence of multicollinearity among the independent variables.

3.4 Evaluate the Model

Evaluating the estimated model is a necessary but often overlooked procedure. However, it is a necessary prerequisite before the estimated model can be claimed as the best model and used to forecast values. The subsections that follow describe some of the most common statistical testing procedures.

Table 4. ANOVA

Model		Sum of Squares	DF	Mean Square	F	sig.
1	Regression	0.884	5	0.177	3.116	0.01842
	Residual	2.214	39	0.057		
	Total	3.098	44			

3.4.1 Fitness of the Model

This is a test for the overall fitness of the model. The examination will reveal whether all or part of the independent variables should remain in the model. The test criterion used is the *F-test* statistic. The null hypothesis to be tested states that all coefficients in the model are equal to zero, that is:

H_0: The regression model is not significant
H_1: The regression model is significant

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The overall *F-test* can be found in the ANOVA table in the statistical output. To interpret the *F-test* of significance, the *p*-value for the *F-test* must be compared to a 5% significance level. From Table 4, the *p*-value 0.018 is less than the significance level of 0.05, then H_0 is rejected and hence the data provide sufficient evidence to conclude that the regression model is significant.

3.4.2 Goodness of Fit

The standard measure of the goodness of fit is the *coefficient of determination*, R^2. From Table 3, the coefficient of determination, R^2 shows that 28.55% of the total variation in CGPA is explained by the independent variables in the model. The correlation coefficient indicates that there is a moderate positive correlation between observed and predicted values.

3.4.3 Statistical Significance of the Independent Variables

The independent is significant when the *p-value* is less than 0.05. Area ($\beta = -0.233$, $p = 0.006 < 0.05$) contributed significantly to the model while gender ($\beta = -0.023$, $p = 0.816 > 0.05$), study ($\beta = 0.173$, $p = 0.170 > 0.05$), sleep ($\beta = 0.212$, $p = 0.745 > 0.05$), and subject ($\beta = -0.720$, $p = 0.271 > 0.05$) are did not. These values are presented in Table 4. From this value, it can be concluded that residential area is significant variable towards students' GPA. Therefore, the estimated model coefficient is a GPA = 4.030 - 0.233Area.

4. CONCLUSION

The Covid-19 pandemic will undoubtedly bring about many changes in people's daily lives. Specifically, students are unable to attend classes as normal. Everything needs to be done online. Online Distance Learning (ODL) can offer benefits as well as drawbacks for students. This study aimed to identify significant factors that might influence students' academic performance during Online Distance Learning (ODL). To achieve the objectives of this study, sleeping hours, study hours, number of subjects taken, residential area and gender were the factors that has been analyzed using Multiple Linear Regression method. The result shows that residential area is a significant factor affecting students' academic performance during pandemic aligning with finding Mahmud et al. (2022). However, there were some challenges faced during this study which is lack of time and respondents. For future research, it is recommended to spend as much time as possible gathering data and increasing the sample size based on additional strata from various academic programs. As a result, the outcome may be more precise. Furthermore, Future studies could investigate the factors influencing GPA or CGPA in face-to-face classes to provide aa comparative analysis.

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6. CONFLICT OF INTEREST STATEMENT

The authors agree that this research was conducted in the absence of any self-benefits, commercial or financial conflicts and declare the absence of conflicting interests with the funders.

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7. AUTHORS' CONTRIBUTIONS

Siti Nor Nadrah Muhamad: Conceptualisation, methodology, formal analysis, investigation and writing-original draft; **Nur Atiqah Najihan Amran**: Conceptualisation, methodology, and formal analysis; **Nur Syuhada Muhammat Pazil**: Conceptualisation, formal analysis, and validation; **All Authors**: Conceptualisation, supervision, writing- review and editing, and validation.

8. REFERENCES

Akomolafe, C. O., & Adesua, V. O. (2016). The impact of physical facilities on students' level of motivation and academic performance in senior secondary schools in South West Nigeria. *Journal of Education and Practice*, *4*(7), 38–39.

Ayodele, T. O., Oladokun, T. T., & Gbadegesin, J. T. (2016). Factors influencing academic performance of real estate students in Nigeria. *Property Management*, *34*(5), 396–414. https://doi.org/10.1108/PM-09-2015-0045

Azizi, S. M., Soroush, A., & Khatony, A. (2019). The relationship between social networking addiction and academic performance in Iranian students of medical sciences: A cross-sectional study. *BMC Psychology*, *7*(1). https://doi.org/10.1186/s40359-019-0305-0

Bagriacik Yilmaz, A. (2019). Distance and face-to-face students' perceptions towards distance education: A comparative metaphorical study. *Turkish Online Journal of Distance Education*, *20*(1). https://doi.org/10.17718/tojde.522705

Bandara, D., & Kanchana Wijekularathna, D. (2017). Comparison of student performance under two teaching methods: Face to face and online. *International Journal of Education Research*, *12*(1).

Cerezo, R., Sánchez-Santillán, M., Paule-Ruiz, M. P., & Núñez, J. C. (2016). Students' LMS interaction patterns and their relationship with achievement: A case study in higher education. *Computers and Education*, *96*, 42–54. https://doi.org/10.1016/j.compedu.2016.02.006

Conijn, R., Snijders, C., Kleingeld, A., & Matzat, U. (2017). Predicting student performance from LMS data: A comparison of 17 blended courses using moodle LMS. *IEEE Transactions on Learning Technologies*, *10*(1), 17–29. https://doi.org/10.1109/TLT.2016.2616312

Daoud, J. I. (2018). Multicollinearity and regression analysis. *Journal of Physics: Conference Series*, *949*(1). https://doi.org/10.1088/1742-6596/949/1/012009

Fish, L. A., & Snodgrass, C. R. (2019). Age and gender and their influence on instructor perspectives of online versus face-to-face education at a Jesuit institution. *Journal of Education for Business*, *94*(8), 531–537. https://doi.org/10.1080/08832323.2019.1595499

Ibrahim, N., Irpan, H. M., Syuhada, N., & Muhammat, B. (2024). Sustaining mental health among educators by understanding factors of students ' failure. *Global Business and Management Research: An International Journal*, *16*(2), 510–518.

Jalali, R., Khazaei, H., Khaledi Paveh, B., Hayrani, Z., & Menati, L. (2020). The effect of sleep quality on students' academic achievement. *Advances in Medical Education and Practice*, *11*, 497–502. https://doi.org/10.2147/AMEP.S261525

https://doi.org/10.24191/jcrinn.v9i2.453

Jiménez, M., Pérez, F., & Gómez, P. (2020). Análisis de los factores tecnológicos sobre el rendimiento académico en una universidad pública en la Ciudad de México. *Formación Universitaria*, *13*(6), 255–266. https://doi.org/10.4067/s0718-50062020000600255

Joksimović, S., Gašević, D., Loughin, T. M., Kovanović, V., & Hatala, M. (2015). Learning at distance: Effects of interaction traces on academic achievement. *Computers and Education*, *87*, 204–217. https://doi.org/10.1016/j.compedu.2015.07.002

Mahmud, N., Muhammat Pazil, N. S., & Azman, N. A. N. (2022). The significant factors affecting students' academic performance in online class: Multiple linear regression approach. *Jurnal Intelek*, *17*(2), 1–11. https://doi.org/10.24191/ji.v17i2.17896

Montgomery, D. C., Peck, E. A., & Vining, G. G. (2021). *Introduction to linear regression analysis*. Wiley.

Motz, B. A., Quick, J. D., Wernert, J. A., & Miles, T. A. (2021). A pandemic of busywork: Increased online coursework following the transition to remote instruction is associated with reduced academic achievement. *Online Learning Journal*, *25*(1), 70–85. https://doi.org/10.24059/olj.v25i1.2475

Motz, B., Quick, J., Schroeder, N., Zook, J., & Gunkel, M. (2019). The validity and utility of activity logs as a measure of student engagement. *ACM International Conference Proceeding Series*, 300–309. https://doi.org/10.1145/3303772.3303789

Mushtaq, I., & Khan, S. N. (2012). Factors affecting atudent's academic performance. *Global Journal of Management and Business*, *12*(9).

Pazil, N. S. M., Mahmud, N., & Azman, N. A. N. (2022). The impact of COVID-19 on academic performance of bachelor's degree students. *Jurnal Pendidikan Sains dan Matematik Malaysia*, *12*(1), 93–100. http://ojs.upsi.edu.my/index.php/JPSMM/article/view/6851

Price Banks, D., & Vergez, S. M. (2022). Online and in-person learning preferences during the COVID-19 pandemic among students attending the City University of New York. *Journal of Microbiology & Biology Education*, *23*(1). https://doi.org/10.1128/jmbe.00012-22

Sardauna, S. S., & Yusof, M. (2018). Factors influencing students' performance in mathematics for better teaching-aids design. *Journal of Science, Technology & Education (JOSTE)*, *6*(1), 1–8.

Shaffee, N. S., Ahmad, E. M., Idris, S. I. Z. S., Ismail, R. F., & Ghani, E. K. (2019). Factors influencing accounting students under-performance: A case study in a Malaysian public university. *International Journal of Education and Practice*, *7*(1), 41–53. https://doi.org/10.18488/journal.61.2019.71.41.53

Wrigley-Asante, C., Ackah, C. G., & Frimpong, L. K. (2023). Gender differences in academic performance of students studying Science Technology Engineering and Mathematics (STEM) subjects at the University of Ghana. *SN Social Sciences*, *3*(1). https://doi.org/10.1007/s43545-023-00608-8

https://doi.org/10.24191/jcrinn.v9i2.453