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THE IMPACT OF ONLINE LEARNING ON STUDENT MOTIVATION WITH TIME MANAGEMENT AS A MEDIATING VARIABLE: A CASE STUDY AT THE OPEN UNIVERSITY

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Abstract

This study aims to analyze the impact of the online learning environment on student motivation levels at the Open University with time management as a mediating variable. In the context of higher education, online learning has become a very important aspect, especially in today's digital era. However, student motivation levels in online learning can be influenced by various factors, one of which is effective time management. This study uses a quantitative approach with an ex-post facto design and involves students at the Open University who are enrolled in online learning programs. Data were collected through questionnaires that measured three main variables: online learning, student motivation, and time management. Data analysis used the Partial Least Squares-Structural Equation Modeling (PLS-SEM) method to test the relationship between variables and identify the role of time management as a mediating variable. The results showed that the online learning environment had a significant positive effect on student motivation levels. Furthermore, time management was found to mediate this effect, meaning that students who effectively manage their time in online learning tend to have higher levels of motivation. These findings have important implications for the management of online learning at the Open University, with a focus on improving the quality of the online learning environment and providing support for students' time management to maximize their motivation in the learning process.

Keywords: online learning environment, student motivation, time management, Open University, PLS-SEM.

1 INTRODUCTION

The development of information technology has transformed the education sector, particularly through online learning. Online learning provides new opportunities and challenges that affect various aspects of education, including student motivation and time management. Initially implemented to overcome the limitations of space and time in traditional education, online learning has now become an integral part of higher education systems around the world. Despite offering greater flexibility and accessibility, online learning faces problems such as low learning motivation and difficulties in time management, which can directly impact the quality of learning and students' academic performance (Shabnam Ara & Tanuja, 2023).

Learning motivation in online learning is crucial for learning effectiveness. Self-Determination Theory states that students will be more motivated if they feel autonomy, competence, and social connectedness in their learning process (Bakali Tahiri & Mouratidis, 2024). One important factor that influences motivation is effective time management. Good time management can help students organize their study schedules efficiently, increase their motivation, and improve their academic performance (Heo et al., 2021) Research shows that effective time management skills have a positive impact on academic motivation and can reduce unproductive behaviors such as "cyberloafing" (Kwala et al., 2024). In addition, time management serves as a mediating variable that links various external and internal factors, such as technology use and self-efficacy, with better learning outcomes (Schlimbach et al., 2023)

Online learning offers time flexibility that allows students to arrange their study schedules according to their needs, which can increase participation and knowledge retention (Kurniawan et al., 2024).With a deeper understanding of the role of time management, this study aims to provide practical recommendations to improve students' academic motivation in online learning

2 RESEARCH METHOD

This research method uses a quantitative approach with a cross-sectional survey design (Creswell & Creswell, 2017) , to explore the impact of online learning on student motivation with time management as a mediator. The sampling method used cluster sampling, resulting in a sample of 147 students from the UPPBJ UT Makassar program.

The research variables were developed by the researcher, adopting various instruments developed by previous researchers, online learning(Moore & Hammond, 2011; Sun et al., 2011) consisting of 4 items, student motivation (Pintrich & De Groot, 1990) consisting of 3 items, time management (Britton & Tesser, 1991; Macan et al., 1990) consisting of 5 items. All variables use a Likert scale with 5 criteria, namely: 1 (strongly disagree), 2 (disagree), 3 (neutral), 4 (agree), 5 (strongly agree).

Data analysis was performed using Smart PLS software version 4.0. Model measurement was carried out by examining factor loading values, where values above 0.70 indicate that the indicators can form variable constructs well. Indicators with factor loading values below 0.70 were considered unable to measure the construct accurately and had to be excluded from the model. To measure reliability, Cronbach's alpha and composite reliability were used, both of which had to be greater than 0.70. Convergent validity was tested using the Average Variance Extracted (AVE) value, which must be greater than 0.50. Meanwhile, discriminant validity was tested using the Heterotrait-Monotrait Ratio (HTMT), which should be below 0.90, which is still considered valid for research in the field of education(Sarstedt et al., 2019) . In addition, the Fornell-Larcker criterion is used to test discriminant validity by ensuring that each latent construct is more dominant in explaining its own indicators than the indicators of other constructs in the model, and is empirically different from other constructs(Henseler et al., 2015).

Algorithm testing in PLS is used to obtain structural and measurement model solutions by estimating the relationships between latent variables and their indicators, as well as the relationships between latent variables in the model. The results of the algorithm test provide path coefficients that describe the relationships between variables and measure the validity and reliability of the construct. Meanwhile, bootstrapping is a statistical method for testing the stability and significance of path coefficients by repeatedly resampling data, producing an estimation distribution used to calculate t-statistics, p-values, and confidence intervals, so that the statistical significance of the relationship between latent variables can be determined.

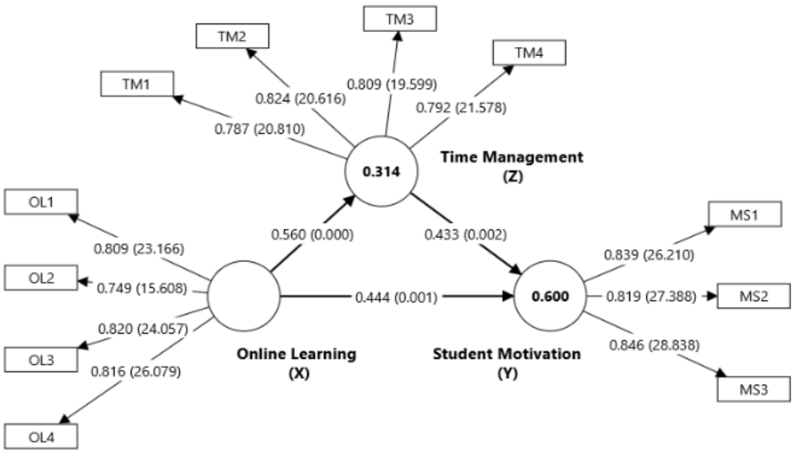

Figure 1 PLS Algorithm and Bootstrapping Test Model

Table 1. Construct Reliability and Validity

Variable	Measurement Item	Indicator	LF	CA	CR	AVE
Student Motivation	MS1	Goal orientation	0.839	0.782	0.873	0.697
	MS2	Perseverance	0.819			
	MS3	Active involvement	0.846			
Online Learning	OL1	Accessibility	0.809	0.811	0.876	0.638
	OL2	Time flexibility	0.749			
	OL3	Quality of materials	0.820			
	OL4	Ease of use of the platform	0.816			
Time Management	TM1	Time planning	0.787	0.816	0.879	0.645
	TM2	Task priority	0.824			
	TM3	Time discipline	0.809			
	TM4	Avoiding delays	0.792			

Table 1 presents information regarding the reliability and validity of the constructs tested in this study. For each variable, such as Student Motivation, Online Learning, and Time Management, there are several measurement items, each of which has indicators with factor loading values that show how strong the relationship is between the indicators and the constructs being measured.

The Student Motivation variable, goal orientation (MS1), perseverance (MS2), and active involvement (MS3) indicators have loading factor values above 0.7, indicating that these indicators are valid in describing the construct of student motivation. Cronbach's Alpha (CA) and Composite Reliability (CR) values are greater than 0.7. The Online Learning variable, with CA 0.811 and CR 0.876, indicates that the construct has good reliability. In addition, Average Variance Extracted (AVE) values greater than 0.5, such as in the Student Motivation construct (AVE 0.697), indicate that these indicators are able to explain most of the variability of the measured construct. Overall, all variables and indicators listed in this table show validity and reliability that meet the requirements for further analysis.

Table 2 Discriminant Validity Criteria

Heterotrait-monotrait ratio (HTMT)			
Variable	Online Learning	Student Motivation	Time Management
Online Learning			
Student Motivation	0.859		
Time Management	0.684	0.851	
Fornell-Larcker criterion			
Online Learning	0.799		
Student Motivation	0.687	0.835	
Time Management	0.560	0.681	0.803

Table 2 presents the results of the discriminant validity test applied using two approaches, namely Heterotrait-Monotrait Ratio (HTMT) and Fornell-Larcker Criterion. Based on the HTMT results, the values produced for all construct pairs indicate that discriminant validity is acceptable, because the HTMT values between Online Learning and Student Motivation are 0.859, between Student Motivation and Time Management are 0.851, and between Online Learning and Time Management are 0.684, all of which are below the recommended threshold of 0.90. This indicates that there are no problems with the discrimination between the constructs tested in the model.

Discriminant validity using the Fornell-Larcker Criterion root of the Average Variance Extracted (AVE) value for each construct is greater than the correlation between constructs. Thus, it can be concluded that the constructs in this model have good discriminant validity, because each construct explains its own indicators more than the indicators of other constructs in the model. Overall, the results of this discriminant validity test show that the constructs used in this research model have adequate discrimination, which supports the validity of the measurements and the relationships between variables in the research model.

Hypothesis testing and 95% confidence intervals for path coefficient parameter estimates include the direct influence between variables at the structural level. This direct effect can be measured using the **f²** (square) measure, with values interpreted as 0.02 (low), 0.15 (medium), and 0.35 (high)(Hair Jr. et al., 2017) . Meanwhile, for the mediation effect, the statistical measure used is the Upsilon V value, which is calculated by squaring the mediation coefficient, as proposed by Lachowicz et al.(2018) with categories of low (0.02), moderate (0.075), and high (0.175) mediation effects.

The overall model evaluation consists of R Square with criteria (Chin, 1998) , namely 0.19 (low effect), 0.33 (moderate effect), and 0.66 (high effect), and Q²predict above 0 (Hair, Jr. et al., 2022) . The SRMR value is below 0.08, according to Schermelleh-Engel et al.,(2003) , with SRMR criteria between 0.08-0.10 considered an "acceptable fit" . The PLS Predict values indicated by RMSE and MAE in the PLS model are lower than those in the linear regression (LM) model, as explained by. (Sarstedt et al., 2019) .

Table 3 Direct and Indirect Effects

Variable	Path coefficient β	P value	Sig	f^2 Upsilon V	VIF	R-Squared	Q2 Square	SRMR
H_1 Online Learning -> Student Motivation	0.444	0.001	Yes	0.338	1.458	0.600	0.461	0.069
H_2 Online Learning -> Time Management	0.560	0.000	Yes	0.458	1.000	0.314	0.297	
H_3 Time Management -> Student Motivation	0.433	0.002	Yes	0.321	1.458	0.600	0.461	
H_4 Online Learning -> Time Management -> Student Motivation	0.242	0.005	Yes	0.168	0.021			

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Based on the analysis results, the SRMR value of 0.069 indicates that the model used fits well with the existing data. The SRMR value is below 0.08 ( ), according to Schermelleh-Engel et al. ((2003)), the SRMR criteria between 0.08-0.10 is considered an "acceptable fit".

The results of the H_1analysis show that online learning has a significant direct effect on student motivation with a path coefficient of 0.444. The very low p-value (0.001) confirms that this relationship is statistically significant. The effect of online learning on student motivation is measured by an f^2 value of 0.338, which indicates a moderate effect. With an R^2 of 0.600, this model is able to explain about 60% of the variation in student motivation influenced by online learning.

The results of the H_2analysis , online learning is also proven to have a significant direct effect on time management with a path coefficient of 0.560. A very small p-value (0.000) confirms that this relationship has very strong statistical significance. The f^2 value of 0.458 indicates that the effect of online learning on students' time management skills is a large effect. Although R^2 of 0.314 indicates that this model can only explain 31.4% of the variation in time management, the Q^2 value of 0.297 indicates moderate predictive power, which means that this model is still relevant in predicting the effect of online learning on time management.

The results of the H_3analysis of time management, as a mediating variable, show a significant direct effect on student motivation with a path coefficient of 0.433. The recorded p-value of 0.002 indicates statistical significance in this relationship. The f^2 value of 0.321 indicates that the effect of time management on student motivation is classified as a moderate effect. With an R^2 of 0.600, this model is able to explain 60% of the variation in student motivation influenced by their time management skills. Q^2, which reached 0.461, shows that this model has good predictive ability, thus providing strong evidence of the importance of time management in increasing student motivation.

Hypothesis H_4 The analysis results show a significant indirect effect between online learning and student motivation through time management as a mediating variable. The path coefficient of 0.242 indicates that online learning has an impact on student motivation through improving their time management skills. The recorded p-value of 0.005 indicates that this indirect effect is also statistically significant. Although the f^2 value of 0.168 indicates that this effect is relatively small , the Upsilon V reaching 0.021 reinforces the finding that this indirect effect still makes an important contribution, albeit a small one.

Based on the analysis results, it can be concluded that online learning has a significant direct effect on student motivation and time management. Online learning not only has a direct impact

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on student motivation, but also through improving time management skills. Although the indirect effect is relatively small, its contribution remains important in shaping student motivation. Overall, this model shows good predictive ability with R^2 and Q^2 values indicating adequate fit, and shows that factors such as time management can mediate the relationship between online learning and student motivation.

3 DISCUSSION

The results of the analysis show that online learning has a significant effect on student motivation. Student motivation and engagement in higher education are very important, especially in the context of online learning. Research by Rahman et al (2021) shows that students' attitudes toward online learning have a significant effect on their level of motivation and engagement, which in turn leads to better learning outcomes (Bai et al., 2021). A positive attitude toward online learning can increase student motivation, strengthen active participation, and increase perseverance in attending lectures (Ferrer et al., 2022) .

The results of the study show that student motivation significantly increases their engagement with self-efficacy and self-monitoring as the main factors mediating this relationship. Strong self-efficacy increases students' confidence, while self-monitoring helps them stay focused, which ultimately increases engagement and academic performance in online learning (Alemayehu & Chen, 2023). A good online learning design can increase student motivation to actively participate and achieve better results (Delıta et al., 2022). Research by Kang & Zhang (2023) shows that the use of online forums can encourage active interaction among students, increase their participation in discussions, and strengthen their motivation to learn, which has a positive impact on academic performance.

Online learning also has a significant influence on students' time management. This relationship shows strong statistical significance. An important aspect to consider is the effectiveness of time management strategies applied by students in the context of online learning. A study shows that an individual's ability to manage time is directly proportional to their success in online learning (Uçar & Ugurhan, 2023). Students who are more skilled at planning and managing their time tend to be more successful in completing tasks and achieving their academic goals (Men et al., 2023). This study also notes that online learning provides opportunities for students to explore various methods to improve their time management skills, including the use of digital tools and time management applications (Nguyen, 2023).

However, it is important to note that although this model shows a strong influence, it can only explain part of the variation in student time management. This suggests that there are other variables that also contribute to this variation, such as psychological support from teachers and peers, which are essential for creating an effective learning environment (Nguyen, 2023). In addition, students' self-discipline in online learning is an important indicator that influences their learning outcomes and time management. One positive aspect of online learning is greater flexibility in scheduling. Students can more easily adjust their schedules to their academic activities, as noted in a study by Soubra et al (2022) which found that flexibility in online learning allows students to manage their academic and personal responsibilities more effectively.

This flexibility is also associated with increased interaction and participation (Mudau et al., 2022). However, this increased flexibility can also be a double-edged sword. A study by Luong and Kim (2021) highlights the importance of trust for teachers in adapting to online learning, which in turn affects how students manage their study time. Students who are not skilled in time management often find it difficult to balance academic demands and their personal lives, as revealed by Henry, who highlighted students' experiences in managing their study time.

According to research by Becker et al. (2022) students engaged in learning are required to develop time management skills in order to adapt to this situation. However, challenges in using technology and personal motivation can also affect the effectiveness of online learning, as highlighted in research by Ahmmed et al (2022) which emphasizes the importance of training to overcome difficulties in online teaching.

Furthermore, independent learning strategies, which are an important component of online learning, play a major role in students' time management. Students who are able to manage their time and study independently will be more successful in an online environment. Research by Mahmud and German (2021) shows that students in Indonesia have experienced significant changes in how they manage the process of seeking knowledge through online learning. This indicates the need for an approach that focuses more on developing students' ability to learn independently in an online environment, with support from instructors who understand the importance of guidance and interaction (Nguyen, 2023).

The results of the study show that online learning has been proven to have a positive and significant influence on students' time management, but there are still several other factors at play. Awareness of the importance of time management skills, support from the academic community, and effective use of technology are key components that can assist in the online learning process (Chen et al., 2023; Riaz et al., 2023).

Online learning has drastically changed the way students and teachers interact, especially in the context of higher education. The significant impact of online learning is related to student motivation, which can be better understood through the role of time management as a mediating variable. In other words, students' ability to manage their time during online learning can be a trigger that affects their motivation to learn. Adequate instructional support, including in terms of time management, can help increase student motivation to learn. When students have good time management skills, they tend to be more capable of actively participating, finding meaning in the material being taught, and overcoming distractions that arise during the learning process (Jr., 2025).

4 CONCLUSION

Online learning has been shown to have a significant influence on student motivation and time management, as well as influencing motivation through time management as a mediating variable. Online learning shows a moderate effect on student motivation and a large effect on time management. Time management, as a mediator, also has a significant effect on student motivation, with the model explaining most of the variation in both. Although the indirect effect between online learning and motivation through time management is relatively small, it is still statistically significant. These findings underscore the importance of online learning and time management skills in increasing student motivation.

REFERENCES

Ahmmed, S., Saha, J., & Tamal, M. A. (2022). Effectiveness of Need-Based Teacher’s Training Program to Enhance Online Teaching Quality. *Education Research International*, *2022*, 1–13. https://doi.org/10.1155/2022/4118267

Alemayehu, L., & Chen, H.-L. (2023). The influence of motivation on learning engagement: the mediating role of learning self-efficacy and self-monitoring in online learning environments. *Interactive Learning Environments*, *31*(7), 4605–4618. https://doi.org/10.1080/10494820.2021.1977962

Bai, S., Hew, K. F., Sailer, M., & Jia, C. (2021). From top to bottom: How positions on different types of leaderboard may affect fully online student learning performance, intrinsic motivation, and course engagement. *Computers & Education*, *173*, 104297. https://doi.org/10.1016/j.compedu.2021.104297

Bakali Tahiri, M. J., & Mouratidis, A. A. (2024). Learning strategies and procrastination as a function of need satisfaction and autonomous motivation: A diary study. *European Journal of Education*, *59*(3). https://doi.org/10.1111/ejed.12645

Becker, T. B., Fenton, J. I., Nikolai, M., Comstock, S. S., Swada, J. G., Weatherspoon, L., & Tucker, R. M. (2022). The Impact of COVID-19 on Student Learning During the Transition From Remote to in-Person Learning: Using Mind Mapping to Identify and Address Faculty Concerns. *Ajp Advances in Physiology Education*, *46*(4), 742–751. https://doi.org/10.1152/advan.00079.2022

Britton, B. K., & Tesser, A. (1991). Effects of Time-Management Practices on College Grades. *Journal of Educational Psychology*, *83*(3), 405–410. https://doi.org/10.1037/0022-0663.83.3.405

Chen, C., Su, S., Lin, Y.-Z., & Sun, C. (2023). The Effect of Time Management and Help-Seeking in Self-Regulation-Based Computational Thinking Learning in Taiwanese Primary School Students. *Sustainability*, *15*(16), 12494. https://doi.org/10.3390/su151612494

Chin, W. W. (1998). Issues and opinion on structural equation modeling. *MIS Quarterly: Management Information Systems*, *22*(1).

Creswell, J. W., & Creswell, J. D. (2017). *Research design: Qualitative, quantitative, and mixed methods approaches*. Sage publications.

Delıta, F., Berutu, N., & Nofrıon, N. (2022). Online learning: The effects of using e-modules on self-efficacy, motivation and learning outcomes. *Turkish Online Journal of Distance Education*, *23*(4), 93–107.

Ferrer, J., Ringer, A., Saville, K., A Parris, M., & Kashi, K. (2022). Students' motivation and engagement in higher education: The importance of attitude to online learning. *Higher Education*, *83*(2), 317–338.

Hair, Jr., J. F., M. Hult, G. T., M. Ringle, C., Sarstedt, & Marko. (2022). A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM) [3 ed]. In *Sage Publishing* (Vol. 3, Issue 1).

Hair Jr., J. F., Matthews, L. M., Matthews, R. L., & Sarstedt, M. (2017). PLS-SEM or CB-SEM: updated guidelines on which method to use. *International Journal of Multivariate Data Analysis*, *1*(2), 107. https://doi.org/10.1504/ijmda.2017.10008574

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8

Heo, H., Bonk, C. J., & Doo, M. Y. (2021). Enhancing learning engagement during COVID-19 pandemic: Self-efficacy in time management, technology use, and online learning environments. *Journal of Computer Assisted Learning*, *37*(6), 1640–1652. https://doi.org/10.1111/jcal.12603

Jr., L. R. (2025). Exploring Determinants of Online Learning Acceptance: The Role of Readiness, Peer Support, and Instructional Support. *The Electronic Journal of E-Learning*, *23*(2), 130–142. https://doi.org/10.34190/ejel.23.2.4048

Kang, X., & Zhang, W. (2023). An experimental case study on forum-based online teaching to improve student's engagement and motivation in higher education. *Interactive Learning Environments*, *31*(2), 1029–1040. https://doi.org/10.1080/10494820.2020.1817758

Khosla, I. (2021). Book Review: Social Research Methods: Qualitative and Quantitative Approaches. *Frontiers in Psychology*, *12*(May), 1–2. https://doi.org/10.3389/fpsyg.2021.696828

Kurniawan, D., Masitoh, S., Bachri, B. S., Wahyuningsih, T., Mulawarman, W. G., & Vebibina, A. (2024). Evaluation of Digital Project Based Blended Learning Model to Improve Students' Critical Thinking and Problem Solving Skills. *Journal of Ecohumanism*, *3*(8). https://doi.org/10.62754/joe.v3i8.4847

Kwala, A. F., Nat, M., & Oluwajana, D. I. (2024). Optimizing academic productivity: examination of the self-determination theory's application in mitigation of cyberslacking behavior. *Journal of Computers in Education*. https://doi.org/10.1007/s40692-024-00339-6

Lachowicz, M. J., Preacher, K. J., & Kelley, K. (2018). A novel measure of effect size for mediation analysis. *Psychological Methods*, *23*(2), 244–261. https://doi.org/10.1037/met0000165

Luong, T.-T., & Kim, E. (2021). A Constructivism-Based Training Course for Hospitality and Tourism Instructors in Vietnam to Improve Their Self-Confidence in Synchronous Online Teaching. *Interactive Technology and Smart Education*, *19*(3), 360–389. https://doi.org/10.1108/itse-04-2021-0070

Macan, T. H., Shahani, C., Dipboye, R. L., & Phillips, A. P. (1990). College students' time management: Correlations with academic performance and stress. *Journal of Educational Psychology*, *82*(4), 760–768. https://doi.org/10.1037/0022-0663.82.4.760

Mahmud, Y. S., & German, E. (2021). Online Self-Regulated Learning Strategies Amid a Global Pandemic: Insights From Indonesian University Students. *Malaysian Journal of Learning and Instruction*, *18*(2), 45–68. https://doi.org/10.32890/mjli2021.18.2.2

Men, Q., Gimbert, B., & Cristol, D. (2023). The Effect of Self-Regulated Learning in Online

Professional Training. *International Journal of Mobile and Blended Learning*, *15*(2), 1–17. https://doi.org/10.4018/ijmbl.318225

Moore, W., & Hammond, L. (2011). Using education assistants to help pave the road to literacy: Supporting oral language, letter-sound knowledge and phonemic awareness in the pre-primary year. *Australian Journal of Learning Difficulties*, *16*(2), 85–110. https://doi.org/10.1080/19404151003763029

Mudau, T. S., Tshivhase, L., & Randa, M. B. (2022). Health Course Lecturers Managing Online Teaching in a Historically Disadvantaged University in South Africa: The Raging Waves. *Journal of Culture and Values in Education*, *5*(1), 195–210. https://doi.org/10.46303/jcve.2022.14

Nguyen, H. B. (2023). PERCEIVED SUPPORT FROM INSTRUCTOR &Amp; PEERS AND STUDENTS' SELF-REGULATED LEARNING DURING TEMPORARY ONLINE PIVOTED LEARNING. *Turkish Online Journal of Distance Education*, *24*(3), 192–208. https://doi.org/10.17718/tojde.1140242

Rahman, M. H. A., Uddin, M. S., & Dey, A. (2021). Investigating the mediating role of online learning motivation in the COVID-19 pandemic situation in Bangladesh. *Journal of Computer Assisted Learning*, *37*(6), 1513–1527. https://doi.org/10.1111/jcal.12535

Riaz, F., Mahmood, S. E., Begum, T., Ahmad, M. T., Alshaikh, A. A., Ahmad, A., Shati, A. A., & Khan, M. S. (2023). Students' Preferences and Perceptions Regarding Online Versus Offline Teaching and Learning Post-Covid-19 Lockdown. *Sustainability*, *15*(3), 2362. https://doi.org/10.3390/su15032362

Sarstedt, M., Hair, J. F., Cheah, J. H., Becker, J. M., & Ringle, C. M. (2019). How to specify, estimate, and validate higher-order constructs in PLS-SEM. *Australasian Marketing Journal*, *27*(3), 197–211. https://doi.org/10.1016/j.ausmj.2019.05.003

Schermelleh-Engel, K., Moosbrugger, H., & Müller, H. (2003). Evaluating the fit of structural equation models: Tests of significance and descriptive goodness-of-fit measures. *MPR-Online*, *8*(2), 23–74.

Schlimbach, R., Lange, T. C., & Robra-Bissantz, S. (2023). A Longitudinal Study on Boosting Students' Performance with a Learning Companion. *International Conference on Information Systems, ICIS 2023: "Rising like a Phoenix: Emerging from the Pandemic and Reshaping Human Endeavors with Digital Technologies."* https://www.scopus.com/inward/record.uri?eid=2-s2.0-85192530751&partnerID=40&md5=61791ff2103cdd7acc5bf95953c4ba91

Shabnam Ara, S. J., & Tanuja, R. (2023). Investigating the Influential Factors of Learner Performance in Online Education using Learning Analytics Approach. *2023 3rd International Conference on Intelligent Technologies (CONIT)*, 1–11. https://doi.org/10.1109/CONIT59222.2023.10205849

Soubra, L., Al-Ghouti, M. A., Abu-Dieyeh, M. H., Crovella, S., & Abou-Saleh, H. (2022). Impacts on Student Learning and Skills and Implementation Challenges of Two Student-Centered Learning Methods Applied in Online Education. *Sustainability*, *14*(15), 9625. https://doi.org/10.3390/su14159625

Sun, S. H., Sun, H. L., Zhu, Y. C., Huang, L. chi, & Hsieh, Y. L. (2011). Concurrent validity of Preschooler Gross Motor Quality Scale with Test of Gross Motor Development-2. *Research in Developmental Disabilities*, *32*(3), 1163–1168. https://doi.org/10.1016/j.ridd.2011.01.007

Uçar, H., & Ugurhan, Y. Z. C. (2023). The Role of E-Learning Readiness on Self-Regulation in Open and Distance Learning. *Turkish Online Journal of Distance Education*, *24*(4), 146–159. https://doi.org/10.17718/tojde.1231705