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The Impact of Online Learning Preferences and Challenges on Learning Effectiveness and Outcomes in Biology Education Students: Using SMART PLS-SEM

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Abstract

This study aims to analyse the impact of learning preferences and challenges of online learning on the effectiveness and learning outcomes of Biology Education students using Partial Least Squares - Structural Equation Modeling (PLS-SEM). Data were collected through an online survey using a Likert-scale questionnaire from 76 fifth-semester students who had participated in online learning for at least five semesters. The research variables included online learning preferences (PD), online learning challenges (TD), online learning effectiveness (ED), and learning outcomes (HD). The results of the analysis showed that online learning preferences and challenges had a significant effect on online learning effectiveness, while online learning effectiveness did not directly affect learning outcomes. Online learning preferences had a significant impact on learning outcomes, but challenges did not show a direct effect on learning outcomes. These findings indicate the importance of strengthening interactive online learning strategies, technical support, and developing motivation to optimise student learning outcomes. The implications of this study include the development of flexible curricula, providing training for lecturers, and integrating appropriate learning technology to create a more effective and inclusive learning experience in the future.

Keywords: Online learning, PLS-SEM, learning effectiveness, learning outcomes, Biology Education

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INTRODUCTION

Modern learning emphasises student-centred learning. This approach aims to increase student involvement in the learning process so that they can develop better critical thinking skills and creativity (Hilda et al., 2020). This learning system also integrates technology and interactive methods, allowing students to learn collaboratively and gain practical experience relevant to the real world. Thus, modern learning not only focuses on mastering the material but also equips students with the skills needed to face future challenges.

After the COVID-19 pandemic, the development of digital information is increasingly used in learning. (Sá & Serpa, 2020). By utilising digital platforms, educators can create a more flexible and adaptive learning environment, allowing students to access educational resources anytime and anywhere. (Alshammary & Alhalafawy, 2023). This system also encourages students to become independent learners who can explore their interests and develop knowledge proactively. The use of this technology not only increases student engagement but also facilitates more dynamic interactions between educators and learners, creating a deeper and more meaningful learning experience (Yehya, 2020). This is becoming increasingly important in the era of globalisation, where the ability to adapt quickly to change and utilise information technology will greatly determine individual success in various fields.

Online learning is increasingly being implemented in university-level learning (Munna & Mazumdar, 2021). With various platforms available, students can now attend lectures from the best lecturers around the world and collaborate with their peers without geographical limitations (Liu et al., 2020). This experience not only broadens academic horizons but also equips students with the skills needed to compete in an increasingly competitive global job market. Active engagement in online learning also encourages students to become more independent and proactive in managing their time and resources, which are essential skills in the professional world (Liu et al., 2020). Being actively involved in online education fosters a sense of community among learners and motivates them to take greater responsibility and initiative in managing their time and resources, which are important skills valued in today's competitive job landscape.

Online learning has become an educational solution during the COVID-19 pandemic, but it brings challenges for students (Simamora, 2020). Some positive impacts include increasing language literacy skills and mastery of information technology (Elberkawi et al., 2021). However, students also experienced confusion, passivity, stress, and technical difficulties such as limited internet connection. The learning media preferred by students included WhatsApp and Google Classroom, with a preference for semi-two-way communication. Despite the challenges, the majority of students rated online learning positively, considering it very good in terms of the learning process. Despite the many challenges that can arise in education, it is remarkable that a large number of students usually perceive their online learning experience positively, as they often find it useful and effective in various important aspects of their overall educational journey.

Now that the pandemic is over, it has left a positive impact on education, namely online learning. Students are faced with the challenge of transitioning back to face-to-face learning, which requires adjustments and adaptations to traditional teaching methods. This process will not only test their ability to adapt but also provide an opportunity to apply the skills they have learned during online learning. Online learning is enjoyable and can increase engagement for some students, while others may find it difficult to switch back to a more conventional face-to-face format.

Based on this, it is necessary to measure the relevance of online learning and evaluate its effectiveness in supporting long-term educational goals. Further research can help identify the best methods to integrate both learning formats, thereby creating a more holistic and inclusive learning experience for all students. The development of a flexible and responsive curriculum to student needs is key to achieving this goal, ensuring that each individual can learn in the way that suits them best. Student engagement in the learning process can be enhanced through the use of innovative technologies, such as interactive platforms and online collaboration tools, which allow them to participate and share knowledge with their peers actively.

METHODS

This research is explanatory quantitative research that aims to test the causal relationship between latent variables through the SEM-PLS approach. SEM-PLS was chosen because the research model involves many indicators and latent variables. The data is non-parametric, assuming a non-normal distribution or a relatively small sample size. The population of the study was students who took online learning in the biology education study program at Sultan Ageng Tirtayasa University. The sample was determined using the non-probability sampling technique with the purposive sampling method, namely 5th-semester students who had taken online learning for at least 5 semesters, totalling 76 students. Data collection used the Survey method by distributing Questionnaires online using the Google Forms platform. The questionnaire was distributed to all 5th-semester biology education students consisting of 3 classes. This study uses latent variables measured by indicators as Exogenous Variables of online learning preferences (PD) and Online learning challenges (TD), Mediating Variables, namely the effectiveness of online learning (ED), Endogenous Variables, namely the impact of online learning on learning outcomes (DD).

The hypotheses proposed consist of:

H1: Online learning challenges have a positive effect on student learning outcomes.
H2: The effectiveness of online learning has a positive effect on student learning outcomes.
H3: Online learning preferences have a positive effect on student learning outcomes.
H4: Online learning challenges have a positive effect on the effectiveness of online learning.
H5: Online learning preferences have a positive effect on the effectiveness of online learning.

The instrument used was a questionnaire with a measurement using a Likert scale of 1-5 used to measure each variable indicator. Statements were designed based on the dimensions and indicators of each variable. Before data collection, the instrument was tested through content validity involving experts using the confirmatory factor analysis (CFA) reliability test, which measured Cronbach's alpha and composite reliability.

Data analysis techniques This study uses Smart PLS version 4.1.0.9, a statistical tool for testing data through PLS-SEM. The reason for choosing this analysis approach is based on data/sample features and moderation and mediation analysis. Data Analysis Techniques Using SEM-PLS include three stages, namely:

Measurement Model (Outer Model)

Evaluating the relationship between latent variables and their indicators. Testing includes Convergent Validity, which is seen from the outer value loading (≥ 0.7) and Average Variance Extracted (AVE) (≥ 0.5)—discriminant Validity Using Fornell-Larcker values Criterion. Construct Reliability Using Composite Values Reliability (≥ 0.7) and Cronbach's Alpha (≥ 0.6).

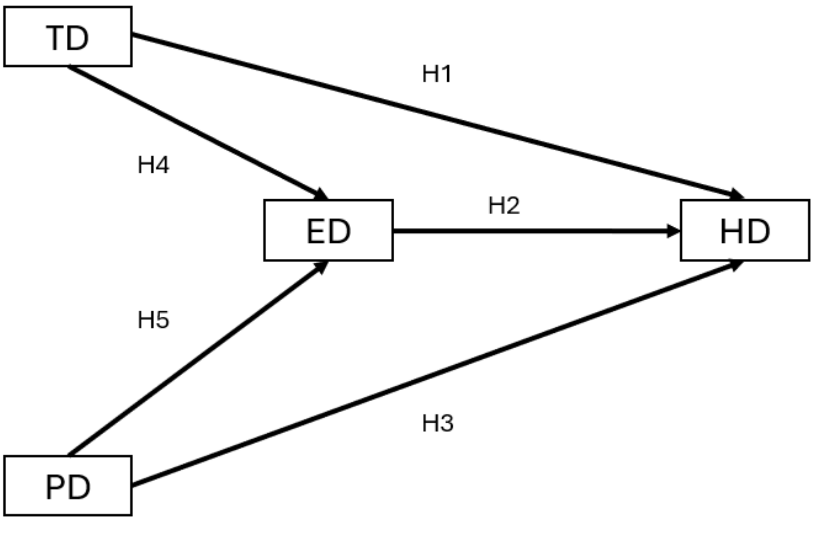

Figure 1. Research design

Table 1. Research Latent Variables

Variables	Information	Indicator
Effectiveness of Online Learning (ED)	The level of success of learning activities carried out online in achieving the learning objectives that have been set	1. Ease of access to materials 2. Learning independence 3. Learning interactions 4. Understanding the material 5. Effectiveness in completing tasks
Preferences for Online Learning (PD)	student tendencies toward online learning methods	1. Flexibility of Time and Place 2. Convenience in online learning 3. Independence in online learning 4. Learning Effectiveness 5. Motivated by online learning
Challenges in Online Learning (TD)	various obstacles or constraints faced by students during online learning	1. Technology Availability and Stability 2. Effectiveness of Interaction and Communication 3. Time Management and Self Discipline 4. Motivation and Concentration in Learning 5. Learning Environment Support
Impact of Online Learning on Learning Outcomes (HD)	the influence of online learning on students' achievement of academic competence.	1. Understanding the Concept of Material 2. Quality of Academic Assignments 3. Practical Skills Mastery 4. Learning Independence 5. Academic Achievement

Structural Model (Inner Model)

Evaluating the relationship between latent variables. Testing includes Path Coefficients (Path Coefficients), which show the strength of the relationship between latent variables. R- Square (R^2): Shows the predictive ability of the model (≥ 0.25 = weak, ≥ 0.5 = moderate, ≥ 0.75 = strong). Effect Size (f^2): Measures the influence of each exogenous variable on the endogenous (≥ 0.02 = small, ≥ 0.15 = medium, ≥ 0.35 = large). Predictive Relevance (Q^2): Using the Stone-Geisser technique to check the predictive ability of the model ($Q^2 > 0$ = predictive model).

Hypothesis Testing

Using t-statistic and p-value to test the significance of the relationship ($t > 1.96$ or $p < 0.05$). Testing is done using the *bootstrapping method* in SmartPLS.

RESULTS & DISCUSSION

Measurement Model (Outer Model)

Evaluation of the measurement model is carried out to ensure that the research instrument meets the validity and reliability criteria. *Convergent Validity* is a way to measure how well a measurement instrument correlates with other instruments that are expected to have the same relationship so that it can provide evidence that the measuring instrument is valid. Based on the results of *the outer loading,* most indicators have values above 0.7. For example, indicators ED4 (0.865), ED5 (0.782), TD1 (0.808), TD2 (0.823), and TD3 (0.782). These values indicate that the indicators are valid in measuring the intended latent variables (Hair et al., 2021). Several indicators, such as HD2 (0.643) and PD2 (0.688), have *outer values loading* below 0.7 but are still acceptable because they are close to the threshold (Chin, 2010). The AVE value for all variables also exceeds 0.5, namely ED (0.680), HD (0.535), PD (0.517), and TD (0.647), which indicates that more than 50% of the indicator variance can be explained by the construct (Fornell & Larcker, 1981). Thus, the results of this analysis confirm that the measurement model used in this study has good validity and can be relied on to represent the latent variables studied.

Discriminant Validity is an important aspect of model evaluation, ensuring that different constructs can be significantly distinguished from each other. The results of the Fornell-Larcker and HTMT analyses showed that all variables met the discriminant criteria. The correlation values between latent variables were lower than the square root of the AVE of each variable, indicating a significant difference between the constructs (Henseller et al., 2015). HTMT for all pairs of variables, such as HD <-> ED (0.696) and TD <-> PD (0.709), are below the 0.85 limit, indicating that these variables have good discriminant validity.

Construct Reliability is a way to assess the internal consistency of the indicators used, which can be measured through Cronbach's value. Alpha and Composite Reliability. In the smartPLS application, construct reliability can be seen in Cronbach's value. Alpha and Composite: The resulting reliability must meet the minimum threshold of 0.7 to indicate that the measurement instrument has a high level of consistency in measuring these variables. *Composite Value Reliability* (Rho-c) for all variables met the criteria ≥ 0.7, with ED (0.809), HD (0.773), PD (0.843), and TD (0.846). *Cronbach's value Alpha* also showed good reliability, although the value for ED (0.533) was slightly below the standard. These results indicate that the instrument has good internal consistency (Nunnally & Bernstein, 1994).

Table 2. Measurement Model Results (outer model)

Measurement	Criteria	Results	Conclusion
Outer Loading	≥ 0.7	Most of the indicators meet the criteria, except HD2 (0.643) and PD2 (0.688).	Valid with the exception of some indicators.
AVE	≥ 0.5	ED = 0.680, HD = 0.535, PD = 0.517, TD = 0.647	Convergent validity is met.
Fornell Larcker	√AVE > Correlation between variables	All variables meet the discriminant criteria.	Discriminant validity is met.
Composite Reliability	≥ 0.7	ED = 0.809, HD = 0.773, PD = 0.843, TD = 0.846	construct.
Cronbach's Alpha	≥ 0.6	ED = 0.533, HD = 0.553, PD = 0.770, TD = 0.727	Reliable with the exception of ED.

Structural Model (Inner Model)

The evaluation of the structural model aims to assess the relationship between latent variables. The results of measuring the Path Coefficient (*Path Coefficient*) show that there is a significant relationship between PD and ED with a coefficient value of 0.329, a T- statistic of 2.642, and a p-value of 0.008. In addition, the relationship between TD and ED is also significant, with a coefficient value of 0.409, *a T- statistic of 3.689, and a p-value of 0.000. This shows that online learning preferences (PD) and online learning challenges (TD) have a significant influence on the effectiveness of online learning (ED). These results are consistent with* Mishra's research et al. (2020), which stated that support for online learning methods and efforts to overcome technical challenges can increase learning effectiveness.

The R^2 value for the ED variable is 0.424, indicating that the PD and TD variables are able to explain about 42.4% of the variance in ED. For the HD variable, the R^2 value is 0.303, meaning that the ED, PD, and TD variables are only able to explain 30.3% of the variance in HD. This value indicates a moderate predictive ability of the model (Cohen, 1988). These results emphasise the importance of considering other variables that may contribute to the variation in the HD variable. Therefore, further analysis is needed to identify additional factors that can improve the prediction model.

Effect analysis *size* shows that the influence of PD on ED has an f^2 value of 0.132 (moderate), while the influence of TD on ED is 0.203 (moderate). Other influences show *an effect of small or insignificant size.* These results indicate that PD and TD make a significant contribution to ED (Chin, 2010). These findings also indicate the need for more in-depth research to explore the interactions between these variables and how they influence each other in a broader context.

Table 3. Structural Model Results (inner model)

Connection	Path Coefficient	T- Statistic	P- Value	Conclusion
PD -> ED	0.329	2,642	0.008	Significant
TD -> ED	0.409	3,689	0.000	Significant
ED -> HD	0.050	0.336	0.737	Not significant
PD -> HD	0.366	2.285	0.022	Significant
TD -> HD	0.216	1,504	0.133	Not significant

These results indicate that the effectiveness of online learning is influenced by the preferences and challenges faced by students. However, this effectiveness does not always have a direct impact on learning outcomes. Therefore, the online learning approach must be supported by strategies that consider technical, pedagogical, and motivational aspects (Zhou et al., 2020; Bao, 2020). In addition, the development of critical thinking and communication skills needs to be strengthened through more interactive and participatory interventions.

Hypothesis Testing

Hypothesis testing aims to determine the significance of the relationship between latent variables in the structural model. This analysis is carried out using the *t-statistic* and *p-value values* generated through the *bootstrapping method* in SmartPLS. A relationship is declared significant if the *t-statistic* value is greater than 1.96 or *the p-values are* less than 0.05 at a 95% confidence level (Hair et al., 2021; Henseler et al., 2015). The following is an in-depth discussion of the results of the hypothesis test presented in the *path table: coefficients* and *total effects*.

Direct Influence

H1: The Effect of Online Learning Challenges on Learning Outcomes (TD -> HD)

The relationship between online learning challenges (TD) and learning outcomes (HD) is not significant, with a coefficient value of 0.216, a t-statistic of 1.504, and a p-value of 0.133. This shows that challenges in online learning do not directly affect student learning outcomes. Research by Martin et al. (2020) stated that the impact of challenges can be minimised through effective technical and pedagogical support. With this support, students can still achieve good learning outcomes despite facing obstacles in the online learning process. This support includes training in the use of technology, provision of adequate resources, and adaptive teaching approaches to increase student engagement. Thus, educational institutions must focus on developing comprehensive support programs to ensure that students can overcome these challenges and achieve their maximum academic potential.

H2: The Influence of Online Learning Effectiveness on Learning Outcomes (ED -> HD)

The relationship between the effectiveness of online learning (ED) and learning outcomes (HD) is not significant, with a coefficient value of 0.050, a *t-statistic* of 0.336, and a p-value of 0.737. These results indicate that the effectiveness of online learning does not directly affect student learning outcomes. This indicates that other factors, such as intrinsic motivation, instructor support, and independent learning strategies, play an important role in determining learning outcomes (Hodges et al., 2020; Bao, 2020). Another study by Sun and Chen (2016) stated that the success of online learning depends on a combination of pedagogical factors, technology, and students' learning readiness. Thus, it is important for educational institutions to not only focus on delivering materials online but also to create an environment that supports students' engagement and motivation in their learning process. This can be achieved through teacher training, providing adequate resources, and developing interactive and engaging curricula.

H3: The Influence of Online Learning Preferences on Learning Outcomes (PD -> HD)

Online learning preference (PD) has a positive and significant effect on learning outcomes (HD) with a coefficient value of 0.366, *a t-statistic of 2.285, and a* p-value of 0.022. This means that students with positive preferences for online learning tend to have better learning outcomes. This finding is in line with research by Alqurashi (2019), which shows that positive perceptions of the online learning environment contribute to increased understanding of material and academic outcomes. In addition, research by Richardson et al. (2017) also found that satisfaction with online learning is positively correlated with academic performance. The results of this study emphasise the importance of creating a supportive online learning environment where students feel engaged and motivated to learn effectively.

H4: The Influence of Online Learning Challenges on Online Learning Effectiveness (TD -> ED)

Online learning challenges (TD) also have a positive and significant effect on the effectiveness of online learning (ED), with a coefficient value of 0.409, *a t-statistic of 3.689, and a* p-value of 0.000. These results indicate that despite challenges such as technical constraints, limited interaction, and unstable internet access, learning effectiveness can remain high if these challenges are addressed properly. This finding is supported by Zhou's research et al. (2020), who underlined the importance of technological readiness and institutional support in overcoming barriers to online learning. Hodges et al.

(2020) also emphasised that innovative solutions such as synchronous and asynchronous learning can help mitigate these challenges. Thus, educational institutions need to develop effective strategies to support online learning, including training for teachers and providing adequate technical resources.

H5: The Influence of Online Learning Preferences on Online Learning Effectiveness (PD -> ED)

The results of the hypothesis test show that online learning preferences (PD) have a positive and significant influence on the effectiveness of online learning (ED), with a coefficient value of 0.329, *a t-statistic of 2.642, and a* p-value of 0.008. This means that the more positive the student's preference for online learning, the higher the perceived effectiveness of learning. These results are in line with research by Mishra et al. (2020), who found that positive attitudes towards online learning, such as convenience and flexibility, have an impact on increasing the effectiveness of the learning process. In addition, a study by Dhawan (2020) stated that technological support and appropriate teaching methods can strengthen this relationship. These findings highlight the importance of the role of teachers in creating a supportive learning environment, as well as the need to provide adequate technological infrastructure to enhance the online learning experience. Developing a curriculum that is responsive to student needs is also a key factor in increasing the effectiveness of online learning, as it can help create a more relevant and engaging learning experience.

Table 4. Hypothesis Test Results

Hypothesis	Path Coefficient	t-Statistics	p- Value	Conclusion
PD -> ED	0.329	2,642	0.008	Significant (Preferences affect learning effectiveness)
TD -> ED	0.409	3,689	0.000	Significant (Challenges affect learning effectiveness)
ED -> HD	0.050	0.336	0.737	Not significant (Effectiveness does not affect learning outcomes)
PD -> HD	0.366	2.285	0.022	Significant (Preferences affect learning outcomes)
TD -> HD	0.216	1,504	0.133	Not significant (Challenges do not affect learning outcomes)

Indirect Influence

The results of the indirect effect analysis showed that the relationship between PD -> ED -> HD and TD -> ED -> HD was not significant, with *p-values of* 0.788 and 0.734, respectively. This indicates that the effectiveness of online learning (ED) does not mediate the relationship between preferences (PD) or challenges (TD) with learning outcomes (HD). These results support Hodges' research et al. (2020), who emphasised the importance of other factors, such as motivation and instructional support, in influencing learning outcomes. This finding highlights the need for a more holistic approach in designing online learning strategies, taking into account other variables that may contribute to the success of the learning process.

Based on these findings, to increase the effectiveness of online learning, educational institutions must provide adequate technical support and training for instructors to overcome challenges in online learning (Dhawan, 2020; Zhou et al., 2020). Since the effectiveness of online learning does not always affect learning outcomes, interventions that increase student learning motivation and readiness are essential to achieving optimal academic outcomes (Hodges et al., 2020; Sun & Chen, 2016). It is important to explore various interactive and innovative methods that can be applied in online learning environments so that students feel more engaged and motivated during the learning process.

Positive preferences for online learning can be strengthened by implementing interactive and collaborative learning strategies, such as group discussions, inquiry-based projects, and technology-based activities (Alqurashi, 2019; Martin et al., 2020). One promising approach is the use of gamification, where game elements are applied in a learning context to increase student engagement and motivation. However, the use of gamification needs to be further studied for its effects on students. Because the level of thinking of students and students is clearly different, further research can help identify specific ways in which gamification can be tailored to meet the unique needs of students, as well as evaluate its impact on their learning outcomes and engagement in the educational process.

Discussion

This study aims to deliver information about preferences and challenges in online learning. Furthermore, it analyses its effect on learning effectiveness and learning outcomes of biology education students. Factors that enhance or hinder the online learning experience. So as to produce strategies that can improve learning outcomes, the results show that although online learning offers flexibility and accessibility, various technical and pedagogical challenges are still the main obstacles to improving student learning outcomes.

The analysis shows that preference for online learning (PD) has a positive and significant influence on the effectiveness of online learning (ED). This indicates that the higher the students' preference for online learning, the higher the supposed effectiveness of their learning process. Another factor is that challenges in online learning (TD) have a significant influence on learning effectiveness, which indicates that despite obstacles, students who are able to overcome these challenges can still experience effective learning. The follow-up to these findings is that the campus is obliged to provide adequate support. Based on this, students can not only overcome the challenges but also optimise their overall learning experience.

Another result is that online learning effectiveness (ED) does not have a significant impact on learning outcomes (HD). An appraisal of the methods and strategies used by lecturers in online learning needs to be done. This is to ensure that lecturers do not choose the wrong methods and strategies to help students achieve the best learning outcomes. This finding not only shows the effectiveness of online learning but also that other factors, such as intrinsic motivation, learning strategies, and instructional support, still play a significant role in determining students' academic success (Hodges et al., 2020). In other words, the effectiveness of online learning cannot directly improve learning outcomes without additional support. Campuses have a role to play in designing programs that focus on online delivery and the resources needed for students to thrive.

A stimulating conclusion from this research is that challenges in online learning do not have a direct influence on student learning outcomes. Rather, their performance is a factor swaying students' motivation and engagement in the learning process, making it important to identify effective ways to overcome these barriers. This shows that even though students face various barriers, such as technology and interaction limitations, they can still achieve good learning outcomes if supported by effective learning strategies (Martin et al., 2020). Based on this, an approach is needed that can generate a learning community that supports students in interacting with each other and sharing experiences to increase motivation in online learning. Therefore, educational institutions need to focus on providing adequate technical and pedagogical support to help students overcome these challenges.

Moreover, this study displays that online learning preferences have a significant influence on learning outcomes. Learning preferences are factors that can influence how students obtain and process information, so understanding these differences is key to producing student learning experiences (Lee et al., 2022). Further research is needed to explore how various factors, such as individual learning styles and social support, can contribute to creating an optimal learning environment for students (Miller & Zhang, 2024). Thus, a deeper understanding of these factors can help educators design curricula and teaching methods that better suit students' needs, thereby improving the overall effectiveness of online learning (Patel, 2023). It is confirmed that students who prefer online learning methods tend to have better academic achievement. Therefore, teachers need to design learning strategies that suit students' preferences to increase their engagement and motivation in the learning process.

CONCLUSION

The results showed that online learning preferences and challenges have a significant influence on the effectiveness of online learning, indicating the importance of these factors in creating an optimal learning experience. Students' preferences for online learning have also been shown to contribute to their learning outcomes directly, emphasising the need to develop learning approaches that are tailored to students' needs and comfort. However, the effectiveness of online learning does not directly affect learning outcomes, and the challenges of online learning do not show a significant relationship to learning outcomes. This indicates that in addition to the effectiveness of online learning, there are other factors, such as motivation, instructional support, and independent learning strategies, that play an important role in determining the achievement of learning outcomes. The practical implications of this study are that educational institutions should focus on strengthening innovative and collaborative online learning strategies, improving technical support, and motivating students to maximise their potential. Further research is needed to explore other variables that may mediate the relationship between online learning and learning outcomes so that a more holistic approach can be designed in the context of online education.

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