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Analyzing the Effectiveness of Online Learning Influenced by Platform Features in Improving Mastery of Educational Technology

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Abstract: The use of technology in education has become increasingly important, especially in this digital era. This study aims to identify effective strategies that can improve the effectiveness of online learning and mastery of educational technology. The methods used include the development of interactive and personalized features on educational platforms, the provision of high-quality content, regular training for teachers and students, and the implementation of blended learning models. In addition, responsive technical support and data-driven evaluation were implemented to ensure continuous improvement. The results showed that the combination of these approaches was able to increase student engagement, facilitate deeper learning, and improve academic outcomes. The findings suggest that policies that support the use of technology in education as well as clear standards and guidelines are needed to ensure the quality and consistency of online learning. The practical implications of this study provide guidance for educational institutions in designing and implementing effective and sustainable online learning programs.

Keywords: Online learning effectiveness, platform effectiveness, interactive features.

Introduction

Online learning features greatly influence learners' technology mastery ability, which leads to the effectiveness of online learning. Technology-based online learning platforms have supported and helped Indonesian learners succeed in online learning education amid the coronavirus pandemic, such as accessing learning materials, learning activities, and learning practices for free. Research to solve this problem has been conducted in the last five years, with a focus on online learning to improve mastery of educational technology.

Much research has been conducted to explore the effectiveness of online learning platforms. Some studies show that there is a positive relationship between online learning technology and learning effectiveness (Amin et al., 2022; Gu et al., 2012; Hongsuchon et al., 2022; Ma et al., 2017; Ratnasari et al., 2021; C.-H. Wang et al., 2013). Hence, the effectiveness of Moodle during the COVID-19 pandemic led to the adoption of online learning as an alternative solution at all levels of education (Ajani, 2021; Gamede et al., 2022). Furthermore, it is also known that e-learning features and user interest affect the improvement of mastery of technology (Ajani, 2021; Hoerunnisa et al., 2019). On the other hand, challenges such as student discipline and lack of internet access may hinder the effectiveness of online learning (Hermanto & Srimulyani, 2021).

The utilization of the Padlet platform as an online learning media during the COVID-19 pandemic has had a positive impact on increasing student activeness and skills in teaching and learning activities (Alghozi et al., 2021). Integration of technology in education through online learning can enhance students' learning experience by using traditional interaction methods (Abrami et al., 2011; Beldarrain, 2006), thus the need to provide access to education for people from remote and marginalized areas, as well as develop critical thinking and enhance students' capacities necessary for the 21st century (Shukla et al., 2020). The effectiveness of using the Edmodo online learning platform shows that online learning using Edmodo has been carried out effectively due to its practicality and accessibility to students (Halil, 2020).

Recent studies have concluded that technological advances have encouraged the use of learning management systems (LMS) to support online learning. The effectiveness of LMS in supporting online learning by analyzing LMS features through workflow testing (Duta et al., 2021; Y. Zhang et al., 2020). The findings show that current technology is quite effective in supporting education, especially online learning. Virtual Learning Platform (VLP) is also able to improve students' skills in designing and producing online virtual laboratories (OVLs) and is effective in improving students' knowledge and practical skills (Ahmed & Hasegawa, 2016, 2019).

The Covid-19 pandemic has brought significant changes to education, forcing a transition from face-to-face learning to online learning. Online learning is effective for students who have smooth internet access and adequate support facilities (Febrianto et al., 2020; Simamora et al., 2020). While platforms such as Madrasah E-Learning, Google Form, Google Meet, and WhatsApp are most favored by teachers due to their ease of use (Putri, 2022; Samsiya et al., 2022; Susanto et al., 2022). Meanwhile, technological characteristics have a significant influence on the acceptance and use of E-learning platforms, with features that support successful learning such as folder sharing and data synchronization functions (Nisa Miftachurohmah et al., 2024). Students' views on the effectiveness of the online learning platform, found that most students agreed the platform could provide significant benefits, such as ease of participating in online activities and challenges that motivate them to stay motivated and disciplined (Sari & Oktaviani, 2021). The role of facilitation conditions and user habits in the use of technology on Online Learning Platforms (OLPs) in Indonesia, emphasizes the importance of persistence and learning outcomes in online platforms to ensure their effectiveness (Ambarwati et al., 2020).

Online learning platforms such as Edmodo, LMS, OVL, OLP, E-Learning, Padlet, and others have proven effective in supporting online learning. However, there is still a gap in the understanding of how specific features of these platforms directly and indirectly influence the mastery of educational technology. This study will conduct a path analysis to identify the factors that influence the effectiveness of online learning through platform features and how they affect the mastery of educational technology. Research questions that need to be answered include: (1) What factors influence the effectiveness of online learning platform features in improving mastery of educational technology? (2) What are the direct and indirect effects of these features on mastery of technology? (3) Are the results of this study consistent with the results of previous studies, and what are the causes of the differences or similarities found? The factors identified in previous studies will be used as a reference to determine whether or not they are sufficient to declare a platform effective.

Research Methods

This study aims to analyze the effect of online learning platform features on mastery of educational technology. The research method used is quantitative, with the following steps:

1. Data Collection:
a. Data was collected through an online questionnaire using Google Forms.
b. Respondents consist of 49 teachers, lecturers, students, and college students who frequently use online learning platforms.
c. The questionnaire uses a Likert scale to measure respondents' opinions, behaviors, and perceptions towards the features of the online learning platform.
2. Questionnaire Design:
a. Questions focus on the technical features and content of the platform, as well as its benefits in improving mastery of learning technologies.
b. b. Variables measured include technical system quality, information quality, staff services, education quality, support systems, and learning systems.
3. Analysis Data:
a. a. Data were analyzed using SPSS version 29 for descriptive statistics and confirmatory factor analysis (CFA).
b. Path analysis was conducted with Smart-PLS version 3 to see the direct and indirect effects of platform features on online learning effectiveness and technology mastery.

4. Stages of Analysis:
a. Validity and Reliability Test: CFA is used to ensure that the instruments used are valid and reliable.
b. Path Analysis: Using Smart-PLS to identify factors that influence the effectiveness of online learning platforms and their impact on technology mastery.
5. Hypothesis Testing:
Using statistical tests to determine the significance of the effect of the independent variable on the dependent variable with a p-value <0.05.
6. Interpretation of Results:
a. a. Comparing the results of this research with previous research to see consistency and differences.
b. b. Identify key factors that influence the effectiveness of online learning platforms and provide recommendations for further development.

This research provides insights into how specific features of various online learning platforms influence educational technology mastery, both directly and indirectly.

Result and Discussion

The research data from the questionnaires distributed were then calculated and analyzed so that the following data results were obtained:

Table 1. Survey result data of online learning platform factors

No	Feature Platform	Point Skala Likert				
		1	2	3	4	5
1	Perceived benefits of online learning platform	6,1%	8,2%	20,4%	34,7%	30,6%
2	Learner Quality Online learning platform	2%	16,3%	28,6%	30,6%	22,4%
3	Quality of Support System Online learning platform	2%	18,4%	28,6%	32,7%	18,4%
4	Quality of Education System Online learning platform	6,2%	14,3%	30,6%	30,6%	18,4%
5	Service Quality of online learning platform staff or technicians	4,1%	14,3%	40,8%	26,5%	14,3%
6	Information Quality The online learning platform you have used	2%	14,3%	34,7%	26,5%	22,4%
7	Technical System Quality The online learning platform you have used	10,2%	10,2%	32,7%	28,6%	18,4%
8	Are features available in the online learning platform fulfill your learning needs?	10,2%	8,2%	32,7%	30,6%	18,4%
9	Its useful features in the online learning platform you use	6,1%	14,3%	30,6%	28,6%	20,4%

The survey gathered respondents' opinions on various features and aspects of the online learning platforms they use, rated on a Likert scale from 1 (strongly disagree) to 5 (strongly agree). A total of 65.3% of respondents gave scores of 4 and 5 for the perceived usefulness of the online learning platform, indicating the majority found the platform useful, while only 6.1% gave a score of 1. For learner quality, 53% gave scores of 4 and 5, indicating fairly high quality, but 18.3% gave scores of 1 and 2, indicating there is room for improvement. The quality of the support system was rated good by 51.1% of respondents with scores of 4 and 5, but 20.4% gave scores of 1 and 2, indicating weaknesses in the support system. The quality of the education system was also rated fairly high by 49% of respondents with scores of 4 and 5, while 20.5% of respondents indicated dissatisfaction. Online staff or technician services received a score of 3 from 40.8% of respondents, indicating adequate service but need for improvement, and 18.4% gave scores of 4 and 5. Information quality was rated good by 49% of respondents with scores of 4 and 5, but 16.3% indicated dissatisfaction. The quality of the technical system was rated as good by

47% of respondents with scores of 4 and 5, while 20.4% indicated technical problems that need improvement. The features in the online learning platform fulfill the needs of 49% of respondents with scores of 4 and 5, but 18.4% feel unfulfilled. The usefulness of the features was rated as moderately useful by 49% of respondents with scores of 4 and 5, while 20.4% found it less useful. From this data, it can be concluded that the majority of respondents are satisfied with various aspects of the online learning platform, but there are some areas that need improvement, especially in the quality of staff service and technical system.

Table 2: Percentage of technology mastery

No	Technology mastery	Point Scale Likert				
		1	2	3	4	5
1	How important is it for you to continue developing your technology skills	10,2%	0	16,3%	26,5%	46,9%
2	How much will mastering technology improve your chances in your future career or education?	4,1	14,3%	20,4%	28,6%	32,7%
3	How often do you attend training or courses to improve your technology skills?	12,2%	10,2%	38,8%	18,4%	20,4%
4	How much is your motivation to learn new technology influenced by your ability to use current technology?	8,2%	6,15%	26,5%	18,4%	40,8%

Table 2 explains that the content of the online learning platform with a Likert scale shows that the scale is very good with point 5 of 46.9% on the content that online learning is very important to develop user skills. The lowest is 20.4% that the training will improve the user's technological skills because based on the literature 60% of the training results will be the skills of the training alumni. Technology Skills Development is 46.9%. Most respondents consider it important to continue developing their technological skills. Career and Education Opportunities 32.7%. Mastery of technology is seen by many respondents as important in improving their career or educational opportunities. Training and Courses 20.4%. Respondents had varying frequencies of attending training or courses, with many attending moderately. Motivation to Learn New Technology 40.8%. Motivation to learn new technologies is strongly influenced by their current capabilities, according to the majority of respondents.

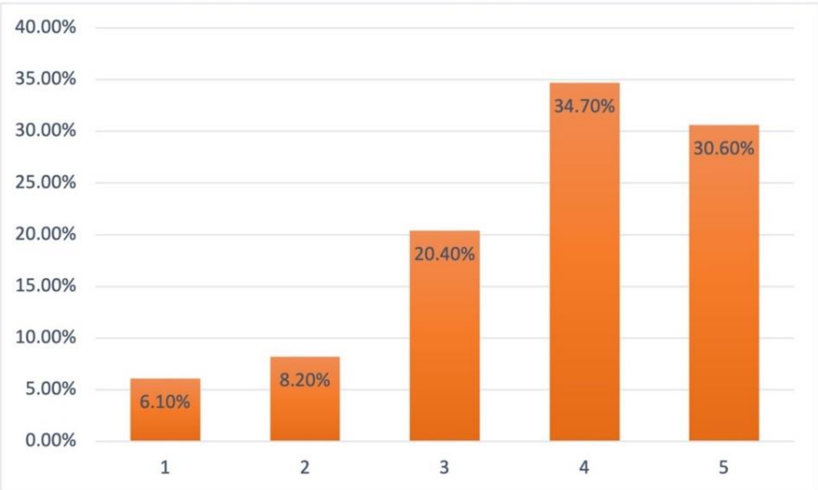

Figure 1. Graph of the benefits or effectiveness of online learning platforms

The results show that technology characteristics have a significant influence on the acceptance and use of E-learning platforms. Appropriate technological features that can support successful learning, such as folder sharing and data synchronization functions, as well as the ability to access files/information across different devices and across operating systems, provide a better understanding of the factors that influence technology acceptance and learning effectiveness in the context of using E-learning platforms. The contribution of this research is to provide a better understanding of the factors affecting E-learning effectiveness and provide suggestions for the development of a better E-learning platform.

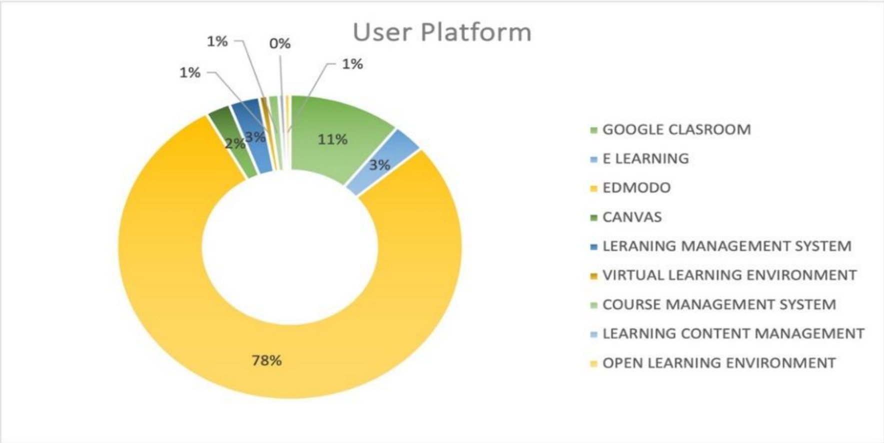

Figure 2: Percentage of online learning platform usage

Google Classroom (78%), This platform is used by a large majority of users, demonstrating the popularity and reliability of Google Classroom as an online learning tool. Ease of use, integration with other Google services, and features that support collaboration may be the main factors that make this platform so desirable. E-Learning (11%) is the second most used platform. This platform may offer a variety of easily accessible courses and materials, as well as flexibility in the learning process. Edmodo (3%) is used by a small percentage of users. This platform is known for its social features that support interaction between students and teachers. Canvas (1%) has a small proportion of users. This shows that although Canvas is a powerful platform with many learning features, it is not as popular as Google Classroom or E-Learning in the context of this survey. Learning Management System (1%) platform used by a small percentage of users. LMS is often used by educational institutions to manage courses, teaching materials, and student-teacher interaction. Virtual Learning Environment (1%) is also used by a minority of users. VLE provides a learning environment that allows interaction and collaboration in a virtual space. Course Management System (1%) has few users, similar to LMS and VLE. CMS helps in organizing and managing courses and learning content. Learning Content Management (1%) is a platform used by a small number of users, which focuses on managing learning content. Open Learning Environment (1%) is a platform used by a small percentage of users. OLE provides flexibility and open access to learning resources. The large majority of users use Google Classroom, showing the dominance of this platform in the world of online learning. E-Learning is also quite popular but with a much smaller percentage than Google Classroom. The use of other platforms such as Edmodo, Canvas, LMS, VLE, CMS, LCM, and OLE shows that although there is a strong preference for certain platforms, some users choose other alternatives that may better suit their specific needs. Furthermore, testing the value of KMO and Bartlett's test aims to see the overall variable relationship without considering other variables. The assumption of this test is that the MSA value must be> 0.5 and the significant value <0.05.

Table 5. KMO and Bartlett's test result values

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.897
Bartlett's Test of Sphericity	Approx. Chi-Square	399.424
	df	36
	Sig.	<.001

The test results in Table 5 show the MSA value of 0.897 and the significant value is 0.001 in theory the data and variables used have met the requirements in factor analysis. Table 6 commonalities test results also meet the requirements of all variables with a value of> 0.5, all of which means that all suspected factors have become factors that can explain the effectiveness of learning platforms that can improve mastery of the technology that uses them. The data assumption requirements have all been met so that it can be carried out to the next stage in factor analysis.

Table 6 Communalities test results

	Initial	Extraction
Kualitas Sistem Teknis	1.000	.700
Kualitas informasi	1.000	.806
Kualitas Pelayanan Staff	1.000	.868
Kualitas Mutu Sistem Pend.	1.000	.854
Kualitas Sistem Pendukung	1.000	.875
Kualitas Pembelajaran	1.000	.784
Manfaat Platform	1.000	.794
Fiturnya Bermanfaat	1.000	.659
Fiturnya Sesuai	1.000	.858

Extraction Method: Principal Component Analysis.

The nine dimensions that measure online course effectiveness were subjected to exploratory factor analysis (EFA). Principal Component Analysis (PCA) was used in the study as recommended when no a priori theory or model measuring a construct exists. Pett et al., 2003, suggested the use of PCA in establishing the initial EFA solution, followed by the varimax (orthogonal) rotation method. The Kaiser-Meyer-Olkin (KMO) measurement verified the sampling adequacy of the analysis, KMO=0.86, and all KMO values were greater than 0.70, which is well above the acceptable limit of 0.50. Bartlett's test values of sphericity were found to be highly significant ($p<0.001$), indicating that the correlation between dimensions is large enough for PCA. These values also supported matrix factorisability. A screen plot, using eigenvalues =1 to visually represent components or factors on a graph explaining the variability of the data. All items had communality values higher than 0.30 (Shukla et al., 2020).

Structural Model Testing (Inner Model)

Testing research data using the Structural Model (Inner Model) is carried out to determine the relationship between constructs, significance values, and R-square and research models. This model will be evaluated using the R-square for the dependent construct T-test and the significance of the structural path parameter coefficients.

Tabelle 9. R-Square

Variable	R Square	R Square Adjusted
Y	0.664	0.649
Z	0.837	0.834

Interpretation of the Smart PLS test results with an R Square (R^2) value for variable Y of 0.664 and for variable Z of 0.837. The R Square Y value is 0.664. The R^2 value of 0.664 indicates that 66.4% of the variance in variable Y can be explained by the independent variables in the model. This means that the model used has a good ability to explain the Y variable, with 66.4% of the variation in Y explained by the model. The remaining 33.6% of the variance in Y is explained by other factors not included in the model. The R Square value of Z is 0.837. The R^2 value of 0.837 indicates that 83.7% of the variance in variable Z can be explained by the independent variables and/or mediators in the model. This indicates that the model used is very good at explaining the Z variable, with 83.7% of the variance in Z explained by the model. The remaining 16.3% of the variance in Z is explained by other factors not included in the model. Thus, the Smart PLS test results with R^2 values show that this model is effective in explaining the effect of platform features on online learning effectiveness and mastery of educational technology. With 66.4% of the variance in online learning effectiveness and 83.7% of the variance in educational technology mastery explained by the model, it can be concluded that online learning platform features play an important role in improving learning effectiveness and technology mastery among users.

Research in line with the finding that the features of online learning platforms play an important role in improving learning effectiveness and technology mastery among users includes a study by Stern, which highlights the importance of technology integration in education (Stern, 2004), and other studies emphasize that interactive features such as discussion forums and online quizzes can increase student participation (Moubayed et al., 2020; Poondej & Lerdpornkulrat, 2019). Rodrigues found that the technical and informational quality of the e-learning platform affects learning satisfaction and effectiveness (Rodrigues et al., 2019), while Sun showed that features of accessibility, interactivity, and technical support can improve users' perceptions of learning effectiveness and encourage technology mastery (Sun et al., 2008).

In addition, a meta-analysis by Means concluded that online learning supported by interactive features and personalization support is more effective than traditional methods, especially in improving technology mastery (Means et al., 2009). These studies support the finding that features in online learning platforms have a significant impact on learning effectiveness and technology mastery among users. The remaining unexplained variance indicates the presence of other external factors that also influence these two variables, which are not included in this model.

Table 10. Nilai F Square

	X1	X2	Y	Z
X1			0.084	
X2			0,260	
Y				4,487
Z				

The results of the analysis using the F square value in Smart PLS show the contribution of the independent variables to the dependent variable in the structural model. The F square value of X1 on Y is 0.084, indicating that variable X1 has a small effect on variable Y. Based on the criteria, the small effect size is in the range of 0.02 to 0.15 (Gignac & Szodorai, 2016), so that X1 makes a significant but small contribution in explaining the variance in Y. The F square value of X2 on Y is 0.260, which indicates that the X2 variable has a moderate effect on the Y variable.

The size of the moderate effect according to Cohen is in the range of 0.15 to 0.35. Therefore, X2 makes a significant contribution in explaining the variance in Y, greater than X1. The F square value of Y on Z is 4.487, which indicates that the Y variable has a very large effect on the Z variable. Cohen's large effect size is above 0.35, and this value far exceeds that threshold. This means that variable Y makes a very significant contribution in explaining the variance in Z, indicating that Y is the key variable in the model that has a dominant influence on Z. Overall, this interpretation reveals that variable X1 has a small influence on Y, variable X2 has a medium influence on Y, and variable Y has a very large influence on Z.

This result provides insight into how strong each of the variables is in the model. These results provide insight into how strongly each independent variable influences the dependent variable in the model, as well as showing that an increase in variable Y is critical to influencing variable Z. The analysis results show that the features of online learning platforms have different effects on learning effectiveness and educational technology mastery. Variable X1, which may represent a specific feature, has a small effect (F square 0.084) on learning effectiveness (Y), indicating a significant but not dominant contribution. In contrast, variable X2 shows a moderate effect (F square 0.260) on learning effectiveness, signaling that this feature has a more substantial contribution. Most significant is the relationship between learning effectiveness (Y) and educational technology mastery (Z), with a very large effect (F square 4.487), emphasizing that improving learning effectiveness through online learning platforms greatly influences educational technology mastery. In conclusion, to improve mastery of educational technology, there needs to be a focus on features that are proven to be more effective in enhancing learning, while features with little effect should be evaluated for further improvement.

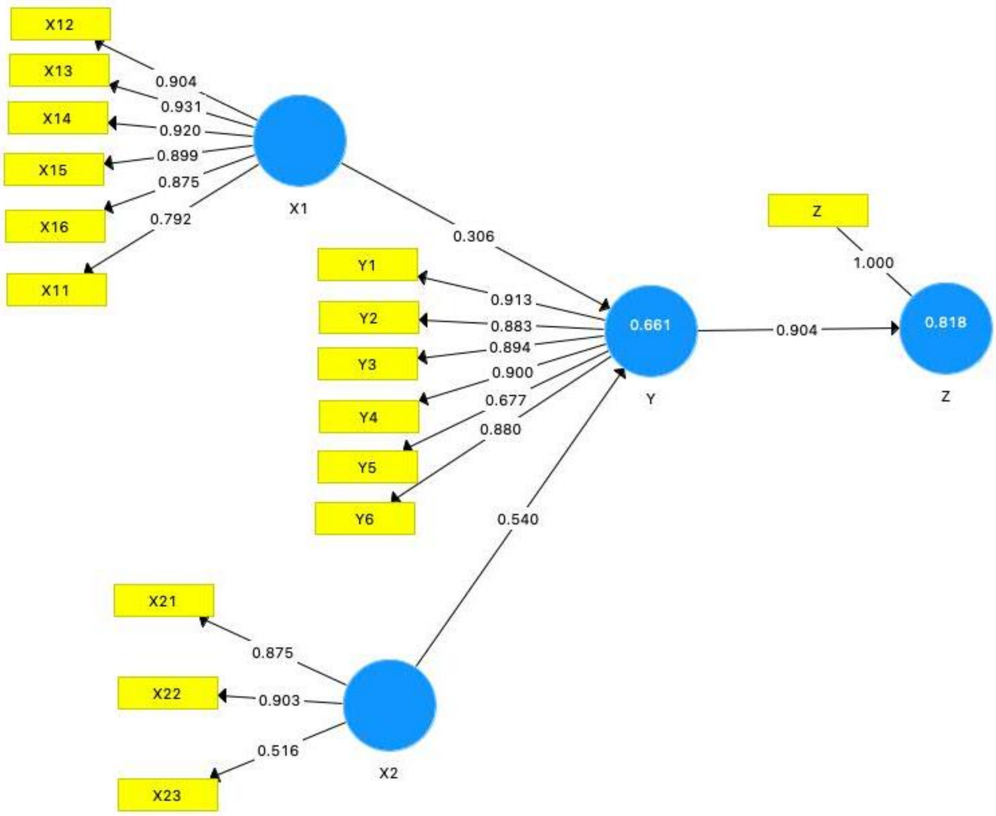

Figure 3. Results of path analysis with Smart PLS

Description :

X1 : Technical features

X2 : Feature Content

Y : Effective Platform

Z : Technology Mastery

The results of the path model analysis using Smart PLS show that the features of the online learning platform have a significant influence on learning effectiveness and mastery of educational technology. Feature X1 has a moderate positive influence on learning effectiveness (path coefficient 0.306), while feature X2 has a stronger positive influence (path coefficient 0.540). Learning effectiveness itself strongly influences mastery of educational technology with a path coefficient of 0.904.

The R^2 value of 0.661 for Y indicates that 66.1% of the variance in learning effectiveness is explained by the platform features, while the R^2 of 0.818 for Z indicates that 81.8% of the variance in technology mastery is explained by learning effectiveness. All indicators have loadings above 0.5, indicating their validity in measuring their respective constructs. Thus, the model confirms that enhancing the features of the online learning platform significantly improves learning effectiveness and mastery of educational technology.

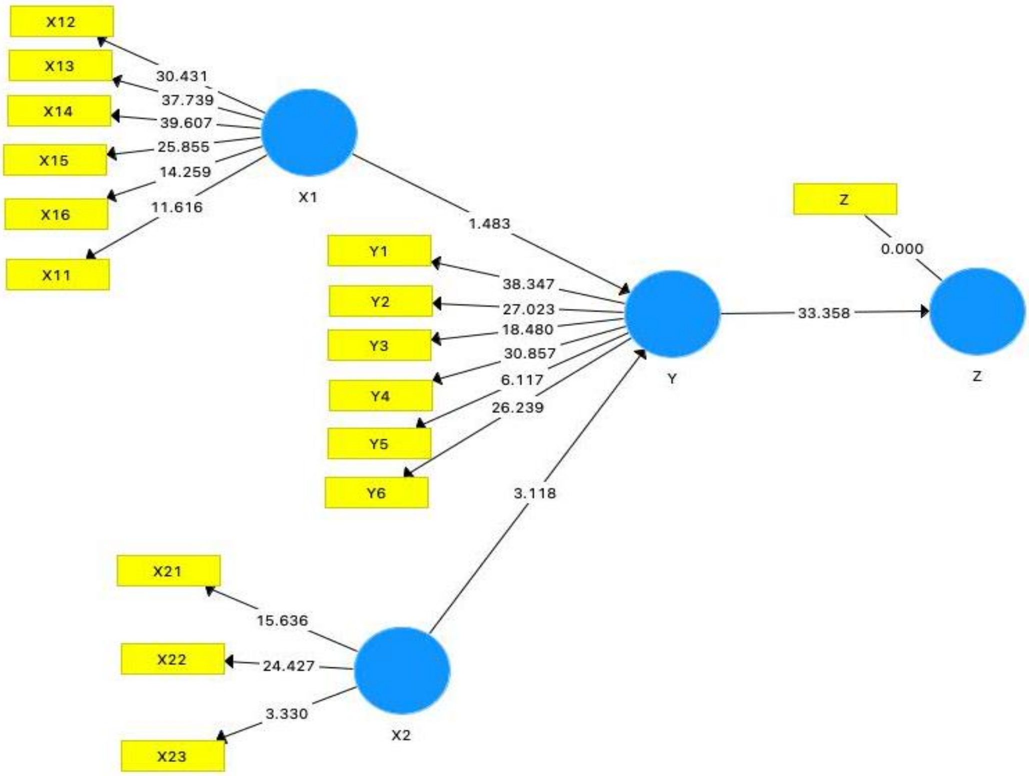

Figure 4. Path coefficients after Bootstrapping

After bootstrapping, the path coefficient results show that the features of the online learning platform (X1 and X2) have a significant influence on learning effectiveness (Y), with path coefficients of 1.483 and 3.118 respectively, indicating that improving X2 features has a stronger impact than X1 on learning effectiveness. Learning effectiveness (Y) itself strongly influences educational technology mastery (Z) with a path coefficient of 33.358, signaling a very large and significant influence. This indicates that improvements in platform features can significantly improve learning effectiveness, which in turn improves educational technology mastery, reinforcing the conclusion that platform features play an important role in both aspects.

Discriminant Validity

This value is the value of the cross-loading factor which is useful for knowing whether the construct has adequate discriminant, namely by comparing the loading value on the intended construct must be greater than the loading value with other constructs, fornell larker criterion. To ascertain whether the research model has good discriminant validity, there are two stages that must be carried out, namely the cross-loading results and the Fornell larger criteria results (Saputro, 2023). The results of the cross-loading test using smartPLS in this study are as follows.

Tabel 11. Uji cross loading

	X1	X2	Y	Z
X1	0.888			
X2	0.835	0.785		
Y	0.757	0.795	0.862	
Z	0.650	0.718	0.904	1.000

The cross-loading test is used in Partial Least Squares (PLS) analysis to assess discriminant validity, namely the extent to which the construct in the model is measured precisely by the indicator (manifest variable) that should measure it. The functions of the cross-loading test are as follows: 1) Evaluation of Discriminant Validity. Assess whether indicators that measure a construct have a higher loading on that construct compared to other constructs. 2) Identify Indicator Validity. Ensure that each indicator is a valid representation of the construct being measured. 3) Model Quality Improvement. Identifying and eliminating invalid or inappropriate indicators, thereby improving the quality and reliability of the model. 4) Structure Clarity Measurement. Shows the clarity of the relationship structure between indicators and constructs in the model. Construct X1, X1 (0.88), and X2 (0.83) have high loadings on Construct X1, indicating that these indicators are valid for Construct X1. The loadings of X1 and X2 on Constructs X2 and Y are lower, indicating good discriminant validity. X2 Construct. X2 (0.78) and Y (0.79) have high loadings on Construct X2, indicating that these indicators are valid for Construct X2. The loadings of Y and Z on the X 1 and Y Constructs are lower, indicating good discriminant validity. Y. Y (0.86) and Z (0.90) have high loadings on Construct Y, indicating that these indicators are valid for Construct Y. The loadings of Y and Z on Constructs X1 and X2 are lower, indicating good discriminant validity. Good cross-loading test results indicate that each indicator has the highest loading on the measured construct and lower on the other constructs, signaling good discriminant validity. If any indicator does not meet these criteria, it is necessary to review whether the indicator is appropriate or needs to be improved or eliminated from the model. Using the cross-loading test, researchers can ensure that the PLS model built has good validity, both in terms of the constructs measured and discrimination between constructs. Model modification needs to be done when the loading factor value that appears is below 0.60. Model modification is carried out by removing indicators that have a loading factor value below 0.60 so that the constructs for all variables have not been eliminated from the model (Nuraeni et al., 2021)

Table 11. Outer loading test before bootstrapping

Variable	X1	X2	Y	Z
X11	0.792			
X12	0.904			
X13	0.931			
X14	0.920			
X15	0.899			
X16	0.875			
X21		0.875		
X22		0.903		
X23		0.516		
Y1			0.913	
Y2			0.883	
Y3			0.894	
Y4			0.900	
Y5			0.677	
Y6			0.880	
Z				1.000

Table 12. Outer loading test after bootstrapping

Variable	X1	X2	Y	Z
X11	0.792			
X12	0.903			
X13	0.931			
X14	0.921			
X15	0.900			
X16	0.875			
X12	0.903			
X21		0.911		
X22		0.907		
Y1			0.930	
Y2			0.901	
Y3			0.885	
Y4			0.913	
Y6			0.866	
Z				1.000

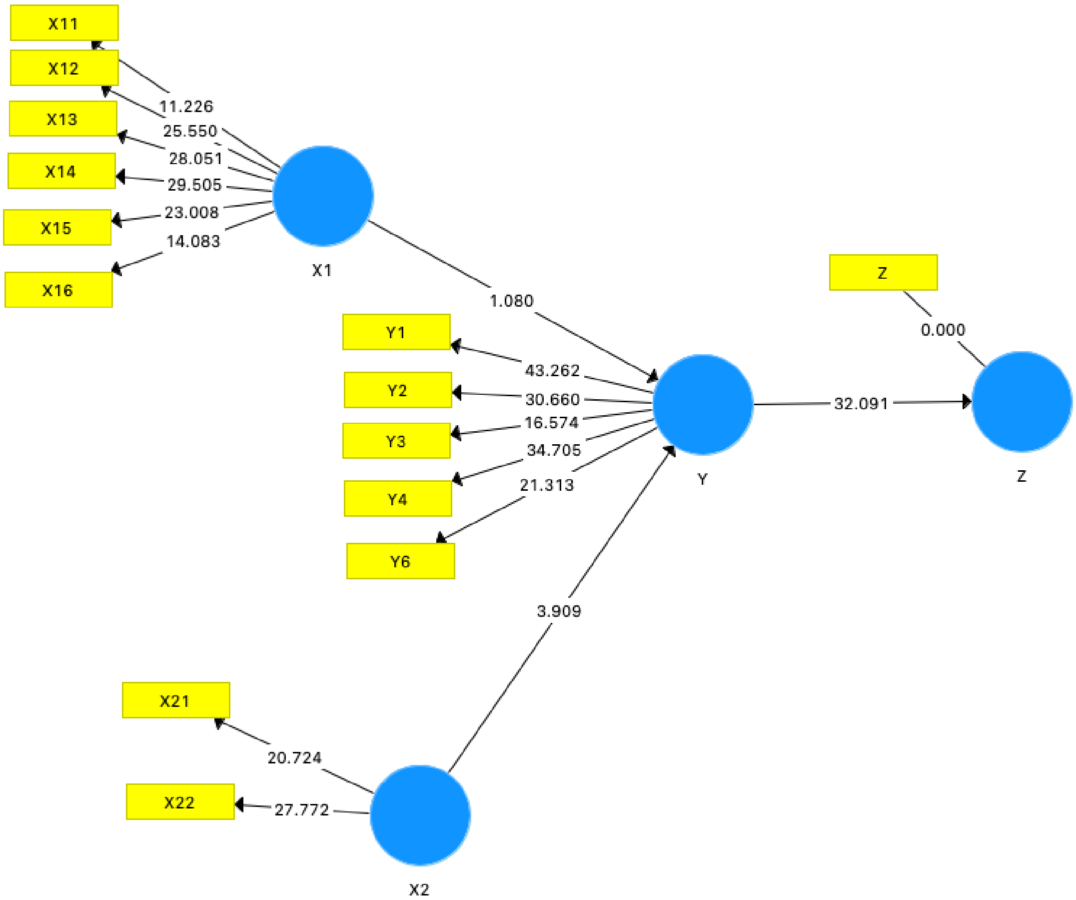

Figure 5. Path coefficient after Bootstrapping and eliminating variables that do not meet the loading factor, namely x23 and y5.

The next stage is to assess convergent validity through the AVE (Average Variance Extracted) value. If a good model has an AVE value above 0.6 (Hiariey, 2018), then the model is categorized as having high convergent validity. After the elimination of the loading factor below 0.6, the model has an AVE value which is obtained as follows. Path models after x23 and y5 are removed due to low loading factors below 0.6.

Table 12. Average Variance Extracted

Variable	Average Variance Extracted (AVE)	Cronbach's Alpha
X1	0.789	0.946
X2	0.827	0.790
Y	0.809	0.941
Z	1.000	1.000

The Average Variance Extracted (AVE) test is one method for assessing construct validity in the Partial Least Squares (PLS) model. AVE measures the amount of variance captured by a construct relative to the amount of variance caused by measurement error. The main functions of the AVE test are: 1) Assessing Convergent Validity, AVE is used to assess convergent validity, namely the extent to which indicators of a construct actually measure the construct. 2) Measuring Measurement Quality, Assessing how well the indicators reflect the intended construct. 3) Model Validation, Assists in the model validation process by ensuring that the construct has an adequate level of validity. Based on the AVE table above, the AVE value is≥ 0.50. AVE of 0. 78 for X1 and X2 of 0.82 and Y of 0.80 indicates that more than 78% of X1, 82% X2, and 80% Y variance of the indicators can be explained by these constructs. This signifies good convergent validity. The implication is that the construct is considered to have adequate convergent validity and the indicators collectively measure the construct well. If there is a low AVE, the following steps need to be taken such as, 1) Review Indicators with Low Loading. Identify indicators with very low loadings and consider removing or replacing them. 2)Add or Remove Indicators. Add new indicators that are more relevant or remove inappropriate indicators to improve convergent validity. 3)Model Improvement. Review the conceptual model and consider making modifications that can improve construct validity. 4) Re-analysis. After making adjustments, re-analyze to see if the AVE value increases and convergent validity improves. Using AVE can ensure that the constructs in the PLS model have sufficient validity and that the indicators actually measure the intended construct. This helps in building a more valid and reliable model for further analysis. Composite Reliability. According to (Prayudi, 2022) the specific CR (Composite Realibilty) value that can or can be accepted in research is in the range of 0.70 to 0.80. A construct can be said to have high reliability if the value is 0.70. The table of composite reliability values is as follows.

Tabel 13. Nilai composite realbility

Variable	Cronbach's Alpha	Composite Reliability
X1	0.946	0.957
X2	0.790	0.905
Y	0.941	0.955
Z	1.000	1.000

E-learning can be divided into synchronous and asynchronous according to time, and the learning space corresponds to synchronous and asynchronous online classrooms respectively. Whether in synchronous or asynchronous classrooms, intelligent interaction, real-time feedback, and personalization should be the fundamental elements that teachers should consider when building an online learning environment. With the development of technology, more and more learning management systems (LMS) provide well-designed interaction, feedback, and personalization tools. Teachers should apply information technology and deeply integrate relevant technological functions with teaching methods to build a smart learning environment. Figure 3 shows the proposed Online Smart Teaching Model, which includes smart interaction, real-time feedback, personalization, content presentation, and class management. Content presentation, classroom management, and note-taking process are the six aspects that facilitate teachers' online intelligent learning environment. Content presentation refers to presenting teaching content in different teaching methodologies and solving important and challenging classroom problems. Class management means that teachers can understand the real-time learning status of students through the platform to provide targeted tutoring to each student. The recording process states that the entire learning process of students is recorded by the system, and targeted learning analysis can be taken (S. Wang et al., 2021). Path analysis showed that SRL had a statistically significant relationship with the quality of the e-learning experience and conceptions of learning. In contrast, there was no correlation between academic achievement and online discussion. However, academic achievement did show a correlation with online discussion (Abouzeid et al., 2021). Satisfaction with online learning is explained by the self-reported sense of community, social capability, and participation. - Sense of community mediated the relationships between social capability and satisfaction, as well as between perceived usefulness and satisfaction. - Students' social capability, perceived usefulness of social awareness tools, and self-reported participation serve as predictors of students' sense of community (Tsai et al., 2008). Learning media used in online learning has a significant influence on learning achievement, with an effect size of 83.3% (Aviory et al., 2022). The path coefficient histogram graph is used in path analysis or structural equation modeling (SEM) to display the distribution of path coefficients between variables in the model. Its uses include visualizing the distribution of the coefficients, showing how the path coefficients are distributed, and whether they follow a certain distribution such as normal and others. Identify outliers to identify coefficient values that may be outliers. Requires further examination. Evaluation of significance to see the distribution of path coefficients can provide an overview of the significance of the relationship between variables. Normality assumption to help check the normality assumption of residuals or path coefficients which is one of the important assumptions in many statistical models. Model validation to ensure that the model built fits the data analyzed. Finally, it provides insight into the stability and reliability of the path coefficients in the model being tested.

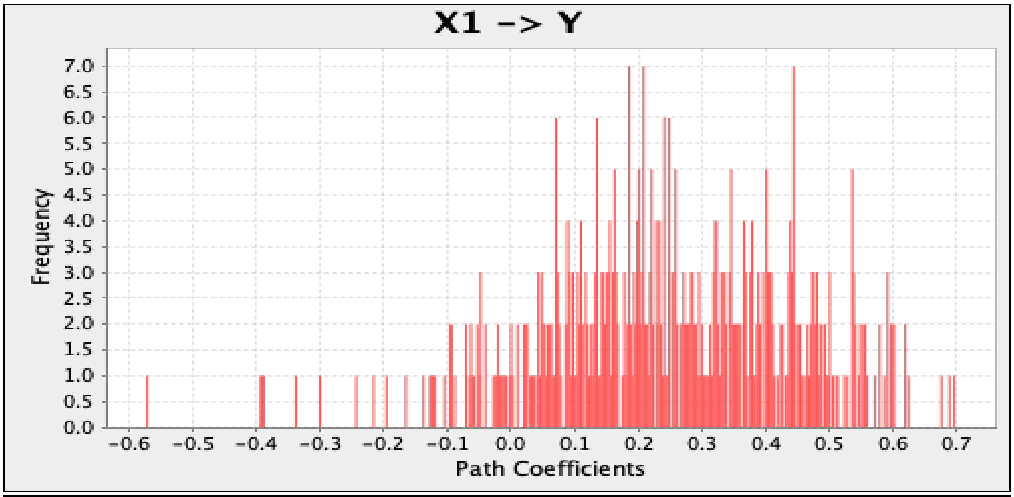

Figure 6. Histogram of path coefficient 1

Figure 6 explains that the X axis as the Path Coefficient is a horizontal axis showing the value of the path coefficient which ranges from -0.6 to 0.7. This path coefficient shows the effect of variable X1 on variable Y. A positive value indicates a positive effect, while a negative value indicates a negative effect. Y-axis as Frequency, The vertical axis shows the frequency or number of occurrences of each path coefficient value in the analyzed data. The Path Coefficient Distribution shows that most of the path coefficients are in the positive range between 0 and 0.5, with the peak of the distribution being around 0.2 to 0.3. This indicates that variable X1 tends to have a positive influence on variable Y. The highest frequency reaches almost 7, which indicates that path coefficient values around 0.2-0.3 appear most frequently in the sample. There are some negative values, but the number is very small, indicating that most of the influence of X1 on Y is positive. The distribution skewed towards positive values indicates that in general, X1 has a positive relationship with Y. That is, an increase in X1 tends to be followed by an increase in Y. The histogram shows the variability in the effect of X1 on Y, with some very small or negative effects. However, the frequency of these values is low, so they may be outliers or special cases in the data. In a practical context, understanding the distribution of these path coefficients can be helpful in evaluating the consistency and strength of the relationship between X1 and Y. For example, if this is an analysis of data in social, business, or educational research, these results suggest that interventions or changes in X1 are likely to have a positive effect on Y. The path coefficient histogram shows that there is a consistent positive influence of variable X1 on variable Y. Most of the coefficient values are in the positive range, with the highest frequency around values of 0.2-0.3, suggesting that increases in X1 tend to be associated with increases in Y. This analysis can be used to support hypotheses or models that describe a positive relationship between the two variables.

Online learning interactions between course network members whose scale of interaction increased also became more frequent during the pandemic. After the outbreak was brought under control, although the scale of interactions decreased, the level and scope of some courses' interactive networks continued to increase; interactions were thus highly effective in these cases. Overall, the pandemic seems to have had a relatively positive impact on online learning interactions. Considering a pair of courses in detail and finding that Economics (a social science course) fared much better than Electrodynamics (a natural science course) in classroom interaction; learners were more willing to take part in classroom activities, perhaps due to the unique characteristics of these courses (J. Zhang et al., 2022).

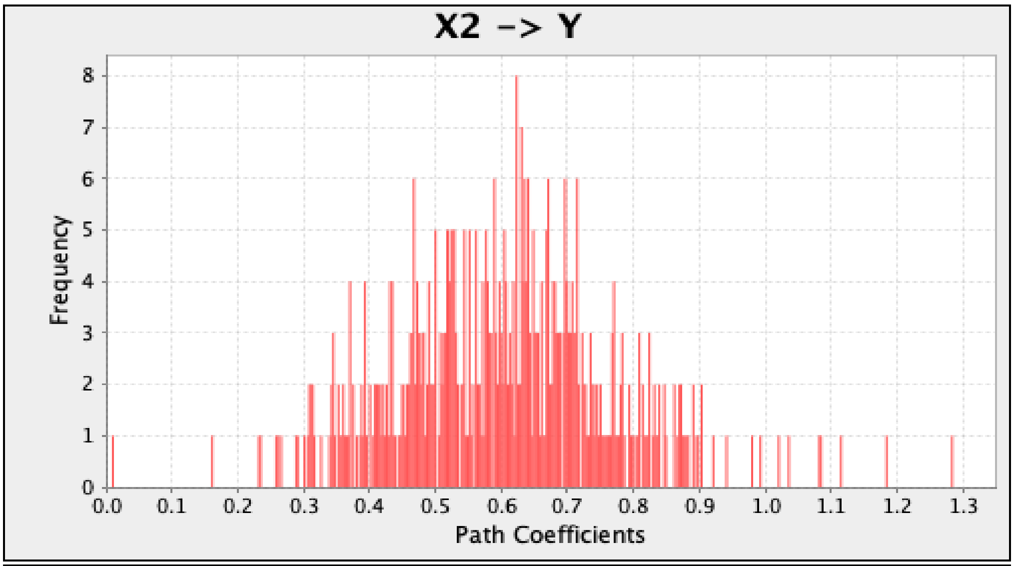

Figure 7. Histogram of path coefficient 2

The distribution of path coefficients in Figure 7 shows that most of the path coefficients are in the positive range between 0.3 and 0.8, with the peak of the distribution being around 0.6 to 0.7. This suggests that variable X2 tends to have a strong positive influence on variable Y. The highest frequency reaches almost 8, which suggests that path coefficient values around 0.6-0.7 appear most frequently in the sample. This distribution indicates that the effect of X2 on Y is generally quite strong and consistent within the indicated range. The predominant distribution in the positive value range indicates that X2 has a strong positive relationship with Y. That is, an increase in X2 tends to be followed by an increase in Y. The histogram shows that there is some variability in the effect of X2 on Y, but most of the effect is positive and significant, especially around values of 0.6-0.7. This distribution suggests that the X2 variable has a significant and consistent influence on Y. For example, in a business context, this could mean that a particular factor represented by X2 consistently improves the outcome measured by Y. The path coefficient histogram shows that there is a strong and consistent positive influence of the X2 variable on the Y variable. Most of the coefficient values are in the positive range of 0.3 to 0.8, with the highest frequency around values of 0.6-0.7, suggesting that increases in X2 tend to correspond to increases in Y. This analysis supports the hypothesis or model that describes a significant positive relationship between the two variables.

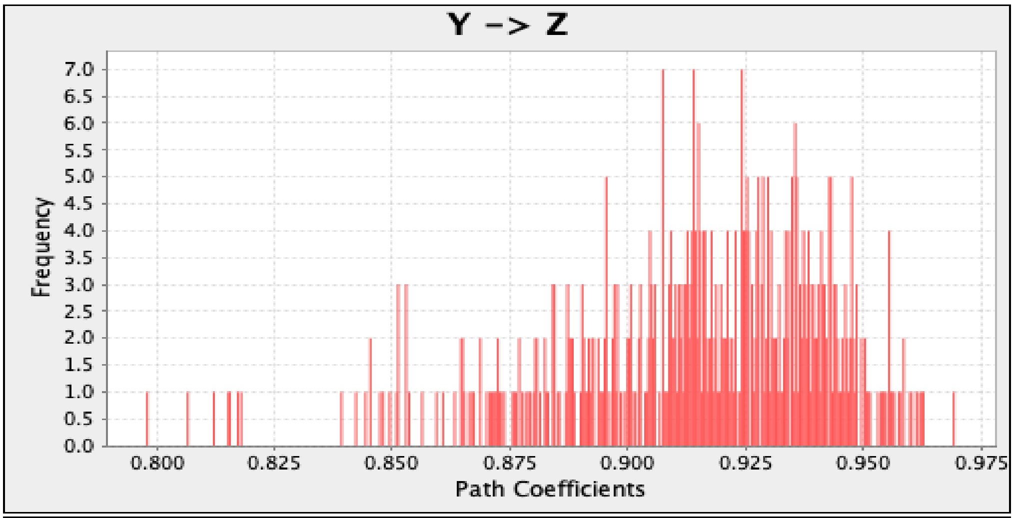

Figure 8. Histogram of path coefficient 3

The path coefficient values range from approximately 0.800 to 0.975. This indicates that the relationship between Y and Z is quite strong, with the majority of the path coefficient values being around 0.90. The distribution of path coefficients shows peaks around 0.90 to 0.925. The highest frequency is found around the value of 0.90, indicating that this value is the most common in the analyzed sample. The skewness and kurtosis of this histogram appear slightly skewed to the left, with some coefficient values falling below 0.85. There are no extreme outliers, but there are some values that are at the left end of the distribution. The spread of the data is that it tends to be centered around a value of 0.90, with some values scattered below and above this range. The spread seen suggests that most of the path coefficient values are fairly consistent. This is in contrast to the results of research in universities that organize technology-based learning, namely the Learning Management System (LMS) through e-study. As a result, most students feel uncomfortable with online learning (65.2%), most students prefer learning with nonaudio visual media (54.3%), almost most students prefer screen-to-screen or online learning (31.5%) and almost most students want interactive way of learning (31.5%) (Setyabudhi & Veza, 2022). The strength of the relationship is that the path coefficient between Y and Z is mostly around 0.90, indicating that the relationship between these two variables is very strong and positive. This value indicates that variable Y makes a significant contribution to variable Z. The consistent and centered distribution around 0.90 indicates good validity and reliability of the tested model. The absence of significant extreme values or outliers indicates that the model is stable. Although the histogram is slightly skewed to the left, the near-symmetrical distribution around the peak value indicates that the assumption of normality of the residuals may be met. This is important for the inferential validity of the model. The high strength of the relationship between Y and Z means that changes in variable Y will have a significant impact on variable Z. Interventions or changes in variable Y can reliably predict changes in variable Z. Based on this strong and consistent distribution of path coefficients, the model can be considered valid and can be used for further prediction. Learning expectations have a positive impact on active online learning while learning complaints and social isolation have a negative impact on active online learning. Based on the results, this study proposes a smart online teaching model and discusses how to promote active online learning in a smart environment (Al-Hunaiyyan et al., 2017; Kinshuk et al., 2016; Mehmood et al., 2017; Zhu et al., 2016).

Conclusion

Google Classroom is the most used platform by users (82%) due to its ease of use, integration with other Google services, and collaborative features. E-Learning (11%) is the second most used platform, as it offers flexibility and a variety of easily accessible courses. Edmodo (3%) and Canvas (1%) are used by a small percentage of users, showing that despite their strong features, they are not as popular as Google Classroom or E-Learning. Other platforms such as Learning Management Systems, Virtual Learning Environments, Course Management Systems, Learning Content Management, and Open Learning Environments are used by only 1% of users each, indicating a strong preference for certain platforms but there are still users who choose other alternatives. The KMO and Bartlett's test showed an MSA value of 0.897 and was significant at 0.001, qualifying for factor analysis. The R-square value shows that 66.4% of the variance of learning effectiveness (Y) and 83.7% of the variance of educational technology mastery (Z) can be explained by the model, emphasizing the importance of platform features in learning effectiveness and technology mastery. Related studies support these findings, suggesting that interactive features and technical support can improve learning effectiveness and technology mastery. Path analysis results show that X2 features have a stronger influence on learning effectiveness than X1, and learning effectiveness strongly influences educational technology mastery. Discriminant validity analysis shows that all indicators are valid for their respective constructs. High AVE values indicate good convergent validity, while composite reliability values indicate high reliability. Overall, enhanced features of online learning platforms can improve learning effectiveness and technology mastery among users, supporting the need for deep technology integration in online education.

Recommendation:

To improve the effectiveness of online learning and mastery of educational technology, it is necessary to develop interactive and personalized features on the platform, as well as provide high-quality and accessible content. Regular training for teachers and students on the use of educational technology, responsive technical support, and the implementation of blended learning models are also important. In addition, regular evaluations and data-driven improvements should be made to ensure continuous improvement. Policies that support the use of technology in education and clear standards and guidelines are also needed to ensure the quality and consistency of learning.

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The authors hereby declare that there is no potential conflict of interest related to this article.

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