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Distance learning impact: Interaction, orientation, multimedia, cognitive engagement, learning performance

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Abstract

Students face challenges in literacy and autonomy in distance learning, particularly due to the lack of faculty control over their participation, which impacts their academic performance. This research aims to analyze the impact of multimedia use, online interaction, and cognitive engagement on students' learning outcomes in Indonesia during the COVID-19 pandemic. Using the ex post facto method, data were collected from 588 students through multistage random sampling techniques and analyzed using Measurement Model Assessment and Structural Equation Modeling. The research results show that the use of multimedia in learning, active interaction between students and lecturers, as well as a clear learning orientation, enhance students' cognitive engagement, which ultimately contributes to improved academic performance. Better interactions, such as discussions with lecturers and peers, as well as the use of data analysis tools, have been proven to enhance the effectiveness of learning. In addition, the use of multimedia in delivering materials and reviewing learning also has a positive impact on students' understanding. This study contributes by identifying effective online learning strategies, including the use of the Zoom platform and multimedia tools, to enhance student engagement and learning outcomes.

Keywords: Cognitive Engagement, Distance Learning, Learning Interaction, Learning Orientation, Learning Performance.

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1. Introduction

The COVID-19 pandemic poses a significant challenge to global education, including in Indonesia, leading to the adoption of remote learning through online platforms [1]. In contrast to traditional learning, online education necessitates both learning independence and cognitive engagement from students. The need for learning independence arises due to limited face-to-face interaction and direct communication between students and lecturers [2]. Amid the COVID-19 pandemic, student cognitive engagement has become a critical factor in the learning process [3]. In traditional learning settings, the intensity of interaction between lecturers and students plays a crucial role, influencing learning performance. Lecturers can employ various methods and learning models to exert control over the learning process. to improve learning performance, such as STEM, collaborative Flipped Learning, Blended Learning, Problem Based Learning, Project Based Learning [4-6].

The main contribution of this research is to empirically discover the causes of performance learning for students in distance learning using online learning. The relationship between Learning Performance and Engagement, perseverance, and concentration of students in the learning process has been studied several times by researchers such as [7, 8]. Studies on student engagement with their learning achievements are sometimes constrained by students' entire time availability in learning, especially in distance learning [9]. Moreover, the social distance pandemic implemented through the Health protocol prevents students from interacting face to face, especially in Indonesia [10, 11]. Students are faced with various learning difficulties in this distance learning [12-14]. Student's difficulties in distance learning, especially in networking, are learning independence, the habit of being controlled in class, the habit of being face to face in class, used to being guided, used to being directed, and other technical difficulties in learning such as internet quota issues, internet networks, wifi/ signal infrastructure, especially those in rural areas.

Online-based learning not only affects students' learning and cognitive performance but also causes learning difficulties experienced by students. This is in line with research conducted by Turmuzi, et al. [15] on Mathematics Education students at FKIP Mataram University; the difficulty of online learning faced by students lies in the effectiveness of the teaching and learning process and technical control factors such as unstable internet networks, limited quotas and also minimal interaction when the online learning process takes place. Learning difficulties will appear from declining academic performance or learning achievement [16]. Improving learning performance starts with learning orientation. Learning orientation is a pattern of awareness and action of a consistent learning process [17]. Learning orientation is based on an individual's internal mindset that encourages individuals to develop competence [18]. Learning orientation includes students' goals, objectives, motives, and concerns with learning [19]. Learning orientation is related to a person's goals, determination, motivation, expectations, worries, and doubts about learning. Therefore, learning orientation can influence students in learning and achieving learning goals through goals. Goals. The use of multimedia in online learning during the COVID-19 pandemic, with the highest use of instant messaging media at 98%. The use of learning applications is 42%, and video-based media is 50%. The use of conference media is only 18% in implementing online learning. Instant messaging is the most widely used media in online learning because learning is only through messages, source: kemendikbud survey 2020. Technology-based learning media, especially on the internet, supports increasing student interest and motivation to learn. A study (2021) found that students use the Internet for various purposes, including learning. However, some students use the internet for personal interests, such as playing games and opening sites unrelated to learning.

Learning performance requires strong motivation, commitment, and cognitive engagement from students, especially in the digital era and learning with online learning methods through multimedia. Based on the phenomenon described, the author is interested in examining the factors influencing student performance in online distance learning.

2. Literature Review

Implementing online learning also affects the decline of students' cognitive engagement due to the low interaction between lecturers and students. Research conducted by Yang, et al. [6] found that distance learning affects the cognition of students involved in distance learning attendance and learning performance. In line with research conducted by, the success and activeness of students in online learning are influenced by student involvement in learning. According to research [20] student involvement in learning can provide motivation for learning, increase a conducive learning environment, and lead to better learning performance. Engagement in learning is a multidimensional psychological construct [20]. Dimensional psychological construction leads to how a person constructs an understanding of their involvement in learning. According to research conducted by Yang, et al. [6] and Azman, et al. [21] student engagement mediates learning performance and student achievement. Students learn well when involved in the learning process. Thus, cognitive engagement improves student learning performance.

3. Methodology

The research to be carried out is ex post facto research. Research is conducted on events that students, namely online learning, have experienced. In this research, the object of research is students. The population of this research is Indonesian students who are studying online. Data collection using questionnaires was distributed to several cities, namely Makassar city representing Eastern Indonesia; Surabaya from East Java; Jakarta from DKI Jakarta, Lampung representing the southern tip of Sumatra; Padang Central Sumatra; and Medan North Sumatra. Sample selection was determined by multistage random sampling by considering regions in Indonesia. Consists of regions in Indonesia. The number of samples according to the requirements of indicator analysis is 54 x 10 = 540 respondents. Respondents who filled out the questionnaire were 588 spreads across Indonesia in the western part of Indonesia 460 and Eastern Indonesia 128 respondents. Measurement Model Assessment and Structural Equational Modelling are tools for analyzing research results. The measurement model is a requirement to test the validity and reliability of the construct variables built. The minimum factor loading value requirement is 0.50 and better above 0.70 [22]. The following presents the data on the measurement results of the construct variables.

4. Results

After collecting the research data, the first step is to conduct data analysis to identify the presence of missing values (missing data), outliers (data that are far from other values), multicollinearity (high correlation between independent variables), and normality tests to evaluate data distribution. From this analysis, 588 data were obtained that were eligible to proceed to the next stage. Furthermore, Confirmatory Factor Analysis (CFA) was conducted to test the validity and reliability of the construct variables developed in the study.

4.1. Structural Equation Model (SEM) Analysis

The validity test used a confirmatory factor analysis (CFA) test in this study. CFA tests unidimensional validity and reliability in measuring construct models that cannot be measured directly. The CFA test has 2 objectives in measuring each indicator conceptualized unidimensional, consistently so that the indicator will form the construct to be studied by looking at the correlation of endogenous and exogenous variables; this can be seen from the factor loading value of each indicator. It is declared valid if the factor loading factor value is above 0.5 [22, 23]. The following is CFA model 1 testing.

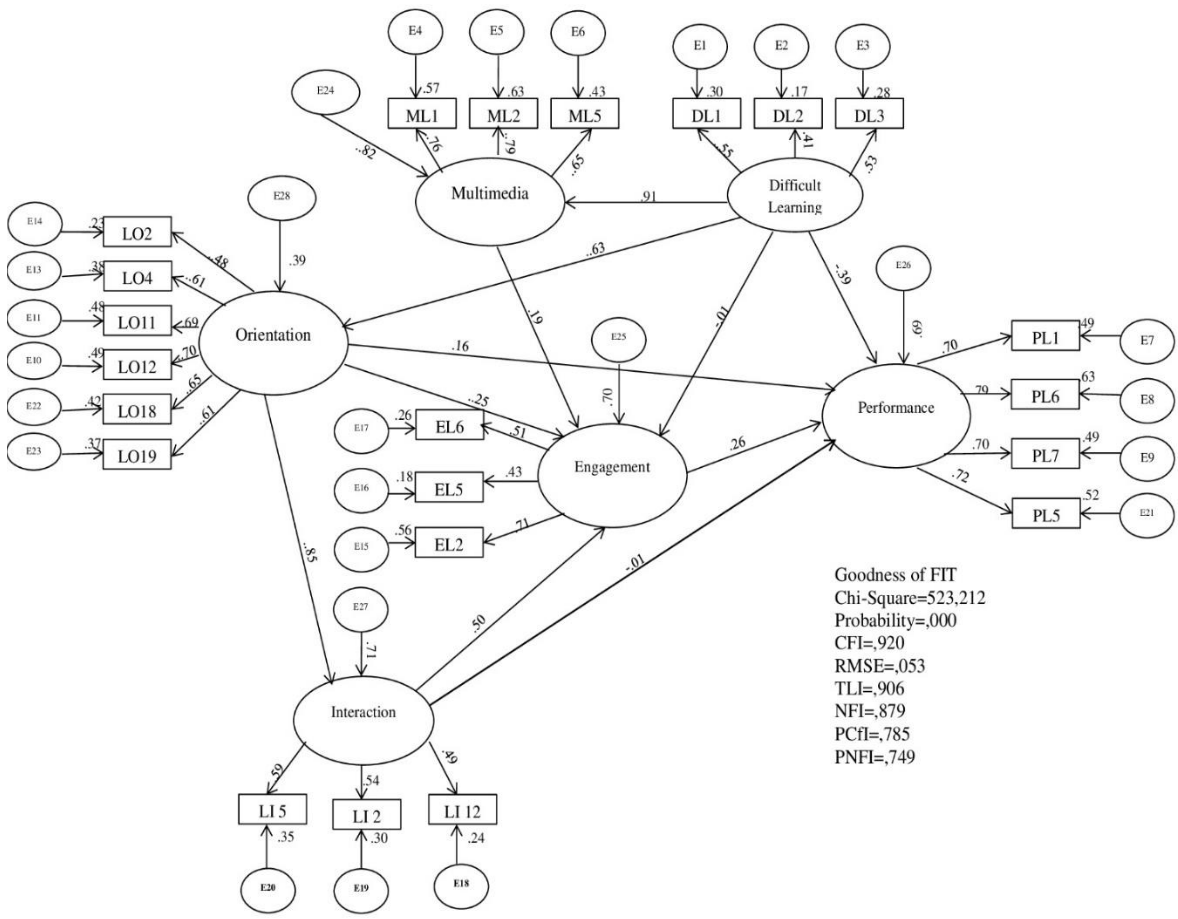

Figure 1.
Initial Empirical Model.

The following is the print output of amos 26 CFA from model 1: Standardized Regression Weights: (Group number 1 - Default model).

The standardized regression estimates show the relative level of influence of each independent variable on the dependent variable in the model. In this analysis, several significant findings can be interpreted. Firstly, difficulty has a significant favorable influence on Orientation (Estimation = 0.628), indicating that the level of learning difficulty contributes to improving students' learning orientation. Furthermore, Difficulty also has a significant favorable influence on Multimedia (Estimation = 0.901), indicating that the higher the level of learning difficulty, the greater the use of multimedia in learning. The Orientation variable significantly positively influences Interaction (Estimation = 0.865), indicating that good learning orientation contributes to increased interaction in learning. In addition, Engagement has a significant favorable influence on Interaction (Estimation = 0.469), Multimedia (Estimation = 0.186), Orientation (Estimation = 0.295), and Difficulty (Estimation = -0.017).

Table 1.
CFA Validity Test.

Variable Correlation			Estimate	Description
Orientation	<---	Difficult	0.628	Invalid
Multimedia	<---	Difficult	0.901	Valid
Interaction	<---	Orientation	0.865	Valid
Engagement	<---	Interaction	0.469	Invalid
Engagement	<---	Multimedia	0.186	Invalid
Engagement	<---	Orientation	0.295	Invalid
Engagement	<---	Difficult	-0.017	Invalid
Performance	<---	Multimedia	0.874	Valid
Performance	<---	Engagement	0.277	Invalid
Performance	<---	Interaction	0.107	Invalid
Performance	<---	Difficult	-0.346	Invalid
DL2	<---	Difficult	0.411	Invalid
ML2	<---	Multimedia	0.795	Valid
PL1	<---	Performance	0.702	Valid
PL6	<---	Performance	0.794	Valid
PL7	<---	Performance	0.703	Valid
LO12	<---	Orientation	0.688	Valid
LO11	<---	Orientation	0.692	Valid
LO4	<---	Orientation	0.611	Valid
EL5	<---	Engagement	0.424	Invalid
PL5	<---	Performance	0.721	Valid
ML1	<---	Multimedia	0.758	Valid
DL1	<---	Difficult	0.550	Valid
DL3	<---	Difficult	0.530	Valid
EL2	<---	Engagement	0.706	Valid
LI5	<---	Interaction	0.582	Valid
EL6	<---	Engagement	0.516	Valid
ML5	<---	Multimedia	0.653	Valid
LI12	<---	Interaction	0.491	Invalid
LI2	<---	Interaction	0.547	Valid
LO18	<---	Orientation	0.643	Valid
LO19	<---	Orientation	0.618	Valid

This shows that the higher the level of student involvement, the greater the influence on interaction, multimedia usage, orientation, and learning difficulty in online learning. Performance variable has a significant positive effect on Multimedia (Estimation = 0.874), Engagement (Estimation = 0.277), Interaction (Estimation = 0.107), and Difficulty (Estimation = -0.346), indicating that the use of multimedia, student engagement, interaction, and the level of learning difficulty influences the level of learning performance. From the standardized regression weight, it is known that some indicators are not valid because they have a loading factor value <0.5. Thus, the item is dropped or discarded from the construct in the following analysis. Thus, the CFA Model_2 is obtained as follows:

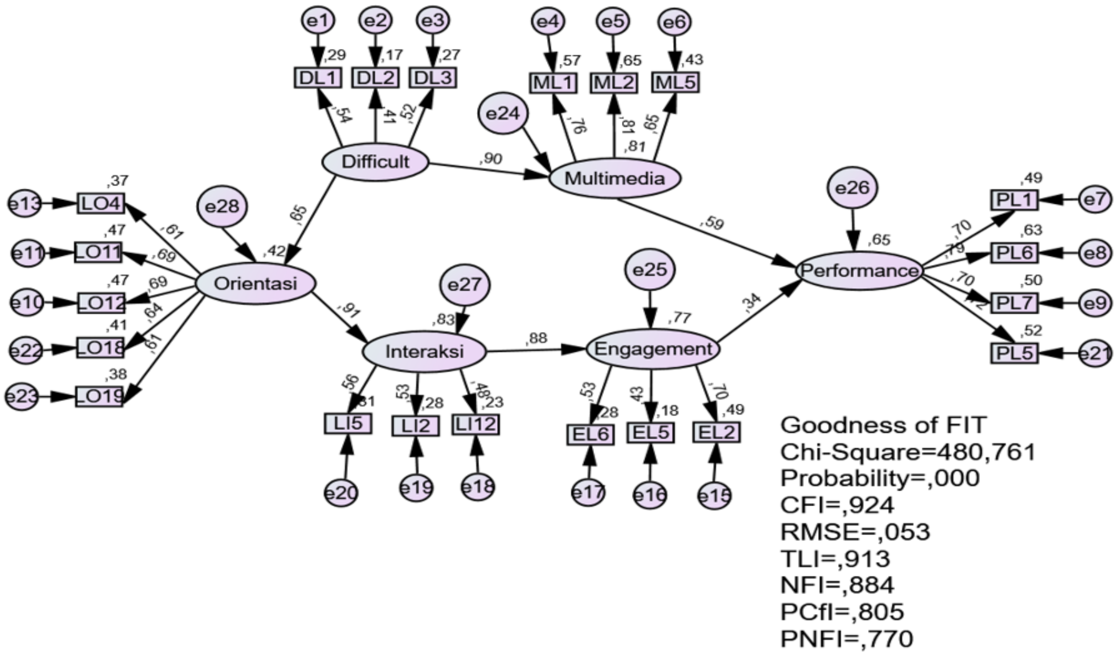

Figure 2.
Modification of the model based on the significance of the relationship between variables.

4.2. Reliability Test

Reliability is a measure of the internal consistency of the indicators of a construct variable that indicates the degree to which each indicator indicates a standard construct variable. Two ways can be used: composite (construct) reliability and variance extracted. The cut-off value of construct reliability is at least 0.70, while the extracted cut-off value is at least 0.50. The results of the reliability test data processing are in the table below:

Table 2.
Reliability Test and Variance Extract.

Variable	Reliability	Variance Extract
Learning Difficulties	0.910	0.580
Learning Orientation	0.948	0.534
Online Interaction	0.844	0.644
Multimedia	0.750	0.601
Cognitive Engagement	0.852	0.511
Learning Performance	0.898	0.620

The test results show that all reliability values are above 0.7. This means that this SEM model's measurement has met the gauge reliability requirements. The variance extract value is also above 0.5. This means that the measurement of this SEM model has met the requirements for good factor extraction.

4.3. Structural Model Evaluation

Outliters data can be seen from the melanosis distance value, which has a value of P1 and P2. One data includes outliers if the resulting p1 and p2 values are <0.05. From the Amos outputs table, it can be seen that the data has p1 and p2 <0.05. Multicollinearity exists if there is a correlation value between indicators with> 0.9. The determinant of the sample covariance matrix = .000. From the results of the calculation output, it can be seen that the value is 0.000. Thus, there is no multicollinearity in this study. However, it is still acceptable because the other SEM assumption requirements are met.

Table 3.
Goodness of Fit Test Results in Indkes

The goodness of the Fit index	Cut-off value	Model of Research	Model
RMSEA	< 0.08	0.053	Good Fit
CMIN/DF	> 2.0	2.633	Good Fit
CFI	>0.90	0.926	Good Fit
PATIO	>0.70	0.848	Good Fit
PNFI	>0.70	0.751	Good Fit
PCFI	>0.70	0.785	Good Fit
FMIN	>0.70	0.799	Good Fit

RMSEA (Root Mean Square Error of Approximation) analysis was conducted to evaluate the level of approximation error in the two models evaluated: the default model and the independence model. The evaluation results show that the default model has an RMSEA value of 0.053, indicating a low approximation error level. The 90% confidence interval for RMSEA in the default model has a lower bound (L.O. 90) of 0.047 and an upper bound (HI 90) of 0.059. This indicates that the default model has a good level of fit with the observed data. In addition, the PCLOSE value of 0.212 indicates that the default model fits well with the data. Model Fit Summary analysis was used to evaluate the fit of the proposed model to the observed data. In this analysis, three models were evaluated: the default, saturated, and independence models. The analysis results show that the default model has a statistically significant chi-square (CMIN) value with appropriate degrees of freedom (D.F.). However, the CMIN/DF ratio shows that the model does not entirely fit the data, indicating a mismatch between the model and the data. Conversely, the saturated model perfectly fits the data as the CMIN and D.F. are both zero. However, this model only provides helpful information as it contains all possible relationships between variables without restrictions. The independence model also shows a statistically significant fit, but a high CMIN/DF ratio indicates a significant mismatch with the data.

The results of the baseline comparisons show a comparison between the three models evaluated: the default, saturated, and independence models. The default model, the initial model proposed, showed a good fit with the research data. The NFI (Delta1) of 0.887, RFI (rho1) of 0.866, IFI (Delta2) of 0.926, TLI (rho2) of 0.913, and CFI of 0.926 indicate that this model has a relatively good fit with the observed data. On the other hand, the saturated model shows a perfect fit with the data. This is indicated by the NFI (Delta1) and IFI (Delta2) values of 1.000 and CFI of 1.000. This model contains all possible relationships between variables without any restrictions. However, the independence model does not fit the data at all. Parsimony-adjusted measures are used to evaluate the parsimony of the models proposed in the analysis. In this evaluation result, three models were evaluated: the default, saturated, and independence models. The evaluation results show that the default model has good parsimony in explaining the data. The Pratio value of 0.848 indicates that this model can explain the data using efficient parameters, i.e., with a relatively optimal number of parameters. In addition, the PNFI value of 0.751 and PCFI of 0.785 indicate that the default model provides reasonable adjustment by considering the complexity of the model. This indicates that the model can provide a good level of adjustment using a relatively small number of parameters. On the other hand, the evaluation results show that the saturated and independent models have a low level of parsimony.

FMIN (Function Minimum) analysis was used to evaluate the degree of fit of the model to the observed data in the three models evaluated: default, saturated, and independent. The evaluation results show that the default model has a minimum function (FMIN) of 0.799, which indicates that this model fits the data well. The model provides moderate adjustment with a prediction error rate (F.O.) of 0.495. The 90% confidence interval for F.O. in the default model shows a lower bound (L.O.) of 0.393 and an upper bound (H.I.) of 0.611. This indicates that the default model provides a good level of adjustment with little prediction error.

Meanwhile, the saturated model has an FMIN of 0.000, which indicates that this model is a perfect fit for the observed data. The model has no prediction error (F.O. = 0), and the 90% confidence interval for F.O. in the saturated model is also 0. This indicates that the saturated model provides a perfect fit without any prediction error. However, the independence model shows a high FMIN of 7.038, indicating that the model has a poor fit to the data. The independence model's prediction error rate (F.O.) is 6.681, indicating a high error rate. The independence model's 90% confidence interval for F.O. shows a lower bound (L.O.) of 6.331 and an upper bound (H.I.) of 7.043. This indicates that the independence model has a poor fit with a significant prediction error.

In conclusion, the FMIN evaluation results show that the default model fits the data well, while the saturated model provides a perfect fit. However, the independence model needs a better fit with a high level of prediction error. This interpretation is based on the FMIN and F.O. values and the 90% confidence interval.

4.4. Hypothesis Testing

Table 4.
Hypothesis Test Results.

Hypothesis	Variable Correlation			Estimate	S.E.	C.R.	P	Label	Result
H_1	Orientation	<---	Difficult	0.515	0.063	8.113	***	par_11	Accepted
H_2	Multimedia	<---	Difficult	0.960	0.102	9.426	***	par_9	Accepted
H_3	Interaction	<---	Orientation	0.845	0.078	10.867	***	par_10	Accepted
H_4	Engagement	<---	Interaction	0.395	0.186	2.127	0.033	par_19	Accepted
H_5	Engagement	<---	Multimedia	0.117	0.147	.799	0.424	par_22	Rejected
H_6	Engagement	<---	Orientation	0.243	0.171	1.421	0.155	par_23	Rejected
H_7	Engagement	<---	Difficult	-0.012	0.174	-.067	0.947	par_25	Rejected
H_8	Performance	<---	Multimedia	0.805	0.233	3.459	***	par_8	Accepted
H_9	Performance	<---	Engagement	0.403	0.217	1.961	0.043	par_20	Accepted
H_{10}	Performance	<---	Interaction	0.131	0.163	.807	0.420	par_24	Rejected
H_{11}	Performance	<---	Difficult	-0.340	0.260	-1.306	0.192	par_26	Rejected

Hypothesis testing compares the C.R. (Critical Ratio) value of 1.96 at the 0.05 significance level. If the C.R. value> 1.96 and the P value <0.05, the hypothesis can be accepted; otherwise, if the C.R. value <1.96 and the P value> 0.05, the hypothesis is rejected [24].

5. Discussion

5.1. Effect of Difficult Learning on Orientation

Learning orientation is the way a person approaches and views the learning process. It includes motivation, learning strategies, preferences, and attitudes toward learning. The relationship between learning orientation and learning difficulties can significantly affect one's academic success [25]. A person's or organization's attitude and tendency to value learning and see it as a worthwhile endeavor is referred to as learning orientation [26]. Researchers have examined the relationship between learning orientation and learning performance, stating that orientation has a significant effect [27]. However, research on the relationship between learning orientation and academic challenge is scarce. It is clear from the search findings that learning orientation is related to favorable outcomes, such as continuing to learn after learning failure, improving new venture performance, and creating new product development capabilities. However, a high learning drive may deter people from sharing their knowledge, especially if new information is complex [28, 29]. A positive and robust learning orientation can help individuals better cope with learning difficulties [30].

5.2. Effect of Learning Difficulty on Multimedia

Various educational media can help overcome the academic difficulties of students with learning disabilities [31]. Different multimedia applications can be used to provide visual, auditory, or kinesthetic experiences to students with learning disabilities, thus helping students to adopt their learning styles [32, 33]. Different multimedia applications can facilitate the acquisition of various academic skills and create various learning opportunities for students with educational disabilities [34, 35]. Multimedia can help students deepen conceptual understanding and engage their prior knowledge, which can be particularly helpful for students with learning difficulties who may have difficulty with text-based learning [36, 37]. A study found that two groups of children with different learning difficulties could benefit from using the same multimedia learning system [37]. This suggests that multimedia learning can be adapted to meet the needs of different learners, including those with learning difficulties [38].

5.3. Effect of Orientation on Interaction

A study found that peer interaction is significant in the learning process, which suggests that orientation has a significant impact [39]. In addition, a strong learning orientation will reduce concerns about protection during interpersonal interactions, enhancing team learning [40]. Specifically, students with high learning goal orientation have more significant performance improvement when they receive future-oriented feedback, while students with high performance proving orientation have more significant improvement when they receive past-oriented feedback [41].

5.4. Effect of Interaction on Learning Engagement

Involvement in wiki programs used in online learning can increase the benefits of student engagement, but there is no evidence to suggest that Wiki improves learning performance [42]. Self-directed learning and cognitive engagement affect students' learning performance [43]. In online learning, students' engagement is strongly influenced by their habits, home environment, work planning, reading, and note-taking habits and accompanied by students' characteristics and preferences in the classroom; the result is that diverger and accommodator styles have better learning achievement in online learning [44]. A good relationship between students and lecturers, with interaction and high dialogue with correspondence and assignments, will help increase students' cognitive engagement [45].

5.5. The Effect of Multimedia on Learning Engagement

Multimedia helps to increase student awareness of learning issues, improve student understanding of content, and increase engagement in the learning process [36, 46]. Almost all students prefer multimedia to aid teaching and learning and prefer this approach to traditional lecture-based teaching [47]. The impact of multimedia in course design on students' learning performance in the online learning experience is significant. Multimedia can help present information in different formats, appeal to diverse learning styles, and stimulate student curiosity and creativity [48]. To use multimedia effectively and avoid obstacles in the learning process, it is essential to select relevant and quality multimedia, integrate multimedia with other activities that engage students, and provide opportunities for students to create their multimedia products to demonstrate learning by sharing ideas [49, 50].

5.6. The Effect of Orientation on Learning Engagement

In educational contexts, learning orientation towards learning engagement shows no significant effect [51-53]. If it does have a significant effect, when accompanied by cognitive engagement, it is closely related. Learning orientation affects the level and quality of cognitive engagement in the learning process [54, 55]. Several factors can explain why learning orientation does not always significantly influence learning engagement. At times, a positive learning orientation may not necessarily reflect an individual's subjective motivation towards certain learning materials [56].

5.7. The Effect of Learning Difficulties on Learning Engagement

Students who experience learning difficulties require a personalized approach to learning [48]. Teachers should be able to adapt teaching styles to accommodate by providing appropriate adjustments and encouraging experiential learning [57]. Engagement and Disengagement in Online Learning is challenging for teachers to engage students online, and challenging learning can be one of the reasons for student disengagement [58]. Course delivery in online classes requires pedagogical strategies to create as many learning and engagement opportunities as possible [59]. Cognitive load, associated with learning difficulties, may mediate the relationship between prior knowledge and learning engagement [60]. Therefore, it is essential to consider the level of learning difficulty when designing pedagogical strategies to increase learning engagement.

5.8. The Effect of Multimedia on Learning Performance

The development of science and technology can potentially develop multimedia in learning. With the development of multimedia, it can facilitate educators in developing learning systems. Multimedia combines more than one type of media, such as text, symbols, images, audio, video, and technology-assisted animation, to improve understanding and memorization [61]. These digital and print elements refer to multimedia-based applications that facilitate a better understanding of concepts. A study found that multimedia positively influence education when well-designed on learning performance. This study shows that instruction with the use of multimedia improves learning performance [62]. Multimedia positively impacts cognitive achievement, learning performance, comprehension, and application [62].

5.9. The Effect of Engagement on Learning Performance

Learning achievement is also influenced by cognitive engagement, motivation, interest level, and difficulty in learning [63]. Student Cognitive engagement is essential to study fluctuations and changes in weekly engagement; what is important to note is feedback from lecturers [64]. about research in the form of experiments conducted [56] it turns out that the design and facilitation of learning activities that involve students in learning reflection can increase student cognitive engagement in learning. The presence of teaching staff in learning is indispensable for cognitive engagement in learning [65].

5.10. The Effect of Learning Interaction on Learning Performance

A study found that online interaction is essential for improving learning performance and learning outcomes in online environments [39]. When learners interact, they are more motivated to learn and more attentive, participatory, and likely to exchange ideas with others. This study shows that social presence is critical to online learning engagement and performance. Online learning interaction can have an impact on learning performance. Interaction and presence are significant predictors of student performance in online learning. Students' online interaction behaviors and experiences can impact learning performance.

6. Future Research Agenda

Student engagement in learning in this study only examines the cognitive aspect; there are still two more dimensions theoretically, namely behavioral engagement and emotional engagement, that can be examined more deeply about learning performance. This research was conducted during the covid 19 pandemic, so some variables were not proven to have a significant relationship during the new regular; further research needs to be carried out in more depth by simplifying the model in the form of 3 or 4 variables and by paying attention to aspects of moderating variables, namely technological literacy in generation Z now.

7. Conclusion

This study examines student learning performance in distance learning using online learning. Students' involvement in learning by using multimedia, interaction, and learning orientation are essential. Furthermore, the results of this study deepen our understanding of multimedia and how students' cognitive engagement positively affects learning performance. The better the interaction between lecturers and students in the form of answering questions from friends and lecturers, using data analysis tools to answer and the form of student questions to lecturers will be able to increase student cognitive engagement. Learning instruction with multimedia methods, multimedia for material review, and the availability of multimedia in e-learning can improve student learning performance. This research also deepens our understanding of the need for lecturers to provide learning orientation through Zoom media, self-assessment, listening to lecturers' explanations well, facilitating learning materials, and looking at lecturers' questions to determine the success of students to interact in online learning. Learning that is easy challenging, and the complexity of online learning determines students' success in learning media and learning orientation.

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