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What Are the Factors Influencing Science Learning in the Discovery Model? An Exploration of Issues to Create Innovation

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Abstract. The issues in science learning are not solely related to individual factors but involve interacting factors, where both internal factors, such as self-efficacy, motivation, epistemological beliefs, and curiosity, as well as external factors such as learning media and technology readiness, dynamically interact to shape students' perceptions and impact their learning. This study identifies and analyzes the factors influencing school science teaching, focusing on developing innovative strategies to address existing challenges. The research method employed is a mixed-method approach, utilizing Partial Least Squares Structural Equation Modeling (PLS-SEM) analysis to test hypotheses and in-depth interviews to explore the challenges, issues, and expectations of science learning. The findings indicate that curiosity significantly impacts engagement in learning (p-value = 0.003) and learning models (p-value = 0.002), suggesting that students' curiosity enhances their engagement in learning and influences the selection of learning models. Motivation significantly affects learning models (p-value = 0.011), not engagement or media usage. Furthermore, technology readiness plays a significant role in engagement in learning (p-value = 0.002) and learning media (p-value = 0.000), but does not influence the learning model choice. Interviews with teachers also revealed that the primary challenge is providing appropriate media to stimulate students, particularly for challenging topics, and the need for more interactive and real-world problem-based media to support discovery learning more effectively.

Keywords: Discovery learning; self-efficacy; motivation; epistemological beliefs; engagement in learning

INTRODUCTION

Science education plays a pivotal role in its implementation across many schools (Markula & Aksela, 2022), challenges related to the preferences and the gap between the teacher's vision and the vision for science education need further exploration (Penuel et al., 2020). The lack of clear teaching objectives, the absence of a philosophy of science perspective in textbooks, curriculum constraints, and inadequate teacher-specific training (Liu et al., 2023) are factors influencing the quality of science education, necessitating prompt solutions. Educators have also reported challenges in teaching science education, including issues with the students themselves, general conditions, actual teaching practices, and the qualifications of the educators (Barenthien & Dunekacke, 2022). These reports indicate that factors influencing the quality of science education are not only related to curriculum aspects or educational policies (Suprapto et al., 2021) but also to individual student factors such as motivation (Firdaus et al., 2025; Papadakis et al., 2023), self-efficacy (Haatainen et al., 2021), and student engagement in the learning process (Lin, 2021).

Another challenge is that science learning is perceived as highly demanding, making students feel disengaged and unmotivated (Noh et al., 2020). Epistemological beliefs become a significant concern in science learning due to students' limited understanding of how knowledge is acquired and understood (Schommer, 2019). This factor is crucial in determining whether students enjoy or comprehend science education. Students who believe knowledge is fixed and unchangeable are less likely to embrace innovation and interactive, technology-based learning methods (Levin & Wadmany, 2005). This factor is closely linked to students' curiosity, as it can encourage them to actively seek out and learn science content beyond the classroom (Kibga et al., 2021). Curiosity must be stimulated at the outset of learning to promote this exploration.

Curiosity and inquisitiveness can leverage cutting-edge technology to captivate the enthusiasm of both educators and researchers, thereby fostering inquiry-based classroom activities (Ruzaman & Rosli, 2020), which can act as a stimulus for students. However, not all students or teachers can integrate technology into learning. This readiness includes technical skills (Kaushik & Agrawal, 2021), access to adequate devices, and a positive attitude toward using technology in education (Nikolopoulou et al., 2021). This factor requires student involvement in the learning process, as students who actively engage in discussions, experiments, or interactions with learning media tend to have more positive perceptions of the learning process (Cho et al., 2021; Rossi et al., 2021).

Students' perceptions of learning will form a dynamic interaction among various factors (Jansen et al., 2014), and the complexity of this issue can influence science learning. Understanding the relationship between internal factors (motivation and self-efficacy) and external factors (learning media and technology readiness) is crucial, as it contributes to the quality of science education (Swarat et al., 2012). Perception can affect how students view learning, impacting motivation and learning outcomes (Schunk & DiBenedetto, 2020). Positive perceptions of learning media and strategies will encourage students to become more active and engaged in the learning process (Cho et al., 2021). Conversely, if students feel that the media or methods used are irrelevant or uninteresting, they will likely demonstrate lower engagement (Lin, 2021; Yang et al., 2023).

Several previous studies have identified internal and external factors affecting science learning. Britner & Pajares (2006) research shows that laboratory experiences and teacher feedback can influence students' self-efficacy in science. This influence was further corroborated by Tsai et al. (2011), who showed that students' beliefs about science impact their learning approaches. Students' beliefs require visual representations, as Rutten et al. (2012) demonstrated, where PhET simulations effectively supported learning, emphasising physics concepts.

Research on the interaction between internal and external factors was also conducted by Jansen et al. (2014), who explored how students' perceptions of science learning are influenced by motivation and self-efficacy. This research aligns with the findings of Yang et al. (2023), where combining digital media and self-efficacy enhances student engagement in science learning. However, studies examining the interaction between these internal and external factors are limited, even though both are critical to science education. This study offers an opportunity to explore these factors more deeply and reveal how they influence science learning.

This research is increasingly vital as it can provide a deeper understanding of how appropriate learning media can stimulate student interest and attention, as well as what innovations can be tailored to the diverse characteristics of students. Additionally, this research has the potential to offer solutions to the challenges faced by teachers in designing more effective and engaging science education processes. This study aims to identify and analyse the factors influencing science learning in the discovery model at schools, focusing on developing innovative strategies to address the existing challenges.

METHODOLOGY

Research Design

The research design employs a mixed-methods approach, integrating quantitative and qualitative methodologies to examine the relationships between variables while exploring the contextual dynamics in depth (Creswell & Creswell, 2018) concerning the factors influencing science learning. The quantitative approach tests the statistical relationships between variables, while the qualitative approach, through in-depth interviews with teachers, aims to understand classroom dynamics that cannot be statistically measured (Tashakkori & Teddlie, 2010). This design was chosen to provide a more comprehensive convergent validity regarding the factors affecting science education and how these factors interact with each other.

Population and Sample

The research population consists of eighth-grade students and teachers from junior high schools in the Special Region of Yogyakarta for the 2025 academic year, utilising the discovery model during the learning process. The selection of eighth-grade students is based on their age, approximately 13-14 years, which corresponds to early adolescence. This age represents a significant period of psychological and social development, making it a key focus for research on behavioral changes, cognitive growth, and social development, which are closely tied to science education. The sampling technique employed is census sampling, resulting in a sample of 179 students and teachers, as shown in Table 1. This study uses source triangulation, involving data from students (quantitative) and data from teachers (qualitative), to provide a more holistic perspective on the research issue. Findings from both sources will complement each other, enhancing the research outcomes' validity.

Table 1. Sample Demographic

Item	Response	Frequency	Percentage (%)
Class Type (code)	VIII-A	31	17,3
	VIII-B	30	16,8
	VIII-C	31	17,3
	VIII-D	31	17,3
	VIII-E	30	16,8
	VIII-F	26	14,5
Respondents' Gender	Male	85	47,5
	Female	94	52,5
Lerning style	Visual	38	21,2
	Auditory	53	29,6
	Kinesthetic	88	49,2
Information Acces	Very Available	26	14,5
	Available	142	79,3
	Not Available	11	6,1
	Very Not Available	0	0

Instrument

The primary instrument for collecting quantitative data is a questionnaire consisting of 4 scales designed to measure the variables under investigation. The questionnaire employs a 4-point Likert scale for each item, facilitating data collection and statistical analysis. The instrument for collecting qualitative data is an interview guide for interviewing teachers. This interview guide will include open-ended questions to explore teachers' challenges, constraints, and needs in teaching science.

Data analysis

Partial Least Squares Structural Equation Modeling (PLS-SEM) analysis was chosen for this study to examine the complex relationships between exogenous, mediating, and endogenous variables (Hair et al., 2019). PLS-SEM is well-suited for this research because it can handle relatively small sample sizes (Hair et al., 2017), measure both direct and indirect effects (Hair et al., 2011), and is compatible with exploratory models (Henseler, 2018). This study involves several variables derived from teacher interviews and developed into factors influencing science learning when teachers apply the discovery learning model. These variables are used to assess student perceptions as the subjects of science learning.

Exogenous Variables (X)
X1: Self-efficacy
X2: Motivation
X3: Epistemological Beliefs
X4: Technology Readiness
X5: Curiosity

Mediating Variable (Z)
Z: Engagement in Learning

Endogenous Variables (Y)
Y1: Perception of Learning Media effectiveness
Y2: Perception of Learning Model's 's effectiveness

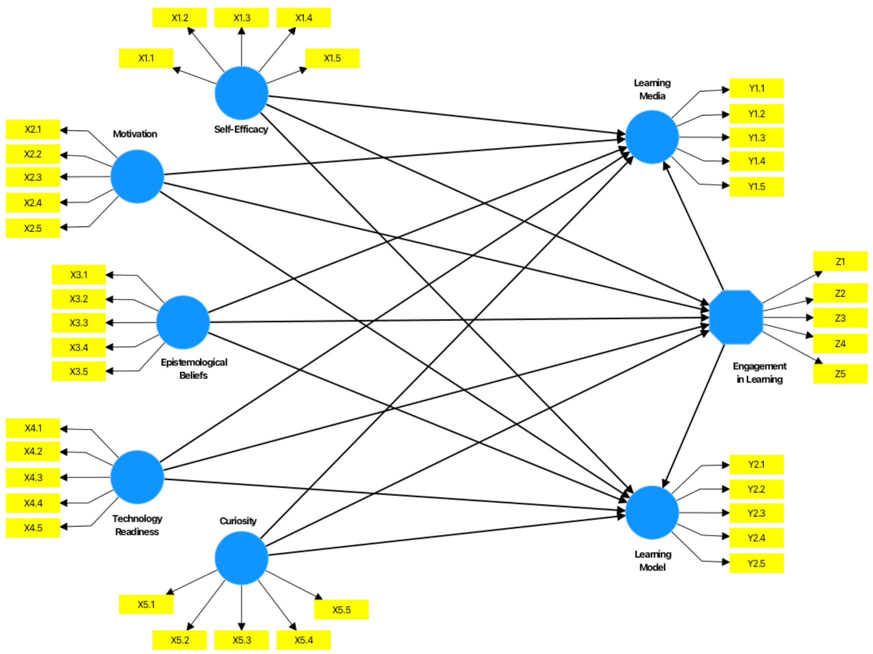

Figure 1. Research Framework

The first step in PLS-SEM analysis is to conduct validity and reliability tests of the instruments. The analysis process begins with testing the validity and reliability of the instruments. Convergent validity is assessed through Confirmatory Factor Analysis (CFA) with the criteria of outer loading > 0.7 and Average Variance Extracted (AVE) > 0.5 (Fornell & Larcker, 1981), while reliability is measured using Composite Reliability (CR) > 0.7 and Cronbach's alpha > 0.7 (Nunnally, 1978). Model fit testing is not a requirement for PLS-SEM, as PLS-SEM emphasizes criteria such as construct validity and reliability, as well as predictive power, as the primary indicators of model quality (Henseler et al., 2015). The next step is path analysis, where the path coefficients (β) and their significance are evaluated through bootstrapping with 5000 subsamples (Hair et al., 2017). Mediation effects are tested using Variance Accounted For (VAF), where values >20% indicate partial mediation and values >80% indicate complete mediation (Hair et al., 2017). The model's predictive power is evaluated using R^2 (Chin, 1998) and Q^2 predictive relevance (Geisser, 1975), with effect size interpreted according to Cohen's criteria (Cohen, 2013).

Qualitative data obtained through in-depth teacher interviews are analyzed using a thematic approach (Braun & Clarke, 2006). The first step in this analysis is transcribing the interviews to make the data easier to interpret. Then, the transcribed data are coded by labeling the data units relevant to the studied topics. After coding, the researcher identifies the main themes from the interviews. These themes are then further analyzed to understand how each theme contributes to a deeper understanding of the challenges faced in science education.

RESULTS AND DISCUSSION

Construct Validity and Reliability

The analysis results in Table 2 present various indicators related to the construct validity and reliability within the research model. Each construct is tested through multiple measurement items, which are evaluated based on loadings, weights, and several other statistical indices such as Composite Reliability (CR), Cronbach's Alpha (CA), Average Variance Extracted (AVE), and Variance Inflation Factor (VIF).

Table 2. Construct Validity and Reliability

Constructs	Items	Loadings	Weights	CA	CR	AVE	VIF
Self-Efficacy (SE)	X1.1	0.538	0.242				1.136
	X1.2	0.630	0.324				1.184
	X1.3	0.503	0.182	0.630	0.766	0.402	1.178
	X1.4	0.739	0.417				1.235
	X1.5	0.723	0.367				1.298
Motivation (Mtv)	X2.1	0.686	0.315				1.349
	X2.2	0.598	0.223				1.268
	X2.3	0.683	0.277	0.719	0.816	0.471	1.355
	X2.4	0.701	0.337				1.317
	X2.5	0.754	0.298				1.486
Epistemological Beliefs (EB)	X3.1	0.668	0.266				1.336
	X3.2	0.702	0.336				1.282
	X3.3	0.709	0.295	0.718	0.815	0.470	1.383
	X3.4	0.761	0.343				1.463
	X3.5	0.573	0.202				1.251
Technology Readiness (TR)	X4.1	0.766	0.281				1.603
	X4.2	0.767	0.271				1.608
	X4.3	0.646	0.238	0.791	0.857	0.546	1.307
	X4.4	0.773	0.306				1.555
	X4.5	0.737	0.253				1.550
Curiosity (Csy)	X5.1	0.811	0.292				1.850
	X5.2	0.751	0.305				1.482
	X5.3	0.697	0.192	0.807	0.866	0.564	1.558
	X5.4	0.754	0.254				1.611
	X5.5	0.738	0.284				1.492
	Y1.1	0.666	0.326	0.691	0.800	0.451	1.237

Constructs	Items	Loadings	Weights	CA	CR	AVE	VIF
Leaning Media (LMe)	Y1.2	0.715	0.304				1.358
	Y1.3	0.794	0.365				1.539
	Y1.4	0.670	0.291				1.333
	Y1.5	0.471	0.171				1.130
Learning Model (LMo)	Y2.1	0.673	0.277				1.376
	Y2.2	0.598	0.224				1.386
	Y2.3	0.692	0.329	0.719	0.816	0.471	1.354
	Y2.4	0.725	0.307				1.398
	Y2.5	0.736	0.312				1.613
Engagement in Learning (EiL)	Z1	0.600	0.220				1.271
	Z2	0.697	0.304				1.354
	Z3	0.617	0.315	0.676	0.793	0.435	1.259
	Z4	0.743	0.309				1.519
	Z5	0.629	0.369				1.209

Indicators such as X1.1, X2.1, X3.1, etc., act as observation variables used to measure and validate larger constructs in PLS-SEM. The relationship between these indicators and constructs is crucial to ensure that the model built accurately reflects the relationships present in the research data. Several indicator values are slightly lower than the generally accepted standards and, such as loadings below 0.70 and Cronbach's Alpha (CA) slightly below the ideal value of 0.70. However, in the context of exploratory research, these values be interpreted differently, and such values can be accepted with the justification that the goal of the research is to explore and understand phenomena in greater depth. This result is particularly true when the constructs or instruments are in the development stage. Exploratory research offers the flexibility to accept these values, provided there is strong justification regarding the relevance and contribution of the items in measuring the intended construct.

The Self-Efficacy construct shows item loadings that vary, with the lowest value being 0.503 for item X1.3 and the highest value being 0.739 for item X1.4. Although some items have loadings lower than 0.70, such as X1.1 (0.538) and X1.3 (0.503), this can be accepted in the context of exploratory research. The Cronbach's Alpha (CA) value for this construct is 0.630, slightly lower than the ideal 0.70, but it is acceptable for exploratory research. The Composite Reliability (CR) value of 0.766 indicates good reliability, suggesting that this instrument is reasonably consistent in measuring the Self-Efficacy construct. However, the Average Variance Extracted (AVE) value of 0.402 suggests that the indicators in this construct explain less than 50% of the variance in the construct, suggesting the potential for improving measurement in this construct in future studies. The Variance Inflation Factor (VIF) value of 1.136 indicates no significant multicollinearity among the items.

The Motivation construct shows loading values ranging from 0.598 for item X2.1 to 0.754 for item X2.5, demonstrating a good contribution from each item to the construct. The Cronbach's Alpha (CA) value of 0.719 indicates good reliability, exceeding the threshold of 0.70, which means the construct has a sufficiently strong internal consistency. The Composite Reliability (CR) value of 0.816 affirms that the Motivation construct is highly reliable. Although the Average Variance Extracted (AVE) value is 0.471, slightly below 0.50, it falls within the tolerance limits for exploratory research. This construct's Variance Inflation Factor (VIF) is 1.349, showing no significant multicollinearity among the items.

The Epistemological Beliefs construct shows item loadings ranging from 0.573 for item X3.5 to 0.761 for item X3.4, with several items having loadings slightly below 0.70, such as X3.5 (0.573). However, this is acceptable in the context of exploratory research. The Cronbach's Alpha (CA) value of 0.718 indicates reasonably good reliability, exceeding 0.70. The Composite Reliability (CR) value of 0.815 indicates that this construct has good internal consistency. However, the Average Variance Extracted (AVE) value of 0.470 is slightly below 0.50, indicating that the indicators in this construct do not fully explain the variance within the construct. Nevertheless, this can be accepted in exploratory research. The Variance Inflation Factor (VIF) value 1.336 also indicates no significant multicollinearity.

The Technology Readiness construct shows excellent loadings ranging from 0.646 to 0.767, indicating strong contributions from all items in this construct. The Cronbach's Alpha (CA) value for this construct is 0.791, indicating excellent reliability, exceeding the 0.70 threshold. The Composite Reliability (CR) value of 0.857 suggests that this construct has high internal consistency. The Average Variance Extracted (AVE) value of 0.546 indicates that the construct explains more than 50% of the variance in its indicators, suggesting that it has excellent convergent validity. The Variance Inflation Factor (VIF) of 1.603 indicates no significant multicollinearity in this construct.

The Curiosity construct shows item loadings ranging from 0.697 to 0.811, with item X5.1 having the highest loading value. The Cronbach's Alpha (CA) of 0.807 indicates excellent reliability, greater than 0.70, meaning this construct has very high internal consistency. The Composite Reliability (CR) value of 0.866 also shows excellent reliability, proving that this instrument is highly consistent in measuring the Curiosity construct. The Average Variance Extracted (AVE) value of 0.564 shows that this construct is very good at explaining the variance in its indicators, indicating strong validity. The Variance Inflation Factor (VIF) value of 1.850 indicates no significant multicollinearity in this construct.

The Learning Media construct shows loadings ranging from 0.471 to 0.794, with item Y1.5 having the lowest loading at 0.471, indicating that this indicator is less intense in measuring the Learning Media construct. The Cronbach's Alpha (CA) value of 0.691 indicates reliability slightly below 0.70, but it is still acceptable for exploratory research. The Composite Reliability (CR) of 0.800 indicates fairly good consistency, although some items show lower contributions. The Average Variance Extracted (AVE) value of 0.451 shows that this construct is not optimal in explaining the variance of its indicators, which should be addressed in future research. The Variance Inflation Factor (VIF) of 1.237 indicates no significant multicollinearity.

The Learning Model construct shows loadings ranging from 0.598 to 0.736, with item Y2.2 having the lowest loading (0.598). The Cronbach's Alpha (CA) value of 0.719 indicates good reliability, exceeding 0.70, indicating that this construct has sufficiently strong internal consistency. The Composite Reliability (CR) of 0.816 shows that this construct is reliable in measuring the intended variable. The Average Variance Extracted (AVE) value of 0.471 indicates that the indicators in this construct do not explain more than 50% of the variance, which warrant attention in future studies. The Variance Inflation Factor (VIF) of 1.613 indicates no significant multicollinearity.

The Engagement in Learning construct shows loadings ranging from 0.600 to 0.743, with item Z1 having the lowest loading (0.600) and Z4 having the highest (0.743). The Cronbach's Alpha (CA) of 0.676 is slightly below 0.70 but is acceptable in exploratory research. The Composite Reliability (CR) of 0.793 indicates reasonably good internal consistency. The Average Variance Extracted (AVE) of 0.435 suggests that the indicators in this construct are less effective in explaining the variance, which requires attention. The Variance Inflation Factor (VIF) of 1.271 indicates no significant multicollinearity.

Most of the constructs in this study show promising results in terms of reliability and validity, with Cronbach's Alpha and Composite Reliability values generally above 0.70 and Average Variance Extracted (AVE) values indicating adequate convergent validity for most constructs. Some constructs, such as Learning Media, Self-Efficacy, and Engagement in Learning, show lower AVE values and loadings, suggesting a need for improvement in measurement in these constructs. However, the low VIF values across all constructs indicate no significant multicollinearity issues, and these results are acceptable in the context of exploratory research.

In addition to construct validity and reliability presented in Table 2, the Heterotrait-Monotrait Ratio (HTMT) analysis serves as a crucial tool for assessing discriminant validity within Structural Equation Modeling (SEM). Discriminant validity ensures that each construct in the model is empirically distinct from others, indicating the absence of excessive overlap or overly strong correlations between constructs. HTMT offers a more robust measure of discriminant validity compared to traditional approaches, such as the Fornell-Larcker criterion, as it evaluates explicitly the ratio between heterotrait correlations (i.e., correlations between different constructs) and monotrait correlations (i.e., correlations within the same construct). An HTMT value is deemed acceptable if it falls below a certain threshold, generally 0.85 or, in some cases, 0.90, indicating sufficient discriminant validity and suggesting that the constructs are distinct and not excessively interrelated. Conversely, HTMT values exceeding these thresholds signal construct overlap, thereby potentially compromising the model's validity.

Table 3. Heterotrait-Monotrait Ratio (HTMT)

	Csy	EiL	EB	LMe	LMo	Mtv	SE
Csy							
EiL	0.766						
EB	0.700	0.642					
LMe	0.715	0.640	0.635				
LMo	0.787	0.773	0.555	0.838			
Mtv	0.814	0.708	0.771	0.695	0.751		
SE	0.726	0.756	0.714	0.602	0.631	0.848	
TR	0.641	0.716	0.622	0.839	0.523	0.568	0.619

Note: Self-Efficacy (SE); Motivation (Mtv); Epistemological Beliefs (EB); Technology Readiness (TR); Curiosity (Csy); Leaning Media (LMe); Learning Model (LMo); Engagement in Learning (EiL)

Table 3 presents the HTMT calculation results used to evaluate discriminant validity within the SEM framework. Most HTMT values across constructs are below 0.85, indicating strong evidence of discriminant validity in the model. For instance, the HTMT value between Curiosity and Engagement in Learning is 0.766, which is below the 0.85 benchmark, suggesting these two constructs are empirically distinct and not overly redundant. Other pairings, such as those between Motivation and Self-Efficacy (0.848) and Learning Model (0.751), show relatively high correlations but remain within acceptable bounds, thus supporting their conceptual independence despite moderate associations. A few HTMT values, such as that between Technology Readiness and Learning Model (0.839), approach the threshold, potentially indicating some conceptual overlap. Nevertheless, the majority of HTMT values, such as those between Learning Media and Epistemological Beliefs (0.635), affirm adequate differentiation among the constructs. Overall, the HTMT results support the discriminant validity of the constructs employed, reinforcing their suitability for further analysis within the SEM framework.

Model fit is a crucial step in statistical analysis used to assess the degree to which an estimated model aligns with the available data. The evaluation of model fit typically involves comparing the estimated model with a more complex or "saturated model," which encompasses all possible relationships among the variables. Several indicators are utilized to gauge the adequacy of the model fit (table 4), such as SRMR (Standardized Root Mean Square Residual), d_ULS, d_G, Chi-square, and NFI (Normed Fit Index).

Table 4. Model Fit

	Saturated model	Estimated model
SRMR	0.086	0.087
d_ULS	6.057	6.244
d_G	1.616	1.644
Chi-square	1502.229	1520.068
NFI	0.533	0.528

Based on the results in Table 4 derived from the model fit table, the model fit analysis between the saturated model and the estimated model reveals a satisfactory level of correspondence, despite some minor discrepancies in specific indicators. The SRMR values for both models are 0.086 for the saturated model and 0.087 for the estimated model, indicating an almost negligible difference between the two, both of which fall within the acceptable range (an SRMR value below 0.08 is typically considered indicative of a good fit). This result suggests that the estimated model effectively represents the interrelationships among the variables, closely approximating the more intricate saturated model.

Subsequently, the d_ULS (Unweighted Least Squares) indicator for the saturated model is 6.057, while for the estimated model it is 6.244, revealing a negligible difference and implying that both models exhibit similar residual errors, regardless of the weights of the variables. The d_G indicator, serving as an alternative to d_ULS by accounting for the distribution of the variables, also yields comparable results: 1.616 for the saturated model and 1.644 for the estimated model, both of which suggest that the estimated model exhibits an excellent fit.

The Chi-square test, which assesses how well the estimated model aligns with the observed data, provides a value of 1502.229 for the saturated model and 1520.068 for the estimated model. Despite the slight increase in the Chi-square value for the estimated model, this difference is marginal and does not indicate any significant issues with model fit. Finally, the NFI value for the saturated model is 0.533, while for the estimated model, it is 0.528, reflecting a slight decrease in the estimated model. However, both values remain within an acceptable range. Ideally, the NFI should be closer to 1. Overall, these results suggest that the estimated model demonstrates an excellent fit to the data, with minimal discrepancies when compared to the saturated model, implying that the estimated model can be deemed a sufficiently accurate representation of the relationships among the variables.

Factors Affecting Science Learning

The path analysis results test the direct relationships between the variables involved in this research model. This path analysis aims to identify each variable's direct effects on the others and determine the significance of these relationships. The path analysis values indicate the strength of the relationships between the variables, while the p-value assesses the statistical significance of these relationships (Figure 2).

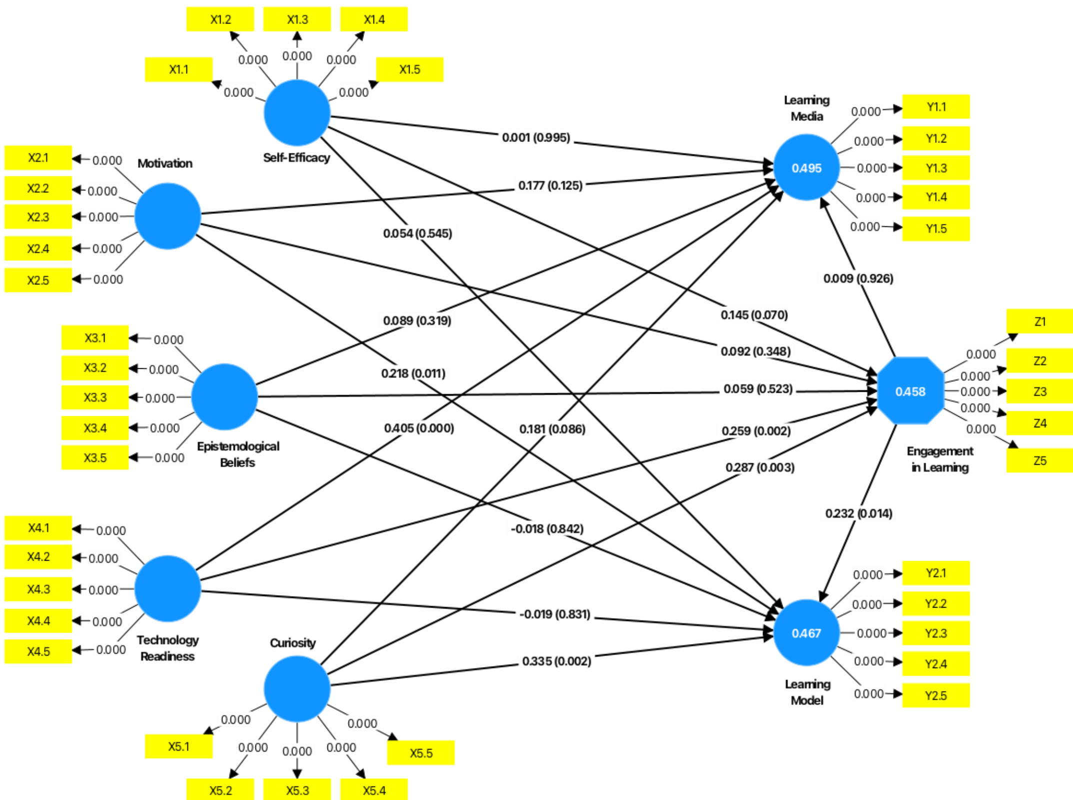

Figure 2. Testing Hypothesis

Table 5. Path Coefficient

	Sample mean	Standard deviation	T statistics
Csy -> EiL	0.287	0.095	3.022
Csy -> LMe	0.184	0.105	1.719
Csy -> LMo	0.337	0.107	3.135
EiL-> LMe	0.009	0.094	0.093
EiL-> LMo	0.228	0.094	2.463
EB-> EiL	0.061	0.092	0.639
EB-> LMe	0.093	0.090	0.996
EB-> LMo	-0.017	0.089	0.200
Mtv -> EiL	0.091	0.098	0.939
Mtv -> LMe	0.173	0.115	1.536
Mtv -> LMo	0.212	0.086	2.536
SE-> EiL	0.154	0.080	1.815
SE-> LMe	0.001	0.082	0.006
SE-> LMo	0.062	0.090	0.606
TR-> EiL	0.256	0.084	3.084
TR-> LMe	0.412	0.090	4.497
TR-> LMo	-0.014	0.089	0.214

The relationship between Curiosity and Engagement in Learning shows a significant result, with a p-value of 0.003, much smaller than the 0.05 threshold. The T-statistic value of 3.022 also indicates a strong and significant relationship. This result suggests that curiosity has a strong positive influence on engagement in learning. Therefore, it can be concluded that the higher an individual's curiosity, the greater the likelihood that students will engage in the learning process. This finding aligns with the Self-Determination Theory (SDT), which states that curiosity, as intrinsic motivation, encourages active engagement (Ryan & Deci, 2020). Empirical studies by Litman (2005) also confirm that students with high curiosity tend to be more exploratory in their learning.

The relationship between Curiosity and Learning Media shows a non-significant result (p-value = 0.086). Although these two variables have a positive influence, the p-value greater than 0.05 suggests that the effect is not strong enough to be considered significant. This result indicates that while curiosity influence the use of learning media, its impact is not substantial within the context of this study.

The relationship between Curiosity and Learning Model shows a significant positive effect (p-value = 0.002, T-statistics = 3.135). The very small p-value and high T-statistics confirm this relationship is statistically significant. This result means that individuals with high curiosity tend to prefer or become more engaged with specific learning models, emphasizing the importance of curiosity in shaping one's approach to learning. This finding is supported by von Stumm et al. (2011), who found that inquisitive individuals are likelier to choose inquiry-based learning methods.

The relationship between Engagement in Learning and Learning Media shows no significant result (p-value = 0.926), indicating no direct and strong relationship between engagement in learning and the use of learning media in this study. Similar results were found for the relationships between Epistemological Beliefs and Engagement in Learning (p-value = 0.523) and Learning Media (p-value = 0.319), showing no significant influence. In other words, epistemological beliefs, or one's views about knowledge, do not have a substantial enough impact on student engagement in learning or the use of learning media.

Additionally, the relationship between Epistemological Beliefs and Learning Model is not significant (p-value = 0.842), suggesting that one's view on how knowledge should be learned does not directly influence the learning model chosen by students. This finding implies that epistemological beliefs not be a significant factor in selecting or accepting a particular learning model. This result contrasts with previous studies (Hofer, 2000), suggesting that epistemological beliefs affect learning approaches. The insignificance of this relationship also be due to the specific context of science learning in Indonesia, which is more structured (Tsai et al., 2011), and the less sensitive measurement of the construct (Schommer-Aikins, 2004).

However, the relationship between Motivation and Learning Model shows a significant result (p-value = 0.011, T-statistics = 2.536), indicating that motivation significantly influences the choice or acceptance of learning models. This result is consistent with the Expectancy-Value Theory (Eccles & Wigfield, 2002), which suggests that motivation affects the selection of learning strategies. However, the relationship between Motivation and Engagement in Learning (p-value = 0.348) and Learning Media (p-value = 0.125) is insignificant, indicating that while motivation plays a crucial role in selecting learning models, it does not significantly influence engagement levels or the use of learning media. This result is likely because extrinsic motivation is insufficient to drive deep engagement (Deci et al., 1999).

The relationship between Self-Efficacy and Engagement in Learning shows a p-value of 0.070, slightly greater than 0.05. This result supports Bandura's theory (Bandura, 1997) that self-efficacy plays a role in learning perseverance, but other factors moderate its effects. Although there is a positive influence between Self-Efficacy and Engagement in Learning, the effect is only marginally significant and needs further exploration in future research. On the other hand, the relationships between Self-Efficacy and Learning Media (p-value = 0.995) and Learning Model (p-value = 0.545) are insignificant, indicating that self-confidence does not directly influence the use of learning media or the chosen learning model.

Meanwhile, Technology Readiness shows significant results in its relationship with Engagement in Learning (p-value = 0.002, T-statistics = 3.084) and Learning Media (p-value = 0.000, T-statistics = 4.497). This result indicates that technology readiness significantly influences engagement in learning and the use of learning media. These results are consistent with studies by Parasuraman (2000) and Dwivedi et al. (2019) regarding the role of technology in enhancing learning participation. High technology readiness tends to encourage individuals to engage more in learning and prefer or use the available learning media. However, the relationship between Technology Readiness and Learning Model is insignificant (p-value = 0.831), suggesting that technology readiness does not directly influence the learning model choice.

The path analysis results show that variables such as Curiosity, Motivation, and Technology Readiness significantly affect several aspects of learning, particularly in the Learning Model and Learning Media. However, other relationships, such as those between Epistemological Beliefs, Self-Efficacy, and Learning Media, do not show significant effects, suggesting that these factors not play a strong role in determining the selection or use of learning models and media. These findings provide important insights into the factors influencing the learning process and can be used to design more effective learning strategies based on the variables that have been proven significant.

The findings of this study are supported by interviews with teachers, which provide a deeper understanding of the challenges faced in science education, particularly regarding learning models, learning media, and how student characteristics affect the learning process. One key finding from the interviews is that the implemented learning model strongly influences students' needs. However, teachers face significant difficulties finding the right media or resources to stimulate students before the learning process begins, especially for more complex and abstract materials.

The Relationship Between Learning Models, Media Limitations, and Student Needs

The analysis process begins with transcribing the interviews to make the data easier to analyze, followed by coding to assign labels to data units relevant to the studied topics. After coding, the researcher identifies the main themes that emerge from the interviews, which are then further analyzed to understand how each theme provides deeper insights into the challenges faced in science education, particularly when implementing the discovery learning model. Table 6 presents the key findings obtained from the thematic analysis of the teacher interviews.

Table 6. Theme Result

Theme	Description	Key Points
Learning Model: Discovery Learning	The discovery learning model increases student engagement in problem-based and discovery-based learning.	Student Engagement, Problem Solving, Discovery-Based Approach
Limitations of Learning Media	Limitations in media that can stimulate students before learning begins, as well as a lack of suitable materials on common platforms.	Material Access Limitations, Media Quality Limitations, Language Issues
Need for Appropriate Learning Media	Interactive and engaging media that can stimulate students' critical thinking is required, especially for complex material.	Student Engagement with Interactive Media, Visualization of Complex Material, Resource Limitations
Development of Learning Media	The development of more comprehensive learning media that aligns with the characteristics of learning models, such as discovery learning.	Innovation in Media Development, Teacher Training, Collaboration with External Parties
Collaboration and Resources	Collaboration between schools and external parties to obtain relevant and affordable student resources.	Enhancing Collaboration, Affordable Access for All Students
Challenges in Implementing Discovery Learning	The main challenge is the lack of suitable media to effectively support the implementation of the discovery learning model.	Media Limitations in Model Implementation

One of the key findings from the interviews is that the learning model applied in the classroom significantly influences how students learn, and therefore, students' needs vary according to the approach used. Teachers often choose the discovery learning model to teach science content. This model, which emphasizes a problem-based and discovery approach, is highly effective in increasing student engagement. Students do not merely passively receive information; they are allowed to discover concepts through practical activities, experiments, and discussions. Discovery learning enables students to actively engage in the learning process by identifying real-world problems around them and solving them independently. The finding that discovery learning enhances student participation is consistent with Bruner (1961) research, which emphasizes the role of active learning in knowledge construction. This model allows students to develop understanding through self-directed exploration (HMELO-SILVER et al., 2007).

Although this model has proven effective in increasing student engagement, a significant challenge teachers face is the difficulty in providing learning media that can stimulate students before learning begins. Teachers' difficulty in providing initial stimulation supports the criticism by Kirschner et al. (2006) that discovery learning requires adequate scaffolding, especially for complex content. The initial stimulus provided to students is critical in the discovery learning model because it can enhance students' curiosity and prepare them to engage in learning more actively. However, not all content needed for discovery learning can be easily found on common platforms like YouTube. Many materials are unavailable or not processed in a way that stimulates the discussions or in-depth exploration required in discovery learning.

The interview results also show that although some learning media, such as the PhET application for simulations, have been used, these media are not sufficient to address various learning needs, especially for more abstract or complex content. For instance, in science education, some abstract concepts, such as theories in physics or chemistry, require more concrete media to help students visualize these concepts. While PhET provides visual simulations for certain concepts, these media often fail to cover all the aspects needed to optimize students' understanding, especially for more complex concepts or material that cannot be easily simulated using available tools. The limitations of PhET simulations in visualizing abstract concepts align with er (2009)findings that the effectiveness of multimedia depends on its alignment with students' cognitive levels.

Additionally, limitations in the language used in learning media pose a separate issue. Some learning media use technical or mathematical language that be difficult for students to understand without additional explanation or teaching. When students encounter complex content that requires basic mathematical knowledge or specialized skills, they often struggle to understand the message conveyed through the media. The issue of understanding technical language reinforces Sweller (2010) cognitive load theory, where overly complex material can overload students' working memory (Firdaus, Amelia, et al., 2025). Therefore, while various resources are available on the internet, not all are adequate to support discovery learning, requiring richer stimuli to trigger critical thinking and in-depth discussions. Media is needed based on the cognitive theory of multimedia learning (CTML), which integrates text, visuals, and interactivity (er, 2009).

Media Needs Suitable for Learning Models

Teachers stated that the learning media needed must be able to provide initial stimuli to students, so they are better prepared to engage in discovery-based learning activities and discussions. However, the existing media are often limited and do not always match the learning model's characteristics. Students need more interactive and engaging media to introduce them to real-world problems relevant to the studied material and facilitate deep exploration. This result is significant for discovery learning, which requires stimuli that allow students to formulate problems, engage in discussions, and discover solutions independently. er (2004) research on prior knowledge activation in learning supports the finding that discovery learning requires strong initial stimuli. Teachers need media that can trigger students' curiosity (Kang et al., 2009), present contextual problems (Hmelo-Silver, 2004), and facilitate scaffolding (Quintana et al., 2004).

Teachers revealed that videos or other media sources that can stimulate students' understanding of more complex content are greatly needed, but the available resources often do not cover all the aspects needed to deliver the material in depth. Teachers also mentioned that visualization media for highly technical content or concepts requiring complex conceptual understanding are essential. Therefore, developing more innovative learning media, aligned with the characteristics of students and the learning models, is crucial to address these gaps. The limitations of visualization media for abstract concepts align with Kozma (2003) findings on the importance of multimodal representation, Ainsworth (2006) work on the functions of multiple representations, and de Jong et al. (2014) regarding inquiry-based simulations.

Based on these findings, teachers suggest that to improve the quality of science learning, more comprehensive learning media must be developed that align with the applied learning model, such as discovery learning. Developing innovative media that can provide more effective stimuli is crucial, especially when teaching abstract or complex content. Teachers also expect further training on developing or adapting learning media to meet specific students' needs, particularly in terms of visualizing material that is difficult to comprehend through theory or verbal explanations alone. Teachers' suggestions about the need for innovative media are supported by Plass et al. (2020) principles of multimedia learning and Chen et al. (2019) on adaptive learning technologies.

Moreover, it is important to enhance collaboration between schools and external parties, such as educational communities or offices, to obtain more relevant and suitable resources for learning needs. Teachers hope that the existing learning media can be more interactive, practical, affordable, and sufficient for all student characteristics, so that all students, regardless of their learning style, can gain maximum benefit.

Although the discovery learning model has proven effective in increasing student engagement, providing the right learning media remains one of the main challenges teachers face. Students' learning needs greatly depend on the learning model used, but the learning process cannot proceed optimally without appropriate media to stimulate students. Therefore, there is a need for the development of more relevant and innovative learning media, which can help students better understand the material, especially complex or abstract content, and support the implementation of more active, discovery-based learning models like discovery learning.

Exploring the Creation of Innovation

Based on the path analysis results and interviews, we can conclude that stimuli support the learning process, particularly in the discovery learning model. The path analysis results show that Curiosity significantly impacts Engagement in Learning and the Learning Model, indicating that students' curiosity plays a significant role in motivating their engagement in learning. However, to facilitate this process, teachers face a significant challenge in providing media to stimulate students before the learning begins. Therefore, developing effective stimulus media is essential to support the success of discovery learning.

One key finding from the interviews is that in discovery learning, the initial stimulus process is significant for sparking students' curiosity and preparing them to engage actively in learning. This stimulus motivates students and provides a context relevant to the material that will be studied. Therefore, effective stimuli will make it easier for students to formulate questions, identify problems, and find solutions in the discovery-based learning process.

However, although students' curiosity significantly impacts Engagement in Learning (p-value = 0.003), the primary challenge teachers face is difficulty finding or developing the right media to stimulate students before the learning begins, especially with abstract content. Therefore, the media developed should be able to provide relevant stimuli and spark students' curiosity so that they can become more deeply involved in this learning model.

One leading solution proposed is the development of stimulus media based on real-world problems that can be directly related to the content to be learned. The interview results indicate that the discovery learning model requires stimulus based on real-world problems because it allows students to discover and solve issues relevant to their lives. The use of documentary videos or real-world simulations presenting problems that students can study and solve is very effective in sparking students' curiosity.

For example, in science education, a video showing a natural phenomenon or a science experiment that triggers interesting questions could be used to provide the necessary stimulus. These videos should be presented challengingly, sparking curiosity, so students feel motivated to explore and discover the answers during the learning process. With real-world problem-based stimuli, students can connect learning to real life more easily and become more engaged in discovery learning activities.

The interview results also found that collaboration with external parties, such as educational app developers or educational communities, is crucial for enhancing the quality of stimulus media used in learning. This collaboration can include the provision of technology-based teaching materials that are more in line with the needs of the discovery learning model. For instance, collaboration with virtual simulation development companies or web-based educational platforms can produce richer and more engaging stimulus media.

Furthermore, collaboration between schools and other educational institutions can help provide more relevant and innovative resources (Firdaus, 2025), such as training courses for teachers on utilizing available stimulus media to support discovery-based learning models. With the help of technology and external resources, more varied and effective stimulus media can be developed to assist students in the learning process.

To support the success of the discovery learning model, it is vital to develop stimulus media that aligns with the characteristics of students and the material being taught. Based on the path analysis results and interviews, Curiosity and Technology Readiness play significant roles in increasing student engagement, and therefore, the media used to stimulate students must be able to spark students' curiosity and enhance active interaction in the learning process. Developing real-world problem-based media, interactive simulations, and collaboration with external parties are key to creating effective media that supports discovery learning. Additionally, teacher training using relevant stimulus media is crucial in creating a more optimal learning experience.

To enhance science learning, particularly within the context of the Discovery Learning model, various aspects of innovation must be considered. Innovations in science education aim to create a more interactive, engaging, and practical learning experience. The following table 7 outlines several aspects of innovation required to support and strengthen the learning process, along with concrete steps that can be taken to achieve these goals.

Table 7. Innovation Framework

No	Aspect of Innovation	Required Innovation
1	Identification of Factors Affecting Science Learning in Discovery Model	Development of learning media that stimulates curiosity and supports student engagement.
2	Building Learning Media Relevant to Discovery Learning	Development of multimedia-based media and interactive simulations that ease the understanding of scientific material.
3	Utilization of Technology to Enhance Engagement in Learning	Integration of technology and educational platforms to support students' exploration of materials in a more contextual manner.
4	Enhancing Learning through Collaboration and External Resources	Collaboration with educational app developers and other educational institutions to create more innovative media.
5	Teacher Training and Competence Development	Organizing training for teachers on the use and adaptation of learning media and the latest technology.
6	Evaluation and Improvement of Learning Models and Media	Continuous evaluation and refinement of learning media and the models used.
7	Creation of Problem-Based Learning Media for Real-World Issues	Development of videos and simulations of real-world problems relevant to the material taught to trigger students' curiosity.

Research Limitation

Several indicators suggest values below the generally accepted standards, potentially impacting the construct validity of the measurement. In the Self-Efficacy (SE) construct, several items exhibit factor loadings lower than 0.70, such as item X1.3 (loading = 0.503). This value indicates that the item contributes less to the measured construct due to various factors. The item is less pertinent, thus failing to adequately represent the dimension intended in the construct. Additionally, the sample population used lacks consistent experiences or perceptions concerning the item. This weakens the item’s relationship with the construct it is supposed to measure, thereby compromising the accuracy of the Self-Efficacy measurement.

Furthermore, Cronbach’s Alpha (CA), which is slightly below 0.70 for certain constructs, such as Self-Efficacy (CA = 0.630), indicates lower internal reliability than the ideal threshold typically accepted. A lower CA can stem from inconsistencies in item responses or substantial variability between items measuring the same construct. For some constructs, items with divergent characteristics or focuses reduce the CA value, as these items are weakly correlated with one another.

The Average Variance Extracted (AVE) for several constructs also yields suboptimal results, falling well below the 0.50 threshold. This is due to the presence of items with low measurement quality, resulting in their inability to account for the majority of the variance within the construct. A low AVE can also be attributed to an insufficient or unrepresentative sample size, which hinders the optimal relationship between items and the construct. In this context, while these items be acceptable in exploratory research, the low AVE values suggest that the construct validity requires further enhancement.

Implication for Practice

Educators must design instructional strategies that stimulate students' curiosity, particularly during the initial stages of learning. The use of learning media that sparks curiosity, such as experimental videos or real-world problems relevant to the topic being studied, can enhance student engagement. Curriculum designers should consider integrating elements that foster students' inquisitiveness, such as incorporating problem-based tasks that encourage students to explore and discover scientific concepts. Policymakers should also allocate resources to support the development and dissemination of learning materials that stimulate curiosity and optimize students' learning experiences.

Moreover, this study reveals that interactive learning media, aligned with the discovery-based learning model, can significantly enhance students' comprehension. Teachers should be trained to select and utilize media that not only conveys information but also encourages students to engage in critical thinking and active participation in learning. Curriculum developers must create materials that not only align with learning objectives but also support the use of diverse media, such as simulation applications or interactive multimedia tools, which enable students to grasp complex and abstract scientific concepts more effectively. Policymakers should ensure that the curriculum accommodates technological advancements that can enrich students' learning experiences.

Teacher training also plays a crucial role in the successful implementation of the research findings. Educators must be equipped with the skills to utilize technology-based learning media and effectively integrate them into their everyday instructional practices. Teacher training curricula should include the use of technology and the development of media suited to the characteristics of students and the needs of discovery-based learning. Curriculum designers must ensure that teacher training programs facilitate the development of practical skills related to the effective use of technology in education. Meanwhile, policymakers need to support continuous training programs to enable teachers to optimize the use of these tools in the learning process.

CONCLUSION AND LIMITATIONS

Conclusion

This study reveals that various factors significantly influence science learning, particularly in the context of the discovery learning model. Curiosity has a substantial positive effect on student engagement and the choice of learning models, emphasizing the importance of intrinsic motivation in enhancing the learning experience. Technology readiness is another critical factor, showing a significant impact on engagement and the use of learning media, reinforcing the role of technology in facilitating active participation in the learning process. Motivation also plays a key role in selecting learning models, but its influence on engagement and media use is less pronounced. Conversely, factors like epistemological beliefs and self-efficacy showed minimal direct effects on engagement or the choice of learning media, suggesting that they not be as influential in the context of science learning in this study. Additionally, while discovery learning is a practical approach, the challenge remains in providing suitable media that can stimulate curiosity and engagement, especially for complex and abstract concepts.

The findings are further supported by interviews with teachers, which underscore the critical need for effective learning media that can spark students' curiosity and enhance their engagement. Teachers face significant challenges in providing the necessary stimuli before learning begins, particularly when dealing with abstract content. Therefore, there is a pressing need for innovative media that aligns with the discovery learning model, providing real-world problem-based stimuli to facilitate deep exploration and active learning.

Limitations

Despite the valuable insights gained from this study, several limitations should be acknowledged. Firstly, the sample size and context, which are specific to certain schools and regions, limit the generalizability of the findings to other educational settings. The study's focus on specific variables such as curiosity, motivation, and technology readiness overlook other potential factors influencing learning outcomes, such as social influences or cultural contexts. Furthermore, the study primarily relied on self-reported data from both students and teachers, which be subject to bias and inaccuracies. Another limitation is the lack of longitudinal data, as the study only provides a snapshot of the current situation without considering how the factors influencing learning evolve. Lastly, while the study highlighted the challenges teachers face in finding suitable media for discovery learning, it did not extensively explore potential solutions for overcoming these challenges or evaluate the effectiveness of existing media in a more controlled environment. Further research could address these limitations by exploring a broader range of factors, employing a more diverse sample, and considering the long-term effects of various learning models and media on student engagement and learning outcomes.

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