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Artificial Intelligence-Based Stimulus Website in the Discovery Learning Model: How Does it Affect Students' Motivation, Metacognition, and Engagement?

Apriana Djara[1]*, Thoriqi Firdaus[1], Agum Yuda Septajati[1], Riski Dewanto[1], Ismail Fikri Natadiwijaya[1], Maryati Maryati[1], Putra Habib Dhitareka[2]

[1]Science Education, Universitas Negeri Yogyakarta, Yogyakarta, Indonesia
[2]Science Education, Universitas Pendidikan Indonesia, Bandung, Indonesia

*Corresponding author: aprianadjara.2023@student.uny.ac.id

ABSTRACT The limitations and conditions faced by teachers who have difficulty accessing or developing cognitive-stimulus learning media for abstract and complex material pose a challenge in themselves for implementing the discovery model. This study aims to evaluate an AI-based stimulus website developed to support the discovery learning model. learning in science learning through user perception, motivation, metacognition, and student engagement. This study employs a quantitative approach based on Partial Least Squares Structural Equation Modeling (PLS-SEM). The results of the analysis show that the influence of learning Comprehension on Engagement has a coefficient of $\beta = 0.437$ ($p = 0.002$), and on motivation and metacognition, $\beta = 0.446$ ($p = 0.000$), indicating that learning comprehension significantly increases student engagement and motivation. Perception of the AI website also has a strong influence on engagement ($\beta = 0.550$, $p = 0.001$) and motivation & metacognition ($\beta = 0.477$, $p = 0.002$). While video quality does not have a significant effect on engagement ($\beta = -0.052$, $p = 0.607$) or motivation & metacognition ($\beta = 0.034$, $p = 0.793$), indicating that psychological and cognitive aspects are more important than technical aspects of video in AI-based learning. Positive perception and conceptual understanding through AI-based websites significantly increase students' motivation, metacognition, and engagement, while the technical quality of the media does not play a dominant role. These results provide recommendations for developers and educators to prioritize interactive designs that support metacognitive reflection and active engagement of students as independent learners in discovery learning that uses AI-based stimuli.

Keywords: Artificial intelligence, Discovery learning, Engagement metacognition, Motivation

1. INTRODUCTION

Technological developments and changes in educational paradigms in the Industry 5.0 and Society 5.0 eras encourage the integration of active learning approaches to create a learning environment that supports student motivation (Kondo et al., 2025). Innovative active learning approaches have also been shown to be effective in developing higher-order thinking skills through methods such as group discussions, role-playing, and collaborative projects (Mulianingsih et al., 2025). Furthermore, improvements in attention, executive function, and learning outcomes can be significantly enhanced through approaches that consider both students' emotional and cognitive aspects (Ballesta et al., 2024). According to Freeman et al. (2014), research shows that active learning strategies can improve student performance by up to 6% compared to traditional lecture methods, underscoring the importance of approaches that encourage students to construct knowledge actively. One model widely applied in the active learning approach learning in science learning is discovery learning (Amrianto & Lufri, 2019; Suardana et al., 2020; Sulistyo & Kartono, 2021). This is because it emphasizes students' problem-solving and independent exploration, especially in learning science concepts that require in-depth understanding and inquiry. (HMELO-SILVER et al., 2007).

Various studies have examined the effectiveness of the discovery model. Learning increases students' motivation,

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engagement, and conceptual understanding in science. Research by Bruner (1961) suggests that active exploration in learning enables students to build more profound knowledge. Research by Hmelo-Silver et al. (2007) emphasized that scaffolding is an essential component of discovery learning, enabling students to develop understanding through directed guidance during the inquiry process. However, research by Kirschner et al. (2006) shows that without sufficient guidance, discovery Learning can burden students' cognition, especially with complex material, limiting its effectiveness and running counter to other opinions.

Although discovery learning, as demonstrated in previous research, is an effective model for increasing motivation (Erwinsyah & Ubaedillah, 2025; Setiaji et al., 2024), metacognition (Junina et al., 2020), and student engagement (Erwinsyah & Ubaedillah, 2025), its implementation often faces obstacles. One of the main challenges identified globally is the limited availability of appropriate and effective learning media (Kirschner et al., 2006). This aligns with the difficulties teachers in Indonesia face in accessing or developing effective learning media as cognitive stimuli, particularly for abstract and complex science learning materials (Sukarjita et al., 2024; Suryanda et al., 2021). This limitation hinders the optimization of discovery potential. learning to motivate and engage students to the maximum.

Current digital resources are not yet fully capable of covering all aspects of complex scientific concepts or providing appropriate scaffolding (R. E. Mayer, 2017). Furthermore, technical language barriers and cognitive load often hinder students' understanding of the material, especially when learning media use technical terms and advanced concepts without adequate explanatory support (Sweller, 2010b, 2010a). This condition indicates the need to develop multimedia-based learning media that integrate text, visuals, and interactivity, in accordance with cognitive theory. Theory of multimedia learning (R. Mayer, 2020), to support the discovery learning process for optimal learning.

According to the OECD (2023) report, the appropriate use of educational technology can improve the quality of learning and strengthen student engagement (OECD, 2023). However, many schools in developing countries have not yet optimized the use of digital media that supports active learning models. This is also evident in the Indonesian learning context, where teachers face limitations in developing or accessing interactive and appropriate learning media (Ministry of Education and Culture, 2021). These limitations have real implications: when students receive ineffective initial stimulus, they tend to experience difficulties formulating problems and carrying out independent exploration.

These limitations can be supported by the use of early stimulus learning media, R. Mayer (2020); R. E. Mayer (2004, 2009, 2017), developing a cognitive theory of multimedia learning (CTML) that emphasizes the integration of text, visuals, and interactivity to support students' mental processes optimally. That is not appropriate to students' cognitive levels, which can create excessive cognitive load that hinders learning (Sweller, 2010b, 2010a). In line with this, Kozma (2003) and Ainsworth (2006) emphasize the importance of multiple representations in learning media to help students understand abstract concepts through various complementary modes of representation. However, research from de Jong et al (2014) shows the limitations of this medium in accommodating students' needs for highly abstract concepts or material that cannot be easily simulated. These media also often use technical language that is not always easily understood by all students, thereby creating additional challenges related to cognitive load and comprehension (Sweller, 2010).

These challenges can be overcome through the use of Artificial Intelligence technology. Intelligence (AI) in education is showing great potential for personalization. (Firdaus, 2025; Huang et al., 2024) AI has emerged as one of the most transformative technological developments of the modern era, with a profound impact on the education sector through adaptive, efficient learning systems (Firdaus, 2025). However, research integrating AI as a stimulus medium in the context of discovery learning remains limited. Learning, especially in science learning, is still limited, and there is a theoretical gap that this research aims to fill, namely the lack of studies that comprehensively integrate the influence of AI-based stimulus media on student motivation, metacognition, and involvement in the discovery model learning, particularly in the context of science learning in Indonesia. This is because teachers in Indonesia face several challenges, including limited stimulus materials that effectively stimulate students' curiosity, resulting in low student engagement and motivation in science learning, which in turn affects overall learning outcomes.

AI serves as a valuable resource for educators to boost students' motivation for learning since it facilitates the personalization of targeted learning experiences and offers interactive tools (like exploration and simulation) that enhance student interest and participation, all while alleviating the mundane workload of teachers, enabling them to focus on delivering quality instruction (Ishmuradova et al., 2025; Yurt, 2024)

This research directly links these challenges to the development of AI-based stimulus media, which is expected to provide richer, more interactive, and more contextually relevant initial stimuli, thereby improving the quality of discovery learning. learning in Indonesia, and can serve as an appropriate model. Furthermore, previous research tends to treat media quality, technology perception, motivation, metacognition, and student engagement as stand-alone variables, without integrating them into a comprehensive conceptual model. This leads to a lack of understanding of how the dynamic interaction among these variables influences student learning outcomes in discovery learning. Learning is still limited. This research makes a significant contribution by developing and testing an AI-based stimulus website to address these shortcomings and by integrating key variables into a single conceptual model, which is tested using PLS-SEM. This study aims to evaluate the AI-based stimulus website developed to support the discovery learning model. learning in science learning through user perception, motivation, metacognition, and student involvement.

Support for the hypotheses of the proposed model

This research is based on several relevant and complementary theoretical frameworks, chosen to address the development of Artificial Intelligence-based stimulus media. Intelligence (AI) in the discovery learning model learning, especially in science learning. The selection of this theoretical framework aims to comprehensively examine the influence of media quality (Video Quality), user perception of technology (Perception), and their impact on learning comprehension, motivation, and metacognition (Motivation & Metacognition), and student engagement (Engagement).

Cognitive Theory of Multimedia Learning (CTML), proposed by Moreno & Mayer (1999), serves as the basis for operationalizing video quality variables. CTML explains how integrating visual and audio information in learning media can optimize students' cognitive processes, using principles such as modality, contiguity, and spatial and temporal visualization to reduce cognitive load. This framework was chosen because it meets the needs of stimulus media that must convey abstract material effectively and efficiently, supporting discovery. learning that requires initial cognitive stimulation (R. E. Mayer, 2017).

The Technology Acceptance Model (TAM) proposed by Davis (1989) examines perceptual variables that focus on how perceived ease of use and the usefulness of technology influence attitudes and behavioral intentions regarding the use of learning media. This model is appropriate for understanding how teachers and students accept and utilize AI-based stimulus media, a new technology that requires special adaptation (Venkatesh & Davis, 2000).

Dual Coding: The theory, coined by Paivio (1971), is used to measure learning Comprehension, with indicators of verbal recall, visual representation, and the connection between the two. Dual Coding The theory emphasizes the importance of processing information simultaneously through verbal and visual channels, thus supporting deeper conceptual understanding and minimizing cognitive load (Paivio, 1991). This theory is particularly relevant in the context of multimedia-based learning media.

Self-Determination Theory (SDT), proposed by Deci & Ryan (2000) for motivation and metacognition variables, was chosen because it emphasizes the role of three basic psychological needs (autonomy, competence, relatedness) in motivating students to learn intrinsically and develop metacognitive awareness. This study adapts this theory to examine how stimulus media can facilitate students' sustained motivation for learning and the use of metacognitive strategies in discovery learning (Ryan & Deci, 2000).

Constructivist Learning. The theory proposed by Vygotsky, namely the variable Engagement, draws on constructivist theory, which emphasizes the importance of intellectual curiosity, hypothesis formulation, collaboration, and reflection in the learning process. This theory is relevant for measuring how stimulus media can trigger students' active involvement in discovery-based learning (Vygotsky, 1978).

This theoretical framework was chosen because it collectively addresses the main problem in this research: the need for effective stimulus media for discovery. learning that can increase student motivation, metacognition, and engagement in science learning. Each theory complements the others in examining the technical aspects of media (video quality), aspects of technology acceptance, cognitive aspects of education, and psychological and social aspects of active learning.

This research posits that understanding learning affects students' involvement, motivation, and metacognitive abilities. Furthermore, it is anticipated that the caliber of AI-driven websites will influence student engagement; students' views are believed to affect motivation and metacognition; and the quality of learning videos is theorized to impact students' engagement, motivation, and metacognitive abilities.

This research aims to evaluate an AI-based stimulus website developed to facilitate discovery learning in science education. The evaluation focuses on identifying the relationships among students' perception of the website, their learning comprehension, and the resulting levels of motivation, metacognition, and engagement during the learning process. In this context, an in-depth evaluation of AI-driven stimulus media is crucial to transform abstract scientific concepts into meaningful learning experiences and to empower teachers and students toward more autonomous, metacognitive, and discovery-based learning.

2. METHOD

2.1 Product design and implementation

This research employed a correlational design using Partial Least Squares Structural Equation Modeling (PLS-SEM) to examine predictive relationships among students' perceptions, learning comprehension, video quality, motivation, metacognition, and engagement. Integration of AI-based stimulus websites in the discovery learning (DL)

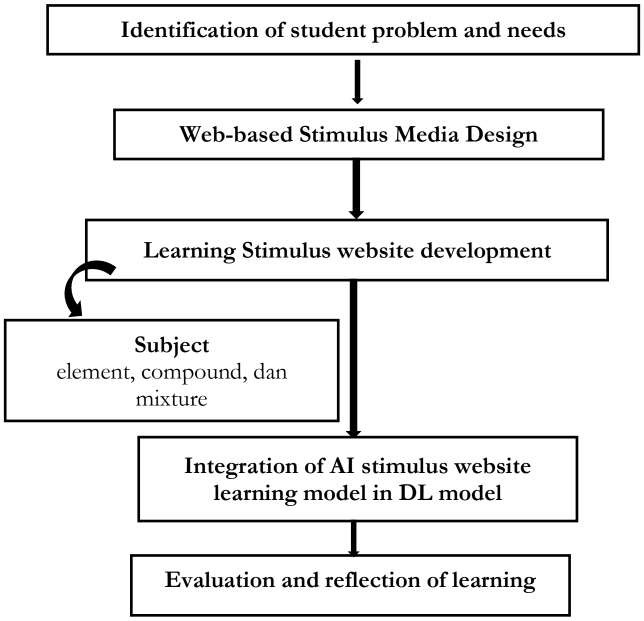

Figure 1 The steps taken in this research

model to fulfill the initial step in the DL syntax (stimulus provision). The design of the stimulus video website and its implementation are shown in Figure 1.

2.2 Research Design, Participant, and Data Collection

This research uses a correlational design with a quantitative approach, employing Partial Least Squares Structural Equation Modeling (PLS-SEM) to test the factors that influence student motivation, metacognition, and engagement in discovery learning after exposure to AI-based video stimuli. PLS-SEM was selected because this study focuses on prediction and theory development rather than theory confirmation, involves multiple latent constructs with complex interrelationships, and uses a relatively small sample size. The study participants consisted of 56 students from two classes. Below 100, PLS-SEM (Kock & Hadaya, 2018) can be used because it does not require the assumption of data normality or model fit assumptions like Covariance-Based Structural Equation Modeling (CB-SEM) (J. F. Hair et al., 2021). However, PLS-SEM can be effective even with small sample sizes, with a statistical power of 0.81 and an effect size (f^2) between 0.437 and 0.506 (Jhantasana, 2023). Class selection was carried out using a random sampling system based on the classes available on that day. Details of participants by socio-demographic categories are presented in Table 1.

In this research, the concept of validity pertains to instrument validity, which ensures that each survey question effectively measures the targeted construct. Specifically, construct validity was assessed using the outer loadings acquired via Partial Least Squares Structural Equation Modeling (PLS-SEM). The figures shown in the table are derived from the pilot test outcomes and data

Table 1 Profile Socio-demographic data (n = 56)

Category	Details	Frequency	Percentage
Class Type	First	28	50%
Class Type	Second	28	50%
Gender	Male	27	51.8%
Gender	Female	29	48.2%
Residence	Rural	49	87.5%
Residence	Urban	7	12.5%
Frequency of Smartphone Use	0-3 Hours/Day	10	17.9%
Frequency of Smartphone Use	4-6 Hours/Day	30	53.6%
Frequency of Smartphone Use	7-10 Hours/Day	13	23.2%
	>12 Hours/Day	3	5.4%
Technological Comfort in Learning	Yes	100	100%
Technological Comfort in Learning	No	0	0%

analysis conducted with SmartPLS software. An item is deemed valid when its outer loading is above 0.70 and when the Average Variance Extracted (AVE) for every construct surpasses 0.50, as suggested by (J. F. Hair et al., 2019). Items with slightly reduced loadings but still above 0.40 can be retained as long as the AVE and composite reliability criteria are met. The validity assessment was performed by analyzing the survey data with SmartPLS, determining convergent validity via outer loadings and AVE, and examining discriminant validity through the Fornell–Larcker criterion and cross-loadings. Consequently, the "validity" column in the table reflects the outer loading values obtained from the PLS-SEM analysis, signifying that the measurement items are valid and suitable for evaluating the constructs in this study. The findings are shown in Table 2.

Table 2 Acceptance threshold in PLS-SEM (J. F. Hair et al., 2019)

Criteria	Threshold	Validity
p-value	<0.05	Valid
t-statistic	>1.96	Valid
Loading	≥ 0.70	Valid
AVE	≥ 0.50	Valid
CR	≥0.70	Valid

This study used a questionnaire developed based on the literature (Creswell & Creswell, 2018; Likert, 1932), and the operationalization of the variables is presented in Table 3. The data collection instrument was a 4-point Likert scale questionnaire (4 = Strongly Agree; 3 = Agree; 2 =

Table 3 Operationalization of research variables

Variable	Theory	Indicators	Validity
Video Quality (X1)	Cognitive Theory of Multimedia Learning (Moreno & Mayer, 1999)	Modality Principle	Modality Principle
Video Quality (X1)	Cognitive Theory of Multimedia Learning (Moreno & Mayer, 1999)	Visual	Valid
Video Quality (X1)	Cognitive Theory of Multimedia Learning (Moreno & Mayer, 1999)	Audio	Valid
Video Quality (X1)	Cognitive Theory of Multimedia Learning (Moreno & Mayer, 1999)	Contiguity Principle	Contiguity Principle
Video Quality (X1)	Cognitive Theory of Multimedia Learning (Moreno & Mayer, 1999)	Spatial	Valid
Video Quality (X1)	Cognitive Theory of Multimedia Learning (Moreno & Mayer, 1999)	Temporal	Invalid
Video Quality (X1)	Cognitive Theory of Multimedia Learning (Moreno & Mayer, 1999)	Cognitive Load	Invalid
Perception (X2)	Technology Acceptance Model (Davis, 1989)	Perceived Ease of Use	Invalid
Perception (X2)	Technology Acceptance Model (Davis, 1989)	Perceived Usefulness	Invalid
Perception (X2)	Technology Acceptance Model (Davis, 1989)	Attitude Towards Using	Valid
Perception (X2)	Technology Acceptance Model (Davis, 1989)	Behavioral Intention to Use	Valid
Perception (X2)	Technology Acceptance Model (Davis, 1989)	Actual Technology Use	Valid
Learning Comprehension (X3)	Dual Coding Theory (Paivio, 1991)	Verbal Recall	Valid
Learning Comprehension (X3)	Dual Coding Theory (Paivio, 1991)	Visual Representation	Valid
Learning Comprehension (X3)	Dual Coding Theory (Paivio, 1991)	Application	Invalid
Learning Comprehension (X3)	Dual Coding Theory (Paivio, 1991)	Explanation	Valid
Learning Comprehension (X3)	Dual Coding Theory (Paivio, 1991)	Connection	Valid
Motivation & Metacognition (Y1)	Self-Determination Theory (Ryan & Deci, 2000)	Autonomy	Valid
Motivation & Metacognition (Y1)	Self-Determination Theory (Ryan & Deci, 2000)	Competence	Valid
Motivation & Metacognition (Y1)	Self-Determination Theory (Ryan & Deci, 2000)	Relatedness	Invalid
Motivation & Metacognition (Y1)	Self-Determination Theory (Ryan & Deci, 2000)	Intrinsic Motivation	Valid
Motivation & Metacognition (Y1)	Self-Determination Theory (Ryan & Deci, 2000)	Metacognitive Awareness	Valid
Engagement Y2	Constructivist Learning Theory (Vygotsky, 1978)	Intellectual Curiosity	Valid
Engagement Y2	Constructivist Learning Theory (Vygotsky, 1978)	Hypothesis Formulation	Valid
Engagement Y2	Constructivist Learning Theory (Vygotsky, 1978)	Active Experimentation	Invalid
Engagement Y2	Constructivist Learning Theory (Vygotsky, 1978)	Collaboration	Valid
Engagement Y2	Constructivist Learning Theory (Vygotsky, 1978)	Reflection	Valid

Disagree; 1 = Strongly Disagree). The questionnaire was distributed directly to the participants.

In this research, the concept of validity pertains to instrument validity, which ensures that each survey question effectively measures the targeted construct. Specifically, construct validity was assessed using the outer loadings acquired via Partial Least Squares Structural Equation Modeling (PLS-SEM). The figures shown in the table are derived from the pilot test outcomes and data analysis conducted with SmartPLS software. An item is deemed valid when its outer loading is above 0.70 and when the Average Variance Extracted (AVE) for every construct surpasses 0.50, as suggested by. Items with slightly reduced loadings but still above 0.40 can be retained as long as the AVE and composite reliability criteria are met. The validity assessment was performed by analyzing the survey data with SmartPLS, determining convergent validity via outer loadings and AVE, and examining discriminant validity through the Fornell–Larcker criterion and cross-loadings. Consequently, the "validity" column in the table reflects the outer loading values obtained from the PLS-SEM analysis, signifying that the measurement items are valid and suitable for evaluating the constructs in this study.

3. RESULT AND DISCUSSION

3.1 Artificial Intelligence-Based Stimulus Website in the Discovery Learning Model

The Artificial Intelligence-Based Stimulus Website, integrated with the discovery learning model, produces a website that is structured and contains guidelines and a collection of stimulus videos for science subjects at the junior high school level, which are accessed free of charge by students, so that it is expected to stimulate students and

Figure 2 Artificial intelligence-based stimulus website

be implemented on complex and abstract materials. The video website image shown in Figure 2 illustrates the implementation in class VIII Middle school for elements, compounds, and mixtures, because the material is abstract and quite complex, and is taught to students. The incorporation of Artificial Intelligence in creating the stimulus website is evident in the generation of educational videos. In particular, AI-driven language models such as GPT were used to develop structured scripts that elucidate scientific concepts in accordance with the junior high school curriculum. The scripts were subsequently converted into animated or narrated videos utilizing various AI platforms. For example, Synthesia and HeyGen generated videos featuring presenters, whereas Pictory and D-ID transformed text and still images into lively, animated content.

3.2 Statistical Analysis

PLS-SEM analysis using SmartPLS-4 software assists in 2 steps of the analysis process (Anderson & Gerbing, 1988): (1) evaluating the reliability and validity of items and constructs through confirmatory factor analysis of all measurement models in Table 3, and (2) evaluating the path effects of the structural model in Table 4. Figure 3 shows the conceptual model and path results, with line arrows indicating the relationships between the concepts defined in the hypothesis.

3.3 Construct Validity and Reliability

The indicators for the constructs' validity and reliability in the research model are shown in Table 3. Each construct is tested through several measurement items, which are evaluated based on loadings, weights, and various other statistical indices such as Composite Reliability (CR), Cronbach's Alpha (CA), Average Variance Extracted (AVE), and Variance Inflation Factor (VIF).

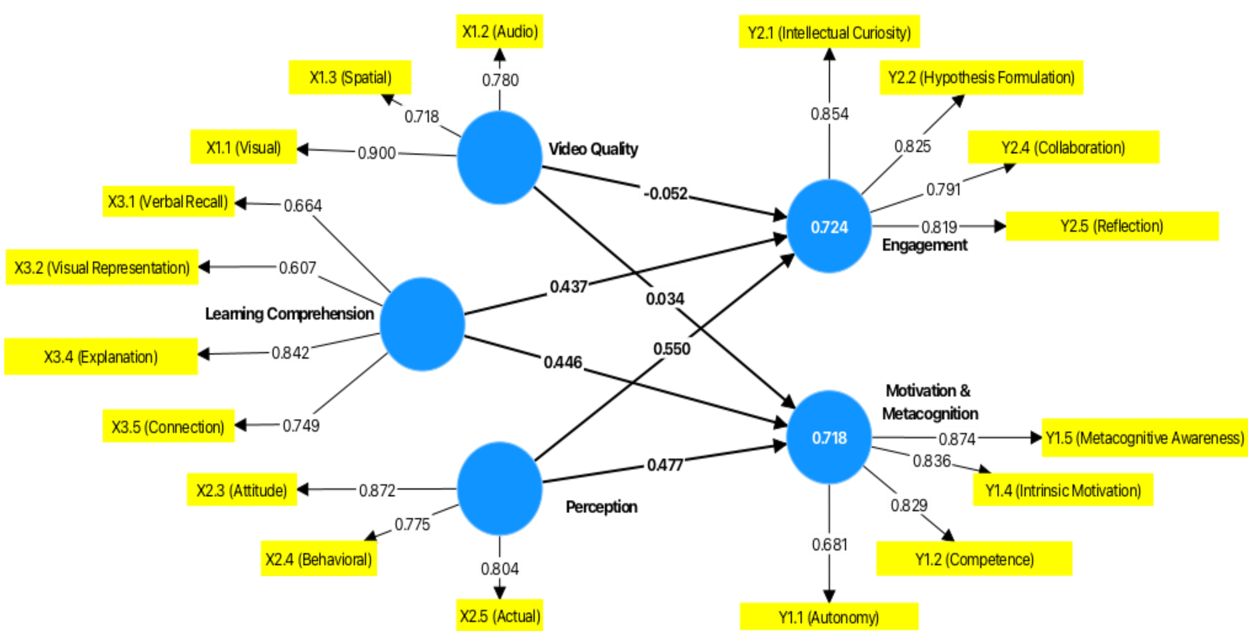

Figure 3 Conceptual framework PLS-SEM and path analysis

Table 4 Construct reliability and validity

Constructs	Items	Loadings	Weights	CA	CR (a)	CR (c)	AVE	VIF
Video Quality	X1.1	0.900	0.604	0.742	0.895	0.844	0.645	1.474
Video Quality	X1.2	0.780	0.313	0.742	0.895	0.844	0.645	1.579
Video Quality	X1.3	0.718	0.294	0.742	0.895	0.844	0.645	1.415
Perception	X2.1	0.872	0.405	0.753	0.760	0.858	0.669	1.978
Perception	X2.2	0.775	0.360	0.753	0.760	0.858	0.669	1.621
Perception	X2.3	0.804	0.458	0.753	0.760	0.858	0.669	1.404
Learning Comprehension	X3.1	0.664	0.307	0.7	0.719	0.810	0.520	1.229
Learning Comprehension	X3.2	0.607	0.246	0.7	0.719	0.810	0.520	1.525
Learning Comprehension	X3.3	0.842	0.384	0.7	0.719	0.810	0.520	1.944
Learning Comprehension	X3.4	0.749	0.432	0.7	0.719	0.810	0.520	1.373
Motivation & Metacognition	Y1.1	0.681	0.222	0.822	0.846	0.882	0.653	1.483
Motivation & Metacognition	Y1.2	0.829	0.363	0.822	0.846	0.882	0.653	1.765
Motivation & Metacognition	Y1.3	0.836	0.310	0.822	0.846	0.882	0.653	1.959
Motivation & Metacognition	Y1.4	0.874	0.331	0.822	0.846	0.882	0.653	2.289
Engagement	Y2.1	0.854	0.313	0.841	0.844	0.893	0.677	2.092
Engagement	Y2.2	0.825	0.323	0.841	0.844	0.893	0.677	1.791
Engagement	Y2.3	0.791	0.270	0.841	0.844	0.893	0.677	1.754
Engagement	Y2.4	0.819	0.308	0.841	0.844	0.893	0.677	1.807

Table 4 presents indicators of the validity and reliability of the constructs in the research framework. Every construct is evaluated using measurement items, and its performance is analyzed based on factor loadings, indicator weights, and various statistical metrics. These comprise Composite Reliability (CR), which indicates the internal consistency of a latent variable (suggested threshold ≥ 0.70)(Henseler et al., 2025)Cronbach's Alpha (CA), assessing the average inter-item correlation under the assumption of tau-equivalence; Average Variance Extracted (AVE), reflecting the share of variance accounted for by the construct relative to measurement error variance; and Variance Inflation Factor (VIF), which identifies multicollinearity among indicator variables. Additionally, Cheung et al. (2024) highlight in their review that providing confidence intervals (CIs) for these indices helps address sampling error and enhances clarity in the interpretation of measurement quality.

The analysis results show that all constructs in the research model meet the criteria for good reliability. The Cronbach's α value (CA) for all constructs was above 0.7 (J. Hair & Alamer, 2022), with Motivation & Metacognition (CA = 0.822) and Engagement (CA = 0.841) as the most consistent constructs. Composite Value Reliability (CR(c)) also exceeded the 0.8 threshold for all constructs, indicating that the items within each construct were strongly correlated with one another and collectively measured the same concept (J. Hair & Alamer, 2022). Video Quality (CR(c) = 0.844) and Perception (CR(c) = 0.858) had high internal consistency, indicating that the AI-based stimuli influenced user perception. However, Learning Comprehension has a CA value of exactly 0.7 and an AVE of 0.520, which, although still meets the criteria, indicates that this construct requires item refinement to increase its measurement precision.

Convergent validity was measured using AVE (Average Variance Extracted) for all constructs, which were all above 0.5, indicating that the items explained more than 50% of the construct variance. Engagement (AVE = 0.677) and Perception (AVE = 0.669) showed the strongest validity, indicating that items such as Y2.1 (loading 0.854) and X2.1 (loading 0.872) effectively captured the concepts being measured. On the other hand, Learning Comprehension has a marginal AVE of 0.520, driven by two items with low loadings (X3.1 = 0.664; X3.2 = 0.607).

The VIF (Variance Inflation Factor) values for all items are below 3, indicating no serious multicollinearity among the indicators in the construct. This reinforces the belief that each item makes a unique contribution to measuring constructs without redundancy. These results support the validity of the measurement model to test the structural relationships between constructs. The high reliability and validity of the Video Quality and Perception constructs confirm that the AI stimulus in the learning website has been successfully operationalized. Meanwhile, Motivation & Metacognition and Engagement, the primary dependent variables, are also reliably measured, so that the results of hypothesis tests at the structural level can be interpreted with greater confidence.

3.4 Testing the research hypothesis

Selection of PLS-SEM in the test hypothesis. Because his abilities in handling data and models with connection mediation as well as moderation in a way simultaneously (Chin, 1998; J. F. Hair et al., 2019). Table 5 shows path coefficients, t-statistics, and p-values for each connection

Table 5 Hypothesis testing (path coefficients, t-statistic values, and p-values)

Hypothesis	Hypothesis	β	M	STDEV	T	Confidence Interval	Confidence Interval	p -value
Hypothesis	Hypothesis	β	M	STDEV	T	2.5%	97.5%	p -value
H 1	X3 -> Y2	0.437	0.442	0.139	3.153	0.168	0.700	0.002
H 2	X3 -> Y1	0.446	0.449	0.118	3.767	0.217	0.680	0.000
H 3	X2 -> Y2	0.550	0.528	0.161	3.423	0.194	0.820	0.001
H 4	X2 -> Y1	0.477	0.452	0.155	3.087	0.127	0.735	0.002
H 5	X1 -> Y2	-0.052	-0.042	0.101	0.515	-0.249	0.153	0.607
H 6	X1 -> Y1	0.034	0.047	0.128	0.263	-0.204	0.304	0.793

specified by the hypothesis, allowing us to identify significant and insignificant paths in a statistical sense.

The results of the pathway analysis showed that four of the six hypotheses (H1-H4) proved to be statistically significant (p-value < 0.05), while two hypotheses (H5 and H6) were not significant. Here is an in-depth interpretation of each hypothesis:

H1: The Influence of Learning Comprehension (X3) to Engagement (Y2)

There is a significant positive effect between learning comprehension (X3) and student engagement (Y2) with a path coefficient (β) of 0.437 (p = 0.002). Every 1-unit increase in X3 will increase Y2 by 0.437 units. This indicates that students who have a better understanding of concepts through AI stimuli tend to be more actively involved in the learning process. This result is in line with the Dual Coding Theory (Paivio, 1991) and the Constructivist Learning Theory (Piaget & Vygotsky). Valid indicators on X3, such as verbal recall, visual representation, and connection (Paivio), indicate that dual representation (verbal-visual) on the AI website facilitates information encoding, thereby encouraging student engagement through constructivist activities such as hypothesis formulation (Vygotsky) and intellectual curiosity (Piaget). However, the invalid application indicator on X3 suggests that students are not yet fully able to apply concepts to real situations, so that engagement is more focused on conceptual exploration than direct practice.

H2: The Influence of Learning Comprehension (X3) to Motivation & Metacognition (Y1)

Learning comprehension (X3) also has a significant effect on motivation and metacognition (Y1) with a path coefficient (β) of 0.446 (p = 0.000). A high β value (0.446) indicates that students' ability to understand AI-based material stimulates intrinsic motivation and metacognitive awareness (such as self-reflection and learning strategies). This finding supports Self-Determination theory (Ryan & Deci, 2000). Students' ability to understand material (X3) through verbal-visual representations (Paivio) increases competence (confidence in abilities) and autonomy (learning independence), which are the pillars of intrinsic motivation—metacognitive indicators. Valid awareness in Y1 (reflection on learning strategies) also shows that good understanding triggers metacognitive awareness, according to the discovery principle. learning where students actively manage their learning process.

H3: The Influence of Perception (X2) on Engagement (Y2)

Students' perceptions of the quality of the AI website (X2) had the most decisive influence on engagement (Y2) with a path coefficient (β) = 0.550 (p = 0.001). This confirms that positive perceptions of the ease of use, usefulness, or design of the AI stimulus significantly increase student participation. The confidence interval value (0.194–0.820) that does not cross zero strengthens the validity of this finding. The strong influence can be explained through the Technology Acceptance Model (TAM) and the Constructivist Model. Learning Theory. Although the perceived indicators ease of use and perceived usefulness on X2 are not valid, attitude validity towards using and actual technology Use (Venkatesh & Davis, 2000) showed that positive attitudes and habits of using AI websites were more influential on student engagement than initial perceptions of usefulness. This extends TAM in an educational context, where actual behavior (such as frequency of access) was the main predictor of constructivist engagement (collaboration and reflection on Y2).

H4: The Influence of Perception (X2) on Motivation & Metacognition (Y1)

Perception (X2) also significantly contributes to motivation and metacognition (Y1) with a path coefficient (β) of 0.477 (p = 0.002). Students who perceive the AI website as a relevant and engaging tool tend to be more motivated to achieve learning goals and develop metacognitive strategies. This finding is in line with the Technology Acceptance Model (TAM), where perceived usefulness (perceived usefulness) is a key factor in determining the effectiveness of the AI website. Students who actively use the AI website (actual indicator) use a valid one. develop intrinsic motivation through repeated interactions with technology, even though perceived usefulness was not considered crucial. This finding supports the idea that, in the context of AI-based learning, attitude (interest in adaptive features) and behavioral Intention are more relevant than the traditional TAM perception, because students tend to be motivated after experiencing the benefits of technology firsthand.

H5 and H6: The Effect of Video Quality (X1) on Engagement (Y2) and Motivation & Metacognition (Y1)

Both hypotheses are insignificant, indicating that video quality (X1) does not directly affect engagement (Y2), i.e., $\beta = -0.052$ ($p = 0.607$), or motivation-metacognition (Y1), i.e., $\beta = 0.034$ ($p = 0.793$). The confidence interval value that crosses zero (H5: -0.249 to 0.153) indicates an inconsistency of the effect. This is caused by external factors, such as limited variation in video quality in the study or the presence of a mediator variable (e.g., X2 or X3) that is more dominant in transmitting the effect of X1. The insignificance can be explained through the Cognitive Theory of Multimedia Learning (Moreno & Mayer, 1999). However, the modality indicators principle (visual-audio) and spatial valid contiguity indicate that video quality is not optimized to reduce temporal confusion or cognitive fatigue. Invalid temporal contiguity (time synchronization) and cognitive load on X1 indicate that video quality is not optimized to minimize temporal confusion or mental fatigue. As a result, even though the video has high resolution, it does not impact motivation and engagement. This theory reinforces the idea that video technical quality is merely a hygiene measure. Minimal prerequisite factors that do not directly improve learning outcomes if holistic multimedia design principles do not support them.

The finding that X2 (Perception) and X3 (Learning) Comprehension) is more influential than X1 (Video Quality), indicating that in the context of AI-based learning, psychological (perception) and cognitive (understanding) factors are more crucial than technical aspects (video quality). This result reinforces the principle of discovery. Learning that student engagement and metacognition are triggered by the ability to understand the material independently, using AI as a facilitator. Although video quality is not significant, it is essential to consider that technical quality is hygiene. factors (minimal prerequisites) that only matter if ignored. AI website development should focus on increasing interactivity and content relevance to strengthen positive perceptions.

This finding confirms that AI-based websites in the discovery model that effectively support learning improve student motivation, metacognition, and engagement when supported by positive perceptions and a strong understanding. Meanwhile, video quality is not the primary determinant, so educators and technology developers should prioritize psychological and pedagogical factors when designing AI-based learning stimuli.

3.5 Affect students' Motivation, Metacognition, and Engagement

This research demonstrates that AI-based websites in the discovery model of Learning significantly improve student motivation, metacognition, and engagement by fostering positive perceptions (X2) and conceptual understanding (X3). These findings answer the research question of how AI stimuli affect learning outcomes, while revising the common assumption that the technical quality of the media (X1) is the dominant factor. These results align with the principles of the modified Technology Acceptance Model (TAM), where actual use and positive attitude are more crucial than perceived usefulness, and they strengthen Dual Coding Theory by highlighting the role of verbal-visual representations in building understanding. The research's primary contribution lies in integrating learning, technology, and motivation theories, asserting that AI is not merely a technical tool but a pedagogical catalyst that empowers students to become independent learners. Practically, these findings call for educators and technology developers to prioritize interactive designs that encourage metacognitive reflection and constructivist engagement.

The finding that perception (X2) and understanding (X3) exert greater influence is in line with Hwang et al.'s (2021) study on self-regulated learning. Still, it contradicts Sweller's (2011) research, which emphasizes cognitive load theory. This contradiction reveals the AI context's uniqueness: psychological and mental factors trump technical ones. Two things cause the insignificance of video quality (X1): (1) high-quality video is considered a hygiene factor (a minimal prerequisite), and (2) the effect of X1 is mediated by X2/X3, which is not tested in this model. These findings revise the Cognitive Theory of Multimedia Learning by emphasizing the importance of optimizing temporal contiguity (content time synchronization) to reduce distraction in AI design. However, sampling limitations (participants were limited to students with adequate technology access) and the invalidity of the application indicator (X3) require careful interpretation of the results. Further research is needed to test the model with mediator variables (e.g., flow experience) and moderators (e.g., digital literacy) to understand the varying impacts of AI.

The insignificance of X1 is an unexpected finding that reflects the paradox of ease of access. Modern students are accustomed to high-quality content, so video resolution is no longer a key differentiator. However, this finding remains relevant to the global trend toward student-centered education. In learning, AI functions as a strategic partner, not a substitute for teachers. Practical implications: educators need to design AI activities that are not only interactive but also facilitate the transfer of knowledge to real-world situations, through problem-based simulations or collaborative projects. Theoretically, integrating Constructivist Learning Theory and Self-Determination Theory in the context of AI paves the way for the development of pedagogical models that balance student autonomy and social interaction.

Given the dominance of X2 and X3, this research broadens the perspective to global issues such as reducing educational disparities through AI personalization. In the future, exploring collaborative AI (such as chatbots that facilitate group discussions) could enrich the social-constructivist approach. Longitudinal research is also needed to test the long-term resilience of AI's impact on motivation and metacognition. Ultimately, the success of AI in education is measured not by the sophistication of its algorithms but by its ability to shape students into adaptive critical thinkers. This vision demands multidisciplinary collaboration between educators, technologists, and policymakers.

4. CONCLUSION

This research demonstrates that website-driven discovery learning with AI prompts greatly enhances students' motivation, metacognitive skills, and engagement by fostering positive attitudes towards technology, encouraging a deeper understanding of concepts, and promoting autonomous investigation. Although video quality was not a key factor, the results emphasize that successful learning relies more on interactivity, relevant content, and metacognitive reflection than on technical elements. AI functions not only as a tool but also as a catalyst, enabling independent learners and prompting educators and developers to create stimuli that foster intrinsic motivation and active engagement. Future studies should also explore mediating factors, such as technology experience across diverse settings.

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