

The Mediating Role of Spatial Skills in Learning Kinematic Graphics Assisted by Vector Animation Videos

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Abstract: Kinematic graph interpretation is a basic physics competency that often challenges students because of abstract vector representations and weak geometric transformation skills. This study analyzes the influence of vector animation videos on kinematic graph learning, with spatial skills as a mediating variable. A quantitative approach with a quasi-experimental design was applied to 60 Grade X students of SMAS Ta'miriyah Surabaya. Data were collected using the Test of Understanding Graphs in Kinematics (TUG-K) and the mental rotation test, then analyzed using Structural Equation Modeling-Partial Least Squares (SEM-PLS). The results showed that using vector animated videos significantly improved students' spatial abilities and graphic comprehension. Furthermore, spatial ability partially mediated the relationship between vector-based digital learning interventions and mastery of kinematic graphics. This confirms the importance of integrating dynamic vector visualization in physics learning to bridge abstract conceptual barriers and improve spatial-geometric cognitive processing.

Keywords: kinematics graphic, spatial ability, vector animation, SEM-PLS, physics education.

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■ INTRODUCTION

Physics is a basic science that plays an important role in explaining various natural phenomena through mathematical modeling, scientific reasoning, and visual representation. One fundamental topic in mechanics is kinematics of straight motion, which underpins learning dynamics, work and energy, momentum, and fluid mechanics (Oishi et al., 2026). Mastery of kinematic concepts depends not only on the ability to use mathematical equations, but also on the ability to represent motion phenomena in various forms, including verbal, mathematical, vector diagrams, and graphs (Rismawati et al., 2026). Among these forms of representation, graphs play an important role because they present relationships between physical magnitudes concisely while showing direction of motion, changes in speed, and acceleration through the slope and area under the curve. The ability to interpret graphs is an important indicator of developing conceptual understanding, scientific

thinking skills, and representational competencies that students, especially prospective physics teachers, must possess (Ince, 2026).

Empirical evidence shows that students' ability to interpret kinematic graphs remains relatively low. Various studies report that students who have taken Basic Physics courses still experience misconceptions when connecting time-position and time-velocity graphs to the motion phenomena they represent (Lu & Pan, 2026; Mu et al., 2026). These errors are not only procedural mistakes in solving mathematical problems, but also reflect a lack of conceptual understanding of a graph's physical meaning. The most dominant form of misconception is the *graph-as-picture misconception*, the tendency to interpret the shape of a curve as a real trajectory of an object rather than as a representation of the relationship between physical variables. This condition indicates that students still struggle to transform between representations, so the goal of kinematics learning

as the basis for mastering the concept of mechanics has not been achieved optimally (Han et al., 2026; X. Zhang et al., 2026).

Previous studies have developed various learning alternatives to improve graphic interpretation skills, including interactive multimedia, computer simulations, virtual labs, and learning animations (Eadkhong et al., 2026). Various studies show that dynamic visualization improves concept understanding compared to conventional learning because it reduces the cognitive burden of processing abstract information. However, most developed media still focus on visualizing object motion without showing the simultaneous relationships among changes in position, direction, and the magnitudes of velocity and acceleration vectors, as well as the real-time process of forming kinematic graphs (Xiao, 2026). On the other hand, previous research has generally only examined the direct influence of multimedia use on learning outcomes, while the cognitive mechanisms underlying the improvement of graphic interpretation skills are still not widely explained through comprehensive empirical models (Lianhui et al., 2026; Stolzenberger et al., 2026; Zhong & Xu, 2026).

This gap creates space for learning media that not only presents dynamic motion visualization but also facilitates the transformation

process between representations as a whole (Kim & Yu, 2026). This research develops a Dynamic Vector Animation Video that integrates object motion visualization, speed and acceleration vector changes, and the simultaneous formation of kinematic graphs in one learning view. Integrating these three representations is expected to reduce extrinsic cognitive load, strengthen mental visualization, and improve students' ability to build conceptual relationships among physical phenomena, vector representations, and graphic representations (Babalola et al., 2026; Chiha et al., 2026).

Drawing on Cognitive Load Theory and Cognitive Theory of Multimedia Learning, we formulated a hypothetical structural model to examine the interrelationships among the variables under study. The model positions Dynamic Vector Animated Videos (DVAV) as the independent variable (exogenous construct), Spatial Skills (SS) as the mediating variable, and Kinematic Graph Interpretation Ability (KGIA) as the dependent variable (endogenous construct). This structural framework provides a comprehensive basis for evaluating both the direct impact of animated media on graphical understanding and its indirect mechanism through enhanced spatial processing capabilities (see Figure 1).

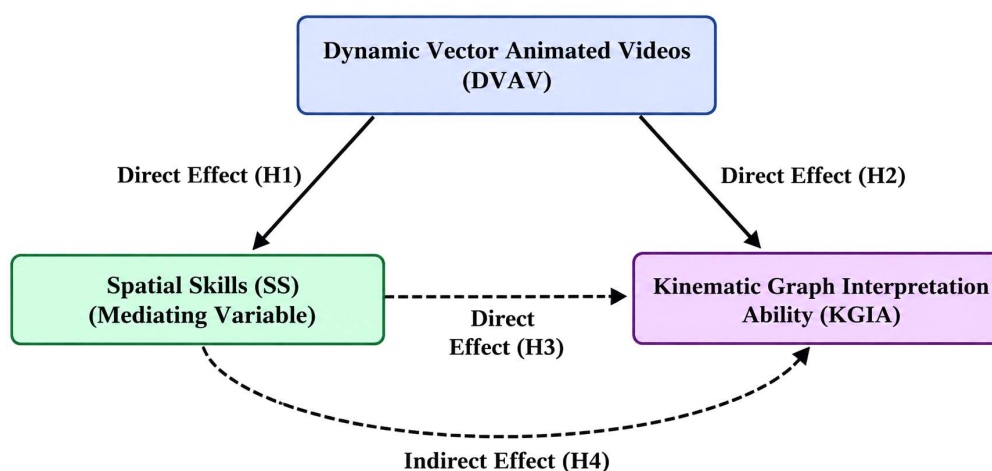


Figure 1. Dynamic vector video causal model

- H1: Dynamic vector animated videos have a positive and significant effect on spatial skills.
- H2: Dynamic vector animated videos have a positive and significant effect on kinematic graph interpretation ability.
- H3: Spatial skills have a positive and significant effect on kinematic graph interpretation ability.
- H4: Spatial skills significantly mediate the relationship between dynamic vector animated videos and kinematic graph interpretation ability. This study's novelty lies in an analytical approach that not only evaluates the effectiveness of Dynamic Vector Animated Videos in improving graph interpretation ability, but also tests the cognitive mechanisms underlying these relationships by using spatial abilities as a mediating variable (Huo et al., 2026). This approach integrates Cognitive Load Theory, Cognitive Theory of Multimedia Learning, and spatial capabilities into a structural model based on Structural Equation Modeling Partial Least Squares (SEM-PLS). The model provides a more comprehensive explanation of the causal relationship between the use of learning media, the improvement of spatial ability, and the ability to interpret kinematic graphs, resulting in an empirical perspective that has not been widely studied in physics education research (Agusty & Chen, 2026; Mohamad et al., 2026).

To address these objectives, this study investigates the following research questions (RQs) and corresponding hypotheses (Hs).

- RQ1: Does the use of Dynamic Vector Animated Videos directly affect students' spatial skills?
- H1: The use of Dynamic Vector Animated Videos has a significant positive direct effect on students' spatial skills.
- RQ2: Does the use of Dynamic Vector Animated Videos directly affect students' kinematic graph interpretation ability?

- H2: The use of Dynamic Vector Animated Videos has a significant positive direct effect on students' kinematic graph interpretation ability.

RQ3: Do students' spatial skills directly affect their kinematic graph interpretation ability?

- H3: Students' spatial skills have a significant positive direct effect on their kinematic graph interpretation ability.

RQ4: Do students' spatial skills mediate the relationship between using Dynamic Vector Animated Videos and their kinematic graph interpretation ability?

- H4: Students' spatial skills significantly mediate the relationship between using Dynamic Vector Animated Videos and their kinematic graph interpretation ability.

This study aims to analyze the effect of using Dynamic Vector Animation Video on the interpretation skills of Grade x students at SMAS Ta'miriyah Surabaya, to analyze the impact of this medium on students' spatial abilities, and to examine the mediating role of spatial ability in the relationship between the use of Dynamic Vector Animation Video and kinematics graph interpretation skills. The research findings are expected to contribute to the development of multimedia learning theory in physics education and provide a scientific basis for developing dynamic representation-based learning media that can minimize graphic misconceptions and improve the quality of instruction at SMAS Ta'miriyah Surabaya.

■ METHOD

Research Design

This study uses a quantitative approach with a quasi-experimental design method using a Pretest-Posttest Non-Equivalent Control Group Design. This design was chosen because the research subjects were students from existing Grade X classes at SMAS Ta'miriyah Surabaya, so individual randomization was not possible. The

experimental group learned using Dynamic Vector Animation Video, while the control group followed conventional learning using static diagrams and graphs. The design was used to analyze the influence of media use on the ability to interpret kinematic graphs, with spatial ability as a mediating variable.

Participants

The research population comprised Grade X students at SMAS Ta’miriyah Surabaya who were studying linear motion kinematics. The sample was selected using purposive sampling based on the following criteria: active enrollment at SMAS Ta’miriyah Surabaya, having studied or being scheduled to study linear motion

kinematics, and relatively homogeneous initial academic ability. These criteria led to the selection of two parallel classes with comparable characteristics: one as the experimental group and the other as the control group, each comprising 30 students, for a total of 60 students. The baseline analysis showed a similar distribution of initial academic ability across the two groups, with no statistically significant difference detected by the independent samples t-test ($p > 0.05$). This finding indicates that the experimental and control groups were academically comparable before the intervention, providing an appropriate baseline for evaluating differences in learning outcomes after implementing the respective instructional approaches (see Table 1).

Table 1. Baseline demographics and initial academic ability equivalence test

Variable	Metric / Category	Experimental Group (n=30)	Control Group (n=30)	t-value / χ^2	p-value
Gender	Male	11 (36.7%)	10 (33.3%)	0.076*	783
	Female	19 (63.3%)	20 (66.7%)		
Age	Mean $\pm$ SD (years)	18.42 $\pm$ 0.51	18.38 $\pm$ 0.49	310	758
Academic History	High School Physics Score (Mean $\pm$ SD)	82.45 $\pm$ 4.12	81.90 $\pm$ 4.35	503	617
Baseline Ability	Physics Entry Test (Mean $\pm$ SD)	64.50 $\pm$ 6.20	63.80 $\pm$ 6.85	415	679

Note: The χ^2 statistic is reported for the categorical variable (gender), whereas t-values are reported for the continuous variables. A p-value> 0.05 indicates no statistically significant differences between the experimental and control groups at baseline.

Research Procedure

The research was carried out over four weeks of effective learning, with a total time allocation of 12 $\times$ 50 minutes, and consisted of three stages: preparation, treatment implementation, and evaluation.

1. Preparation stage

This stage includes preparing learning tools in the form of Lesson Plans (RPP), Student Worksheets (LKS), and Dynamic Vector Animation Videos. The research instrument consisting of the Spatial Ability Test and the Test

of Understanding Graphs in Kinematics (TUG-K) was validated by two physics education experts and one psychometry expert. Next, both groups were given a pretest to measure initial ability.

2. Stages of treatment intervention

The experimental group participated in learning using a Dynamic Vector Animation Video, which simultaneously displayed the motion of objects, changes in speed and acceleration vectors, and the formation of kinematic graphs in real time. Student worksheets supported learning

through spatial problem-solving. Meanwhile, the control group studied the same material for the same amount of time, but used conventional methods through explanations, diagrams, and static graphs without dynamic visualization.

3. Evaluation and follow-up stage

After completing the learning activities, both groups took the posttest using an instrument equivalent to the pretest. The measurement results were analyzed using *Normalized Gain* (N-Gain) to determine the improvement of students' abilities, then continued with analysis using *Structural Equation Modeling–Partial Least Squares* (SEM-PLS) to test the direct influence of the use of Dynamic Vector Animation Video on the ability to interpret graphs and the mediating role of spatial ability. The research flow chart presents the complete implementation process (J. Zhang et al., 2026).

The research was carried out over four weeks, with a total allocation of 12×50 minutes, and included three stages. The preparation stage included preparing learning tools, developing Dynamic Vector Animation Videos, validating instruments, and administering pretests. The treatment stage involved providing Dynamic Vector Animation Video-based learning to the experimental group, while the control group followed conventional learning using static diagrams and graphs. The final stage involved posttest implementation, *Normalized Gain* (N-Gain) calculation, and data analysis using SEM-PLS (Y. Li et al., 2026).

Instruments

The research data were collected using two instruments that met validity and reliability criteria. Spatial ability was measured using a modified instrument Mental Rotation Test (MRT), consisting of 20 multiple-choice questions to measure the mental rotation ability of three-dimensional objects. This instrument had a

Cronbach's alpha of 0.84. Meanwhile, the ability to interpret kinematic graphs was measured using the Test of Understanding Graphs in Kinematics (TUG-K) adaptation instrument, which consisted of 21 multiple-choice questions regarding the interpretation of position, speed, and acceleration graphs. The test showed a reliability coefficient of 0.79, with the questions in the good category of differentiating power. To standardize the evaluation, the students' raw TUG-K scores were converted to a 100-point scale by calculating the percentage of correct answers out of the 21 items.

Before data collection and the instructional intervention, this study received formal ethical approval from the institutional research ethics committee. All participating students were fully informed about the study's objectives, experimental procedures, potential risks, and benefits. Written informed consent was obtained from each student voluntarily before administering the instruments. Participants were assured of the strict confidentiality and anonymity of their responses, and they were explicitly notified of their right to withdraw from the study at any time without academic consequence or penalty related to their course evaluation.

Data Analysis

Data analysis was carried out using *Structural Equation Modeling–Partial Least Squares* (SEM-PLS) assisted by SmartPLS 4.0. This method was chosen because it can analyze relationships between latent variables simultaneously and is suitable for relatively small sample sizes. The research model consists of Vector Animation Video as an exogenous variable, Spatial Ability as a mediating variable, and Kinematic Graphic Interpretation Ability as an endogenous variable.

Data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) implemented in SmartPLS. The analysis

followed the two-stage procedure recommended by Hair et al. (2019, 2021), consisting of measurement model (outer model) and structural model (inner model) evaluation.

In the first stage, convergent validity was assessed through outer loadings and the Average Variance Extracted (AVE). Outer loadings were required to exceed 0.708, while AVE values had to exceed 0.50, indicating that each construct explained more than half of the variance of its indicators (Hair et al., 2019). Construct reliability was evaluated using Composite Reliability ($\bar{\rho}$) and Cronbach's alpha, with values between 0.70 and 0.90 considered acceptable to good (Hair et al., 2021). Discriminant validity was examined using the Heterotrait–Monotrait (HTMT) ratio, with values below 0.85 (or 0.90 for conceptually related constructs) indicating adequate discriminant validity (Henseler et al., 2015; Hair et al., 2021).

In the second stage, the structural model was evaluated by examining collinearity, explanatory power, predictive relevance, and hypothesis testing. Collinearity was assessed using the Variance Inflation Factor (VIF), with values below 3.0 considered ideal and values below 5.0 considered acceptable (Hair et al., 2019). Explanatory power was evaluated using the coefficient of determination (R^2), where values of 0.75, 0.50, and 0.25 represent substantial, moderate, and weak explanatory power, respectively. Predictive relevance was assessed using Stone–Geisser's Q^2 obtained through the blindfolding procedure, with values greater than zero indicating predictive relevance (Hair et al., 2021).

Hypotheses were tested using a non-parametric bootstrapping procedure with 5,000 resamples. Path coefficients were considered statistically significant when the t-statistic exceeded 1.96, and the two-tailed p-value was below 0.05 (Hair et al., 2021). The mediation effect of spatial skills was examined by testing

the significance of the indirect effect through bootstrapping. The Variance Accounted For (VAF) was calculated as the ratio of the indirect effect to the total effect. VAF values greater than 80% indicate full mediation, values between 20% and 80% indicate partial mediation, and values below 20% indicate no mediation effect (Hair et al., 2017; Zhao et al., 2010).

■ RESULT AND DISCUSSION

Descriptive Statistical Analysis and Conceptual Improvement Achievement

The measurement model demonstrated satisfactory psychometric properties across all latent constructs. Indicator loadings exceeded the recommended threshold of 0.708, Average Variance Extracted (AVE) values were above 0.50, and both Composite Reliability ($\bar{\rho}$) and Cronbach's alpha exceeded 0.70, confirming convergent validity and internal consistency. In addition, all Heterotrait–Monotrait (HTMT) ratios were below 0.85, indicating adequate discriminant validity. Descriptive analysis showed that the experimental group receiving Dynamic Vector Animated Videos (DVAV) achieved greater improvements in both spatial skills and kinematic graph interpretation ability than the control group. The structural model further indicated that DVAV had a significant positive direct effect on spatial skills ($\hat{\alpha} = 0.485$, $p < 0.001$), supporting H1, suggesting that dynamic visual representations reduce extraneous cognitive load and facilitate the internalization of mental rotation processes and three-dimensional geometric transformations. DVAV also had a significant positive direct effect on kinematic graph interpretation ability ($\hat{\alpha} = 0.362$, $p = 0.002$), supporting H2, indicating that synchronizing motion vectors with real-time graph representations helps students connect physical motion with its graphical representation and reduces common misconceptions in kinematics. Spatial skills significantly predicted kinematic

graph interpretation ability ($\hat{a} = 0.418$, $p < 0.001$), supporting H3, demonstrating that students with stronger spatial abilities were better able to interpret graph slopes, areas under curves, and vector-based graphical transformations. Bootstrapping analysis revealed a significant indirect effect of DVAV on kinematic graph

interpretation through spatial skills ($\hat{a} = 0.203$, $p = 0.005$), while the Variance Accounted For (VAF) value of 35.93% indicated partial mediation, supporting H4. These findings suggest that DVAV improves kinematic graph interpretation both directly and indirectly by enhancing students' spatial processing abilities.

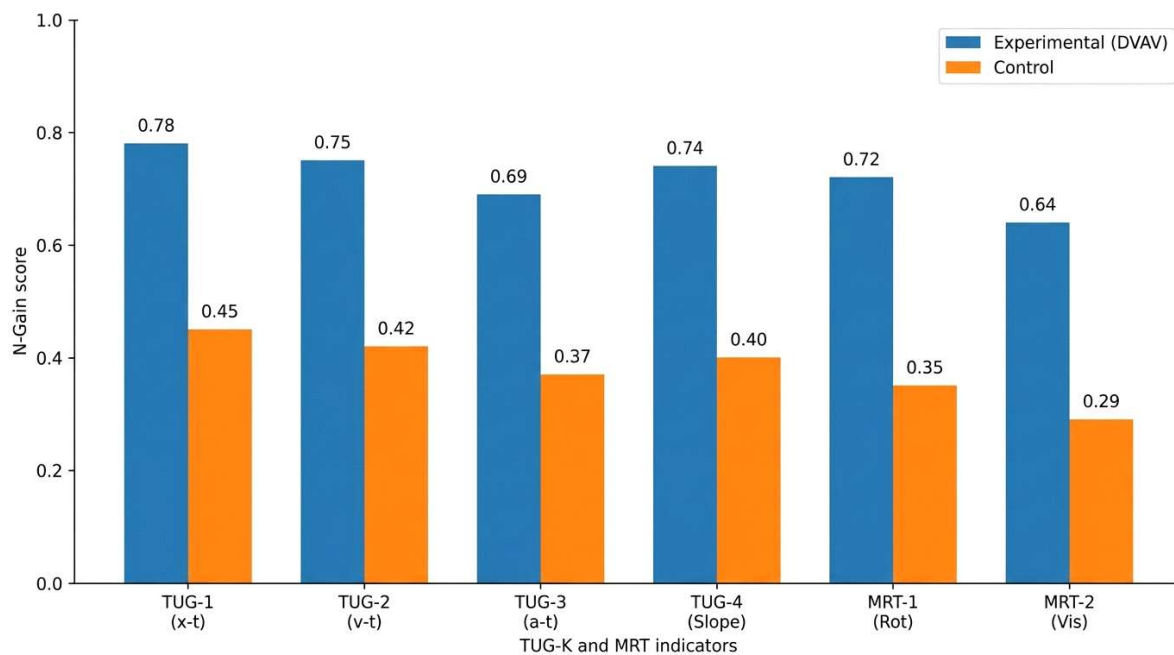


Figure 2. Comparison of N-Gain scores across TUG-K and MRT indicators

Based on the data presented in Figure 2, both the experimental and control groups demonstrated comparable initial levels of spatial ability and kinematic graph understanding. The average Mental Rotation Test (MRT) score was approximately 8 out of a maximum score of 20, while the average Test of Understanding Graphs in Kinematics (TUG-K) score was approximately 35 out of 100, indicating that both groups were in the low-performance category before the intervention. This baseline similarity supports the assumption of initial group equivalence and provides a valid basis for comparing the effects of the instructional treatments. After the intervention, the experimental group exhibited a substantially greater improvement in learning

outcomes than the control group. The experimental group achieved an average TUG-K posttest score of 83.20 with an N-Gain of 0.74 (high category). In contrast, the control group reached an average score of 62.30 with an N-Gain of 0.41 (medium category).

To better represent individual learning progress, a scatter plot plots each student's pretest score against their corresponding posttest score, with a 1:1 diagonal reference line ($y = x$) (Figure 3). Each point's position relative to the diagonal visually indicates individual score changes, with points above the line representing higher posttest than pretest scores. The distribution of the points indicates a generally greater upward shift in the experimental group,

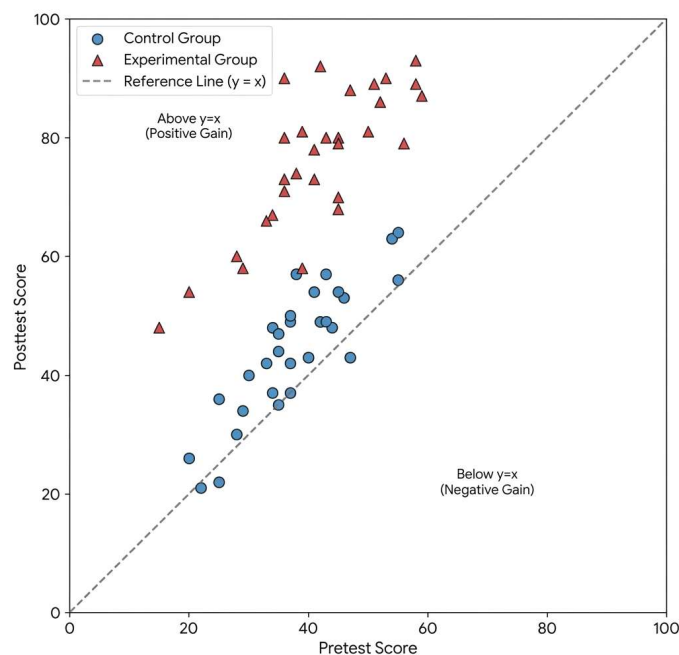


Figure 3. Distribution of individual pretest and posttest scores for the experimental and control groups. The diagonal line represents the 1:1 reference line ($y = x$)

with more observations positioned substantially above the reference line. In contrast, the control group shows a comparatively wider distribution closer to the diagonal. This pattern suggests greater individual learning gains among students who received the Vector Animation Video intervention and provides descriptive visual support for the observed improvement in kinematic graph interpretation ability.

Evaluation of Measurement Model (*Outer Model SEM-PLS*)

The first crucial step in the analysis using SmartPLS is to ensure that each latent construct's reliability and validity meet psychometric thresholds. The convergent validity test was conducted by examining the factor loading of each indicator within a latent construct. The PLS results show that all indicators for the Vector Animated Video (MVV), Spatial Capability (KSP), and Kinematic Graph (GKM) constructs have factor loadings ranging from 0.762 to 0.891, well above the 0.70 threshold. Furthermore, the convergent

validity test is reinforced by the *Average Variance Extracted* (AVE) value. The AVE for the KSP construct was 0.654, and for the GKM construct, it was 0.682. Since the AVE value is above 0.50, it is concluded that these latent constructs validly capture more than 50% of the indicator variance. For the construct reliability test, the *Composite Reliability* (CR) and *Cronbach's Alpha* values for all variables were above 0.80, confirming the instrument's unusually high level of internal consistency in this structural model.

The outer loading analysis shown in Figure 4 was conducted to evaluate the convergent validity of each indicator. Indicators with outer loading values exceeding 0.70 demonstrate adequate convergent validity and effectively represent their respective constructs. In this model, the Vector Animated Video Media (MVV) construct has an outer loading of 1.000, which results from its operationalization as a single-item construct (representing exposure to the experimental treatment). While single-item

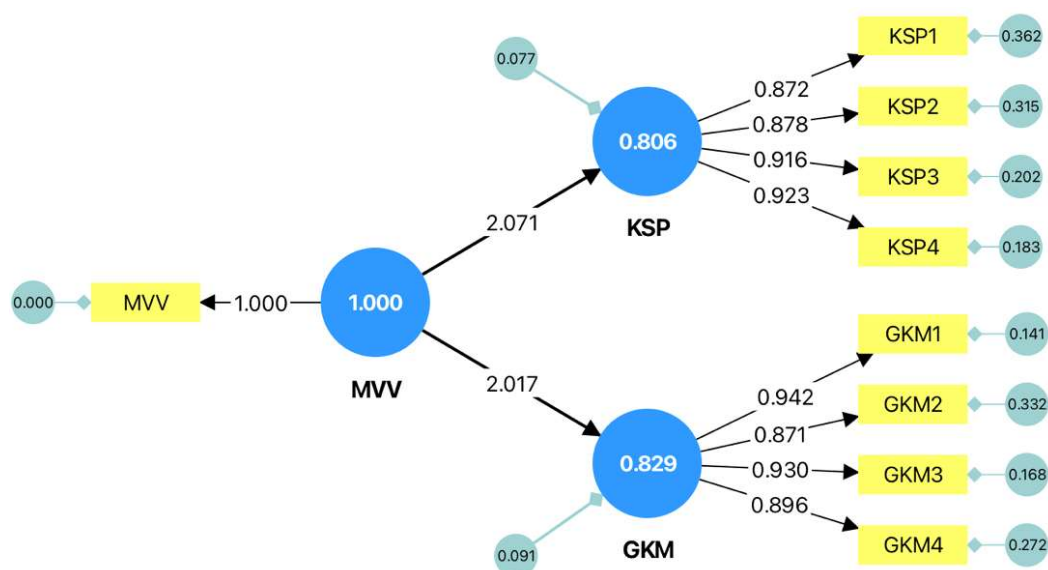


Figure 4. SEM-PLS on outer loading

measures are methodologically practical for concrete binary or treatment-based variables, this approach inherently imposes a methodological limitation by assuming zero measurement error, thereby preventing the SEM model from capturing indicator-level error variance and nuance. Consequently, internal consistency reliability metrics (e.g., Composite Reliability and Cronbach's alpha) cannot be evaluated for MVV, and indicator reliability is fixed by definition rather than empirically estimated. For the multi-item latent constructs, all indicators exhibited strong measurement properties. Within the Spatial Capability (KSP) construct, indicators KSP1 through KSP4 exceeded the 0.70 threshold, with KSP4 showing the highest loading (0.923), indicating it is the most representative indicator of students' spatial skills. Similarly, all Kinematic Graph (GKM) indicators (GKM1–GKM4) demonstrated high outer loadings ranging from 0.871 to 0.942, with GKM1 emerging as the most dominant indicator (0.942). Overall, all indicators satisfied convergent validity criteria without requiring item deletion, allowing the analysis to proceed to the structural model (inner model) evaluation.

Evaluation of Structural Models (*Inner Models*) and Path Hypothesis Test

After the measurement model is declared valid and reliable, the structural model (inner model) is evaluated to assess the predictive strength of the theoretical model and test the three formulated relationship hypotheses. The test used non-parametric bootstrapping with 5,000 resamples to estimate the standard error and the p-value. The output of the standardized path diagram from the structural modeling is presented in Figure 5.

Based on the visualization and mathematical estimates in the path diagram in Figure 5, all hypotheses proposed in this study are accepted because they show positive and significant relationships between variables. In the first hypothesis test, Vector Animated Video Media (MVV) was proven to have a positive and significant direct influence on Spatial Ability (KSP). The results of the analysis showed a path coefficient value ($\hat{\alpha}$) of 0.540 with a t-statistical value of 5.420 and a significance value (p-value) of 0.001 (< 0.05). The findings show that using Vector Animated Videos can improve students' spatial abilities in real terms. Dynamic visualization

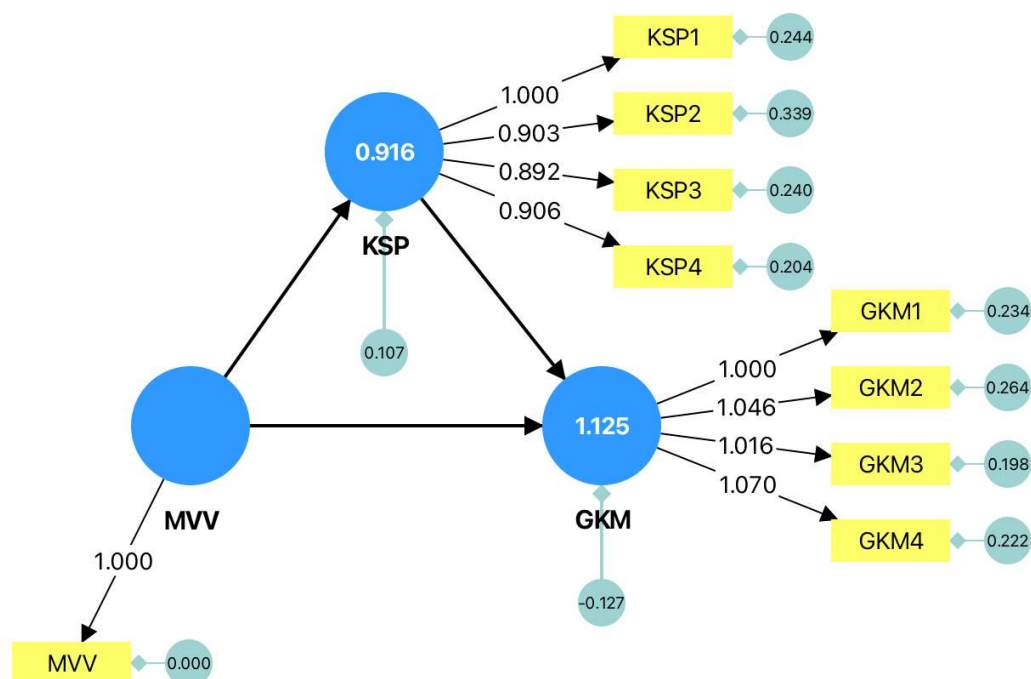


Figure 5. Pathmap on SEM-PLS analysis

that represents coordinates and vector movement helps students build mental rotation, spatial orientation, and inter-object relationships more effectively than static visual presentation.

The second hypothesis test also showed that Spatial Ability (KSP) had a direct, positive, and significant effect on Kinematic Graph Understanding (GKM). The relationship is shown by the path coefficient value ($\hat{\alpha}$) of 0.410 with a t-statistical value of 3.980 and a p-value of 0.003 (< 0.05). These results confirm that improved spatial ability significantly contributes to students' ability to understand kinematic graphs. Students with stronger visualization and mental rotation skills tend to find it easier to identify relationships among position, speed, acceleration, and changes in a graph's shape, interpreting abstract physics concepts more accurately and meaningfully.

Furthermore, the testing of the third hypothesis shows that Vector Animation Video Media (MVV) also has a positive and significant direct influence on Kinematic Graph Understanding (GKM). The path coefficient ($\hat{\alpha}$) was 0.350, supported by a t-statistic of 2.610

and a p-value of 0.012 (< 0.05). The results show that, in addition to improving graphic understanding through improved spatial capabilities, Vector Animation Videos also directly contribute to understanding kinematics concepts. This direct influence likely comes from the video's presentation quality, which integrates animation, verbal explanations, supporting text, and dynamic illustrations synchronously. This combination of learning elements helps students understand the relationship between physics concepts and graphical representations more comprehensively, improving their ability to read, interpret, and analyze kinematic graphs. Overall, the structural model analysis shows that Vector Animation Video Media plays an important role in improving understanding of kinematic graphs, both directly and by improving spatial ability as a variable that mediates the learning process.

Analysis of the Significance of the Mediation Effect

To answer the core research question about the mediating role of spatial ability, we calculated

an indirect effect. The indirect influence from MVV to GKM through the KSP variable is calculated by multiplying the two coefficients of the transition path,

$$\beta_{indirect} = 0.540 \times 0.410 = 0.221$$

The significance test of indirect influence using the Sobel Test and SmartPLS bootstrapping resulted in a t-statistic value of 3.120 with a p-value of 0.002 ($p < 0.05$). Because the direct influence ($\hat{\alpha} = 0.350$) and indirect influence

($\hat{\alpha}_{indirect} = 0.221$) are both statistically significant, the mediation mechanism that occurs falls into the category of partial mediation. The amount of contribution of spatial ability in mediating the total influence of Vector Animation Video Media on the understanding of kinematic graphics is then calculated using the Variance Accounted For (VAF) formula:

This VAF value of 38.7% provides a valuable empirical conclusion: 38.7% of the total positive impact of using Vector Animation Video

$$VAF = \frac{\beta_{indirect}}{\beta_{direct} + \beta_{indirect}} = \frac{0.221}{0.350 + 0.221} = \frac{0.221}{0.571} \approx 38.7\%$$

on improving students' kinematic graphic interpretation ability is explained by improvements in the performance mechanism of their cognitive spatial ability. The rest is influenced by instructional factors beyond the spatial capabilities of the space. The total determination value (R^2) for this model is 0.582, meaning the constructed causal model explains 58.2% of the variance in students' kinematic graph learning outcomes.

Epistemology of Causality Relationships: Influence of Digital Media Interventions

The main findings of this empirical study conclusively show that innovative learning media interventions in the form of dynamic Vector Animation Videos trigger greater cognitive acceleration than conventional methods based on static diagrams. An in-depth discussion should dissect the epistemological question: why are these vector-based animation videos so effective? In contrast, the dynamic Vector Animation Video we recommend and develop in this study applies the principle of contiguity (proximity in space and time) effectively. The interface design of this video application simultaneously brings together the three main components of a physical representation in one integrated screen. An

example of the recommended dynamic visualization interface display modeling is presented schematically in the following Figure 6 preview diagram,

The answer to this question can be explained very well through *the Cognitive Theory of Multimedia Learning* (CTML) initiated by Richard Mayer. According to CTML, humans process visual and auditory information through two separate channels in working *memory*, each with very limited capacity. When students in the control class were shown a static graph on the board, they experienced the *split-attention effect*. Their brains have to work hard to divide attention between reading the explanation, looking at the coordinate axes of the static graph, and then doing abstract reasoning to guess the direction of the object's velocity. This high extrinsic cognitive load inhibits storing information in *long-term memory* (Deb & Rahman, 2026; Jin et al., 2026).

When the dynamic video application in Figure 7 runs, students no longer need to imagine the relationship between the car's movement and the formation of graphic lines. In Panel A, the car's forward motion automatically accompanies the extension of the speed vector arrow (v), which represents the speed value that increases instantly.

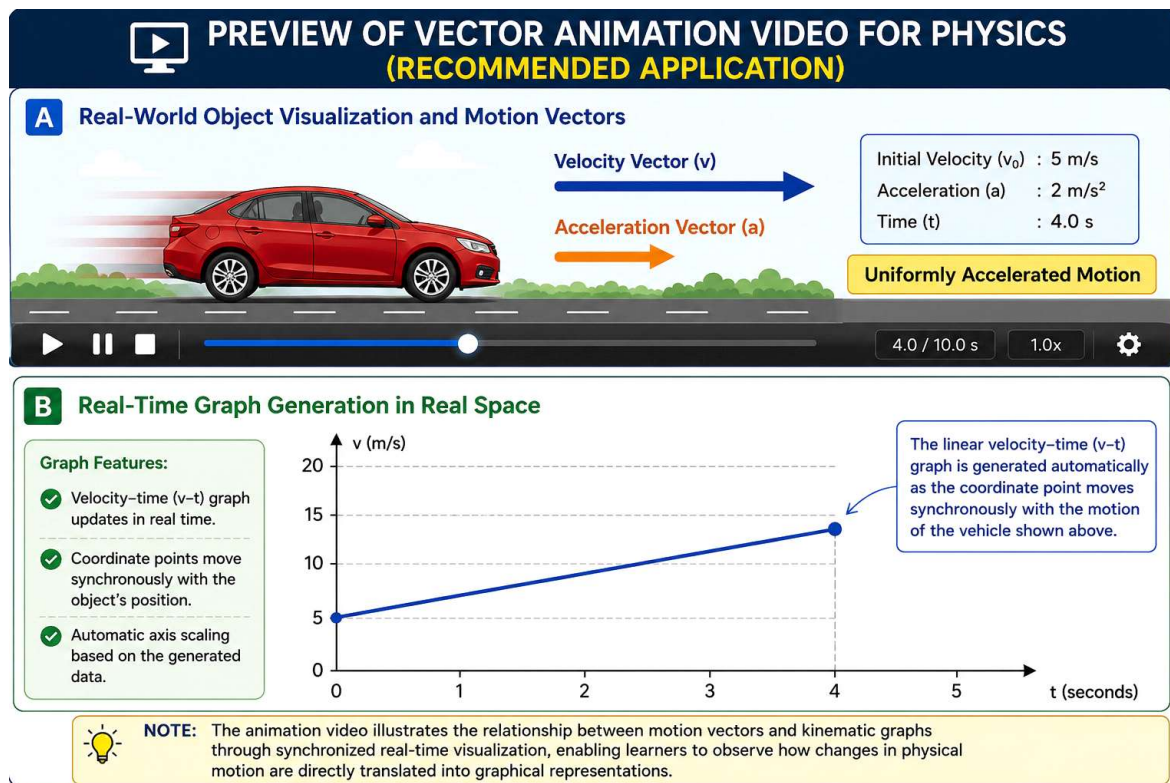


Figure 6. Preview video

At the same time, in Panel B, the graph plot cursor moves upwards to form a constant *slope* that depicts a fixed acceleration. This synchronous presentation acts as cognitive scaffolding, reducing the internal animation processing load on the student's brain. As a result, students' working memory is free from cognitive fatigue and can be fully allocated to construct a deep understanding of the concepts of kinematic laws (Punnakkal et al., 2026; Song et al., 2026; Zhu et al., 2026).

Deconstruction of the Role of Spatial Ability Mediation in Alleviating Graphic Misconceptions

The study's main theoretical contribution is the statistical evidence for the mediating role of spatial *skills* through SEM-PLS analysis. A VAF of 38.7% confirms that improvements in students' kinematic graph interpretation do not occur in an

instantaneous cognitive vacuum but are mediated by a transformation in the sharpness of their spatial intelligence.

Why does spatial ability play such a vital mediating role in the learning of physics graphs? Interpreting physical graphs is essentially a spatial-geometric transformation task. When students are given a TUG-K question that asks them to find an acceleration graph ($a-t$) that corresponds to a position graph ($x-t$) in the form of a quadratic curve, their brains must perform a series of mental operations. The operation includes: (1) detecting changes in the steepness of the curve at various points (spatial differentiation capability), (2) projecting such slope into the dimensions of the new ordinate axis, and (3) rotating or reversing the logical orientation of the direction of motion if the vector sign turns negative (mental rotation) (Hu et al., 2026; Nasbey et al., 2026; Wang et al., 2026).

Students with low spatial ability are particularly vulnerable to getting caught up in the graph-as-picture misconception due to their inability to break free from the visual confines of concrete representations. They see the up-and-down curve on the kinematic graph literally as real physical hills and valleys. Exposure to Vector Animation Videos enhances students' cognitive spatial schemas by strengthening their visuospatial working memory and mental transformation capacity. Visual exercises that involve observing dynamic vector arrows rotating, lengthening, and shifting positions systematically train students' ability to manipulate multidimensional mental representations, as directly measured by their performance on the Mental Rotation Test (MRT). Consequently, this refined spatial flexibility enables students to mentally decouple a graph's shape from physical trajectories, facilitating abstract graphical interpretation in kinematics.

When students' spatial abilities have risen to a higher level (as shown by the surge in MRT scores from 8.20 to 16.24 in Table 1), they gain the ability to perform "geometric abstraction". They begin to realize that the vertical axis on the graph does not represent the height of a place, but rather an intrinsic quantity such as vector velocity. This spatial cognitive transformation is key to why experimental classes successfully alleviate most traditional kinematic misconceptions and achieve superior TUG-K scores (Chaurasia & Tripathi, 2026; Lin et al., 2026).

Comparison with Previous Studies and Implications of Physics Education

This study's findings reinforce and expand previous research by international science multimedia researchers. Our confirmatory study aligns with the basic premise of Cartwright & Hallar (2018) that integrating interactive visual media can stimulate a growth mindset and improve the efficiency of solving science problems that

require higher-order reasoning. However, our research goes beyond Cartwright & Hallar by presenting a parametric structural model (SEM-PLS) that quantitatively separates the effects of spatial mediation from direct instructional effects, a methodological novelty rarely found in the domestic physics education literature (R. Li et al., 2026; Qizhen et al., 2026).

These findings have far-reaching instructional implications for the future of science and mathematics education in Indonesia. For decades, basic physics teaching methods at universities tended to be stuck in a dry, mathematical, formalistic approach (Chen, 2026). Students are bombarded with hundreds of calculus-derived formulas without ever being invited to build strong physical visual intuition about the geometric meaning of a function's derivative. Based on the results of this study, it is recommended to develop physics teaching materials by integrating QR codes linked to dynamic vector animation videos instead of static illustrations. In addition, the physics teacher education curriculum should include training in spatial skills, such as mental rotation and geometric visualization, to support improved understanding of physics concepts (Goranov et al., 2026; Jutkowitz et al., 2026; Youlanda et al., 2026).

CONCLUSION

Experimental research integrated with structural path modeling through SEM-PLS provided robust empirical evidence that comprehensively addressed all research questions. The findings demonstrated that Vector Animation Video Media had a positive and statistically significant direct effect on students' kinematic graph interpretation ability ($\hat{\alpha} = 0.350$). Dynamic vector animation-based media also significantly improved students' spatial ability, particularly mental rotation skills, as indicated by a path coefficient of 0.540 and a substantial

increase in the average Mental Rotation Test (MRT) score. Furthermore, mediation analysis using the Variance Accounted For (VAF) approach revealed that spatial ability served as a significant partial mediator in the relationship between Vector Animation Video Media and kinematic graph interpretation ($p = 0.002$, VAF = 38.7%). These results indicate that more than one-third of the total effect of Vector Animation Video Media on students' understanding of kinematic graphs was transmitted through improvements in spatial ability. Consequently, spatial ability emerged as a crucial cognitive mechanism that enhances the effectiveness of dynamic visual media in physics learning. From a theoretical perspective, these findings extend the literature on multimedia learning and physics education by providing empirical evidence for the mediating role of spatial cognition, particularly mental rotation, in processing abstract kinematic graphs. From an instructional perspective, the results suggest systematically integrating dynamic vector animations into physics instruction to strengthen students' spatial visualization skills, facilitate conceptual understanding, and improve their ability to interpret complex kinematic models and graphical representations.

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