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ORIGINAL RESEARCH PAPER

The role of engineering-related attitude and learning interest on mechanical reasoning: A structural equation modeling study

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Abstract
The results of previous research have not revealed the factors that influence mechanical reasoning, as a preparatory step to improve the mechanical reasoning abilities of engineering students. Based on this, the purpose of this study is to determine a factor model of engineering-related attitude and interest in learning in influencing mechanical reasoning. This study used a cross-sectional study design. The sampling technique used was purposive sampling, involving 30 mechanical engineering students and 72 civil engineering students from the Faculty of Engineering at Universitas Islam Ogan Komering Ilir Kayuagung. The study was conducted using a questionnaire with four Likert-type scale options. The questionnaire consisting of 13 items on mechanical reasoning, 8 items on engineering-related attitudes, and 8 items on interest in learning. The research data were analyzed using Structural Equation Modeling (SEM) using the SmartPLS4 application. SEM analysis involves two stages: measurement model testing and structural model evaluation. Overall, the results of the PLS-SEM model evaluation show that all indicators have met convergent validity and reliability, the independent variables do not experience multicollinearity, 42.1% of the variation in the mechanical reasoning variable can be explained by the relationship between the indicators that form the construct, and both engineering-related attitudes and learning interests are important and significant factors in influencing mechanical reasoning ability. This study contributes to the existing literature in mechanical reasoning by providing an empirically validated structural model that clarifies the significant roles of engineering-related attitudes and learning interest in explaining variations in students' mechanical reasoning ability.

Keywords: engineering-related attitude, interest in learning, mechanical reasoning, structural equation modeling

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INTRODUCTION

Curriculum and policy papers around the world view reasoning as crucial for students in both daily life and educational settings. In many educational institutions across the world, pupils' ability to think and reason is deemed crucial. A significant multinational education effort aims to define the development and evaluation of these competencies (Hačatrjana & Namsone, 2024). Reasoning ability in this context relates to cognitive processes including cause-and-effect relationships, induction, deduction, analogy, and problem-solving. Simply put, reasoning ability is the essential capacity to comprehend complex information. As the mind grows, so will this capacity. Therefore, in order to deliver effective instruction, teachers must have a thorough comprehension of pupils' mental processes (Izzaty et al., 2024).

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Mechanical reasoning is the foundation of human intelligence and a driver of technological and cultural progress because it is highly creative, flexible, and allows for innovation, problem solving, and adaptation to a variety of environments (Sun et al., 2025). Mechanical reasoning relies on mental simulations, tools that allow us to predict how our actions will impact the surrounding environment. These versatile simulations are crucial for helping us think about things in new ways, but they cannot explain how we quickly create and change our plans. We argue that knowing what types of actions to consider is also crucial for rapid tool use, both from an initial understanding of what actions are beneficial and from updating these beliefs by observing the results of our actions in simulations and in the real world (Allen et al., 2020).

Engineering applications require mechanical reasoning, but students still struggle to predict, analyze, and model mechanical systems using formal symbolic notation (Grondin & Fu, 2023). The research is also in line with the results of research at the Islamic University of Ogan Komering Ilir Kayuagung which shows that the engineering talent category is dominated by the medium category; for the mechanical engineering study program, it is 73.07% and for the civil engineering study program, it is 77.14% (MS & Saud, 2024). The results of this study have not yet revealed the factors that influence mechanical reasoning, as a step to prepare for improving the mechanical reasoning abilities of engineering students. Therefore, further research is needed to map the factors that influence mechanical reasoning.

There are several abilities or skills required by an engineer, including engineering related attitude (Kőycű & de Vries, 2016; Laguador & Dotong, 2020; Setiawan & Raharjo, 2019) and interest in engineering (Radzi & Sulaiman, 2018; Reynolds et al., 2019). Students' general attitudes toward engineering show a fairly positive image of the discipline (Kőycű & de Vries, 2016), reflected in their views on the relevance of engineering in modern life, its broad career opportunities, and their belief that technical competence plays an important role in solving real problems in society.

In cognitive and educational psychology, the concept of learning interest is recognized as a crucial factor in student engagement, motivation, and achievement. Learning interest encourages students to investigate, understand, and internalize educational material. When students are genuinely interested in what they are learning, they are more likely to exert more effort, challenge difficulties, and seek deeper understanding (Sulfiani et al., 2024). Interest in learning is a student's desire and fascination with the subject, as well as their attention and activeness in happily and contentedly acquiring new knowledge and experiences. One component that influences optimal learning outcomes is interest. If students engage in learning activities with interest, they will feel a strong sense of importance. As a result, they will strive to focus their attention on matters related to the activity and do so with pleasure, free from the influence of others (Andriyanto, 2024).

Previous research has not mapped the factors that influence mechanical reasoning using a sophisticated and comprehensive modeling approach, so that the relationships between variables that potentially contribute to this ability have not been fully described or measured with sufficient accuracy. One of the most effective tools is structural equation modeling (SEM). Structural modeling (SEM) has the ability to analyze constructs or variables at a deeper level than path analysis and multiple regression. As a result, this method has greater predictive power. Using SEM, researchers can create research models with multiple variables, examine constructs or variables that are unobservable or cannot be directly measured (unobserved), test for measurement error (measurement error) for observed constructs or variables (observed), and find solutions to various research problems (Hidayat & Wulandari, 2022).

PLS-SEM, originally known as partial least squares path modeling, is a computationally efficient estimator for SEM. It demonstrates the ability to rapidly describe (complex) cause-and-effect relationships. To describe model parameters, PLS-SEM uses an iterative algorithm based on generalized least squares regression to calculate weights. Next, construct scores are used to reflect model parameters (Schuberth et al., 2023).

Based on this, the purpose of this study is to determine a factor model of engineering-related attitude and interest in learning in influencing mechanical reasoning, such that the underlying relationships among these constructs can be identified and empirically validated. The research hypotheses are: (1) engineering-related attitude can significantly influence mechanical reasoning (H1), and (2) interest in learning can significantly influence mechanical reasoning (H2).

RESEARCH METHOD

This study uses a cross-sectional study design and is quantitative in nature. A cross-sectional study, sometimes referred to as prevalence or transversal research, describes the attitudes, actions, or other characteristics of study participants at a particular moment in time. The sampling technique used was purposive sampling, involving 30 mechanical engineering students and 72 civil engineering students from the Faculty of Engineering at Universitas Islam Ogan Komering Ilir Kayuagung.

The study was conducted using a questionnaire consisting of 13 items on mechanical reasoning (Mackellar, 2015), 8 items on engineering-related attitudes (Dewaters et al., 2017), and 8 items on interest in learning (Robinson et al., 2021). Each item was equipped with four Likert-type scale options.

The research data were analyzed using Structural Equation Modeling (SEM) using the SmartPLS4 application. SEM analysis involves two stages: measurement model testing and structural model evaluation (Firdaus et al., 2025). Measurement model testing was conducted to obtain the reflective construct value by estimating the loading and p-value. Indicator loadings were in the range of 0.70 and statistically significant (sig) at 0.50 or below. Meanwhile, the p-value was between 0.40 and 0.70. Internal consistency reliability was examined using Cronbach's alpha (α) and Composite Reliability (CR). The cut-off value for both measures was 0.70 (Hair & Alamer, 2022).

The structural model coefficients for the relationships between constructs are obtained from estimating a series of regression equations (Hair et al., 2021). Evaluation of the structural model is carried out using the following steps: (1) Determine the collinearity of the model. When two or more predictors measure the same underlying construct, they are said to be collinear (Kock, 2015). If all VIFs resulting from the full collinearity test are equal to or lower than 3.3, the model can be considered free from common method bias; (2) Determine the coefficient of determination (R2). R2 shows the variance explained in each predictor construct and is a measure of the explanatory power of the relationship between constructs in the model, as presented in Table 1 (Hair et al., 2021; Hair & Alamer, 2022); (3) Evaluate the size and significance of the path. This step is carried out to see the strength of the effect and the meaningfulness of the path. The path significance coefficient (β) is classified according to Table 2 (Hair & Alamer, 2022).

Table 1. Explanatory power

Coefficient of Determination (R^2)	Explanatory Power
0 – 0.10	Weak
0.11 – 0.30	Modest
0.31 – 0.50	Moderate
> 0.50	Strong

Table 2. Path significance

Significant Coefficient	Strength of Effect
0 – 0.10	Weak
0.11 – 0.30	Modest
0.31 – 0.50	Moderate
> 0.50	Strong

RESULTS AND DISCUSSION

The research results will be explained in two parts, namely measurement model testing and structural model evaluation.

Measurement model testing

The first step in PLS-SEM analysis to guarantee the validity and reliability of study constructs is measurement model evaluation (Subhaktiyasa, 2024). The first analysis carried out was convergent validity analysis. The goal of convergent validity analysis is to determine the degree of appropriate link between the indicators utilized in the same construct or factor. The findings of factor loading indicators on pertinent factors will be taken into account in convergent validity analysis (Fithri et al., 2024).

The convergent validity analysis results (See Figure 1) show that several indicators have been declared valid with a factor loading > 0.7 (Hair & Alamer, 2022). In the Engineering Related Attitude (ERA) variable, there are three valid indicators (ERA2, ERA3, ERA8) with outer loading values of 0.886 to 0.944. The Interest in Learning (IL) variable has three valid indicators (IL1, IL4 and IL6) with outer loadings of 0.878 to 0.910. The Mechanical Reasoning (MR) variable has four valid indicators (MR1, MR3, MR5, and MR7) with outer values of 0.906 to 0.933. These results indicate that all indicators demonstrate adequate convergent validity and are therefore retained for further structural model analysis.

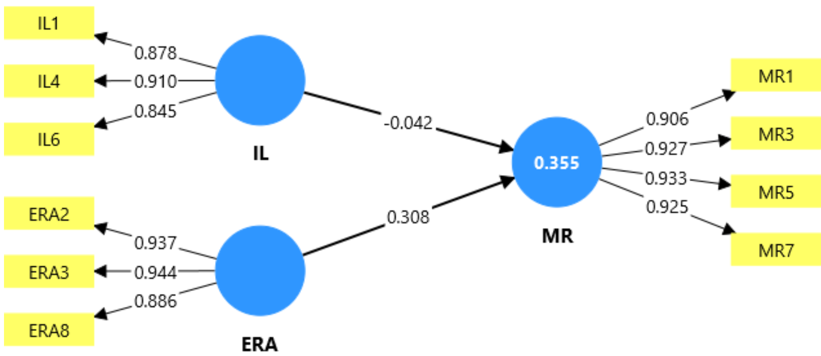

Figure 1. Model factor.

The next analysis was the average variance extracted (AVE) and reliability analysis. The results of these two analyses are displayed in Table 3.

Table 3. Validity and reliability results

Variable	Average Variance Extracted (AVE)	Cronbach's Alpha	Composite Reliability (rho_c)
ERA	0.873	0.951	0.965
IL	0.784	0.862	0.916
MR	0.852	0.943	0.958

The average extracted variance (AVE) for every item in each construct is the metric used to assess the convergent validity constructs. We must square each indicator's loading on a construct and compute the mean value average in order to determine the AVE. An appropriate AVE is 0.50 or more, meaning that the concept accounts for at least 50% of the item variance (Purwanto & Sudargini, 2021). The results of the AVE test show that all variables have AVE > 0.5, so all variables are declared valid.

Composite reliability, sometimes referred to as construct reliability to assess the internal consistency in scale categories, is comparable to Cronbach's alpha. In every intended cut-off line, the constructs attained ≥0.70. The latent variable becomes dependable in subsequent analysis when Cronbach's alpha is greater than or equal to 0.70. The construct was deemed credible since the composite values also exceeded 0.70 (Mia et al., 2022). The results of the Cronbach's alpha and composite reliability tests show that all variables have a value of more than 0.7 so that all variables are declared reliable.

Structural model evaluation

At the structural model evaluation stage, the first thing to do is check for collinearity. The degree to which the other variables in the analysis are connected or can be utilized to explain a specific variable is known as multicollinearity. High multicollinearity may have an impact on the final outcomes. The variance inflation factor (VIF) value was used to determine whether multicollinearity was present in this investigation. VIF values of five or higher indicate the existence of the multicollinearity issue (Miah et al., 2023).

The VIF values for ERA → MR were 1.421 and for IL → MR were 2.153, indicating that all values were below the threshold of 5. Therefore, it can be concluded that multicollinearity was not a problem in this study. According to Hair et al. (2021) the Variance Inflation Factor (VIF) is used to detect high correlations between independent variables. A VIF value <5 indicates that the correlation between predictors is within reasonable limits and does not interfere with model estimation. In fact, some literature, such as Kock (2015) states that a VIF value ≤ 3.3 can be considered an indicator of the absence of bias due to multicollinearity or potential common method bias.

Therefore, the low VIF results confirm that the independent variables in this study do not have a significant correlation between them, thus distorting the regression estimates. This also indicates that the model used has good estimation stability, and that the tested indicators can provide a valid contribution in explaining variation in the mechanical reasoning variable.

The second stage is determining the coefficient of determination. The amount of variance explained by the independent variables is indicated by the R2 value. Consequently, a higher R2 value improves the structural mode's capacity for prediction (Mohamed et al., 2018). The results of the analysis show that the R2 value obtained is 0.421 indicates that 42.1% of the Mechanical Reasoning variable can be explained by the constructs or indicators that influence it. In the context of analysis using Partial Least Squares Structural Equation Modeling (PLS-SEM), this level of explanatory power is included in the moderate category (Hair et al., 2021; Hair & Alamer, 2022). Thus, the R^2 value of 0.421 reflects that the model has quite good predictive ability because it is close to the moderate category limit. This means that 42.1% of the variation in the Mechanical Reasoning variable can be explained by the relationship between the indicators that form the construct, while the remainder is influenced by other factors outside the research model. This finding illustrates that the model used is able to explain the phenomenon adequately and is acceptable in social and educational research.

Table 4. The results of the significance path

Regression Path	Hypothesis	T statistics (|O/STDEV|)	P values	Result
ERA → MR	H1. Engineering-related attitude can significantly influence mechanical reasoning.	3.425	0.001	Significant
IL → MR	H2. Interest in learning can significantly influence mechanical reasoning.	3.596	0.000	Significant

The final stage is testing the significance of the path. Bootstrapping with a resample of 5000 was used to evaluate the moderation effects of the moderator and evaluate the significance of path coefficients (Miah et al., 2023). The results of the significance path test of this research path are shown in Table 4.

The results of the regression path analysis indicate that Engineering-Related Attitude (ERA) has a significant effect on Mechanical Reasoning (MR), as evidenced by a t-statistic of 3.425 and a p-value of 0.001, thus supporting Hypothesis H1. This finding indicates that engineering-related attitudes contribute significantly to improving mechanical reasoning ability.

Furthermore, Interest in Learning (IL) was also shown to have a significant effect on mechanical reasoning, as evidenced by a t-statistic of 3.596 and a p-value of 0.000, thus rejecting Hypothesis H2. This indicates that students' learning interests substantially influence their ability to understand and solve mechanical problems. Overall, these two results confirm that both engineering-related attitudes and learning interests are important and significant factors in influencing mechanical reasoning ability.

The results of this study align with those of Xu & Zhou (2022), who discovered that 21st-century thinking skills and talents, including as problem-solving and reasoning, are positively influenced by attitudes toward science, engineering, and technology. This study highlighted the significance of students' attitudes toward engineering in enhancing cognitive abilities and employed structural equation modeling. The results of this study are also in line with a study of Sholihah and Listanti (2022) which shows that interest in learning is significantly related to mathematical reasoning ability, which is logically in line with mechanical reasoning because both are forms of higher thinking skills that are influenced by students' motivation and interest in learning (Sholihah & Listanti, 2022).

Therefore, future learning designs should integrate strategies that strengthen students' engineering-related attitudes and foster higher learning interest to further enhance their mechanical reasoning skills. By doing this, educators can establish a more encouraging and stimulating learning environment that inspires students to delve deeper into engineering concepts, fosters long-term academic motivation, and eventually helps students become more capable and self-assured mechanical reasoning learners.

CONCLUSION

The results of the research and discussion can be concluded that the PLS-SEM model evaluation shows that all indicators have met convergent validity and reliability, the independent variables do not experience multicollinearity, 42.1% of the variation in the Mechanical Reasoning variable can be explained by the relationship between the indicators that form the construct, and both engineering-related attitudes and learning interests are important and significant factors in influencing mechanical reasoning ability. This study contributes to the existing literature in mechanical reasoning by providing an empirically validated structural model that clarifies the significant roles of engineering-related attitudes and learning interest in explaining variations in students' mechanical reasoning ability.

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Not available.

DECLARATION

Author contribution

All authors contribute in the research and/or writing the paper, and approved the final manuscript.

Firdaus MS	Conceptualizing the research idea, leading the investigation, setting up the methodology, and writing the original draft.
Deliansyah Pasayu	Assisting the investigation, assisting the data analysis, revising the draft.

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Conflict of interest
All authors declare that they have no competing interests.

Ethics declaration
We as authors acknowledge that this work has been written based on ethical research that conforms with the regulations of our institutions and that we have obtained the permission from the relevant institutes when collecting data. We support the International Journal on Education Insight (IJEI) in maintaining the high standards of personal conduct, practicing honesty in all our professional practices and endeavors.

The use of artificial intelligence
We do not use any generative AI tools to write any part of this paper.

Additional information
Not available.

REFERENCES

Allen, K. R., Smith, K. A., & Tenenbaum, J. B. (2020). Rapid trial-and-error learning with simulation supports flexible tool use and physical reasoning. *PNAS, 117*(47), 29302–29310. https://doi.org/10.1073/pnas.1912341117/-/DCSupplemental.y

Andriyanto, Y. D. (2024). Relationship between learning interest and learning outcomes of Catholic religious education students in Grade III of St. Don Bosco Catholic Elementary School Palangkaraya. *Journal of Childhood Development, 4*(2), 459-469. https://doi.org/10.25217/jcd.v4i2.5104

Dewaters, J., Moosbrugger, J. C., & Sharma, P. (2017). Development and application of a questionnaire to measure student attitudes toward and understanding of engineering. *ASEE Annual Conference and Exposition* (vol. 2017-June). https://doi.org/10.18260/1-2--28153

Firdaus, E., Andrikasmi, S., Hermita, N., & Wijaya, T. T. (2025). Investigating factors influencing bullying behavior reduction and gender differences in higher education: A structural equation modeling approach. *Acta Psychologica, 253*(1), 1–11. https://doi.org/10.1016/j.actpsy.2025.104747

Fithri, P., Hasan, A., Syafrizal, S., & Games, D. (2024). Validation studies a questionnaire developed to measure incubator business technology performance using PLS-SEM Approach. *Andalasian International Journal of Applied Science, Engineering and Technology, 4*(1), 64–78. https://doi.org/10.25077/aijaset.v4i1.132

Grondin, M. M., & Fu, K. (2023). How does students' use of speech ground and embody their mechanical reasoning during engineering discourse? *ASEE Annual Conference and Exposition* (vol. 2023-June, pp. 1–20). https://doi.org/10.18260/1-2--43365

Hačatrjana, L., & Namsone, D. (2024). Breaking down the concept of students' thinking and reasoning skills for implementation in the classroom. *Journal of Intelligence, 12*(11), 109. https://doi.org/10.3390/jintelligence12110109

Hair, J., & Alamer, A. (2022). Partial Least Squares Structural Equation Modeling (PLS-SEM) in second language and education research: Guidelines using an applied example. *Research Methods in Applied Linguistics, 1*(3), 1–16. https://doi.org/10.1016/j.rmal.2022.100027

Hair, J., Hult, G., Ringle, C., Sarstedt, M., Danks, N., & Ray, S. (2021). *Partial Least Squares Structural Equation Modeling (PLS-SEM) using R*. Springer Nature. https://doi.org/10.1007/978-3-030-80519-7

Hidayat, R., & Patricia Wulandari. (2022). Structural Equation Modelling (SEM) in research: Narrative literature review. *Open Access Indonesia Journal of Social Sciences, 5*(6), 852–858. https://doi.org/10.37275/oaijss.v5i6.141

Izzaty, R. E., Setiawati, F. A., & Istikomah, F. (2024). The effect of educational levels and gender on students' reasoning ability and mechanical aptitude. *Cypriot Journal of Educational Sciences, 19*(4), 309–325. https://doi.org/10.18844/cjes.v19i4.8953

Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. *International Journal of E-Collaboration, 11*(4), 1–10. https://doi.org/10.4018/ijec.2015100101

Kőycű, Ü., & de Vries, M. J. (2016). What preconceptions and attitudes about engineering are prevalent amongst upper secondary school pupils? An international study. *International Journal of Technology and Design Education, 26*(2), 243–258. https://doi.org/10.1007/s10798-015-9305-4

Laguador, J. M., & Dotong, C. I. (2020). Engineering students' challenging learning experiences and their changing attitude towards academic performance. *European Journal of Educational Research, 9*(3), 1127–1140. https://doi.org/10.12973/EU-JER.9.3.1127

Mackellar, C. (2015). *Mechanical, Spatial & Abstract Reasoning*. Vivid Publishing.

Mia, M. M., Zayed, N. M., Islam, K. M. A., Nitsenko, V., Matusevych, T., & Mordous, I. (2022). The strategy of factors influencing learning satisfaction explored by first and second-order Structural Equation Modeling (SEM). *Inventions, 7*(3), 59. https://doi.org/10.3390/inventions7030059

Miah, M. S., Singh, J. S. K., & Rahman, M. A. (2023). Factors influencing technology adoption in online learning among private university students in Bangladesh post COVID-19 pandemic. *Sustainability*, *15*(4), 3543. https://doi.org/10.3390/su15043543

Mohamed, Z., Hasbiah Ubaidullah, N., & Ilyana Mohd Yusof, S. (2018). An evaluation of structural model for independent learning through connectivism theory and Web 2.0 towards students' achievement. In *International Conference on Applied Science and Engineering (ICASE 2018)* (pp. 1-5). Atlantis Press.

MS, F., & Saud, E. (2024). Engineering aptitude-mechanical reasoning of engineering students: Rasch analysis. *Edutainment: Jurnal Ilmu Pendidikan dan Kependidikan, 12*(2), 56–64. https://doi.org/10.35438/e.v12i2.927

Purwanto, A., & Sudargini, Y. (2021). Partial Least Squares Structural Squation Modeling (PLS-SEM) analysis for social and management research: A literature review. *Journal of Industrial Engineering & Management Research, 2*(4), 114–123. https://doi.org/10.7777/jiemar.v2i4

Putu Gede Subhaktiyasa. (2024). PLS-SEM for multivariate analysis: A practical guide to educational research using SmartPLS. *EduLine: Journal of Education and Learning Innovation, 4*(3), 353–365. https://doi.org/10.35877/454ri.eduline2861

Radzi, N. A. M., & Sulaiman, S. (2018). Measuring students' interest towards engineering in technical school: A case study. *Journal of Technology and Science Education, 8*(4), 231–237. https://doi.org/10.3926/jotse.369

Reynolds, B., Mehalik, M. M., Lovell, M. R., & Schunn, C. D. (2019). Increasing student awareness of and interest in engineering as a career option through design-based learning. *International Journal of Engineering Education, 25*(4), 788–798.

Robinson, B., Tretter, T., Lewis, J. E., & Hawkins, N. (2021). Measuring First-Year Engineering Majors Interest in Engineering. In *2021 ASEE Virtual Annual Conference Content Access*. https://doi.org/10.18260/1-2--37493

Schuberth, F., Hubona, G., Roemer, E., Zaza, S., Schamberger, T., Chuah, F., Cepeda-Carrión, G., & Henseler, J. (2023). The choice of structural equation modeling technique matters: A commentary on Dash and Paul (2021). *Technological Forecasting and Social Change, 194*, 122665. https://doi.org/10.1016/j.techfore.2023.122665

Setiawan, H., & Raharjo, F. (2019). Knowledge, skills and attitudes of civil engineers in Indonesia. *IOP Conference Series: Materials Science and Engineering, 615*(1), 012030. https://doi.org/10.1088/1757-899X/615/1/012030

Sholihah, U., & Listanti, A. (2022). Analyzing students' mathematical reasoning from the perspective of learning interest. *Beta: Jurnal Tadris Matematika, 15*(2), 157-166. https://doi.org/10.20414/betajtm.v15i2.535

Sulfiani, B., Nurhayati, N., Abdullah, E., Takwa, E. S., Fitriani, F., & Nesti, V. A. (2024). Increasing student learning interest through cooperative learning. *Journal La Edusci, 5*(3), 162–168. https://doi.org/10.37899/journallaedusci.v5i3.1354

Sun, H., Gao, Q., Lyu, H., Luo, D., Li, Y., & Deng, H. (2025). *Probing Mechanical Reasoning in Large Vision Language Models*. Arxiv Preprint. http://arxiv.org/abs/2410.00318

Xu, S. R., & Zhou, S. N. (2022). The effect of students' attitude towards science, technology, engineering, and mathematics on 21st century learning skills: A structural equation model. *Journal of Baltic Science Education, 21*(4), 706–719. https://doi.org/10.33225/jbse/22.21.706