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Analysis of Mathematical Logic and Computational Thinking Abilities of Informatics Engineering Students on Learning Achievement in Calculus Courses

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Abstrak

Penelitian ini bertujuan untuk mengkaji hubungan antara kemampuan logika matematika dan berpikir komputasional dengan prestasi belajar mahasiswa dalam mata kuliah Kalkulus. Studi ini melibatkan 66 siswa semester pertama Program Studi Teknik Informatika pada tahun akademik 2022/2023. Tes untuk mengukur kemampuan berpikir logika dan komputasional serta instruksi untuk mengumpulkan data tentang prestasi belajar adalah bagian dari metode pengumpulan data. Analisis data dilakukan menggunakan korelasi Pearson bivariat dan regresi linear berganda, dengan pengujian prasyarat yang mencakup uji normalitas, homoskedastisitas, multikolinearitas, dan autokorelasi. Hasil analisis menunjukkan terdapat hubungan yang signifikan antara berpikir komputasional dengan prestasi belajar (r = 0,715), antara logika matematika dengan prestasi belajar (r = 0,781), serta antara berpikir komputasional dan logika matematika (r = 0,661). Temuan ini mengindikasikan pentingnya integrasi kemampuan logika matematika dan berpikir komputasional dalam proses pembelajaran Kalkulus, yang dapat diupayakan melalui pendekatan pedagogis yang tepat serta pengembangan media pembelajaran yang mendukung.
Kata Kunci: kemampuan berpikir komputasi; logika matematika; prestasi belajar kalkulus

Abstract

This study aims to examine the relationship between mathematical logic skills and computational thinking with students' academic performance in the Calculus course. This study involved 66 first-semester students of the Computer Engineering Study Program in the 2022/2023 academic year. Tests to measure logical and computational thinking abilities, as well as instructions for collecting data on learning achievements, are part of the data collection methods. Data analysis was conducted using bivariate Pearson correlation and multiple linear regression, with prerequisite tests including normality, homoscedasticity, multicollinearity, and autocorrelation tests. The analysis results show a significant relationship between computational thinking and academic achievement (r = 0.715), between mathematical logic and academic achievement (r = 0.781), as well as between computational thinking and mathematical logic (r = 0.661). These findings indicate the importance of integrating mathematical logic skills and computational thinking in the learning process of Calculus, which can be pursued through appropriate pedagogical approaches and the development of supportive learning media.
Keywords: computational thinking; mathematical logic; calculus learning achievements

I. Introduction

A deep understanding of mathematics is essential for mastering Calculus, a core subject that is often a significant milestone in measuring a student's ability to solve complex mathematical problems. Many students find overcoming Calculus courses challenging due to their reputation as a stumbling block. The high difficulty level in Calculus creates a real challenge, and some students face difficulty achieving good academic performance in this course. Teaching Calculus is not only about mastering formulas and theory but requires understanding and applying complex mathematical concepts in real-world situations to achieve optimal results in Calculus courses. Learning Calculus requires mathematical logic skills and Computational Thinking (computational thinking skills).

Mathematical logic is the ability to think scientifically, calculate using structured methods, apply rational thinking, and use inductive and deductive reasoning. Moreover, this type of intelligence involves the skill to detect abstract patterns and interpret the relationships that link them. Mathematical logic skills involve analyzing problems logically, carrying out mathematical calculations, and scientific investigations into the issues faced. Mathematical logic is the scientific ability to solve problems by understanding concepts and connecting abstract patterns with procedural steps.

Mathematical logic is the ability to think scientifically, calculate using structured methods, apply rational thinking, and use inductive and deductive reasoning. In addition, this form of intelligence encompasses the capability to recognize abstract patterns and comprehend the connections among them (Devianti, 2013). Mathematical logic skills involve the ability to analyze problems logically, carry out mathematical calculations, and carry out scientific investigations into the issues at hand (Morris, 2023). Mathematical logic ability is the scientific ability to solve problems through understanding concepts and connecting abstract patterns with procedural steps (Zulfairanatama & Hadi, 2013).

Stimulating mathematical logic abilities will increase intellectual development, especially in logical thinking, information processing, cognitive skills, memory, reasoning, understanding ideas, classification, problem-solving, and focus of attention. Cognitive skills refer to actions that enable individuals to understand or acquire the knowledge necessary to utilize information (Wanti & Aprianti, 2018). Logical-mathematical intelligence plays a vital role, as it encompasses critical thinking, problem-solving abilities, and learning through numerical concepts by examining cause-and-effect relationships (Senouci & Nacera, 2022). One method for measuring intelligence is observing a person's ideas and knowledge expressed through various symbols, including images, language, and mathematics. Symbolic systems and visual representations are relevant in multiple fields of science in everyday life and have a central role in overcoming various existing tasks or problems(Fatimah et al., 2020).

Mathematical skills can more strongly predict the level of computational thinking so that computational thinking may have a closer correlation with mathematics than with language skills(Guggemos, 2021). Computational thinking is a form of thinking used to solve problems, initially emerging from computer science, but can be applied in various aspects or other scientific disciplines using problem-solving processes. Computational thinking involves the creative process of applying solutions to problems, which includes considering ideas, opportunities, and challenges that arise to find the right solution (Megawati et al., 2023).

In the field of computing, computational thinking skills are highly valuable as they enhance an individual's capacity to think critically, creatively, and logically when addressing complex problems, whether in computing contexts or everyday situations. Advanced advances in computing technology can create bolder, innovative breakthroughs in various aspects of human life because technology can make it easier to solve problems and understand complex systems (Swaid, 2015). Computational thinking skills involve the ability to comprehend and address complex problems by applying concepts and methods from computer science, including decomposition, abstraction, algorithm design, and generalization. Within this framework, students are encouraged to enhance their communication abilities while fostering creative and logical thinking throughout the problem-solving process (Litia et al., 2023).

Computational thinking is a vital skill for students, as they will encounter scenarios in which computing plays a crucial role. Students must be able to face computing challenges not only in work situations but also in real life and when facing ongoing changes in the world economic system (Bower et al., 2017; Revika et al., 2024). Computational thinking represents a set of attitudes and abilities that are applicable not only to computer scientists but to individuals across various fields. Integrating computational thinking into various classroom subjects is essential to enhance analytical capacity (Risnandar & Al Maki, 2022).

Computational thinking includes solving problems using logical and structured thinking, which includes problem decomposition analysis, selection and application of algorithms, use of data representation, application of abstractions, and verification of hypotheses (Christi & Rajiman, 2023). A literature review demonstrates that computational thinking and intelligence share similar definitions. Researchers consider these two concepts as highly essential methods for problem-solving and the ability to perform abstractions. Computational thinking is often described as a method for solving problems, especially in a computing context, with critical features such as the ability to perform abstraction and pattern recognition, problem-solving skills, data management, and the ability to design and implement algorithms(Boom et al., 2018). Someone with high computing skills can face challenges that rely on logic. Mathematical-logical intelligence encompasses the capacity for logical reasoning and learning through numerical understanding and the analysis of cause-and-effect relationships. Individuals with this intelligence are known as systemic thinkers who are skilled in mathematical problem-solving and can solve puzzles (Özgür, 2020).

This study seeks to examine the relationship between computational thinking abilities and mathematical logic in relation to the Calculus learning outcomes of Informatics Engineering students. Mathematical logic is the key to understanding the basics of calculus, while computational thinking skills are needed to solve mathematical problems using algorithms and computational approaches. The findings of this study are expected to offer valuable insights for educators in enhancing student performance in Calculus courses and promoting stronger integration of mathematical logic and computational thinking skill development within the Informatics Engineering curriculum.

This study is essential because mathematical logic and computational thinking are fundamental skills required in Informatics Engineering, yet they are often underutilized in learning processes, particularly in Calculus courses. Many students struggle to connect abstract Calculus concepts with the analytical and systematic approaches inherent in these two abilities. By examining the extent to which these skills contribute to learning achievement, the study provides a foundation for developing more effective teaching strategies. It supports the integration of 21st-century skills into higher education curricula.

The novelty of this study lies in its simultaneous analysis of the influence of two key cognitive abilities, mathematical logic, and computational thinking, on students' performance in Calculus, specifically among Informatics Engineering students. Previous studies have typically examined these variables separately or in non-mathematical contexts. Moreover, this research employs a quantitative approach using correlation and multiple regression analysis, supported by thorough prerequisite statistical tests, offering strong empirical evidence. The findings contribute to developing more integrated and cognitively relevant learning models that align with the demands of the digital era.

II. Method

This research is quantitative, using an ex-post facto approach (cause and effect analysis) in its research methodology. This approach involves examining cause-and-effect relationships by observing the effects and then looking for causal factors through data collection. This study aims to examine the relationship between students' computational thinking skills and mathematical logic abilities with their academic performance in Calculus courses, specifically among those enrolled in the Informatics Engineering study program. Therefore, the dependent variable in this research is students' Calculus learning achievement, while the independent variables are mathematical logic abilities and computational thinking abilities. The subjects were 66 first-semester Informatics Engineering Study Program students, University of Darussalam Gontor, 2022/2023. The research instruments used were multiple choice test questions to measure mathematical logic abilities and description tests to measure students' computational thinking abilities. DAssessing final semester exam scores in the Calculus course provides a means to obtain data on student's achievements in learning Calculus.

Multiple linear regression was used to evaluate the study's data, and tests for normality, heteroscedasticity, multicollinearity, and autocorrelation were required (Nursiyono & Nadeak, 2016).

The normality test is conducted to assess whether the residuals are normally distributed or originate from a population with a normal distribution. A regression model is considered valid if the residuals exhibit a standard or near-normal distribution. Normality is evaluated using the Kolmogorov-Smirnov and Shapiro-Wilk tests, with the criterion that a significance (Sig) value greater than 0.05 indicates normally distributed residuals, whereas a Sig value less than 0.05 suggests the residuals deviate from normality.

Heteroscedasticity is a condition where the variance of the residuals is not the same for each observation in the regression model. In the multiple linear regression analysis prerequisite test, it is imperative to avoid meeting the heteroscedasticity testing requirement. Detecting heteroscedasticity can be done graphically by examining scatter plots of the residual distribution. If the scatter plot results look spread out and do not have a particular pattern, then the heteroscedasticity assumption is not met.

Multicollinearity refers to a strong or exact linear correlation between two or more independent variables within a regression model. Ideally, multicollinearity should be absent in such models. To assess this, Tolerance (TOL) and Variance Inflation Factor (VIF) values are used. If the VIF value is less than 10.00 and the TOL value is larger than 0.10, the regression model is said to be free of multicollinearity.

The autocorrelation assumption refers to the existence of components or residual values that correlate with themselves, be it a correlation between different observations or samples at the same time (cross-autocorrelation) or a correlation between the exact words or illustrations at other times (serial correlation). In this test, the expectation is that the autocorrelation assumption is not met; therefore, the non-autocorrelation assumption must be fulfilled. The Durbin Watson (DW) value serves as the criteria for determining the completion of the non-autocorrelation assumption in the multiple linear regression model. With the requirements that if DW = 2 or close to it, then the model meets the non-autocorrelation assumption, and if DW = 0 or close to it, then the model does not meet the non-autocorrelation assumption.

After fulfilling all the conditions required for regression analysis, the following action is to conduct hypothesis testing to determine the significance of the coefficients and regression model obtained. Hypothesis testing uses the F-test and the t-test.

The whole regression equation's significance is evaluated using the F-test. The purpose of this test is to ascertain whether the dependent variable is significantly impacted by all independent variables taken together. The significant value (Sig.) of the F-test derived from the ANOVA output in IBM SPSS Statistics 22 serves as the basis for the choice. The regression equation is regarded statistically significant if the Significance F value is less than 0.05, and not significant if the value is more than 0.05.

The significance of each regression coefficient is then assessed using the t-test. This test establishes if each independent variable has a statistically significant partial impact on the dependent variable within the framework of the regression model. The t-test's significance (Sig.) value is used to make the judgment; a Sig. value less than 0.05 indicates a significant effect, while a value more than 0.05 indicates the regression coefficient is not significant.

The next step is to use the least squares approach to estimate the regression coefficients or parameters. The regression model is then built using these coefficients and can be expressed mathematically as follows:

$$\hat{Y} = b_0 + b_1X_1 + b_2X_2$$

Information:

$\hat{Y}$ as the response/dependent variable is Calculus learning achievement

X_1 as a predictor/independent variable is the computational thinking ability

X_2 as a predictor/independent variable is the mathematical logic ability

b_0 is the intercept

b_1 and b_2 are the regression coefficients of the independent variables X_1 and X_2

The subsequent step involves calculating the correlation coefficient, which serves to identify the strength and direction of the relationship among the three variables: computational thinking ability, mathematical logic ability, and calculus learning achievement. The correlation coefficient is measured using the Pearson Product-Moment formula, symbolized as rxy. This coefficient is then interpreted to assess the degree of association between the variables (Quadratullah, 2014), it is presented in Table 1.

Table 1.
Level of Relationship Between Two Variables

Correlation Coefficient (r_{xy})	Relationship Level
$r_{xy} = 1$	Perfect
$0.75 \leq r_{xy} < 1$	Very strong
$0.5 \leq r_{xy} < 0.75$	Strong
$0.25 \leq r_{xy} < 0.5$	Weak
$0 < r_{xy} < 0.25$	Very weak
$r_{xy} = 0$	There isn't any

The coefficient of determination (R2), which is used to assess the regression model's goodness of fit to the observed data, is then calculated. The degree to which the independent variables help to explain the variance in the dependent variable is shown by this coefficient. R2 has a value between 0% and 100%, or 0 and 1. A value nearer 1 suggests that the regression model accurately depicts the relationship between the variables and that the independent factors have a significant impact on the dependent variable.

III. Result and Discussion

This research has three data groups: computational thinking ability data (CTA), mathematical logic ability data (MLS), and calculus learning achievement data (CLA). Data on computational thinking abilities and mathematical logic were obtained from tests on research subjects. In contrast, data on Calculus learning achievement were students' final semester grades in the Calculus course. Descriptive analysis of the three data is presented in Table 2.

Table 2.
Results of Descriptive Analysis of Data

	CTA	MLS	CLA
N	66	66	66
Range	48	40	43
Minimum	50	57	52
Maximum	98	97	95
Std. Deviation	10,187	8,836	9,521
Variance	103,773	78,079	90,654

1) Normality Test

In this research, the normality assessment was conducted using the Kolmogorov-Smirnov and Shapiro-Wilk tests, facilitated by the IBM SPSS Statistics 22 software. The outcomes of the normality test for computational thinking ability data are displayed in Table 3.

Table 3.
Data Normality Test Results for Computational Thinking Abilities

Test	Statistics	df	Sig.
Kolmogorov-Smirnov	,099	66	,178
Shapiro-Wilk	,982	66	,449

As shown in Table 3, the significance values (Sig.) for the Kolmogorov-Smirnov and Shapiro-Wilk tests on the computational thinking ability data are 0.178 and 0.449, respectively. Since both values exceed the 0.05 significance threshold, it can be concluded that the data for computational thinking ability are normally distributed. The normality test results for the mathematical logic ability data are presented in Table 4.

Table 4.
Data Normality Test Results for Mathematical Logic Abilities

Test	Statistics	df	Sig.
Kolmogorov-Smirnov	.109	66	,050
Shapiro-Wilk	,976	66	,217

Table 4 indicates that the significance values (Sig.) for the Kolmogorov-Smirnov and Shapiro-Wilk tests on the mathematical logic ability data are 0.05 and 0.217, respectively. Since these values are equal to or greater than the 0.05 significance level, it can be concluded that the mathematical logic ability data are normally distributed. The normality test results for the calculus learning achievement data are presented in Table 5.

Table 5.
Normality Test Results of Calculus Learning Achievement Data

Test	Statistics	df	Sig.
Kolmogorov-Smirnov	.104	66	.073
Shapiro-Wilk	,979	66	,312

Table 5 shows that the probability values (Sig) of Kolmogorov-Smirnor and Shapiro-Wilk for calculus learning achievement data are 0.073 and 0.312, respectively. This value is greater than the significance level of 0.05, so it is concluded that the calculus learning achievement data is usually distributed.

2) Heteroscedasticity Test

Heteroscedasticity testing is carried out graphically by looking at the scatter plot *of* residuals. Scatterplot results are presented in Figure 1.

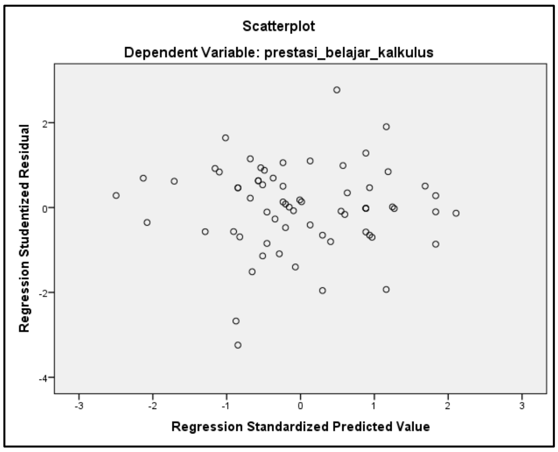

Figure 1. Residual Scatterplot.

Figure 1 shows that the scatter plot results look spread out and do not have a particular pattern, so the heteroscedasticity assumption is not met; in other words, the homoscedasticity assumption is met.

3) Multicollinearity test

They tested whether multicollinearity is conducted by looking at the TOL and VIF values in the Collinearity *Diagnostics calculation* using *IBM SPSS Statistics 2 2*. The results of the TOL and VIF values are presented in Table 6.

Table 6.
Collinearity Diagnostics Results

Variable	B	TOLL	VIF
computational thinking abilities	,329	,563	1,776
mathematical logic skills	,591	,563	1,776

Table 6 shows that the value of 0.563 is more than 0.1, and the VIF value of 1.776 is less than 10. This indicates that there is no multicollinearity in the regression model.

4) Autocorrelation test

Autocorrelation was tested using the Durbin-Watson (DW) method, with calculations performed through IBM SPSS Statistics 22. The Durbin-Watson test produced a DW value of 2.004, which is close to 2, indicating that the regression model satisfies the assumption of no autocorrelation.

5) Hypothesis test

The F-test is utilized to determine whether the independent variables collectively have a significant effect on the dependent variable. The hypotheses for the F-test are formulated as follows:

H_0: Computational thinking ability and mathematical logic ability do not have a significant influence on students' Calculus learning achievement.

H_1: Computational thinking ability and mathematical logic ability have a significant influence on students' Calculus learning achievement.

The analysis was conducted using IBM SPSS Statistics 22, and the results of the F-test are presented in Table 7.

Table 7.
ANOVA Results

Model	Sum of Squares	df	Mean Square	F_{count}	Significant-F
Regression	4009.702	2	2004,851	67,085	,000
Residual	1882,783	63	29,885		
Total	5892.485	65			

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Referring to Table 7, the Significance-F value is 0.000, which is less than the 0.05 threshold. This indicates that computational thinking ability and mathematical logic ability jointly have a significant effect on the learning achievement variable.

The t-test is employed to assess whether each independent variable individually has a significant impact on the dependent variable within the regression model. The hypotheses for the t-test are stated as follows:

H_0: Computational thinking ability and mathematical logic ability do not individually have a significant influence on learning achievement.

H_1: Computational thinking ability and mathematical logic ability individually have a significant influence on learning achievement.

The results of the t-test are determined by examining the significance (Sig.) value or p-value. The output of the t-test analysis is presented in Table 8.

Table 8.
Results of t-test Processing

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	5,724	6,138		,933	,355
	Computational thinking skills	,329	,089	,352	3,711	,000
	Mathematical logic skills	,591	.102	,549	5,782	,000

For the computational thinking ability variable, the significance (Sig.) value obtained is 0.000, indicating that the null hypothesis (H_0) is rejected. This confirms that computational thinking ability has a partial and statistically significant influence on students' Calculus learning achievement. Similarly, the mathematical logic ability variable also has a Sig. value of 0.000, leading to the rejection of H_0 and indicating that this variable also has a partial effect on Calculus learning outcomes.

6) Linear Regression Model

The results from the multiple linear regression analysis demonstrate a significant relationship between computational thinking ability, mathematical logic ability, and students' performance in Calculus. This is validated through hypothesis testing on both the regression equation and its coefficients. The influence of these independent variables on students' learning achievement in Calculus is represented by the following multiple linear regression equation, derived using IBM SPSS:

$$Y = 5.724 + 0.329X_1 + 0.102X_2$$

Where:
Y = Calculus learning achievement
X_1 = Computational thinking ability
X_2 = Mathematical logic ability

This equation implies that for every one-unit increase in computational thinking ability (X_1), the predicted value of Calculus achievement (Y) increases by 0.329. Similarly, a one-unit increase in mathematical logic ability (X_2) results in a 0.102 increase in Y. Since both coefficients are positive, it can be concluded that students with strong computational thinking and mathematical logic skills tend to achieve better outcomes in Calculus.

7) Correlation Coefficient

The degree to which the three variables—computational thinking ability, mathematical logic ability, and calculus learning achievement—are related is determined by the correlation coefficient. Using IBM SPSS 20, the Pearson correlation analysis was carried out; Table 9 displays the findings.

Table 9.
Results of Pearson Correlation Analysis

Variable Relationships	Coefficient Value	Sig value.
Computational thinking skills – Mathematical logic skills	0.661	0,000
Computational thinking ability – calculus learning achievement	0.715	0,000
Logical_mathematics ability – calculus learning achievement	0.781	0,000

As shown in Table 9, a positive correlation exists among the three variables. The correlation coefficient between learning achievement and computational thinking ability is 0.715, while the correlation between learning achievement and mathematical logic ability is 0.781. Additionally, the correlation coefficient between computational thinking ability and mathematical logic ability is 0.661. These values indicate that the relationships fall within the strong category. Moreover, the significance (Sig.) value for all relationships is 0.00, which is below the 0.05 threshold, confirming that the correlations among computational thinking ability, mathematical logic ability, and students' Calculus learning achievement are statistically significant

Table 10.
Coefficient of Determination Results

R^2	F count	df1	df2	Sig. F
0.680	67,085	2	63	0,000

According to Table 10, the R Square (R^2) value is 0.680, meaning that mathematical logic and computational thinking skills account for 68% of the variation in students' Calculus learning achievement. Other factors not included by the model are responsible for the remaining 32%. Thus, it can be said that students' performance in calculus is significantly influenced by these two cognitive abilities. Furthermore, the significance of the F test is evaluated by the Sig. F Change value. The significance value is 0.000, which is less than the 0.05 cutoff, as indicated in Table 10. This finding confirms the value of the coefficient of determination in assessing the contribution of mathematical logic and computational thinking to learning outcomes by showing that the F test is statistically significant.

Other mathematical thinking skills are closely related to computational thinking. Cognitive thinking skills can increase problem-solving skills by 58.7%, organized thinking skills by 62.6%, critical thinking skills by 58.3%, and logical thinking skills by 57.8%, with an average of 59.35%, according to Syarifuddin's research (Syarifuddin et al., 2016). Pupils with strong computational thinking abilities are able to approach problems methodically, logically, and structurally (Angraini et al., 2022). Students with problem-solving skills are able to approach problems logically, structurally, and methodically (Candraningtyas & Khusna, 2023).

This study's results show a positive correlation between computational thinking, mathematical logic abilities, and students' Calculus learning achievement. Computational thinking involves breaking down problems and using algorithms, supported by mental flexibility to generate creative solutions, while design thinking emphasizes user-centered analysis, solution development, and iterative testing (Mohammed, 2023). Students with strong logical-mathematical intelligence typically exhibit traits such as the ability to easily analyze situations and understand cause-and-effect relationships (Azinar et al., 2020). No specific skills have been previously identified that directly examine the connection between computational thinking and creative problem-solving. However, in this context, a moderately strong and significant relationship was found, indicating that as students' computational thinking abilities increase, their capacity for creative problem-solving also improves (Paf & Dinçer, 2021).

IV. CONCLUSION

The findings of this study demonstrate a good relationship between students' learning achievement in calculus and their computational thinking and mathematical reasoning skills. This is demonstrated by the coefficient of determination of 0.68, which indicates that 68% of students' learning achievement in calculus is influenced by their capacity for mathematical reasoning and computational thinking. Furthermore, the correlation analysis results indicate that there is a 0.715 correlation between learning achievement and computational thinking ability, a 0.781 correlation between learning achievement and mathematical logic ability, and a 0.661 correlation between computational thinking ability and mathematical logic ability.

The study found a significant relationship between mathematical logic and computational thinking abilities and students' achievement in Calculus. Those with stronger skills in these areas tended to perform better academically, particularly in understanding concepts and solving problems. This highlights the need to integrate these cognitive skills into Calculus learning through effective teaching strategies and appropriate learning media. The findings also suggest the importance of early educational interventions to strengthen these abilities and better prepare Informatics Engineering students for academic success and future professional demands.

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References

Angraini, L. M., Arcat, A., & Sohibun, S. (2022). Pengaruh Bahan Ajar Berbasis Multimedia Interaktif terhadap Kemampuan Computational Thinking Matematis Mahasiswa. *JNPM (Jurnal Nasional Pendidikan Matematika)*, *6*(2), 370. https://doi.org/10.33603/jnpm.v6i2.6937

Azinar, J. A., Munzir, S., & Bahrun. (2020). Students' logical-mathematical intelligence through the problem-solving approach. *Journal of Physics: Conference Series*, *1460*(1). https://doi.org/10.1088/1742-6596/1460/1/012024

Boom, K. D., Bower, M., Arguel, A., Siemon, J., & Scholkmann, A. (2018). Relationship between computational thinking and a measure of intelligence as a general problem-solving ability. *Annual Conference on Innovation and Technology in Computer Science Education, ITiCSE*, 206–211. https://doi.org/10.1145/3197091.3197104

Bower, M., Wood, L. N., Lai, J. W. M., Howe, C., & Lister, R. (2017). Improving the computational thinking pedagogical capabilities of school teachers. *Australian Journal of Teacher Education*, *42*(3), 53–72. https://doi.org/10.14221/ajte.2017v42n3.4

Candraningtyas, S. R., & Khusna, H. (2023). Computational thinking ability becomes a predictor of mathematical critical thinking ability. *Alifmatika: Jurnal Pendidikan Dan Pembelajaran Matematika*, *5*(2), 247–263. https://doi.org/10.35316/alifmatika.2023.v5i2.247-263

Christi, S. R. N., & Rajiman, W. (2023). Pentingnya Berpikir Komputasional dalam Pembelajaran Matematika. *Journal on Education*, *5*(4), 12590–12598. https://doi.org/10.31004/joe.v5i4.2246

Devianti, A. (2013). *Panduan Lengkap Mencerdaskan Otak Anak Usia 1-6 Tahun*. Araska.

Fatimah, S., Johar, R., & Zubainur, C. M. (2020). Students' logical mathematical intelligence in completing mathematical problems with natural disaster context. *Journal of Physics: Conference Series*, *1470*(1). https://doi.org/10.1088/1742-6596/1470/1/012022

Guggemos, J. (2021). On the predictors of computational thinking and its growth at the high-school level. *Computers and Education*, *161*(March 2020), 104060. https://doi.org/10.1016/j.compedu.2020.104060

Litia, N., Sinaga, B., & Mulyono, M. (2023). Profil Berpikir Komputasi Siswa dengan Menggunakan Model Pembelajaran Problem Based Learning (PBL) Ditinjau dari Gaya Belajar di SMA N 1 Langsa. *Jurnal Cendekia : Jurnal Pendidikan*

Matematika, *7*(2), 1508–1518. https://doi.org/10.31004/cendekia.v7i2.2270

Megawati, A. T., Sholihah, M., & Kintan Limiansih. (2023). Implementasi Computational Thinking dalam Pembelajaran Matematika di Sekolah Dasar. *Jurnal Review Pendidikan*, *9*(2).

Mohammed, F. R. (2023). The mediating role of cognitive flexibility in the relationship between computational thinking and design thinking among students at the college of information technology. *Journal of Social and Educational Research*, *2*(2), 61–67.

Morris, E. (2023). Multiple Intelligences in the Classroom. *Multiple Intelligences in the Classroom*. https://doi.org/10.4324/9781315175386

Nursiyono, J. A., & Nadeak, P. P. H. (2016). *Setetes Imu Regresi Linear*. Media Nusa Creative.

Özgür, H. (2020). Relationships between computational thinking skills, ways of thinking and demographic variables: A structural equation modeling. *International Journal of Research in Education and Science*, *6*(2), 299–314. https://doi.org/10.46328/ijres.v6i2.862

Paf, M., & Dinçer, B. (2021). A Study of the Relationship between Secondary School Students' Computational Thinking Skills and Creative Problem-Solving Skills. *TOJET: The Turkish Online Journal of Educational Technology*, *20*(4), 1–15.

Quadratullah, M. . (2014). *Statistika Terapan: Teori, Contoh Kasus, dan Aplikasi dengan SPSS*. ANDI OFFSET.

Revika, S. P., Yahfizham, Y., William Iskandar Ps, J. V, Estate, M., Percut Sei Tuan, K., & Deli Serdang, K. (2024). Studi Literatur Analisis Algoritma Pemrograman Pengaruh Computational Thinking pada Pembelajaran Matematika. *SABER: Jurnal Teknik Informatika, Sains Dan Ilmu Komunikasi*, *2*(1), 17–29. https://doi.org/10.59841/saber.v2i1.606

Risnandar, & Al Maki, W. F. (2022). Metode Computational Thinking Untuk Pengabdian Masyarakat Dalam Peningkatan Kemampuan Bahasa Pemrograman Python Siswa Smk (Studi Kasus: Smk Asshiddiqiyah Karangpawitan, Garut) Computational Thinking Method for the Community Service in Improving Python Pro. *Jurnal Pengabdian Masyarakat Teknologi Informasi Dan Informatika (DIMASLOKA)*, *1*(1), 1–7.

Senouci, B., & Nacera, B. (2022). Level of logical-mathematical intelligence among middle school students. *Journal of Legal and Social Studies*, *7*(2), 36–59.

Swaid, S. I. (2015). Bringing Computational Thinking to STEM Education. *Procedia Manufacturing*, *3*(Ahfe), 3657–3662. https://doi.org/10.1016/j.promfg.2015.07.761

Syarifuddin, M., Risa, D. F., Hanifah, A. I., & Nurussa'adah. (2016). *Experiment computational thinking : upaya meningkatkan kualitas problem solving* *anak melalui permainan gorlids*. *3*(6), 1–15.

Wanti, S., & Aprianti, E. (2018). Peningkatan Kecerdasan Logika- Dini Kelompok a Di Kober Warna Plus. *Jurnal Ceria*, *1*(4), 8.

Zulfairanatama, G., & Hadi, S. (2013). Kercerdasan Logika Matematika Berdasarkan Multiple Intelligences Terhadap Kemampuan Matematika Siswa SMP di Banjarmasin. *EDU-MAT Jurnal Pendidikan Matematika*, *1*(1), 18–26.

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