The Computational Thinking Profile of Vocational Students in Solving Mathematical Problems in Terms of Logical-Mathematical Intelligence

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Abstract: Computational thinking has been widely recognized as an effective problem-solving approach and plays a crucial role in the digital era, making it essential for students to master. These skills can be developed through engagement with mathematical problems such as Bebras tasks, which require logical reasoning, problem-solving abilities, and logical-mathematical intelligence. This study aims to describe students' computational thinking skills in solving mathematical problems containing Bebras tasks based on their levels of logical-mathematical intelligence and to determine the extent of its contribution. The study involved 55 tenth-grade students from a Center of Excellence Vocational School in Bali, an institution designed to enhance students' competencies, particularly in preparation for the digital world. A mixed-method approach was employed, combining qualitative methods to analyze students' computational thinking skills and quantitative methods to measure the contribution of logical-mathematical intelligence. The results indicate that students with high, moderate, and low logical-mathematical intelligence mastered five, three, and one indicators of computational thinking, respectively. Additionally, logical-mathematical intelligence contributed 81.1% to students' computational thinking skills. These findings suggest that higher levels of logical-mathematical intelligence are associated with greater mastery of computational thinking. In conclusion, logical-mathematical intelligence has a significantly strong contribution to students' computational thinking skills.

Keywords: Computational Thinking, Mathematical Problems Containing Bebras Task, Logical Mathematical Intelligence, Center of Excellence Vocational School

INTRODUCTION

The digitalization in the 21st century has led to an extraordinary increase in the flow of knowledge, making the use of computers in various fields inevitable (Aminah *et al*., 2022; Threekunprapa & Yasri, 2020; Puente & Perez, 2023). The learning process in the world of education is also required to adapt and create new innovations (Ayub *et al*., 2021 & Pambudi *et al*., 2023). In order to meet these challenges, students need to be equipped with 21st-century skills that focus on analytical thinking, technological programming, critical analysis, complex problem-solving, as well as system analysis and evaluation (Angeli & Giannakos, 2020; Helsa *et al.*, 2023; Miftah *et al.*, 2024). These skills are part of computational thinking (Munawarah *et al*., 2021; Izu *et al.*, 2017; Farib *et al.,* 2019). Computational thinking in this study is defined as a thinking ability that involves the application of computational concepts and logic to understand, formulate, and solve problems effectively. Computational thinking can enhance analytical abilities, facilitate the use of technology, and train complex problem-solving skills (Rahaju *et al.*, 2019 & Yunianto *et al.*, 2024). Moreover, Wing as cited in Sondakh *et al.* (2020) states that Computational Thinking (CT) is a computational concept used to approach and solve problems. In line with this statement, research by Persson (2022) has also recognized computational thinking as an efficient approach to problem-solving, making it highly demanded in the digital work environment.

Recognizing the importance of CT in supporting digitalization in the 21st century, the Indonesian government has realized the significance of implementing CT-based learning in schools (Rafiepour & Farsani, 2021; Saputra & Zaulmaulida, 2021; Setiarini *et al.*, 2023). This is because the computational thinking as an approach can help students structure complex problem-solving into simpler steps (Nuvitalia *et al.*, 2022 & Sulistya, 2021). CT-based learning is highly suitable for students, especially the students at Center of Excellence Vocational School, because they have been prepared to enter the professional world, which includes the digital work environment (Zamzami *et al.,* 2020 & Ersozlu *et al.,* 2023). CT-based learning also refers to the initiatives taken by the Indonesian government to integrate computational thinking into the national education system, particularly through programs that match the demands of industry 4.0 and the digital economy (Ersozlu *et al.,* 2023). Based on this information, CT is an interesting topic that has been widely studied in educational research. However, studies that specifically focus on the integration of CT into mathematics learning at the vocational high school (SMK) level are still relatively new and worth further investigation, especially considering the characteristics of vocational school students who tend to have a strong orientation toward the workforce and a high demand for advanced thinking skills (Aminah *et al*., 2022).

However, the learning process at the Center of Excellence Vocational School has not extensively trained students' computational thinking skills, particularly their problem-solving abilities (Nuvitalia *et al.,* 2022). This is evident from the field observations, where vocational high school students in Indonesia still weak in solving mathematical problems (Tresnawati *et al.,* 2020). Indahsari & Fitriana (2019) found a similar fact on their research of 33 10th-grade students from a vocational high school in Cimahi. They found that only 2.57% of the students were able to understand the problem, 8.63% were able to develop a plan, and only 15% were able to create and revise their plans. The implementation of computational thinking should be promoted mathematics learning activities in the classroom to prepare students for the workforce.

Efforts to train CT skills in students can be carried out through mathematical problems containing Bebras tasks (Dagiene *et al.,* 2022). Mathematical problems containing Bebras tasks are defined as problem-solving activities embedded with computational concepts and challenges that encourage logical reasoning, pattern recognition, algorithmic thinking, and decomposition. Bebras is an activity specifically designed to train students' computational thinking abilities (Ayub *et al.,* 2021; Dagiene *et al.,* 2022; Izu *et al.,* 2017; Zamzami *et al.,* 2020). The use of mathematical problems containing Bebras task to train students' computational thinking skills is an appropriate solution. This is because each mathematical problems containing Bebras task contains all five aspects of computational thinking (Mufidah, 2018). Computational thinking requires proficiency in calculation, problem formulation, and solving complex mathematical calculations. This proficiency is known as logical mathematical intelligence (Faizah, 2017). Logical mathematical intelligence is defined as the ability to analyze and solve mathematical problems using logic and structured reasoning, which directly supports students' mastery of computational thinking skills. Additionally, logical thinking ability is one of the competency standards for vocational high school graduates (Permendiknas, 2006). Therefore, if you want to train students' computational thinking skills, it is important to consider their logical mathematical intelligence (Yuliana, 2015).

Based on the description above, in this era of digitalization, teachers should take advantage of technological and information developments through CT-based mathematics learning using mathematical problems containing Bebras tasks. However, prior to that, teachers need to consider students' logical mathematical intelligence (Khotijah, 2016). The use of mathematical problems containing Bebras tasks is not a new concept. The research result by Nuvitalia *et al.* (2020) describe that the use of mathematical problems containing Bebras tasks can enhance students' computational thinking abilities. However, there is no empirical and definitive information stating the contribution of logical mathematical intelligence to students' computational thinking abilities in solving mathematical problems containing Bebras tasks. Additionally, Mufidah (2018) mentions that there are differences in the profiles of students' computational thinking based on their levels of logical mathematical intelligence. The research does not clearly reveal the extent of that contribution. Therefore, the author raises the issue of the profile of computational thinking abilities of vocational high school students in terms of students’ logical mathematical intelligence.

This study aims to describe students' computational thinking skills in solving mathematical problems involving Bebras tasks based on their levels of logical-mathematical intelligence and to determine the extent of its contribution. Accordingly, the research questions are: (1) What is the profile of vocational high school students' computational thinking skills in terms of their logical-mathematical intelligence? (2) To what extent does logical-mathematical intelligence contribute to these skills in solving mathematical problems involving Bebras tasks?

Computational Thinking

Computational thinking (CT) is a thinking process that involves computational steps or algorithms to obtain problem-solving (Angeli & Giannkos, 2020 and Threekunprapa & Yasri, 2020). Computational thinking has the characteristic of breaking down problems into simpler components. Another perspective, presented by Ian Horswill, states that computational thinking is an algorithmic approach to finding solutions of problems based on given input (Budiyanto *et al.*, 2022 & Dagiene *et al.,* 2017). This viewpoint suggests that computational thinking is a problem-solving skill that emphasizes logical reasoning. Angeli & Giannkos (2020) and Rahmawati *et al.* (2024)

describe the five components of computational thinking, which include decomposition, pattern recognition, abstraction/generalization, algorithms, and debugging. Decomposition is a method of breaking down a problem into simpler parts, making it easier to understand (Purwasih *et al.,* 2020 & Izu *et al.,* 2017). Pattern recognition involves identifying patterns, equations, relationships, and utilizing known information. Algorithmic thinking is a method of obtaining a solution using sequential steps (Purwasih *et al.,* 2020). Abstraction involves selecting relevant information to use and disregarding unnecessary information (Prahmana *et al.,* 2024). Debugging is the process of reviewing and checking the problem-solving process to ensure correctness and accuracy (Sondakh *et al.,* 2020). To avoid overlapping interpretations of CT components, the integration of CT in this study, through mathematical problems involving Bebras tasks, does not necessarily have to include all five CT components simultaneously. For example, decomposition the process of breaking down complex problems into smaller, manageable parts can be emphasized when students are required to analyze multi-step Bebras problems. The integration can involve only one or several components, depending on the mathematical topic and the context of the Bebras tasks used.

Mathematical Problems Containing Bebras Tasks

In mathematics learning, mathematical problems containing Bebras task are used to improve students; computational thinking skills. Bebras refers to an activity specifically designed to train students' computational thinking skills (Ayub *et* al., 2021; Bavera *et al.,* 2020; Izu *et al.,* 2017; Yuliana, 2015). The term "Bebras" is derived from the Lithuanian word for "beaver" (Rahaju *et al.,* 2019). The beaver is used as a symbol of challenge because in their daily activities, beavers strive hard to achieve their goals perfectly (Mufidah, 2018). The purpose of organizing the Bebras competition in international level is to promote computational thinking and problem-solving skills Kalelloglu *et al*., 2022 & Khotijah, 2016). Each question in Bebras encompasses the five aspects of computational thinking (Mufidah, 2018) and is presented in the form of descriptions accompanied by images to facilitate students' understanding of the problems. Since each question incorporates the five components of computational thinking, students are required to think algorithmically in solving them (Hubwieser & Mühling, 2014).

Logical Mathematics Intelligence

In this study, logical-mathematical intelligence is defined as the ability to manipulate algebraic expressions, recognize patterns, and apply logical reasoning in solving mathematical problems (Kasus, 2014). This scope was chosen because these aspects form the core of logical-mathematical intelligence as described by experts and are most relevant to the context of the Bebras tasks and the mathematics content used in this study (Suarca *et al*., 2016). Logical-mathematical intelligence itself refers to the ability to conduct scientific investigations and analyze problems logically in order to discover or create mathematical formulas based on logical rules, numerical pattern analysis, and logical thinking in problem-solving (Dwita *et al*., 2022; Khotijah, 2016). By focusing on these aspects, this research aims to more precisely explore the relationship between logical-mathematical intelligence and students' computational thinking abilities. Another perspective is presented by Walters, the important aspects of logical-mathematical intelligence include the ability to: perform mathematical calculations, think logically, solve problems, use deductive and inductive reasoning, and recognize patterns or relationships (Dwita *et al*., 2022). From these explanations, it can be concluded that logical-mathematical intelligence is the ability to understand numerical concepts, perform mathematical calculations, solve problems, and think logically (Wulandari & Fatmahanik, 2020).

Center of Excellence Vocational School

The Center of Excellence Vocational School is an expansion of a Vocational School that includes certain expertise programs through collaboration with the World of Work Industry. Vocational School with this program is also used as a foothold and center for improving the quality of performance for other vocational schools (Suherman *et al.*, 2022). In the learning process, the curriculum used at the Center of Excellence Vocational School involves the professional world and is competency-oriented according to the interests of the students' vocational interest. Pudyastuti *et al.* (2022) explained that the existence of a Center of Excellence Vocational School is aimed at producing graduates who are ready to enter the workforce or become entrepreneurs through a comprehensive alignment of vocational education.

METHODS

Research Design

The research employs a mixed-methods approach, defined as a procedure for collecting and analyzing data using both qualitative and quantitative methods (Masrizal, 2021; Am *et al*., 2015). In this study, qualitative analysis is used to understand the underlying reasons for the relationship between logical-mathematical intelligence and computational thinking, while quantitative analysis is used to investigate whether logical-mathematical intelligence correlates with computational thinking. The qualitative approach is used to describe the profile of students' computational thinking skills in solving mathematical problems containing Bebras tasks in terms of their level of logical-mathematical intelligence. A quantitative approach, specifically simple linear regression, is used to determine the extent to which logical-mathematical intelligence contributes to students' computational thinking skills in solving mathematical problems involving Bebras tasks. This research employs two variables, namely the independent (predictor) variable and the dependent (criterion) variable. In this research, the independent variable is the level of students' logical-mathematical intelligence, and the dependent variable is students' computational thinking skills.

Subject

The study population consisted of 137 tenth-grade students specializing in automotive studies at the Center of Excellence Vocational School in Bali Province, enrolled in the 2022/2023 academic year. This population was chosen because it is based on lessons in the automotive vocational field which are dominated by mathematics subjects (Mirati, 2015). Then the sample selection was carried out using Non-Probability Sampling technique, namely Purposive Sampling. Purposive sampling is known as a sampling technique based on the considerations of the researcher or evaluator by looking at which sample is the most useful and representative (Telaumbanua, 2021). This sampling process resulted in a sample of 55 tenth-grade students from the Center of Excellence Vocational School, who were selected as participants in this study.

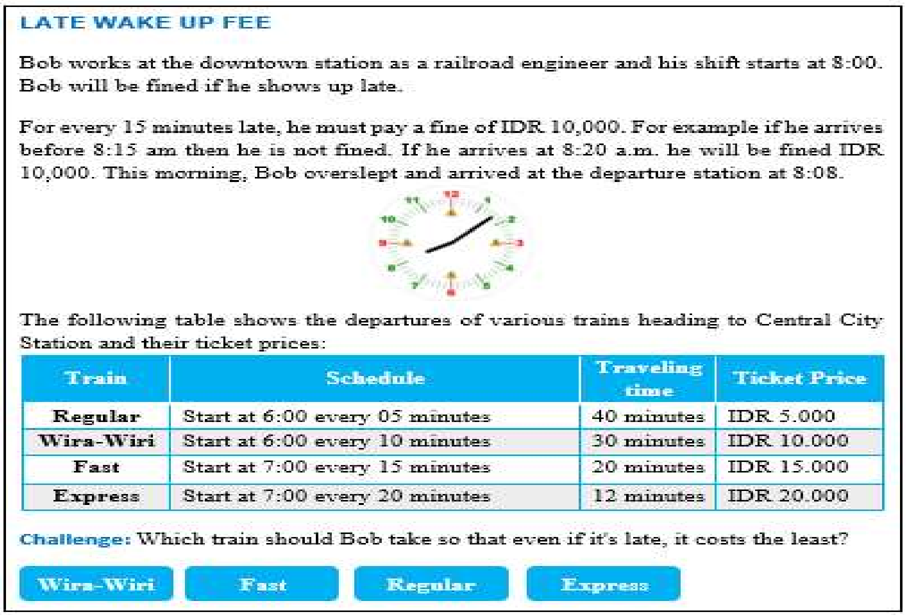
Data Collection

There are two methods of data collection in this research, namely the test method which includes a written test of students' logical mathematical intelligence and a written test of computational thinking skills (Alanda *et al.,* 2019) and the interview method by giving questions orally (Sumartini, 2016).

Logical mathematical intelligence in this study is defined as students' ability to understand numerical concepts, patterns, algebra, and logical reasoning. To determine whether students possess a high, moderate, or low level of logical-mathematical intelligence, a test instrument adapted from Rejeki (2021) is used. The logical-mathematical intelligence test consists of 25 objective questions to be completed within 50 minutes. Students receive 1 point for each correct answer and 0 points for incorrect answers. The test sheet includes four indicators of logical-mathematical intelligence: numerical ability, algebraic concepts, number sequences/patterns, and logic (reasoning) (Rejeki, 2021). Numerical capability is one of the indicators of logical-mathematical intelligence, which relates to the ability to process, understand, and interpret numerical data. Algebra concept ability is one of the indicators of logical-mathematical intelligence, which relates to the ability to understand, manipulate, and solve problems involving algebraic concepts. This ability includes skills in identifying variables, formulating equations or inequalities, and solving them logically and systematically. Series/pattern of number ability is one of the indicators of logical-mathematical intelligence, which relates to the ability to recognize, understand, and predict numerical patterns or sequences. This ability involves skills in analyzing regularities within a number series, determining the rule that forms the pattern, and applying that rule to identify the next or missing element. Logic (reasoning) ability is one of the indicators of logical-mathematical intelligence, which relates to the capacity to think rationally, draw conclusions both deductively and inductively, and solve problems based on logical relationships between pieces of information. This ability involves skills in analyzing premises, identifying implications, evaluating the truth of statements, and determining valid conclusions. Therefore, students are considered to possess logical-mathematical intelligence if they are able to complete or answer a set of tests encompassing the four indicators.

At first, the logical mathematical intelligence test consisted of 35 objective items. After being validated, the test was tested on 30 students. Thus, 29 valid questions, 6 invalid questions were obtained. At a significance level of 0.05, the critical value obtained was 0.361. Out of the 29 questions, 29 had higher r-value than r-table, indicating their validity. After analysis, the Kuder Richardson Formula 20 (KR-20) reliability coefficient was found to be 0.892. Subsequently, a differential power test was conducted on the 29 questions that were both valid and reliable. The results of the differential power test showed that 4 questions had poor discriminatory power, leaving 25 questions suitable for use as a post-test.

The instrument for the computational thinking skills test was adapted from the challenges of Bebras and modified to suit the vocational school students' domain. This instrument consists of 2 essay-type items with a time allocation of 60 minutes. The mathematical problems containing Bebras task instrument for the computational thinking skills test is presented in Figure 1.



LATE WAKE UP FEE

Bob works at the downtown station as a railroad engineer and his shift starts at 8:00. Bob will be fined if he shows up late.

For every 15 minutes late, he must pay a fine of IDR 10,000. For example if he arrives before 8:15 am then he is not fined. If he arrives at 8:20 a.m. he will be fined IDR 10,000. This morning, Bob overslept and arrived at the departure station at 8:08.

The following table shows the departures of various trains heading to Central City Station and their ticket prices:

Train	Schedule	Traveling time	Ticket Price
Regular	Start at 6:00 every 05 minutes	40 minutes	IDR 5.000
Wira-Wiri	Start at 6:00 every 10 minutes	30 minutes	IDR 10.000
Fast	Start at 7:00 every 15 minutes	20 minutes	IDR 15.000
Express	Start at 7:00 every 20 minutes	12 minutes	IDR 20.000

Challenge: Which train should Bob take so that even if it's late, it costs the least?

Wira-Wiri Fast Regular Express

Figure 1. Mathematical Problems Containing Bebras Task Instrument

The scoring for each question is divided into 5 components of computational thinking, namely: decomposition, pattern recognize, algorithms, abstraction/generalization, and debugging. Each student's answer will be given a score in the range 0-3. The interview instrument that researchers used in this study was based on Sulistya (2021). The interview guide contains several questions to ask to students related to students' computational thinking skills. The interview instrument contains questions related to the five indicators of computational thinking.

Procedure

Before conducting the research, the researcher prepared instruments which included logical-mathematical intelligence instruments, computational thinking instruments, and interview instruments. The instruments that have been compiled, then validated by experts and tested first on students outside the research sample to ensure the effectiveness of the instruments.

When researchers began to conduct research, students were first given a logical-mathematical intelligence test to group students into three categories of logical-mathematical intelligence, namely high (S1), medium (S2), and low (S3). After being grouped, students were given a computational thinking skills test in the form of Bebras questions. From the results of the answers to the computational thinking skills test, the researchers conducted interviews to students' answers.

The researcher tested the validity of the data by making comparisons between the results of the computational thinking skills test and the results of the interviews. If the two data that have been collected have the same tendency, then the data can be said to be valid. Based on the answers to the computational thinking test and interview results, 3 subjects were purposively selected to represent students' abilities at each level of logical-mathematical intelligence. Then an analysis of the answers of the three subjects was carried out and outlined in the form of a description. Finally, to see the contribution, a simple linear regression test was carried out to describe the relationship of one independent variable (level of logical-mathematical intelligence) with one dependent variable (computational thinking skills).

Data Analysis

The researcher conducted a qualitative analysis to describe the profile of students' computational thinking skills. Prior to qualitative data analysis, the data on students' logical intelligence test results were categorized into three levels with reference to the opinion of Sudjana (2013), which classifies them into three categories: high, medium, and low.

Quantitative analysis was carried out using simple linear regression to see the contribution of logical-mathematical intelligence to students' computational thinking abilities. Data on the results of logical mathematical intelligence tests and computational thinking skills tests were analyzed using descriptive statistical tests. Then a classical assumption test was carried out with the help of SPSS version 25. This was intended so that parametric statistical tests could be applied. This test includes: normality test, linearity and significance of the regression direction, multicollinearity, heteroscedasticity, and autocorrelation. After the classical assumption test is fulfilled, a hypothesis test is carried out with simple linear regression. Guidelines for providing an interpretation of the correlation coefficient R that has been obtained refers to the opinion (Sugiyono, 2016) in Table 1.

Correlation Coefficient	Interpretation
0.00	Nothing
0.00 – 0.19	Very Low
0.20 – 0.39	Low
0.40 – 0.59	Medium
0.60 – 0.79	High
0.80 – 0.99	Very High
1.00	Perfect

Table 1. Guidelines for Interpreting the Correlation Coefficient

To determine the contribution of logical mathematical intelligence to CT skills, the coefficient of determination R^2 is calculated by squaring the correlation coefficient. The research methodology described in this study can be utilized by teachers and other researchers to examine similar topics or conduct further studies to explore the profile of computational thinking and logical-mathematical intelligence, either at different educational levels or involving other relevant variables.

RESULTS

Qualitative Research Result

The qualitative findings describe students' computational thinking profiles based on their levels of logical-mathematical intelligence in solving Bebras-based mathematical problems. Computational thinking is analyzed through five indicators: decomposition, pattern recognition, algorithmic thinking, abstraction, and debugging, while logical-mathematical intelligence is classified into three levels: high, medium, and low, in order to obtain more in-depth and diverse results.

The following are the answers of students with high logical-mathematical intelligence (S1).

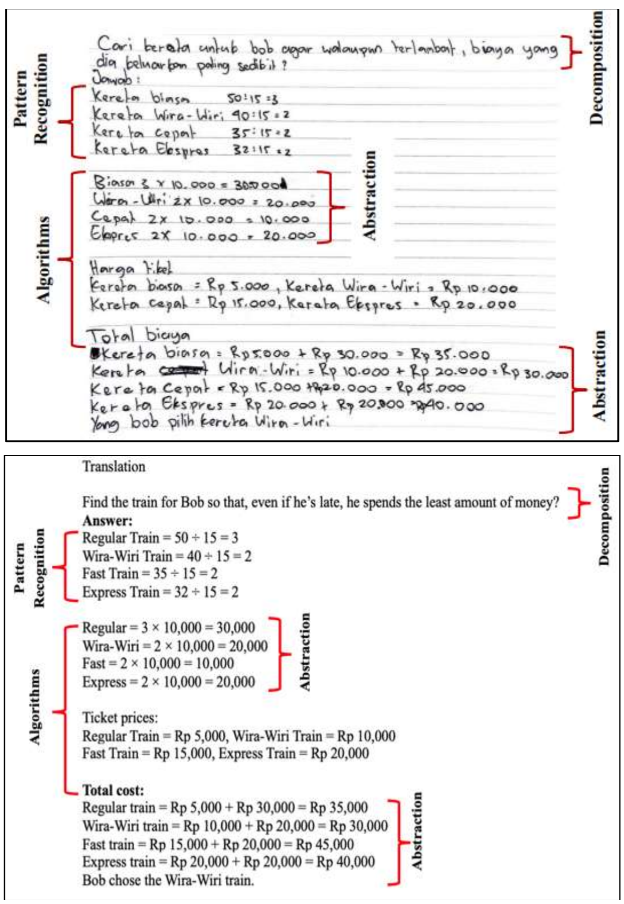


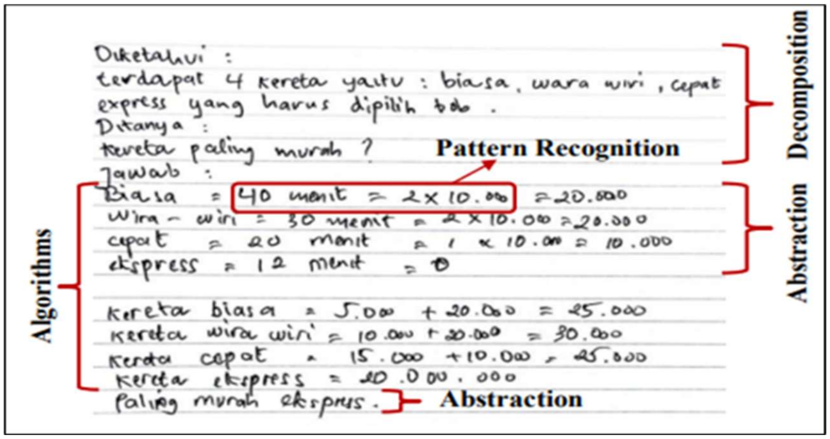
Figure 2. Answers of Students with High Logical Mathematical Intelligence (S1)

Based on the answer above, an interview is conducted to clarify the steps of solving Bebras problems according to the indicators of computational thinking. The excerpts from the interview are provided in Appendix 3.

The interview findings indicate that even though the student did not write down the known information on the answer sheet, subject S1 was able to clearly explain both the given and the required information in the Bebras questions. This indicates that subject S1 demonstrated strong decomposition skills. Based on the student's answers and the interview results, it can be concluded that the decomposition ability of students with high logical-mathematical intelligence is classified as very good, which supports their ability to solve problems involving Bebras tasks. The interview results also show that subject S1 applied the same pattern to determine Bob's fine for each train. In addition, subject S1 was able to clearly identify patterns in late fines and demonstrated a strong understanding of the rules for imposing fines. This indicates that subject S1 has mastered pattern recognition skills. Based on the student's answers and the interview results, it can be concluded that subject S1 applied appropriate solution steps. This indicates that subject S1 has a strong mastery of algorithmic thinking skills. The interview findings further indicate that subject S1 identified the train with the lowest cost, *Wira-Wiri*. Subject S1 was able to describe the identified pattern and explain how to determine the fines for each train in a consistent manner. This indicates that subject S1 has mastered the skills of abstraction and pattern generalization. Additionally, the interview results indicate that after being asked to review the answer, subject S1 was able to verify that the obtained solution was correct. This demonstrates that subject S1 has strong debugging skills.

Based on the examination and analysis of students' answers, as well as in-depth interview results, it was found that students with high logical-mathematical intelligence are able to master all five indicators of computational thinking, but tend not to write down the given and required information in the problems. Therefore, students with high logical-mathematical intelligence also demonstrate a high level of computational thinking skills in solving mathematics problems.

The following are the answers of students with moderate logical-mathematical intelligence (S2).



Translation

Decomposition
What is being known:
There are 4 trains namely Regular Train, Wira-Wiri Train, Fast Train, and Express Train.
The train must be selected by Bob.
What is being asked:
Which trains is the cheapest?
Answer:

Pattern Recognition

Algorithms
Fine fee
Regular Train, Bob is late for 40 minutes = 2 times the fine = 2 x IDR 10,000 = IDR 20,000
Wira-Wiri train, Bob is late for 30 minutes = 2 times fine = 2 x IDR 10,000 = IDR 20,000
Fast Train, Bob is late for 20 minutes = 1 time fine = 1 x IDR 10,000 = IDR 10,000
Express train, Bob is 12 minutes late = no fine

Abstraction

Total cost of ticket price and fines
Regular Train: IDR 5,000 + IDR 20,000 = IDR 25,000
Wira-Wiri Train: IDR 10,000 + IDR 20,000 = IDR 30,000
Fast Train: IDR 15,000 + IDR 10,000 = IDR 25,000
Express Train: IDR 20,000 + IDR 0.00 = IDR 20,000
So, the train with the cheapest cost is the Express Train – Abstraction

Figure 3. Answers of Students with Moderate Logical Mathematical Intelligence (S2)

Based on the answers above, interviews were conducted in order to clarify the stages of solving Bebras questions in accordance with the indicators of computational thinking. The excerpts from the interview are provided in Appendix 4.

Based on the interview excerpts, it was concluded that even though students wrote information that was known and asked incompletely on the answer sheet, the S2 subject was able to explain precisely the information that was known and asked in the Bebras questions. This shows that subject S2 has medium decomposition skills. The interview excerpt also shows that subject S2 applies the same patterns in finding fines on each train. However, subject S2 has not been able to correctly mention the pattern of late fines, where subject S2 only calculates travel time without calculating train departure schedules. This shows that subject S2 has medium pattern recognition skills. In relation to the results of the answers and interviews, it was concluded that the S2 subject had used the appropriate resolution steps, although on the answer sheet they were not written clearly. This shows that subject S2 has medium algorithmic thinking skills. From the interview findings, it can be seen that subject S2 gets the train with the cheapest cost, namely the express train. Subject S2 was able to describe the patterns found; however, because the pattern identified was not quite correct, the conclusion of the answer obtained by subject S2 was also incorrect. This indicates that the S2 subject has not yet optimally mastered the skills of abstraction and pattern generalization. Considering the overall interview results, it can be concluded that the S2 subject did not check their answers before they were collected. In addition, after being asked to review their answer, subject S2 was not able to find mistakes and correct errors on the answer sheet. This shows that subject S2 has not mastered debugging skills well.

Based on the examination and analysis of students' answers, as well as in-depth interview results, it was found that students with moderate logical-mathematical intelligence are able to master three indicators of computational thinking, namely decomposition, pattern recognition, and algorithmic thinking, but tend to work hastily and without sufficient thoroughness when solving problems. Therefore, students with moderate logical-mathematical intelligence also demonstrate a moderate level of computational thinking skills in solving mathematical problems involving Bebras tasks.

The following are the answers of students with low logical-mathematical intelligence (S3).

Diketahui: Bob bekerja di stasiun pusat kota sebagai teknisi mesin kereta api dan jam kerjanya di mulai pukul 8:00. Bob akan di denda jika datang terlambat. Untuk setiap 15 menit terlambat, ia harus membayar denda sebesar RP. 10.000,-. Misalnya jika ia tiba sebelum pukul 8:15 maka ia tidak di denda. Jika ia datang pukul 8:20 maka ia akan di denda RP.10.000,-. Pagi ini, Bob ketiduran dan tiba di stasiun keberangkatan pukul 8:08.

Decomposition

Jawab: Harga tiket kereta biasa = RP 5.000, kereta wira-wiri = RP 10.000, kereta cepat = RP 15.000, kereta Ekspres = RP 20.000

Translation

What is being known:
Bob Works at the Downtown station as a railroad engineer and his shift starts at 8:00. Bob will be fined if he shows up late. For every 15 minutes late, he must pay a fine of IDR 10,000. For example, if he arrives before 8:15 am then he is not fined. If he arrives at 8:20 a.m. he will be fined IDR 10,000. This morning, Bob overslept and arrived at the departure station at 8:08.

Dekomposition

Answer:
Ticket Price

Regular Train	: Rp5.000
Wira-Wiri Train	: Rp10.000
Fast Train	: Rp15.000
Express Train	: Rp20.000

Figure 4. Answers of Students with Low Logical Mathematical Intelligence (S3)

Based on the answers above, interviews were conducted in order to clarify the stages of solving Bebras questions in accordance with the indicators of computational thinking. The excerpts from the interview are provided in Appendix 5.

Based on the interview excerpts, it was concluded that even though he only wrote down the information he knew on the answer sheet, subject S3 was able to explain exactly the information that was known and asked in the Bebras questions. This shows that subject S3 has good mastery of decomposition skills. The interview excerpt also shows that subject S3 was confused in determining the fines for each train. Then, subject S3 only used the ticket prices of each train to calculate the cheapest cost. It was concluded that subject S3 had not been able to correctly identify the pattern of late fees. This shows that subject S3 has not mastered pattern recognition skills. Drawing on students' responses and interview findings, in working on these questions, there was only one step taken by subject S3. To find the cheapest price, subject S3 looked at the ticket prices of each train without calculating the fines. According to subject S3, the fines for each train were the same, while the ticket prices were different. It was concluded that subject S3 had not used systematic solution steps. This shows that subject S3 has not mastered algorithmic thinking skills. Referring to the interview findings, it can be seen that subject S3 did not explain the pattern of late fees, which led to an inaccurate solution. This occurred because subject S3 was unable to recognize the existing patterns. By considering only the ticket prices, subject S3 immediately concluded that the train with the lowest cost was the Regular Train. Subject S3 assumed that late fees had no effect on the total cost, as the fine was the same for each train, IDR 10,000. This indicates that subject S3 has not mastered abstraction and pattern generalization skills. According to insights gained from the interviews, it can be concluded that subject S3 did not check the answers before submitting them. In addition, when asked to review the answers, subject S3 did not know where the error was and was unable to correct it. This shows that subject S3 has not yet mastered debugging skills.

Based on the examination and analysis of students' answers, as well as in-depth interview results, it was found that students with low logical-mathematical intelligence are only able to master one indicator of computational thinking, namely decomposition, and tend to have difficulty understanding the meaning of the questions, although their numeracy skills are fairly good. Therefore, students with low logical-mathematical intelligence also demonstrate a low level of computational thinking skills in solving mathematical problems involving Bebras tasks.

Based on the above description, the qualitative findings of this study indicate that logical-mathematical intelligence serves as the primary foundation for the development of computational thinking in mathematics learning. The higher the students' logical-mathematical intelligence, the greater their ability to break down complex problems into simpler parts, analyze patterns, develop systematic strategies, and apply mathematical concepts in a digital context. Therefore, logical-mathematical intelligence and computational thinking should be developed simultaneously in mathematics learning, so that students are not only proficient in calculations but also well-prepared to face a data-driven and automated world.

Quantitative Research Result

Previously, qualitative results indicated a relationship between logical-mathematical intelligence and computational thinking skills in mathematics learning. The following section presents the quantitative research findings, which examine the contribution of students' logical-mathematical intelligence to the improvement of their computational thinking skills in mathematics learning.

Results of Descriptive Statistics Logical Mathematical Intelligence Test Data

The central tendency of logical mathematical intelligence data obtained from the test results for 55 subjects is presented in Table 2.

Mean	Median	Mode	Standard Deviation	Maximum Value	Minimum Value
52.11	56	32	18.88	88	20

Table 2. Central Tendency of Logical Mathematical Intelligence Test Data

Based on the mean value and standard deviation, logical mathematical intelligence data is classified into 3 categories as shown in Table 3.

Value Range	Absolute Frequency	Relative Frequency	Criteria
$X \geq 70.99$	10	18%	High
$33.23<X<70.99$	29	53%	Medium
$X \leq 33.23$	16	29%	Low

Table 3. Frequency of Data Classification Criteria for Logical mathematical Intelligence

Results of Descriptive Statistics Computational Thinking Skills Test

The central tendency of data on computational thinking skills obtained from the test results for 55 subjects are presented in Table 4.

Central Tendency					
Mean	Median	Mode	Standard Deviation	Maximum Value	Minimum Value
58.24	60	23.34	23.88	96.67	23.34

Table 4. Central Tendency of Computational Thinking Skills Test

Based on the mean value and standard deviation, computational thinking skills data is classified into 3 categories as shown in Table 5.

Value Range	Absolute Frequency	Relative Frequency	Criteria
$X \geq 82.12$	10	25.5%	High
$34.36<X<82.12$	31	56.4%	Medium
$X \leq 34.36$	14	18.2%	Low

Table 5. Frequency of Data Classification Criteria For Computational Thinking Skills

Normality Test Results

The normality test uses the Kolmogorov Smirnov test. The data is normally distributed if the value. The normality test results are presented in Table 6.

Testing	*Sig (2 – tailed)* K-S Value	Condition	Information
RES _Y	0.200	*Sig (2 – tailed)* > 5%	Normally distributed

Table 6. Normality Test Result

Based on the results in the table it is known that the significance value of 0.2 is greater than 0.05. So it can be concluded that the data is normally distributed.

The Result of the Linearity and The Significance of The Regression Direction

The relationship between variables is linear if the value. The significance value is obtained from the SPSS output results in the Deviation from Linearity line ANOVA table. The following presents the results of the linearity test in Table 7.

Independent Variable	Dependent Variable	Sig. Deviation from Linearity	Information
X	*Y*	0.149	Linear

Table 7. Linearity Test Results

Based on the results in the table it is known that the Deviation from Linearity Significance value is 0.149 greater than 0.05. So, it can be concluded that there is a linier relationship between logical mathematical intelligence and computational thinking skills

Multicollinearity Test Results

In the regression model, it is preferable to avoid multicollinearity. The criteria for variables that do not exhibit multicollinearity are if the variables have values $VIF<10$ and tolerance>0.1. The results of the multicollinearity test are presented in Table 8.

Independent Variable	Dependent Variable	Tolerance	VIF	Information
X	*Y*	1.00	1.00	Does not contain multicollinearity

Table 8. Multicollinearity Test Results

Based on the results in the table it is known that the VIF value of 1.00 is less than 10 and the Tolerance value of 1.00 is greater than 0.1. So, it is concluded that the variable does not contain multicollinearity.

Heteroscedasticity Test Results

In the heteroscedasticity test, the Glejser test was used. The criteria for data that does not have heteroscedasticity if the value of *Sig>5%*. The following presents the results of the heteroscedasticity test in Table 9.

Independent Variable	Dependent Variable	Significance Value	Information
X	$|\_|RESY$	0.204	There is no evidence of heteroscedasticity.

Table 9. Heteroscedasticity Test Results

Based on the results, it is known that the significance value of 0.204 is greater than 0.05. So, it can be concluded that the data does not evidence of heteroscedasticity.

Autocorrelation Test Results

The autocorrelation test was carried out using the Durbin Watson test. The criteria for data that satisfy the autocorrelation test if the DW value is greater than 1.526 and less than 2.3986. The following shows the results of the autocorrelation test in Table 10.

Independent Variable	Dependent Variable	*DW*	Information
X	Y	1.846	There is no autocorrelation

Table 10. Autocorrelation Test Results

Based on the results, it is known that the Durbin Watson value is 1.846 which is greater than 1.526 and less than 2.3986. So, it can be concluded that the data does not evidence of autocorrelation.

Hypothesis Test Results

Based on the results of the one-way correlation test using SPSS, logical-mathematical intelligence (X) showed a statistically significant relationship with computational thinking skills (Y), with a significance value of less than 0.01. Because $Sig = 0.000<0.01$, so H_o was rejected. So, it can be concluded that there is a contribution of logical-mathematical intelligence to computational thinking skills.

Simple Linear Regression Test Results

Regression Function	*R*	R^2	*Relatively Contribution*	*Effective Contribution*
$\hat{Y}$=1.139X-1.114	0.901	0.811	87.8%	71.2%

Table 11. Simple Linear Regression Test Results

The further explanation regarding the results of the simple linear regression test in Table 11 are as follows:

1. The R value obtained is 0.901, it means that the relationship between logical-mathematical intelligence and computational thinking skills is in a very strong category.
2. The value R^2 obtained is 0.811, it means that the contribution of logical-mathematical intelligence level simultaneously to computational thinking skills is 81.1%. The remaining 18.9% % is the contribution of other variables that were not examined in this research.
3. The SR value obtained is 87.8% indicates that the contribution of the logical mathematical intelligence variable to the computational thinking skillls variable, without considering other variables outside the research variables, is 87.8%.
4. The SE value obtained is 71.2% indicates that the contribution of logical mathematical intelligence variable to the computational thinking skills variable is 71.2%, while the remaining 28.8% is the contribution of other variables that were not examined in this research.
5. The obtained simple linear regression equation is $\hat{Y}$=1.139X-1.114. The constant value of -1.114 indicates that if students don't have logical mathematical intelligence (X), their computational thinking ability (Y) is -1.114. The regression coefficient of logical mathematical intelligence 1.139, indicates that for every unit increase in logical mathematical intelligence (X), the computational thinking skill (Y) of students increases by 1.139. This simple linear regression equation interprets that as the logical mathematical intelligence (X) increases, the computational thinking ability (Y) of students also increases, and vice versa.

DISCUSSION

The results of this qualitative study are important in the early stages, as differences in mathematical intelligence influence students' computational thinking (CT) skills. Therefore, in mathematics learning, it is essential to incorporate CT by providing differentiated instruction based on each student's mathematical intelligence characteristics. The findings from this qualitative research can serve as a foundation or a preliminary step for conducting a quantitative study to examine the relationship between logical-mathematical intelligence and students' computational thinking skills in solving mathematical problems involving Bebras tasks.

Based on the description of the research results and the analysis presented, the following conclusions can be drawn: (1) Students with high logical-mathematical intelligence are able to master all five indicators of computational thinking but tend not to write down the information known and the questions asked; students with moderate logical-mathematical intelligence are able to master three indicators of computational thinking, namely decomposition, pattern recognition, and algorithmic thinking, but often work in a hurry and are not thorough in solving problems; students with low logical-mathematical intelligence are only able to master one indicator of computational thinking, namely decomposition, and tend to have difficulty understanding the meaning of the questions, although their numeracy skills are quite good. (2) The level of logical-mathematical intelligence has a very high contribution to the computational thinking abilities of 10th-grade students at the Center of Excellence Vocational School in Bali. (3) The practical implications for teachers and mathematics curriculum developers based on these findings are that mathematics learning should actively foster computational thinking skills integrated into the mathematics curriculum. Logical-mathematical intelligence serves as the primary foundation for the development of computational thinking in mathematics learning.

Computational thinking is a thinking process to solve problems that leads to solutions using computational steps or algorithms (Threekunprapa & Yasri, 2020; Lockwood & Mooney, 2018). Students who possess computational thinking skills can solve problems using logical and systematic steps (Yunianto *et al.,* 2024; Zamzami *et al.,* 2020). In this study, to obtain data on students' computational thinking skills, a test containing mathematical problems embedded with Bebras tasks was administered to the research subjects (Rahmawati *et al.,* 2024; Munawarah *et al.,* 2021). The results of our analysis revealed a clear distinction in computational thinking performance among students with high, moderate, and low logical-mathematical intelligence (Aminah *et al.,* 2022; Faizah *et al.,* 2017; Mufidah, 2018).

This study show that students with high logical-mathematical intelligence successfully mastered all five computational thinking indicators. While this aligns with previous studies (Mufidah, 2018; Purwasih *et al.*, 2024), we found a unique behavioral tendency: these students often did not write down the given information or the questions, even though they demonstrated strong understanding. This observation adds a behavioral dimension that is not emphasized in earlier studies. Although Dwita *et al.* (2022) and Ersozlu *et al.* (2023) also mentioned this behavior, our research further connects it to efficiency in processing and internalizing information, which may stem from cognitive confidence. This contrasts with Wulandari & Fatmahanik (2020), who argued that such students tend to document both knowns and unknowns explicitly. Hence, our findings emphasize the variability in strategy even among high performers, pointing to possible instructional adjustments.

Students with moderate logical-mathematical intelligence demonstrated mastery of three computational thinking indicators, decomposition, pattern recognition, and algorithmic thinking (Purwasih *et al.*, 2024; Setiarini *et al.*, 2023; Threekunprapa & Yasri, 2020). This corroborates existing literature (Nuvitalia *et al.*, 2022; Mufidah, 2018), yet our study offers a new insight: these students frequently rushed through the tasks and lacked thoroughness, leading to incomplete answers. While Faizah *et al.* (2017) acknowledged limitations in logical analysis among moderate students, our research brings attention to process-related behaviors, such as time mismanagement and inadequate attention to task structure. This behavioral tendency weakens their computational thinking implementation despite moderate intelligence levels. Such a pattern was also noted in Aminah *et* *al.* (2022), yet our study emphasizes its instructional implications more directly.

As for students with low logical-mathematical intelligence, our research confirms they generally master only the decomposition aspect of computational thinking (Angeli & Giannakos, 2020 & Tresnawati *et al.*, 2020). Consistent with Faizah *et al.* (2017), these students exhibited low interest in numerical and analytical tasks. However, a distinct contribution from our findings is that while some of these students possessed reasonable numeracy skills (Khotijah, 2016), they struggled to interpret verbal information in the problems, leading to significant comprehension gaps (Asmal, 2020 & Izu *et al.,* 2017). This highlights a disconnection between procedural skills and semantic understanding. Our study, therefore, not only confirms prior conclusions but also adds depth by highlighting this semantic barrier as a critical challenge for low-ability students.

These findings are generally supported by previous research. For instance, studies by Faizah *et al.* (2017), Pudyastuti *et al.* (2022), and Saputra & Zulmaulida (2021) confirm the influence of logical-mathematical intelligence on computational thinking skills. Similarly, Lockwood & Mooney (2018) and Setiarini *et al.* (2023) support the use of Bebras tasks in developing these skills. However, some research (Dwita *et al.,* 2022; Mufidah, 2018; Purwasih *et al.*, 2024) suggests that other cognitive factors may also play significant roles. In light of these perspectives, our study provides a distinctive contribution by linking cognitive levels with observable problem solving behavior such as skipping written elements or working hastily thereby offering a more behaviorally grounded instructional lens. Thus, while our findings align with the dominant discourse, they also enrich it by emphasizing the behavioral nuances associated with each intelligence level and their pedagogical implications.

CONCLUSIONS

Based on the description of the research results and the analysis presented, it can be concluded that students with high logical-mathematical intelligence are able to master all five indicators of computational thinking, although they tend not to explicitly write down the known and unknown information in the questions. Students with moderate logical-mathematical intelligence are able to master three indicators (decomposition, pattern recognition, and algorithmic thinking), but often work hastily and lack thoroughness in solving problems. Meanwhile, students with low logical-mathematical intelligence are able to master only one indicator, namely decomposition, and tend to have difficulty understanding the meaning of the questions, although their numeracy skills are relatively good. Logical-mathematical intelligence serves as the primary foundation for the development of computational thinking in mathematics learning. The higher the level of students' logical-mathematical intelligence, the greater their ability to break down complex problems into simpler components, analyze patterns, design systematic strategies, and apply mathematical concepts in a digital context. Therefore, logical-mathematical intelligence and computational thinking should be developed simultaneously in mathematics learning so that students are not only proficient in calculation but also prepared to face a data-driven and automated world.

Teachers should first diagnose students' logical-mathematical intelligence before integrating computational thinking into mathematics learning. Furthermore, teachers should adopt different approaches for students with high, moderate, and low levels of logical mathematical intelligence to effectively develop computational thinking skills in mathematics lessons. For example, students with high logical-mathematical intelligence may benefit from more complex and exploratory computational tasks, while those with moderate or low intelligence levels may require structured guidance and scaffolded support. Based on this study, future researchers are encouraged to examine other factors that influence computational thinking skills in mathematics learning, such as 21st-century skills. Specifically, they could investigate the profile of computational thinking in terms of critical thinking, creativity, collaboration, and communication, either partially or holistically, in the context of mathematics learning. Such research could provide a broader understanding of how these skills interact and contribute to students' ability to solve mathematical problems using computational thinking approaches. Thus, this study has successfully described students' computational thinking skills in solving mathematical problems involving Bebras tasks based on their level of logical-mathematical intelligence, as well as determined the extent to which logical-mathematical intelligence contributes to students' computational thinking skills. The results of this study are recommended as a guide for mathematics teachers to apply its findings by integrating computational thinking into mathematics learning through problem-solving using Bebras-based tasks.

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APPENDIX 1

Sample Questions Based on the Four Indicators of Logical-Mathematical Intelligence

The theories and sample questions related to the four indicators of logical-mathematical intelligence used in this study are presented as follows.

Part I: Numerical Capability is one of the indicators of logical-mathematical intelligence, which relates to the ability to process, understand, and interpret numerical data. Students with strong numerical capability demonstrate a high level of logical-mathematical intelligence, whereas those with low numerical capability exhibit a lower level of logical-mathematical intelligence. An example of a logical-mathematical intelligence test item that falls under the numerical capability indicator is presented as follows.

Part I: Numerical Capability

1. If the calculation result $504 : a = 36$, then $a = \ldots\ldots$
   A. 12
   B. 14
   C. 16
   D. 19
   E. 24

The example above illustrates a condition designed to assess students' numerical capability, as indicated by their ability to calculate or determine the value of aaa as the divisor of 504 to obtain the result of 36. If students are able to solve this problem correctly, it can be concluded that they possess a high level of logical-mathematical intelligence.

Part II: Algebra Concept Ability is one of the indicators of logical-mathematical intelligence, which relates to the ability to understand, manipulate, and solve problems involving algebraic concepts. This ability includes skills in identifying variables, formulating equations or inequalities, and solving them logically and systematically. Students with strong Algebra Concept Ability demonstrate a high level of logical-mathematical intelligence in the domain of symbol- and relation-based problem-solving, whereas those with low ability in this area exhibit a lower level of logical-mathematical intelligence. An example of a logical-mathematical intelligence test item that falls under the Algebra Concept Ability indicator is presented as follows.

Part II: Algebra Concept Ability

2. If $x < 0, y < 0$ and $|x| > |y|$, the the relationship between x and y is ….
   A. $x = y$
   B. $x \neq y$
   C. $x > y$
   D. $x < y$
   E. x dan y can not be determined

The example above presents a condition designed to assess students' Algebra Concept Ability, as indicated by their capacity to understand the relationship between two variables, x and y, by considering their signs and absolute values. This problem requires students to analyze the given information, apply the concept of absolute value, and draw the correct conclusion regarding the relationship between x and y. Successfully solving this problem demonstrates a high level of logical-mathematical intelligence in the domain of algebraic concept understanding.

Part III: Series/Pattern of Number Ability is one of the indicators of logical-mathematical intelligence, which relates to the ability to recognize, understand, and predict numerical patterns or sequences. This ability involves skills in analyzing regularities within a number series, determining the rule that forms the pattern, and applying that rule to identify the next or missing element. Students with strong Series/Pattern of Number Ability demonstrate a high level of logical-mathematical intelligence in the domain of pattern-based reasoning, whereas those with low ability in this area often struggle to identify numerical regularities. An example of a logical-mathematical intelligence test item that falls under the Series/Pattern of Number Ability indicator is presented as follows.

Part III: Series/Pattern of Numbers Ability

9. 1, 3, 7, 13, 21, 31, 43, ...
   A. 55
   B. 57
   C. 59
   D. 60
   E. 62

The example above presents a condition designed to assess students' Series/Pattern of Number Ability, as indicated by their capacity to recognize and determine numerical patterns within a sequence. This problem requires students to analyze the regularity of the given number series, identify the applicable rule of progression, and predict the next number in the sequence. Successfully solving this problem demonstrates a high level of logical-mathematical intelligence in the domain of pattern-based reasoning.

Part IV: Logic (Reasoning) Ability is one of the indicators of logical-mathematical intelligence, which relates to the capacity to think rationally, draw conclusions both deductively and inductively, and solve problems based on logical relationships between pieces of information. This ability involves skills in analyzing premises, identifying implications, evaluating the truth of statements, and determining valid conclusions. Students with strong Logic (Reasoning) Ability demonstrate a high level of logical-mathematical intelligence in the domain of general reasoning, whereas those with low ability in this area tend to struggle in connecting facts and drawing accurate conclusions. An example of a logical-mathematical intelligence test item that falls under the Logic (Reasoning) Ability indicator is presented as follows.Through the mathematical intelligence test, which includes the four components mentioned above as illustrated in the example, a comprehensive and objective mapping of students' logical-mathematical intelligence can be obtained. This ensures that the research results are accountable and free from bias.

Part IV: Logic (Reasoning) Ability

19. Premise 1 : Randu wood is a type of wood that is useful.
    Premise 2 : Useful wood is expensive.
    The conclusion from these two premises is: .....
    A. All very useful wood is not cheap
    B. Randu wood is expensive
    C. Randu wood is not for sale
    D. All wood that is cheap is randu wood.
    E. All wrong

The example above presents a condition designed to assess students' Logic (Reasoning) Ability, as indicated by their capacity to draw a valid conclusion based on two given premises. This problem requires students to analyze the logical relationship between the first and second premises and then determine a conclusion that is accurate and consistent with the provided information. Successfully solving this problem demonstrates a high level of logical-mathematical intelligence in the domain of logical reasoning.

APPENDIX 2

Guidelines for Evaluating Computational Thinking Tests

Guidelines for evaluating computational thinking tests according to Sulistya, (2021) are presented in the following table.

Aspects of Computational Thinking	Assessment Criteria	Score
Decomposition	Students are able to write down or mention known information and questions asked in the questions correctly and completely.	3
	Students are able to write down or mention the information that is known and the questions asked in the questions correctly but incompletely.	2
	Students are able to write down or mention information that is known or information that is asked correctly.	1
	Students are able to write down or mention information that is known and questions that are asked in questions incorrectly.	0
Pattern Recog-nize	Students are able to recognize the patterns contained in the questions and use them to carry out appropriate solutions	3
	Students are able to recognize the pattern contained in the prob-lem and use it to carry out an almost precise solution	2
	Students are able to recognize the patterns contained in the questions and use them to carry out solutions with most of the calculation steps being inaccurate	1
	Students are not able to recognize the patterns contained in the questions and are unable to use them to make solutions that are not quite right	0
Algorithm Thinking	Students are able to write down or mention the steps of comple-tion correctly	3
	Students are able to write down or mention the completion steps almost precisely	2
	Students are able to write down or mention the completion steps with most of the calculation steps being inaccurate	1
	Students are not able to write down the steps of completion	0

Abstraction/ Generalization	Students are able to describe the pattern found into an appropriate solution and draw conclusions from the pattern found correctly	3
	Students are able to describe the patterns found into an appropriate solution and draw conclusions from the patterns found inaccurately	2
	Students only write or mention conclusions without being accompanied by calculation steps	1
	Students do not write down or mention conclusions and do not write down the final results of calculations	0
Debugging	Students are able to ensure the correctness of the answer and correct the answer appropriately if there is an error.	3
	Students are able to ensure the correctness of the answer and correct the answer inaccurately	2
	Students are able to ensure the correctness of their answers and have not been able to correct errors in their answers	1
	Students are not able to ensure the correctness of their answers and correct them	0
	Total Score	15

APPENDIX 3

Interview Excerpts of Students with High Logical-Mathematical Intelligence (S1)

Based on the answers of students with high logical-mathematical intelligence (S1) in Figure 2, an interview was conducted to clarify the steps involved in solving Bebras problems according to the indicators of computational thinking.

Decomposition

In Figure 2, it can be seen that subject S1 did not write down the known information but wrote down the problems asked in the questions. Then conducted interviews related to decomposition skills. The excerpts from the interview results are presented as follows.

R : What information is known in the problem?
S : Known information about fines and ticket prices, Ma'am. If Bob is late, he will be fined IDR 10,000 for every 15 minutes late. Then if Bob arrives before 8.15 he will not be fined, but if he arrives past 8.15 he will be fined. One day Bob overslept and arrived at the departure station at 8:08. To get to work, there are four trains that Bob can choose from with different ticket prices and departure times.
R : Then, state what problems was asked?
S : The question asked is which train should Bob take so that even if he is late, the expenses for fines and tickets are the least?

Based on the interview, it can be concluded that even though the student did not write down the known information on the answer sheet, the S1 subject was able to explain exactly the information that was known and asked in the Bebras questions. This shows that subject S1 mastered decomposition skills well. Based on students' answers and interview results, it can be concluded that the decomposition ability of students with high logical-mathematical intelligence is classified as very good, which helps them solve problems involving Bebras tasks.

Pattern Recognition

Figure 2 shows that S1 subject was also able to recognize the pattern contained in the question. When looking for a solution to the problem, subject S1 first looked for how many fines that Bob would get on each train. It can be seen that the method used by S1 subjects is to divide Bob's arrival time at work by 15 minutes. Then conducted interviews related to pattern recognition skills. The excerpts from the interview results are presented as follows.

R : What was the first thing you did when answering the Bebras question?
S : First, I looked for fines on Regular Train, by finding the time of arrival at Bob's work. The Regular Train starts at 6:00 and departs every 5 minutes, while Bob arrives at the departure station at 8:08. He will be able to catch the Regular Train at 8:10, then it will take 40 minutes so he will be at work by 8:50. So Bob was 50 minutes late, so by choosing the Ordinary Train Bob was fined 3 times. Then look for other train fines using the same method ma'am.
R : Why is the Regular Train, Bob was fined 3 times?
S : Since the fine is calculated every 15 minutes late, calculate a multiple of 15 which is closer to 50.

The interview above shows that subject S1 applied the same pattern to determine Bob's fine for each train. In addition, subject S1 was able to clearly identify patterns of late fines and demonstrated a strong understanding of the rules for imposing fines. This indicates that subject S1 has mastered pattern recognition skills.

Algorithms

Figure 2 shows that S1 subject has taken systematic steps to find a solution to the problem. It can be seen that in working on the questions there are three steps carried out by S1 subject. Then conducted interviews related to algorithms skills. The excerpts from the interview results are presented as follows.

R : Describe the steps you took to solve the problem?
S : First, I searched for fines in Regular Train. The method is the same as before Ma'am. Then I look for fines for other trains using the same method. Second, I multiplied the number of fines by the cost of each fine, which is IDR 10,000. Third, add up the ticket prices with the fines for each train, ma'am and choose the train with the smallest total cost.

Based on the results of the answers and interviews, it can be concluded that subject S1 used the correct solution steps. This indicates that subject S1 has a strong mastery of algorithmic thinking skills.

Abstraction

In Figure 2, it can be seen that subject S1 can describe the patterns that have been obtained. In addition, subject S1 can also conclude the answer of the question correctly. Then conducted interviews related to abstraction skills. The excerpts from interview results are presented as follows.

R : After compiling the steps for solving the problem, how do you conclude the answer you got?
S : So, the train chosen by Bob with the lowest total ticket cost and fine is the Wira-Wiri Train, Ma'am.
R : How do you describe the pattern you found?
S : After I got the pattern of late fines for Regular Trains, I also looked for fines on other trains using the same method. Then the number of fines on each train is multiplied by IDR 10.000

Based on the interview, it can be seen that subject S1 identified the train with the lowest cost, *Wira-Wiri*. Subject S1 was able to describe the identified pattern and explain how to determine the fines for each train in the same way. This indicates that subject S1 has mastered the skills of abstraction and pattern generalization.

Debugging

The researcher then continued the interview to see debugging skills. The excerpts from interview results are presented as follows

R: Have you checked your answers before submitting them?
S: Yes, Ma'am
R: Now, try to check again, is there a mistake in the answer you made?
S: I'll see first Ma'am (while reading the answer sheet). I think my answer is correct Ma'am and the calculations I made were also not wrong. So, I believe my answer is correct ma'am.

Based on the results of the interview, it can be concluded that after S1 subject was asked to reviewed their answer, it was seen that the S1 subject was able to ensure that the answers obtained were correct. This shows that the S1 subject has mastered debugging skills well.

APPENDIX 4

Interview Excerpts of Students with Moderate Logical-Mathematical Intelligence (S2)

Based on the answers of students with moderate logical-mathematical intelligence (S2) in Figure 3, an interview was conducted to clarify the steps involved in solving Bebras problems according to the indicators of computational thinking.

Decomposition

In Figure 3, it can be seen that subject S2 wrote down information that was known incompletely and wrote down the problems asked in an unclear manner. Then conducted interviews related to decomposition skills. The excerpts from interview results are presented as follows.

R : What information is known in the problem?
S : Known information is about Bob who works as a mechanic and arrives late at work. Bob's working hours start at 8.00 and every 15 minutes late, Bob will be fined IDR. 10,000. If Bob comes before 8.15, he will not be fined, but if he is later than 8.15 he will be fined. In addition, the table contains information on the departure schedules and travel times of the four trains that Bob can choose to arrive at his workplace.
R : Then, try to state what problems were asked?
S : Which train requires the cheapest cost?

Based on the interview excerpts, it was concluded that even though students wrote information that was known and asked incompletely on the answer sheet, the S2 subject was able to explain precisely the information that was known and asked in the Bebras questions. This shows that subject S2 has medium decomposition skills.

Pattern Recognition

Figure 7 shows that subject S2 applies the same rules to find the number of fines in each train. The method used by S2 is to divide the travel time by 15 minutes. This shows that the S_2 subject already recognizes the pattern of giving fines on the questions, but the patterns found are not correct. Then conducted interviews related to pattern recognition skills. The excerpts from interview results are presented as follows.

R : What was the first thing you did when answering the Bebras question?

S : At first, I was looking for fines for all four trains, Ma'am. For example, the Regular Train takes 40 minutes, then I divide by 15 minutes. Because it will be fined every 15 minutes late. So, the Regular Train will be fined 2 times, because once a fine of IDR 10,000 means 2 times a fine of IDR 20,000. For Wira-Wiri, Fast, and Express trains, the method is the same with Regular train, Ma.am.

R : Why do you divide the travel time by 15 minutes?

S : Because the travel time affects the time Bob arrives at the office

The interview excerpt above shows that subject S2 applies the same patterns in finding fines on each train. However, subject S2 has not been able to correctly mention the pattern of late fines. Where subject S2 only calculates travel time without calculating train departure schedules. This shows that subject S2 has medium pattern recognition skills.

Algorithms

Figure 3 shows subject S2 has taken systematic steps to find a solution to the problem. In working on the questions, there are two steps taken by subject S2. Then conducted interviews related to algorithms skills. The excerpts from interview results are presented as follows.

R : Describe the steps you took to solve the problem?

S : At first, I looked up how many times Bob would be charged a late fee if he departed on each train and I multiplied the number of fines by IDR 10,000. Then I added up the cost of the fine with the ticket price of each train. From the total cost of fines and ticket prices, I chose the train with the cheapest cost, Ma'am.

Based on the results of the answers and interviews, it was concluded that the S2 subject had used the appropriate resolution steps. Although in answer sheet is not written clearly. This shows that subject S2 has medium algorithmic thinking skills.

Abstraction

In Figure 3, it can be seen that subject S_2 can describe the patterns that have been obtained. However, subject S2 has not been able to conclude the answer of the question correctly. Then conducted interviews related to abstraction skills. The excerpts from interview results are presented as follows.

R : After compiling the steps for solving the problem, how do you conclude the answer you got?

S : The train with the cheapest total ticket costs and fines is the Express Train, Ma'am

R : How would you describe the patterns you found?

S : After I got how much fine Bob will get on each train, then I multiply the number of fines on each train by IDR 10,000

Based on the results of the interview above, it can be seen that subject S_2 gets the train with the cheapest cost is Express train. Subject S2 was able to describe the patterns found. However, because the pattern found was not quite right, the conclusion of the answer obtained by subject S2 was not correct. This indicates that the S2 subject has not yet optimally mastered the skills of abstraction and pattern generalization.

Debugging

The researcher then continued the interview to see debugging skills. The excerpts from interview results are presented as follows.

R: Have you checked your answers before submitting them?
S: Not yet, Ma'am, because I was short on time so I didn't have time to check again
R: Now, try to check again, is there a mistake in the answer you made?
S: I'll see first, Ma'am (while reading the answer sheet). I don't see the mistake, Ma'am, because I think this answer is correct.

Based on the results of the interviews, it can be concluded that the S2 subjects did not check their answers before it was collected. In addition, after being asked to reviewed their answer, subject S2 has not been able to find mistakes and correct errors on the answer sheet. This shows that subject S2 has not mastered debugging skills well.

APPENDIX 5

Interview Excerpts of Students with Low Logical-Mathematical Intelligence (S3)

Based on the answers of students with low logical-mathematical intelligence (S3) in Figure 4, an interview was conducted to clarify the steps involved in solving Bebras problems according to the indicators of computational thinking.

Decomposition

In Figure 4, it can be seen that subject S3 only wrote down the known information but did not write down the problems asked in the questions. Then conducted interviews related to decomposition skills. The excerpts from interview results are presented as follows.

R : What information is known in the problem?
S : Bob Works at the Downtown station as a railroad engineer and his shift starts at 8:00. Bob will be fined if he shows up late. For every 15 minutes late, he must pay a fine of IDR 10,000. For example, if he arrives before 8:15 am then he is not fined. If he arrives at 8:20 a.m. he will be fined IDR 10,000. This morning, Bob overslept and arrived at the departure station at 8:08.
R : Then, try to state what problems were asked?
S : Looking for a train with the lowest cost

Based on the interview excerpts, it was concluded that even though he only wrote down the information he knew on the answer sheet, S_3 subject was able to explain exactly the information that was known and asked in the Bebras questions. This shows that subject S3 has good mastery of decomposition skills.

Pattern Recognition

Figure 4 shows that subject S3 did not write a pattern of late fines for each train. The subject of S3 is directly based on the ticket price of each train. Then conducted interviews related to pattern recognition skills. The excerpts from interview results are presented as follows.

R : What was the first thing you did when answering the Bebras question?
S : I use the ticket price for each train Ma'am.
R : Why are you using ticket prices? Then what about the fine that Bob got?
S : I think the choice of the train depends on the ticket price, ma'am. While fines are not counted

The interview excerpt above shows that subject S3 was confused in finding fines on each train. Then subject S3 only uses the ticket price of each train to calculate the cheapest cost. It was concluded that the S3 subject had not been able to correctly mention the pattern of late fines. This shows that subject S3 has not mastered pattern recognition skills.

Algorithms

Figure 4 shows that when looking for a solution to the Bebras problem, subject S3 only looks at the ticket prices for each train in determining the train with the cheapest cost. Then conducted interviews related to algorithms skills. The excerpts from interview results are presented as follows.

R : Describe the steps you took to solve the problem?
S : I only saw the ticket price for each train Ma'am. Then I get the train with the cheapest cost.
R : Don't you add the fine fee to the ticket price?
S : I think the fine for each train is IDR 10,000. The difference is the ticket price. So I only use the ticket price.

Based on the results of the answers and interviews, in working on these questions there is one step taken by the S3 subject. To find the cheapest price, subject S3 look at ticket prices on each train, without calculating the fine. According to subject S3, the fines for each train are the same, while the ticket prices are different. It was concluded that the S3 subject had not used systematic completion steps. This shows that the S3 subject has not mastered algorithmic thinking skills.

Abstraction

In Figure 4, it can be seen that subject S3 has not been able to describe the pattern of late fines. Then conducted interviews related to abstraction skills. The excerpts from interview results are presented as follows.

R : After compiling the steps for solving the problem, how do you conclude the answer you got?
S : The train that costs the least for Bob is Regular Train, Ma'am
R : How would you describe the patterns you found?
S : Look at the ticket price, Ma'am
Regular Train = IDR 5,000, Wira-Wiri Train = IDR 10,000, Fast Train = IDR 15,000, and Express Train = IDR 20,000
So, the cheapest is the Regular Train. So, the train that Bob chose is Regular Train

Based on the interview results above, it can be seen that subject S3 did not explain the pattern of late fines, which led to an inaccurate solution to the questions. This is because subject S3 was unable to recognize the existing patterns. By looking only at the ticket prices, subject S3 immediately concluded that the train with the lowest cost was the Regular Train. Subject S3 assumed that late fees had no effect on the total train cost, as the fine was the same for each train, IDR 10,000. This indicates that subject S3 has not mastered the skills of abstraction and pattern generalization.

Debugging

The researcher then continued the interview to see debugging skills. The excerpts from interview results are presented as follows.

R: Have you checked your answers before submitting them?
S: Not yet ma'am, because my time is up
R: Now, try to check again, is there a mistake in the answer you made?
S: I'll see first Ma'am (while reading the answer sheet). Sorry Ma'am, I don't know where is the mistake from my answer

Based on the results of the interviews, it can be concluded that the S3 subject did not check their answers before submitting them. In addition, after being asked to review the answers, the S3 subject did not know where the error was and was unable to correct it. This shows that the S3 subject has not yet mastered debugging skills.