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The Relationship between Linguistic Intelligence and Computational Thinking among Fifth Grade Students of Elementary School

Idam Ragil Widianto Atmojo✉[1], **Roy Ardiansyah**[2], **Joko Tri Widianto**[3], **Dwi Yuniasih Saputri**[4] **& Maryam Faizah**[5]

[1,2,3,4] Faculty of Education and Teacher Training, Universitas Sebelas Maret, Surakarta, Indonesia
[5] Faculty of Education and Teacher Training, Universitas Islam Negeri Maulana Malik Ibrahim, Malang, Indonesia

✉ idamragil@fkip.uns.ac.id

Abstract. This study aims to determine whether there is a relationship between linguistic intelligence and computational thinking. The research method employed is quantitative, utilizing a correlational research design. The research sample comprised 73 students from 4 elementary schools in the Laweyan District, Surakarta City. Data collection involved a test instrument in the form of a descriptive test to assess both linguistic intelligence and computational thinking. Data analysis included prerequisite tests and hypothesis testing. The results indicate a significant overall relationship between linguistic intelligence and computational thinking, with a significance value of 0.000 ($p < 0.05$) and a Pearson correlation coefficient of 0.493 with the moderate category. The relationship between each indicator of linguistic intelligence and computational thinking shows significant and positive correlations for the rhetoric, explanation, and metalinguistics indicators, with $p < 0.05$. In contrast, the mnemonics indicator does not demonstrate a significant relationship, with a $p > 0.05$. These findings can serve as a reference for further research. The significant relationship between linguistic intelligence and computational thinking suggests that enhancing linguistic skills, particularly rhetoric, explanation, and metalinguistics, could improve students' computational abilities, guiding future educational strategies.

Keywords: Computational Thinking; Elementary School; Linguistic Intelligence; Relationship; Quantitative Research

1. Introduction

In this respect, the 21st century has also changed the types of skills, knowledge and competencies required for success in the modern society (Atalay & Mutlu, 2023). Education plays a significant role in enhancing students' skills so that they can be globally competitive and take significant roles in these changes. Achieving the SDGs in the era of Society 5.0 often requires a framework of 21st-century skills known as the 7Cs: critical thinking, creativity, communication, collaboration, career & learning self-reliance, cross-cultural understanding, and computing/ICT literacy (Sunarti, et. al 2021).

Computational thinking (CT) is considered a crucial element of 21st-century skills related to general problem-solving, alongside other fundamental elements such as communication, digital literacy, critical thinking, and creativity (Tsarava et al., 2022; Lu et al., 2022). CT emphasizes not only hardware but also cognitive skills like generating and exchanging ideas, categorizing, concluding, making decisions, and executing ideas to gather up-to-date information (Muzana et al., 2021). CT is one of the eight practices in science and engineering applications within the Next Generation Science Standards (NGSS) and the National Research Council (NRC) (Cırıt & Aydemir, 2023). It was first used to solve cognitive processes by applying computer programming rules (Lye & Koh, 2014). CT is also believed to enhance students' problem-solving abilities, particularly in 21st-century learning, so that students will be able to formulate, solve, and uncover solutions through computer-based information processing needed by most other scientific fields (Richardo et al., 2023). CT will assist individuals in problem-solving across various disciplines through four key skills: decomposition, abstraction, pattern recognition, and algorithms (Cansu & Cansu, 2019).

Computational thinking is a cognitive process that involves developing problems and solutions so that information processing agents can implement these solutions efficiently (Chen, 2023). Additionally, it enhances students' cognitive skills as children in the preoperational stage rely on their perception to solve problems (Sırakaya, 2020). Previous literature has explained computational thinking to better understand its nature and outcomes, reviewing past research on CT from the perspectives of definitions, interventions, models, and evaluations (Angraini et al., 2023). In their study, they classified computational thinking into six aspects: decomposition, abstraction, algorithm design, debugging, iteration, and generalization (Santos, 2023). Over the last decade, computational thinking has garnered significant attention from education researchers, and the concept has been understood from various perspectives (Skills, 2023). For instance, computational thinking is associated with problem-solving, artifact creation, situational learning, cognitive tools usage, and "thinking like a computer scientist" (Nouhaila & Hassane, 2024). Besides definitions, various frameworks for computational thinking have been proposed. For example, Brennan and Resnick (2012) identified three main aspects of computational thinking: computational concepts, computational practices, and computational perspectives (Colin, 2021). Regarding early childhood education in computational thinking, recent studies have started discussing the types of robots and programming tools used, the characteristics of activities, computational thinking evaluation, and influential researchers and countries in this field (Abdulrasool, 2023). Since 2017, Shute et al. (2017) have conceptualized computational thinking as a general term encompassing aspects such as "Abstraction, Algorithm Design, Evaluation, Generalization, Iterative Improvement, Information Representation, Effective Communication, and Problem Decomposition" (Amiri, 2018). Computational thinking should become a fundamental skill for every student in school education. However, it remains unclear which features of computational thinking can be integrated into the curriculum of primary and secondary education (Triantafyllou, 2024).

Furthermore, computational thinking is a thought process involving formulating problems and effective solutions in information processing. It is a skill requiring practice and is crucial for advanced problem-solving abilities (Helsa, 2023). Although closely related to computers, computational thinking can be applied across various fields, including linguistics, mathematics, natural sciences, and social sciences. In mathematics, computational thinking is classified as a cognitive skill (Gong, 2020). Therefore, for educators or prospective educators, understanding how students' computational thinking abilities influence the learning process, as well as the benefits, stages, characteristics, and challenges of applying computational thinking, is essential (Yilmaz & Karaoglan Yilmaz, 2023). Primary school students also have the opportunity to learn, understand, and apply computational thinking in various aspects of daily life. When facing problems or aiming to achieve goals, students can address issues with effective, efficient, and optimal solutions (Su & Yang, 2023). The benefits of computational thinking include facilitating problem observation and finding multiple solutions that lead to effective and efficient problem resolution (Ching & Hsu, 2024). The more solution options found, the more likely a problem can be well-addressed, work becomes more professional and efficient, and there is greater sensitivity to issues, fostering specific innovations and more practical systems for problem-solving (Silva, 2021). Computational thinking plays a crucial role in learning situations and helps students enhance their understanding of mathematics and knowledge skills (Cansu & Cansu, 2019). Furthermore, computational thinking has the potential to develop critical, imaginative, and rational thinking skills in addressing complex problems, both in computer environments and everyday situations (Rodríguez-García, 2020).

Computational thinking consists of attitudes and skills to apply general information. Originating from computer science, it uses basic concepts to design systems, solve problems, and understand human activities and behaviors. This thinking process is used across various fields, making it an important model of thought that should be learned and applied by everyone, not just computer scientists (Huang et al., 2023). Learners must use logical thinking to break down abstract problems into smaller components, solve problems step by step, and predict outcomes after independent thinking or group discussion (Alfaro-Ponce et al., 2023). Papert speculated about the impact of computers and computer culture on the future of education and schools and presented ideas for developing computational thinking (Liu et al., 2023). Although he did not use the term, he referred to the application of computational thinking for problem-solving, emphasizing the use of programming blocks and recursive principles to identify and fix errors. This helps children develop skills applicable to other situations (Verawati et al., 2023).

This further reinforces that the concepts and practices used in Computational thinking involve computer science and other disciplines such as science, mathematics, social sciences, biology, arts, languages, and engineering (Aminah et al., 2023). Thus, Computational thinking can be integrated across all areas, including science education. Science learning in elementary schools essentially provides the foundation to solve everyday problems, as science seeks answers to questions of what, why, and how regarding natural phenomena related to structure and nature, changes, and dynamics (Kurniawan et al., 2019). When linked with Computational thinking, it suggests that its application at the elementary school level involves both plug-in programming frameworks and unplugged activities (Suwahyo, 2020). This approach allows students to explore natural phenomena and the structure of scientific knowledge while developing algorithmic thinking and problem-solving skills, creating a synergy between scientific understanding and the essential Computational thinking skills needed to tackle challenges in the digital era.

Wing states that for every activity involving reading, writing, and arithmetic, teachers should integrate Computational thinking into the analytical skills of each student (Wing, 2006). One of the important intelligence is linguistic intelligence. Linguistic intelligence is one of the eight constructs of multiple intelligence classified by Gardner as one of the highest levels of intelligence (Ariffin et al., 2024). Multiple intelligence theory explains that intelligence cannot be measured by a single dimension, such as IQ alone (Syafii et al., 2022). Integrating elements of multiple intelligences into the curriculum should also be an educational agenda within the integrated curriculum concept which aims to create a skilled generation along with providing human resources and a more prosperous life (Setyawan, 2024). The theory of multiple intelligence helps students identify their strengths by recognizing that everyone has different skills, strengths, and weaknesses. This theory argues that there are eight types of intelligence, including visual-spatial, linguistic, logical-mathematical, bodilykinesthetic, musical, interpersonal, intrapersonal, and naturalistic (Hamid & Amirudin, 2022).

Linguistic intelligence is the ability to use language effectively for poetic self-expression and making an impression on others. This type of intelligence is closely related to language learning (Garavand, 2023). Core characteristics of linguistic intelligence include the ability to use language effectively for reading, writing, speaking, and effective communication (Thomas & Perwez, 2024). Effective communication, both verbal and written, is a crucial skill for professionals (Kafi & Huda, 2023). The definition of intelligence has evolved over time. Previously, intelligence was viewed as a singular trait measurable through IQ tests, including language and math tests (Mubarok, 2020). Verbal intelligence is one of the eight types of intelligence that help people use language effectively to express themselves poetically and impress others (Saidi, 2020). Linguistic intelligence is a type of multiple intelligence that "enables people to communicate and understand the world through language." Writers, poets, and teachers exemplify this intelligence in its mature form (Xia et al., 2024). Effective activities for linguistically intelligent students include individual reading, reading aloud, brainstorming, memorizing linguistic facts, small group discussions, and advising (Thambu et al., 2021). Linguistic intelligence relates to language and vocabulary, both written and oral. Individuals with high linguistic intelligence not only possess strong language skills but also have abilities in storytelling, debating, arguing, interpreting, presenting reports, and performing tasks related to speaking and writing (Garavand et al., 2023). Howard Gardner's theory of multiple intelligences, which underpins this research, posits that everyone has different types of intelligence, including verbal intelligence (Salayev, 2024).

Linguistic intelligence plays a crucial role in speaking skills by involving the ability to understand and manipulate language effectively (Hasbullah et al., 2023). It is the intelligence required to express opinions effectively and efficiently, both orally and in writing, through the processing of words and language (Doblon, 2023). Individuals with high linguistic intelligence have strong argumentative abilities, can persuade others, and effectively entertain and teach through words (Almelhes, 2023). Linguistic intelligence facilitates communication and helps unite people when communication is crucial in social life (Wang et al., 2023). It is beneficial for easing communication, which is important in social and business contexts for connecting people (Kusumawarti et al., 2020). This is an example of linguistic intelligence that demonstrates human ability to organize and structure phrases and sentences (Yavich & Rotnitsky, 2020). However, this ability alone does not fully indicate one's level of talent; it also depends on an individual's intuitive knowledge of linguistic forms (Wajiha Kanwal et al., 2020).

1.1. Problem Statement

Consequently, students who are proficient in language also tend to have strong CT skills (Wu et al., 2024). Introducing CT early on can enhance students' interest and literacy. Introducing K-12 students to CT has been slower and more sporadic. In these cases, computational thinking becomes a research activity that includes inventing appropriate new models of computation (Aho, 2020). Despite the potential benefits of computational thinking (CT) in enhancing students' academic success and career readiness, its introduction in K-12 education remains inconsistent and fragmented (Wu et al., 2024). This sporadic implementation creates a challenge in effectively integrating CT into the curriculum, which is essential for students to develop systematic, logical approaches to problem-solving across subjects, including mathematics and science (Mustahib et al., 2023). Furthermore, the role of linguistic intelligence in supporting CT processes, such as problem representation and solution communication, has not been thoroughly examined. Understanding the relationship between linguistic intelligence and CT is crucial as it could provide insights into how language skills contribute to students' computational abilities, which are increasingly important in the digital age (Muhamad et al., 2024). Investigating this relationship will help identify effective strategies for integrating CT into educational frameworks and improving students' academic and career outcomes.

1.2. Related Research

Additionally, indicators such as cooperative learning & critical thinking, creative thinking, and algorithmic thinking showed positive correlations (Liao, Chiang, Chen, & Parker, 2022). studied the relationship between computational thinking and learning satisfaction among non-STEM students. Their results highlighted the crucial role of computational thinking and enjoyment in self-exploration and self-efficacy (Boucinha, Barone, Reichert, Brackmann, & Schneider, 2019). Investigated the relationship between linguistic intelligence, students' learning motivation, and English learning outcomes. Examined the impact of Scratch-based learning media on students' learning motivation. Their findings showed that this approach enhanced students' understanding and enthusiasm for programming. Furthermore, the use of Scratch in classrooms improved elementary school students' computational thinking abilities, particularly in concepts and practices (Pikhart, 2020).

This research differs from previous studies. The topic selection is based on the premise that to welcome the Society 5.0 era, education must contribute to and adapt to changes in human civilization. Thus, education must develop necessary skills, including computational thinking. It is considered a fundamental skill alongside reading, writing, speaking, and mathematical operations (Fernandes, Da Silva Aranha, Lucena, & De Souza Fernandes, 2020). Students need to possess linguistic intelligence, learning enjoyment, and computational thinking to optimize their learning process. The selection of linguistic intelligence as the X1 variable is based on the consideration that it is related to thinking processes, including computational thinking. The X2 variable, learning enjoyment, is an essential aspect that must be present in students, associated with a positive attitude that is a determining factor in enhancing computational thinking.

1.3. Research Objectives

The objective of this research is to determine the relationship between linguistic intelligence and computational thinking among fifth-grade elementary school students in Laweyan District.

2. Theoretical Framework

2.1. Computational Thinking

Purwasih et al. (2024) Computational thinking is an important skill that covers a wide range of areas. computational thinking as a thought process activity that is related to problem formulation and obtaining solutions so that these solutions can be used efficiently by information processors. Suwahyo, (2020) computational thinking is a way to overcome problems in a way that can be actualized with personal computer.

Li et al. (2020) emphasized that in every life activity there is a need for computational thinking, which includes the process of solving problems, designing systems, and understanding human behavior, by utilizing basic computer science concepts in every life activity. Denning & Tedre, (2021) define computational thinking as a systematic study of algorithmic processes that describe and transform information: theory, analysis, design, efficiency, implementation, and application (Lodi & Martini, 2021). Lubis & Sinaga, (2021) computational thinking is a tool in problem solving that involves logical, orderly and comprehensive thinking processes as part of high-level thinking abilities. The problem-solving ability is a logical thinking process in determining the most appropriate way to solve a problem (A. B. Lubis et al., 2019). These difficulties are the problems that we need to solve in order to access information and continue our lives (Önal, 2023).

Based on the opinions of the experts above, it can be synthesized that computational thinking or what is known as *computational thinking* is a thinking activity that involves logical, orderly and comprehensive reasoning related to efforts to solve problems with appropriate representation and build solutions based on computer science concepts.

2.2. Linguistic Intelligence

Halil, (2017) linguistic intelligence is intelligence related to the capacity to process and understand information and communication from interlocutors, both in local and international contexts, through oral or written media. Fadhli et al., (2019) linguistic intelligence is expertise in applying vocabulary effectively and efficiently.Linguistic intelligence is a person's ability to use language effectively and accurately, both spoken and written.

Wahid & Hayani, (2024)reveal that a child's capacity to digest information and messages through listening to stories, reading carefully a narrative, explaining things, showing sensitivity to the order of words and sounds, and having a strong memory for names and dates is known as linguistic intelligence.

Based on the explanation that has been presented, it can be synthesized that linguistic intelligence is a complex ability that involves understanding, use and sensitivity to language, both spoken and written. Linguistic intelligence not only includes the ability to communicate effectively and accurately in a variety of contexts, but also involves the process of language learning, efficient use of vocabulary, and application of language to complete specific tasks.

3. Method

3.1. Research Design

This research method is quantitative research. This study approach employs a quantitative correlational research design. Correlational research involves collecting data to determine the existence and strength of correlations between two or more variables. This study employs a quantitative correlational research design to explore the relationship between linguistic intelligence and computational thinking among fifth-grade students.

a. Defining Variables: The study begins by clearly defining the two key variables: linguistic intelligence, which encompasses students' abilities to effectively use language for reading, writing, and speaking, and computational thinking, which involves skills such as problem-solving, logical reasoning, and systematic analysis.

b. Sample Selection: The research involves a sample of 73 fifth-grade students drawn from four elementary schools located in the Laweyan District, Surakarta City. This sample is selected to ensure a representative mix of participants for analyzing the correlation between the two variables.

c. Data Collection: Data is gathered through a descriptive test specifically designed to measure both linguistic intelligence and computational thinking. The test includes a range of questions and tasks aimed at evaluating the students' abilities in language use and their computational problem-solving skills.

d. Data Analysis: The collected data is analyzed using statistical methods to determine the strength and nature of the relationship between linguistic intelligence and computational thinking. This involves calculating the Pearson correlation coefficient, which measures the degree of linear correlation between the variables, and performing hypothesis testing to assess the statistical significance of the observed correlations.

e. Interpretation of Results: The results are interpreted to understand how variations in linguistic intelligence are associated with differences in computational thinking. This interpretation provides insights into whether stronger linguistic skills correlate with better computational thinking abilities among the students.

f. Reporting: The findings are documented and presented in a comprehensive report, which includes an analysis of the correlations, discussion of the implications for educational practices, and recommendations for future research. The report aims to highlight how enhancing linguistic intelligence might influence computational thinking and offer guidance for integrating these insights into educational strategies.

3.2. Participant

The study focuses on fifth-grade students from the Laweyan District in Surakarta City, with a sample of 73 participants drawn from four elementary schools: SDN Mangkubumen Lor, SDN Dukuhan Kerten, SDN Sayangan Surakarta, and SDN Tegalrejo No.98 Surakarta. These students are typically between 10 to 11 years old and are enrolled in the fifth grade, representing a mix of both male and female students. They are primarily engaged in academic activities consistent with their grade level, such as language arts and mathematics. The sample includes students from diverse socioeconomic backgrounds within the district, reflecting the local cultural and educational context of Surakarta City.

3.3. Data Collection

The conducted research investigates three variables: (1) linguistic intelligence and (2) computational thinking. Data collection in the form of tests was employed to measure data for the variables of computational thinking and linguistic intelligence. A test comprises a series of questions that must be answered by an individual to assess their level of aptitude or to reveal specific characteristics of the test subject (Widoyoko, 2016). The tests administered in this study were designed to measure variable X1, linguistic intelligence, and variable Y, the computational thinking ability of fifth-grade students. The linguistic intelligence and computational thinking tests were conducted as written examinations in an essay format, providing several questions formulated according to their respective indicators. The essay format was chosen with the aim of accurately assessing students' understanding of concepts, requiring psychological involvement, strategies, and representations used in decision-making, problem-solving, and learning new ideas (Ennis, 1996).

3.4. Data Analysis

Data analysis was conducted using SmartPLS 3 software. PLS analysis was used to determine the relationships between the dependent and independent variables (Razzouki et al., 2024).The tests performed included validation with cross-loadings for discriminant validity, reliability testing with construct reliability and validity, and hypothesis testing with the inner model. The study utilized Partial Least Squares (PLS) analysis with the assistance of SmartPLS 3.0.

The following are the steps for data analysis in this study:

3.4.1 Prerequisite Tests for Data Analysis

Prerequisite tests are conducted prior to hypothesis testing. These prerequisite tests consist of data normality tests and linearity tests. The steps in conducting the prerequisite tests for data analysis are as follows:

3.4.1.1. Uji Normalitas

The Normality Test is a test used to determine whether the distribution of data in a data group or variable is normally distributed or not. Normality Test can be used to determine whether the data obtained is normally distributed or comes from a normal population. The normality test was carried out using the Kolmogorov-Smirnov method using SPSS version 25 with a significance threshold of 5%.

3.4.1.2 Linearity test

The linearity test is employed to determine whether two or more variables have a linear relationship. In this research, the linearity test serves as a prerequisite for correlation analysis. This technique is utilized to avoid biased and inaccurate data analysis. The interpretation of the linearity test follows a rule that compares the significance value of the deviation from linearity obtained from the linearity test with the alpha value. The linearity test is conducted using SPSS 25 Statistics for Windows, with a significance level of 0.05. If the Sig value is ≥ 0.05, the relationship is considered linear; if it is ≤ 0.05, the relationship is deemed non-linear.r (Song, 2022).

3.4.1.3. Uji Hipotesis

Hypothesis testing is a strategy for evaluating claims or hypotheses about a population parameter using data from a sample. Through hypothesis testing, researchers can address research questions by either rejecting or accepting the proposed hypotheses. This process allows for empirical assessment of theoretical propositions and enables researchers to draw evidence-based conclusions about the relationships or phenomena under investigation. (Ardyan et al., 2023). Hypothesis testing is carried out when all prerequisite tests have been fulfilled. The simple correlation test and multiple correlation test are hypothesis tests used in this research.

Hypothesis testing is carried out to test whether there is a relationship between the correlation coefficient is calculated using a formula and then analyzed to determine the level of relationship between variables.

Table 1. Interpretation of Correlation Coefficient

No	Koefisien korelasi	Strength of Relationship
1	0,00-0,199	Very Weak
2	0,20-0,399	Weak
3	0,40-0,599	Moderate
4	0,60-0,799	Strong
5	0,80-0,100	Very Strong

Source: (Sugiyono, 2017, p. 257)

If the correlation coefficient value has been obtained, the next step is to interpret the hypothesis, namely if r count < T table or significant value (Sig. 2 tailed) > 0.05 then Ha is rejected, but if r count > T table or significant value (Sig. 2 tailed) < 0.05, then Ha is accepted.

3.5. Validity and Reliability

3.5.1. Validity

Validity testing is carried out to determine the extent to which the research instrument or tool used truly represents the variables being studied. A valid instrument means that the measuring tool used to obtain data to measure is accurate (Sugiyono, 2019, hlm. 125). The higher the validity of the instrument, the more precise the measuring instrument is in measuring the data.

The linguistic intelligence and computational thinking test instruments were tested for content validity through expert judgment. The expert validator of linguistic intelligence is an expert in the field of linguistics in the computational thinking test is an expert in the field of computation. An expert validator in the field of language is needed to assess whether the language used in the instrument is communicative according to the respondents who are intended, and an expert validator in the field of construction is also needed to assess the suitability of the construction of the instrument to be used. The three validators validate the computational thinking instrument. The coefficient for the questionnaire instrument is then determined. Its validity is determined using the Aiken item validity index and the algorithm shown in the Aiken V index acquisition formula is then analyzed to assess the level of validity of an instrument. Based on the Aiken table, an instrument is said to be valid if it has a V index of at least 0.80 with the conditions, a 5% error rate, 5 raters, and 5 choice scales (Aiken, 1985).

3.5.2. Reliability

Reliability test is an index that shows the extent to which a measuring instrument can be trusted. Therefore, reliability test can be used to determine the consistency of the measuring instrument, namely whether the measuring instrument remains constant after repeated measurements are carried out. The purpose of test reliability is to ensure that respondents complete the scale with consistent answers. Sugiyono (2018, p. 268) states that an instrument is reliable if the instrument is used more than once in measuring a variable, it will produce stable research data. Testing the reliability of the descriptive test instrument and the research scale uses the Cronbach's Alpha technique. The Cronbach's Alpha formula is not only used for reliability tests on instruments that have dichotomous scores, but also on polytomous scales. Reliability tests include:

3.5.2.1. Difficulty Level of Essay Tests

The difficulty level of a test item is determined by the proportion of respondents who correctly answer the item out of the total number of respondents (Budiyono, 2016, pp. 99-100).

3.5.2.2. Discrimination Power of Essay Tests

Budiyono (2020, p. 102) states that the discrimination power of a test item is considered good if a higher proportion of respondents or students from the high-performing group answer the item correctly compared to the low-performing group. The discrimination power indicator is determined by examining the correlation coefficient between the item score and the overall test score.

The reliability criteria of the instrument are interpreted based on the reliability coefficient produced using the Alpha formula. The range of the reliability coefficient is $0 < \alpha < 1$. According to Steiner's interpretation of reliability coefficients, an alpha value of 0.7 is considered acceptable. Therefore, instrument items with an alpha value greater than 0.7 can be considered reliable.

Internal consistency reliability is used as an initial criterion for evaluating the measurement model. Reliability testing uses indicators such as Cronbach's alpha (α), rho_A, and Composite Reliability (CR), as detailed in Table 1 below.

Table 2. Reliability Test

	α ≥ 0.70	rho_A ≥ 0.70	CR ≥ 0.70	AVE ≥ 0.50
Rhetoric	0.846	0.867	0.906	0.762
Mnemonics	0.741	1.286	0.865	0.765
Explanation	1.000	1.000	1.000	1.000
Metalinguistics	0.899	1.036	0.950	0.905

Reliability testing uses indicators such as Cronbach's alpha (α), rho_A, and Composite Reliability (CR), with values considered reliable if they exceed 0.70 (Gorai et al., 2024). Table 1 shows the results of the reliability testing. Based on Table 1, it is evident that reliability testing using Cronbach's alpha (α), rho_A, and Composite Reliability (CR) is deemed reliable if the values exceed 0.70. The analysis of Table 1 reveals that all constructs range from 0.741 to 1.000 for α, 0.867 to 1.286 for rho_A, and 0.865 to 1.000 for CR, indicating that each construct measurement surpasses the 0.7 threshold. The results demonstrate that the linguistic intelligence instrument is reliable. The next evaluation focuses on convergent validity, which aims to determine the validity of the relationship between each indicator and its latent variable. This is measured using Average Variance Extracted (AVE), with indicators meeting convergent validity criteria if AVE ≥ 0.50. The results of convergent validity range from 0.762 to 0.905.

Cross-loading tests for discriminant validity are presented in Table 2 below. The criterion is accepted if the measurement items correlate more strongly/higher with the measured variable and less with other variables (Arshad et al., 2024).

Table 3. Validity Test

	X1	X2	X3	X4	Y
X1.1	0.833	0.327	0.286	0.235	0.501
X1.2	0.920	0.244	0.206	0.041	0.456
X1.3	0.864	0.299	0.139	0.145	0.328
X2.1	0.328	0.767	0.319	0.306	0.167
X2.2	0.296	0.970	0.706	0.418	0.444
X3.1	0.252	0.657	1.000	0.247	0.488
X4.1	0.149	0.338	0.158	0.930	0.233
X4.2	0.163	0.447	0.286	0.972	0.366
Y	0.506	0.403	0.488	0.329	1.000

Table 3 shows that the measurement items for the first linguistic intelligence indicator, rhetoric, range from 0.833 to 0.864, indicating that these measurements are higher than those for other variables. The second linguistic intelligence indicator, mnemonics, ranges from 0.767 to 0.970, showing that these measurements correlate more strongly than the other three indicators. The explanation indicator, with a value of 0.706, also shows that the measurement correlates more strongly than other variables, and the metalinguistics indicator, with values of 0.930 and 0.972, similarly shows that the measurement correlates more strongly than other variables. The variable Y, which is computational thinking, also shows a value of 1.00, indicating that the measurement correlates more strongly than other variables.

4. Findings

4.1. Linguistic Intelligence Data of Grade V Learners

Linguistic intelligence data is data obtained from filling out linguistic intelligence essay tests by grade V students with a total of 73 respondents. The mode of the data with a score of 62; median 62; mean 59.88; minimum value 21; maximum value 90; standard deviation 18.36; and variance 337.1. The frequency distribution table and histogram of linguistic intelligence data in the research sample can be seen in table 4 below:

Table 4. Linguistic Intelligence Frequency Distribution Data

No.	Class Interval	Frequency (f)	Frequency Percetage (f%)	Cumulative Frequency Percentage (fk%)
1.	21 - 31	4	11%	11%
2.	32 - 42	5	10%	21%
3.	43 - 53	6	12%	33%
4.	54 - 64	15	22%	55%
5.	65 - 75	11	18%	73%
6.	76 - 86	18	26%	99%
7.	87 - 97	1	1%	100%
	Total	73	100%	

The following are the results of the research sample data category of linguistic intelligence data for fifth grade students of SD Se-Kecamatan Laweyan which are presented in Table 5.

Table 5. Category Data of Students' Linguistic Intelligence Score

No	Score Earned	Category	Frequency	Frequecy Percentage
1	X > 78,15	High	12	16%
2	41,57 < X < 78,15	Medium	45	63%
3	X < 41,57	Low	15	21%

(Source: Processed Primary Data, 2024)

Based on table 5, it shows that the highest frequency of 46 fifth grade students of elementary school in Laweyan sub-district has a level of linguistic intelligence in the medium category with a score interval of 41.48 - 78.2. Then the low linguistic intelligence category with a score interval of less than 41.48 occupies the second position which has a score of 15. While the high linguistic intelligence category with a score interval of more than 78.2 shows a score of 12 students.

Based on the data above, it can be synthesized that the level of linguistic intelligence of class V elementary schools in Laweyan District in the 2023/2024 academic year is classified as being in the medium category.

4.2. Data on Computational Thinking of Class V Learners

Computational thinking data is data obtained from fifth grade students after filling out the questions given by the researcher, with a total of 73 respondents. Data mode with a score of 52; median 52; mean 50.15; minimum value 10; maximum value 90; standard deviation 21.6; and variance 469.93. The frequency distribution table and histogram of learning pleasure data in the research sample can be seen in table 6 below.

Table 6. Frequency Distribution Data of Computational Thinking

No.	Class Interval	Frequency (f)	Frequency Percentage (f%)	Cumulative Frequency Percentage (fk%)
1.	10-21	11	15%	15%
2.	22-33	7	10%	25%
3.	34-45	9	12%	37%
4.	46-57	19	26%	63%
5.	58-69	13	18%	81%
6.	70-81	11	15%	96%
7.	82-93	3	4%	100%
	Total	73	100%	

(Source: Processed Primary Data, 2024

The following are the results of the research sample data category of computational thinking data for fifth grade students of elementary schools in Laweyan District which are presented in Table 7.

Table 7. Category Data of Students' Computational Thinking Score

No.	Score Range	Category	Frequency	Frequency Percentage
1.	$X < 17,6$	Very Low	8	11%
2.	$17,6 \leq X < 39,3$	Low	13	18%
3.	$39,3 \leq X < 60,98$	Medium	25	34%
4.	60,98 ≤ X < 82,6	High	24	33%
5.	82,6 < X	Very High	3	4%

(Source: Processed Primary Data, 2024)

Based on table 7 shows that the highest frequency of 25 fifth grade students of elementary school in Laweyan sub-district has a level of computational thinking in the medium category with a score interval of 39.3 - 60.98. The high computational thinking category shows the second highest frequency of 24 students with a score interval of 60.98-82.6. Then the low computational thinking category shows the frequency of 13 students with a score interval of 17.6 - 39.3. While the category of very low computational thinking with an interval score of less than 17.6 shows a frequency of 8 students, as well as in the category of very high thinking with an interval of more than 82.6 shows a frequency of 3 students. It can be synthesized from the data above that the level of computational thinking of fifth grade students of SD Se-Kecamatan Laweyan is in the medium category.

4.3. Prerequisite Test Results

Prerequisite test analysis is carried out as a condition before carrying out hypothesis testing in research. The analysis prerequisite test carried out in this study is in the form of normality test and linearity test. The following are the results of the prerequisite test analysis carried out in the study as follows:

Normality test is one of the prerequisites before hypothesis testing is carried out. The normality test is carried out to ascertain whether the data is normally distributed or not. The normality test of the research data was carried out using the Kolmogorof Smirnov normality test method with the help of SPSS 25. The following are the results of the normality test presented in table 8 below:

Table 8. Normality Test Result Data

One-Sample Kolmogorov-Smirnov Test

		Unstandardized Residual
N		73
Normal Parameters[a,b]	Mean	.0000000
	Std. Deviation	18.76108590
Most Extreme Differences	Absolute	.051
	Positive	.051
	Negative	-.041
Test Statistic		.051
Asymp. Sig. (2-tailed)		.200[c,d]

a. Test distribution is Normal.
b. Calculated from data.
c. Lilliefors Significance Correction.
d. This is a lower bound of the true significance.

(Source: Processed Primary Data, 2024)

Table 8 shows that in the normality test the Asymp. Sig. (The significance value (0.200) is greater than the a significance level, namely 0.200 > 0.05. So it can be concluded that the residual value of the data is normally distributed.

The linearity test was conducted to test the linearity relationship between the Linguistic Intelligence (X) and Computational Thinking (Y) variables based on the data acquisition that has been done. The linearity test can be interpreted and determined that the value is linear, by comparing the significance value of linearity divergence > alpha (0.05). The following data presents the linearity test results in table 9 for the linearity test of variable X with Y.

Table 9. Linearity Test Result Data of Linguistic Intelligence with Computational Thinking

ANOVA Table							
			Sum of Squares	df	Mean Square	F	Sig.
Linguistic Intelligence with Computational Thinking	Between Groups	(Combined)	12296.795	20	614.840	1.484	.128
		Linearity	8210.119	1	8210.119	19.821	.000
		Deviation from Linearity	4086.676	19	215.088	.519	.941
	Within Groups		21538.547	52	414.203		
	Total		33835.342	72			

(Source: Processed Primary Data, 2024)

Based on table 9, the linearity test of linguistic intelligence (X) and computational thinking (Y) obtained a significance value of Deviation from Linearity of 0.941> 0.05, it is stated that the relationship between linguistic intelligence and computational thinking is linear.

4.4. Hypothesis Test

Model fit test was performed to assess whether the model and data are suitable for examining the effect of variables (Cusipag et al., 2024). The criterion is that the SRMR (Standardized Root Mean Square Residual) must be less than 0.10. Based on Table 10, the SRMR value in this study is 0.083 < 0.10, indicating that the model and data are suitable for examining the effect of variables.

Table 10. Model Fit Test

	Saturated model	Estimated model
SRMR	0.083	0.083
d_ULS	0.309	0.309
d_G	0.225	0.225
Chi-square	98.153	98.153
NFI	0.743	0.743

Hypothesis testing in this study was conducted using SmartPLS 3 with inner model test. The inner model test was performed to assess the significance of the effect of exogenous variables on endogenous variables (Vanisri & Padhy, 2024). The criteria used to determine the effect of the model are p < 0.05 or T > 1.96. The inner model test results are presented in Table 4 below.

Table 11. Inner Model Test

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
X1 -> Y	0.398	0.396	0.097	4.104	0.000
X2 -> Y	-0.062	-0.035	0.175	0.357	0.721
X3 -> Y	0.381	0.359	0.175	2.176	0.030
X4 -> Y	0.196	0.194	0.088	2.215	0.027

Based on Table 11, the p-value and T-value for the linguistic intelligence indicator of rhetoric with CT are 0.000 and 4.104, respectively. The p-value and T-value for the linguistic intelligence indicator of mnemonics with CT are 0.721 and 0.357, respectively. The p-value and T-value for the linguistic intelligence indicator of explanation with CT are 0.030 and 2.176, respectively. The p-value and T-value for the linguistic intelligence indicator of metalinguistics with CT are 0.027 and 2.215, respectively. From these results, it can be summarized that out of the four linguistic intelligence indicators, only mnemonics does not have a significant relationship with CT, while the other three indicators (rhetoric, explanation, and metalinguistics) do have a significant relationship with CT. The hypothesis testing results based on the path coefficient can also be seen in Figure 1 below:

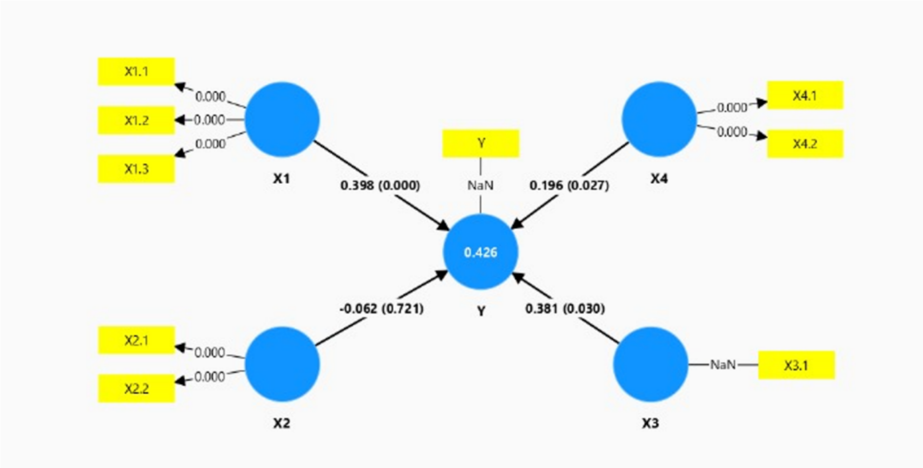

Figure 1. Hypothesis Testing Based on Path Coefficient

Based on Figure 1, the hypothesis based on the path coefficient can be interpreted to mean that linguistic intelligence has a relationship with CT. According to the path coefficient test for the four linguistic intelligence indicators—rhetoric, mnemonics, explanation, and metalinguistics—the mnemonics indicator shows no relationship with CT, with a p-value of 0.721 (p-value > 0.05), indicating no significant relationship. In contrast, the other three indicators show a positive relationship, with each indicator having $p < 0.05$: rhetoric with $p = 0.000$, explanation with $p = 0.030$, and metalinguistics with $p = 0.027$.

5. Discussion

The presence of a relationship between linguistic intelligence and CT means that an increase in linguistic intelligence is accompanied by an increase in CT, and vice versa. Intelligence is often associated with problem-solving abilities and abstract reasoning (Boom et al., 2018). The concept of the mediating role of linguistic intelligence encompasses the interaction between linguistic intelligence, academic self-efficacy and student engagement, with linguistic intelligence acting as a bridge between these constructs or acting as an intermediary (Mujiono, 2024). Jensen (2021) presents reasoning and problem solving as factors in an open definition of intelligence (Jensen, 2021). It can be synthesized that problem-solving and abstract reasoning are frequently linked with intelligence. This underscores a strong relationship between these two concepts. Von Ahn and Dabbish (2008) state that CT leverages human intelligence to solve computational problems that are beyond the capabilities of computer programs but can be effectively handled by humans (Von Ahn & Dabbish, 2008).

Research indicates a positive relationship between syntactic cognitive structuring in natural language and programming abilities in children aged 3 to 6 years (Marinus et al., 2018). These findings suggest that children who are better at syntactic structuring in natural language tend to have stronger programming skills, possibly due to the connection between cognitive abilities in understanding and using natural language structures. Additionally, other research has shown a weak to moderate positive correlation between CT and verbal abilities in children aged 10 to 16 years (Román-González et al., 2018). The positive correlation between linguistic intelligence and CT indicates that better verbal-linguistic abilities are associated with stronger CT skills, though the strength of this relationship is within the weak to moderate range. In relation to the study, fifth graders as research subjects fall into the age range of 10 to 16 years. This age range is a critical period for the development of children's language abilities. During this stage, abstract thinking, logic, and reasoning skills further develop, including in the context of CT.

Linguistic intelligence also plays a role in shaping a child's mindset. If a child has good language skills, their mindset is likely to be well-formed, enabling them to express themselves effectively, both in written form and oral communication, structured in coherent sentences It can be understood that verbal-linguistic intelligence is the language ability possessed by every human being either orally or in writing, and can use words effectively, besides using language competently in listening, writing, reading, and speaking (Nu et al., 2022). Thoughts are not merely expressed through words but are born from the words themselves. Every thought tends to connect one thing with another, forming relationships between concepts or objects. In connection with the study, good language skills can facilitate a systematic, structured CT process and logically relate various concepts. The following is a discussion of the relationship between each linguistic intelligence indicator and CT.

5.1. Relationship between Rhetoric and Computational Thinking

The first indicator of linguistic intelligence, rhetoric, has a positive and significant relationship with CT. This finding reveals that rhetoric, as the art of persuasion and effective communication, is closely linked to the fundamental concepts of CT. Brummett (2015) explains how rhetoric helps simplify complex concepts into more easily understood ideas, similar to the abstraction process in CT (Brummett, B. (2022) . Furthermore, emphasizes that effective rhetoric relies on the ability to decompose arguments into smaller, structured parts for better analysis and communication. In relation to pattern recognition. Based on these statements, it can be concluded that rhetoric and CT have a mutually reinforcing relationship in developing communication and problem-solving skills.

5.2. Relationship between Mnemonics and Computational Thinking

The mnemonics indicator does not show a relationship with CT based on hypothesis testing results. Mnemonics and CT operate within different cognitive domains. Mnemonics focuses on techniques for enhancing memory and information retention, while CT emphasizes a systematic approach to problem-solving and system design. These cognitive domains operate independently, with mnemonics being more focused on information storage and retrieval, whereas CT involves more complex and abstract problem-solving processes. Research by Atmatzidou & Demetriadis, (2016) reinforces the finding that, regarding the development of CT through robotics education, there is no correlation between the use of mnemonics techniques and the enhancement of CT skills (Atmatzidou & Demetriadis, 2016). This study highlights the importance of problem-based and experiential learning approaches in developing CT, without indicating a significant role for mnemonics strategies. Mnemonics ability is not a significant predictor of success in tasks requiring CT. Conversely, factors such as logical reasoning and abstract problem-solving are found to be more influential. These findings reinforce the idea that mnemonics and CT operate independently within human cognitive processes.

5.3. Relationship between Explanation and Computational Thinking

The explanation indicator shows a positive relationship with CT. Lombrozo, (2016) states that effective explanations often involve abstraction, which is the simplification of complex concepts into more understandable ideas, similar to the abstraction process in CT (Lombrozo, 2016). Furthermore, good and effective explanation skills utilize decomposition by breaking topics into smaller, more comprehensible parts, aligning with the principle of decomposition in programming (Fisher & Keil, 2016). In terms of pattern recognition, effective explanations often use certain patterns or structures to facilitate understanding, similar to the pattern recognition skills in CT.

5.4. Relationship between Metalinguistics and Computational Thinking

The third indicator, metalinguistics, has a positive relationship with CT. Metalinguistics is used as a tool to discuss language itself, showing a strong connection with the concepts of CT. Metalinguistics involves abstraction in discussing language, similar to the concept of abstraction in CT (Preston, 2019). Furthermore, metalinguistics analysis often involves decomposing language into smaller components, such as syntax and semantics, aligning with the decomposition principles in programming (Oliver, 2022). Metalinguistics also helps in recognizing patterns in the use and structure of language, akin to the pattern recognition skills in CT (Gisborne & Trousdale, 2008).

In the discussion section, there is a link between the results obtained and the basic concepts and/or hypotheses, and there is a match or conflict with the research results of other researchers. Discussions should include well-established citations of relevant research.

In this study, while the findings offer valuable insights into the relationship between linguistic intelligence and computational thinking among fifth-grade students, several limitations must be acknowledged. Firstly, the sample size was relatively small, comprising 73 students from only four elementary schools in the Laweyan District of Surakarta. This limited and localized sample may restrict the generalizability of the results. A larger and more diverse sample, encompassing students from different regions and socioeconomic backgrounds, would provide a more comprehensive understanding of this relationship. Secondly, the study employed a descriptive test instrument to measure both linguistic intelligence and computational thinking. Although this method yields useful data, it may not fully capture the complexity of these constructs. Utilizing standardized or multi-faceted assessment tools could offer a more thorough evaluation of linguistic intelligence and computational thinking. Thirdly, while the study identified significant relationships between linguistic intelligence and computational thinking for certain indicators—namely rhetoric, explanation, and metalinguistics—no significant relationship was found for the mnemonics indicator. This discrepancy raises questions about the reasons behind the lack of significance for mnemonics, which may be attributable to limitations in the test design or specific characteristics of mnemonics themselves. Additionally, the cross-sectional design of the research only provides a snapshot of the relationship between variables at a single point in time, precluding causal inferences. Longitudinal studies are necessary to explore how changes in linguistic intelligence over time may influence computational thinking.

The study opens several avenues for future research. Expanding the sample to include a larger and more diverse group of students from various regions and educational contexts could enhance the generalizability of the findings. Furthermore, employing more comprehensive measurement tools for both linguistic intelligence and computational thinking could offer deeper insights. Investigating the reasons behind the non-significant relationship for the mnemonics indicator could also provide valuable information. Additionally, conducting longitudinal studies could shed light on how improvements in linguistic intelligence might affect computational thinking over time.

The significant findings of this study highlight a moderate overall relationship between linguistic intelligence and computational thinking, with a Pearson correlation coefficient of 0.493 and a significance value of 0.000 ($p < 0.05$). This indicates that higher levels of linguistic intelligence are associated with better computational thinking skills among fifth-grade students. Specifically, the positive correlations observed for the rhetoric, explanation, and metalinguistics indicators suggest that these aspects of linguistic intelligence are crucial for developing computational thinking abilities. The implications of these findings are twofold: educators should consider incorporating activities that enhance rhetorical, explanatory, and metalinguistic skills into the curriculum to support and improve students' computational thinking skills. Furthermore, the study provides a foundation for future research to develop more effective educational strategies and tools that bridge linguistic intelligence and computational thinking in educational settings.

6. Conclusion

The findings of this study reveal a significant correlation between linguistic intelligence and CT. Among the four linguistic intelligence indicators—rhetoric, mnemonics, explanation, and metalinguistics—only mnemonics do not show a significant relationship. The mnemonics indicator, with a p-value of 0.721 (moderate category), does not correlate with CT ($p > 0.05$). In contrast, the other indicators exhibit a positive relationship with CT, each with $p < 0.05$: rhetoric has $p = 0.000$, explanation has $p = 0.030$, and metalinguistics has $p = 0.027$. The findings of this study underscore the significant relationship between linguistic intelligence and computational thinking (CT), particularly through the indicators of rhetoric, explanation, and metalinguistics, which all showed strong positive correlations with CT. This suggests that educational strategies should emphasize the development of these specific linguistic skills to enhance students' computational thinking abilities. The lack of a significant relationship between mnemonics and CT indicates that mnemonic techniques may not be as effective in this context. Therefore, educators should focus on integrating activities that bolster rhetorical, explanatory, and metalinguistic skills into the curriculum. Additionally, these findings highlight the need for further research to explore why mnemonics did not correlate significantly with CT and to examine how these relationships evolve over time and across different educational settings.

Limitation

This study provides useful insights into the relationship between linguistic intelligence and computational thinking among fifth-grade students; however, it is important to acknowledge several limitations that could impact the validity and generalizability of the findings. First, Sample Size and Generalizability: The study was conducted with a sample of 73 students drawn from just four elementary schools located in the Laweyan District of Surakarta. This relatively small and geographically confined sample limits the generalizability of the results. The findings may not accurately represent the broader population of fifth-grade students in other regions or educational contexts. To enhance the applicability of the results, future research should include a larger and more diverse sample that spans different geographic areas and socioeconomic backgrounds. The research employed a descriptive test instrument to measure both linguistic intelligence and computational thinking. While this method provided valuable data, it may not fully capture the complex nature of these constructs. Descriptive tests often have limitations in scope and may not address all dimensions of linguistic intelligence and computational thinking. Future studies could benefit from using more comprehensive and standardized assessment tools that offer a multi-dimensional approach to evaluating these abilities. The study found significant relationships between linguistic intelligence and computational thinking for certain indicators, such as rhetoric, explanation, and metalinguistics, but did not find a significant relationship for mnemonics. This discrepancy raises questions about why mnemonics did not show a significant correlation. It is unclear whether this result is due to limitations in the test design, the specific characteristics of mnemonics, or other factors. Further research is needed to investigate why mnemonics did not demonstrate a significant relationship and whether this indicator requires a different methodological approach. The research utilized a cross-sectional design, which means it provides a snapshot of the relationship between linguistic intelligence and computational thinking at a single point in time. This design does not allow for causal inferences or an understanding of how changes in linguistic intelligence might influence computational thinking over time. Longitudinal studies would be necessary to explore how variations in linguistic intelligence impact computational thinking as students progress through different educational stages. The study did not account for other potential variables that could affect the relationship between linguistic intelligence and computational thinking, such as students' prior knowledge, teaching methods, or socio-economic factors. These confounding variables could influence the observed relationship and may provide additional context for understanding the results. Future research should consider controlling for these variables to clarify the specific contributions of linguistic intelligence to computational thinking.

Addressing these limitations in future research will be essential for obtaining a more nuanced and generalizable understanding of the relationship between linguistic intelligence and computational thinking and for developing effective educational strategies that support both areas.

Recommendation

The study on the relationship between linguistic intelligence and computational thinking among fifth-grade elementary school students suggests integrating these two aspects into the curriculum through interdisciplinary approaches, the use of educational technology, and enhancing the role of parents in supporting learning at home. Additionally, it recommends the development of accurate measurement instruments and further research to understand other factors influencing this relationship. The findings of this study could also serve as a foundation for educational policies that promote the development of multiple intelligences in the national curriculum and the implementation of technology in primary education.

To address the limitations identified in this study, several key recommendations are proposed. Firstly, expanding the sample size to include a larger and more diverse group of students from various regions and socio-economic backgrounds will enhance the generalizability of the findings. Secondly, employing more comprehensive and standardized measurement tools can provide a fuller understanding of the complex nature of linguistic intelligence and computational thinking. Additionally, investigating why mnemonics did not show a significant relationship with computational thinking is essential for refining assessment methods. Longitudinal studies are recommended to explore how changes in linguistic intelligence affect computational thinking over time, while controlling for potential confounding variables such as prior knowledge and teaching methods will help clarify the specific contributions of linguistic intelligence. Lastly, integrating these insights into educational strategies by focusing on enhancing rhetorical, explanatory, and metalinguistic skills, and incorporating technology and parental support, could lead to more effective teaching practices and policies that promote the development of both linguistic and computational skills.

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Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this research. The study was conducted independently, and no external parties influenced the objectivity or integrity of the findings.

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