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Reflective and Impulsive Cognitive Tempo and Mathematics Achievement in a Frontier, Outermost, and Disadvantaged Junior High School in Indonesia

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Abstract

Conceptual tempo reflects individual differences in the balance between response speed and accuracy and may be particularly relevant to mathematics learning, where careful reasoning and verification are required. This study aimed to describe the distribution of conceptual-tempo profiles, compare mathematics achievement between Reflective and Impulsive students, and examine the statistical association between these two cognitive-style groups and mathematics achievement in a 3T (frontier, outermost, and disadvantaged) junior high school in Indonesia. A quantitative correlational design was employed. From a population of 210 students in Grades VII-IX, 138 students were selected through proportionate stratified random sampling followed by simple random sampling. Conceptual tempo was assessed using the Matching Familiar Figures Test (MFFT), while mathematics achievement was measured using a researcher-developed 30-item test. MFFT classification identified 51 Reflective students (36.96%), 19 Impulsive students (13.77%), 68 Slow-Inaccurate students (49.27%), and no Fast-Accurate students. Inferential analysis focused on the 70 Reflective and Impulsive students. Reflective students achieved higher mathematics scores ($M = 61.12$, $SD = 10.84$) than Impulsive students ($M = 34.88$, $SD = 9.18$). Dummy-coded regression showed a statistically significant association between cognitive-style membership and mathematics achievement, $F(1, 68) = 87.70$, $p < .001$, $R^2 = .563$, with an estimated group difference of 26.24 points ($B = 26.238$). These findings extend evidence on Reflective-Impulsive differences to an underrepresented 3T educational context while also revealing substantial conceptual-tempo heterogeneity within the broader student sample.

Keywords: Conceptual Tempo; Reflective-Impulsive Cognitive Style; Mathematics Achievement; Matching Familiar Figures Test; 3T Education

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INTRODUCTION

Mathematics achievement is an important component of students' academic development because mathematics learning requires logical reasoning, accurate information processing, and the ability to apply concepts across increasingly complex problems. International assessments continue to emphasize mathematics proficiency as an important indicator of students' preparedness for higher-order reasoning, technological literacy, and future learning in science- and technology-related fields (OECD, 2020). However, mathematics achievement is not distributed uniformly across educational settings. Students in rural and under-resourced schools may experience differences in instructional support, access to learning materials, and opportunities for individualized assistance, creating conditions in which learner characteristics can become particularly relevant to academic performance (Hitt et al., 2020; Guenther et al., 2023).

This issue is especially pertinent in Indonesian frontier, outermost, and disadvantaged (3T) educational settings, where students may learn under conditions characterized by constrained resources and heterogeneous academic readiness. Although contextual conditions alone do not determine achievement, they can shape the learning environment in which students process information, solve problems, and regulate their responses. Understanding individual cognitive characteristics that are associated with mathematics performance is therefore important for developing more responsive instructional practices in such settings.

One cognitive characteristic relevant to mathematics learning is conceptual tempo, which refers to individual differences in the balance between response speed and accuracy during decision making (Kagan, 1966). Conceptual tempo concerns not simply how quickly a student responds, but how response latency interacts with the accuracy of the selected answer. These differences are particularly relevant to mathematics because successful problem solving often requires students to interpret information carefully, select appropriate procedures, monitor intermediate steps, and verify final answers. Cognitive characteristics related to response regulation have also been associated with students' arithmetic understanding and mathematical problem-solving performance (Wong, 2023).

Conceptual tempo is commonly assessed using the Matching Familiar Figures Test (MFFT), which classifies individuals according to combinations of response latency and response accuracy. Four profiles can be identified: Reflective, Impulsive, Slow-Inaccurate, and Fast-Accurate (Cairns & Cammock, 1978). Reflective students generally demonstrate relatively longer response times accompanied by greater accuracy, indicating more deliberate evaluation before responding (Schürmann et al., 2025; Mohamad and Tasir, 2023). In contrast, Impulsive students tend to respond more rapidly and may devote less time to examining alternatives, increasing the likelihood of errors when tasks require careful verification. Slow-Inaccurate students combine longer response times with lower accuracy, whereas Fast-Accurate students combine shorter response times with higher accuracy.

Among these profiles, the Reflective-Impulsive contrast has received particular attention because it represents opposing patterns in the speed-accuracy trade-off. Reflective processing is generally associated with greater deliberation and monitoring, whereas impulsive processing is characterized by relatively rapid responding with less extensive evaluation. These characteristics are especially relevant to mathematical tasks involving analytical reasoning, multistep computation, and precision. Previous studies have reported that Reflective students tend to demonstrate stronger performance than Impulsive students in tasks requiring mathematical reasoning and careful problem solving (Aini et al., 2020; Çelik & Arslan, 2022). Similar differences have also been reported in Indonesian mathematics-education settings, where Reflective and Impulsive students display distinct patterns of numeracy and problem-solving performance (Dewi & Nugraheni, 2023).

The theoretical prominence of the Reflective-Impulsive distinction is grounded in the original conceptual-tempo framework (Kagan, 1966; Messer, 1970). Subsequent research has continued to identify these two profiles as meaningful contrasting tendencies in information processing, particularly in tasks requiring controlled reasoning and evaluation of alternative responses (Ho & Kozhevnikov, 2023). At the same time, the remaining MFFT profiles should not be considered irrelevant. Earlier work has shown that Fast-Accurate and Slow-Inaccurate combinations can represent distinct speed-accuracy patterns that warrant separate interpretation (Fitzpatrick et al., 1977). Research on reflective decision making likewise emphasizes the importance of careful processing for accuracy in complex judgments (Käosaar et al., 2023).

Accordingly, a complete description of the MFFT profile distribution is important before narrowing the inferential analysis to the Reflective-Impulsive contrast. This distinction is particularly relevant to the present study because the sampled students were distributed across more than two conceptual-tempo profiles. Describing the full distribution preserves information about cognitive heterogeneity, while focusing the inferential analysis on Reflective and Impulsive students enables a theoretically interpretable comparison between the two opposing poles of the conceptual-tempo continuum.

Previous studies have demonstrated meaningful relationships between cognitive-style characteristics and mathematical performance (Hasbullah, 2020; Gronchi et al., 2024). Nevertheless, two gaps remain relevant. First, empirical evidence on conceptual tempo in 3T educational settings remains limited compared with research conducted in more commonly represented school contexts. Second, studies frequently emphasize only the Reflective-Impulsive contrast without first documenting the broader distribution of speed-accuracy profiles within the sampled population. As a result, less is known about how the two focal groups are situated within the complete conceptual-tempo composition of students in underrepresented educational settings.

The present study addresses these gaps by combining two levels of analysis. At the descriptive level, it maps the complete distribution of MFFT conceptual-tempo profiles among junior high school students in a 3T setting. At the inferential level, it focuses specifically on differences in mathematics achievement between Reflective and Impulsive students and examines the statistical association between membership in these two groups and mathematics achievement. This approach preserves the broader empirical characteristics of the sample while maintaining a theoretically focused inferential comparison.

Mathematics achievement was assessed using a 30-item instrument representing four curriculum domains - Numbers and Arithmetic, Algebra, Geometry, and Statistics and Probability - and three cognitive levels: Remembering (C1), Understanding (C2), and Applying (C3). By representing several content domains and levels of cognitive demand, the assessment provides a broader measure of mathematics achievement than a task limited to a single mathematical topic.

Accordingly, this study aimed to: (1) describe the distribution of MFFT conceptual-tempo profiles among junior high school students in a 3T educational setting; (2) compare mathematics achievement between Reflective and Impulsive students; and (3) examine the statistical association between Reflective-Impulsive cognitive-style membership and mathematics achievement.

Based on conceptual-tempo theory and previous empirical evidence, the following hypotheses were proposed:

1. H1: Reflective students demonstrate significantly higher mean mathematics achievement than Impulsive students.
2. H0: There is no significant difference in mean mathematics achievement between Reflective and Impulsive students.

These hypotheses establish a direct link between the theoretical framework, the comparison of the two focal conceptual-tempo groups, and the inferential analysis used in the study.

METHOD

Research Design and Analytical Framework

This study employed a quantitative correlational research design to examine the association between students' conceptual tempo and mathematics achievement. A correlational design was appropriate because conceptual tempo was treated as a naturally occurring learner characteristic and neither cognitive style nor mathematics achievement was experimentally manipulated.

Conceptual tempo is grounded in Kagan's reflection-impulsivity framework, which describes individual differences in response latency and accuracy during decision making (Kagan, 1965). Subsequent research using the MFFT has continued to recognize the Reflective-Impulsive distinction as a central dimension of conceptual tempo (Messer, 1970; Cairns & Cammock, 1978).

Recent studies have further examined reflection-impulsivity through the combined assessment of response speed and accuracy (Viator et al., 2022), while research on processing speed indicates that speed-accuracy characteristics are relevant to academic performance (Lovett et al., 2022). Accordingly, the present study retained all four MFFT profiles for descriptive reporting but restricted the inferential analysis to Reflective and Impulsive students because the principal hypothesis concerned the contrast between these two opposing poles of conceptual tempo. Slow-Inaccurate and Fast-Accurate students were therefore not treated as equivalent to either focal group. This analytical focus is consistent with studies examining reflective and impulsive characteristics in mathematics learning (Widyastuti et al., 2024; Mardiyati, 2018; Widodo & Hartati, 2024).

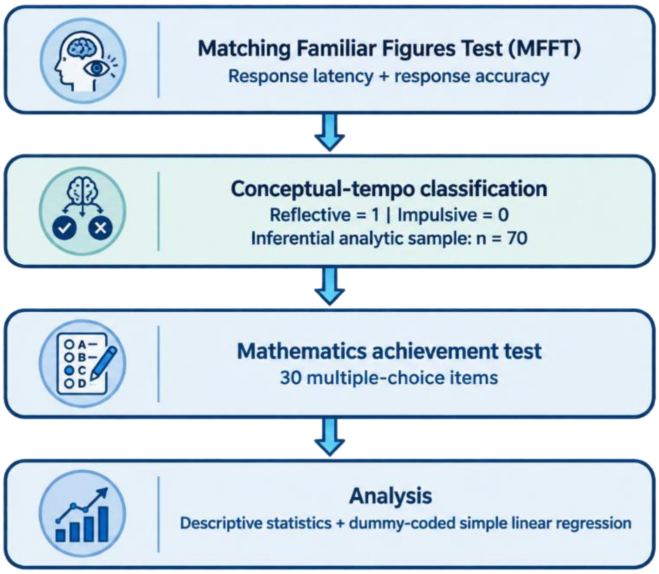

Figure 1. Research design and analytical framework

Figure 1 summarizes the analytical framework of the study, linking conceptual-tempo classification to mathematics achievement and the subsequent descriptive and inferential analyses. For the regression analysis, cognitive style was dummy-coded as Reflective = 1 and Impulsive = 0. This framework is consistent with contemporary perspectives linking cognitive processing, inhibitory control, and reasoning performance (Gronchi et al., 2024).

Study Population and Sampling Procedure

The study population consisted of 210 students enrolled in Grades VII-IX at a public junior high school located in a 3T (frontier, outermost, and disadvantaged) area in Indonesia. The population was distributed across eight classes: VII A, VII B, VII C, VIII A, VIII B, VIII C, IX A, and IX B.

The initial required sample size was estimated using Slovin's formula (Equation 1) with a 5% margin of error:

$$n = \frac{N}{1 + N(e)^2} \qquad (1)$$

where n represents the required sample size, N represents the total population, and e represents the margin of error. Substituting the population size into the equation resulted 138 samples. Thus, 138 students were selected from the population before conceptual-tempo classification.

A two-stage probability-sampling procedure was then employed. In the first stage, Proportionate Stratified Random Sampling was used, with each class treated as a stratum. The number of students selected from each class was determined according to that class's proportion of the total population. In the second stage, Simple Random Sampling was conducted within each stratum to select individual participants. This combination of proportional allocation and random selection supports representation across class strata while reducing systematic selection bias (Etikan & Bala, 2020; Taherdoost, 2020; Creswell & Creswell, 2023).

Table 1 presents the population size, proportional allocation, and number of sampled students from each of the eight classes. The proportional procedure resulted in a total initial sample of 138 students.

Table 1. Population and Proportionate Sample Distribution

Class	Population (N)	Proportion (N/210)	Sample allocation (n)
VII A	23	0.1095	15
VII B	23	0.1095	15
VII C	24	0.1143	16
VIII A	24	0.1143	16
VIII B	24	0.1143	16
VIII C	23	0.1095	15
IX A	35	0.1667	23
IX B	34	0.1619	22
Total	210	1.0000	138

Figure 2 illustrates the complete sampling and analytic-selection process, beginning with the population of 210 students, followed by sample-size determination, proportional allocation, random student selection, MFFT classification, and selection of the Reflective-Impulsive analytic sample.

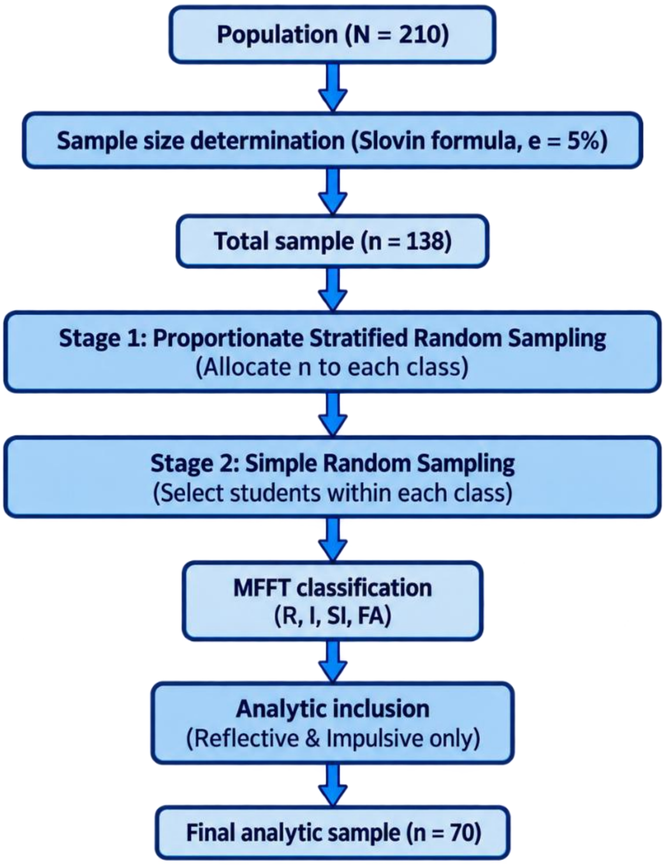

Figure 2. Flowchart of sample-size determination, two-stage sampling, MFFT classification, and analytic-sample selection.

Conceptual-Tempo Classification and Analytic Sample

All 138 sampled students completed the MFFT and were classified into one of four conceptual-tempo profiles according to their combined response latency and response accuracy. The MFFT classification produced 51 Reflective students, 19 Impulsive students, 68 Slow-Inaccurate students, and no Fast-Accurate students. Table 2 summarizes both the complete MFFT distribution and the composition of the final inferential sample.

Table 2. Distribution of the Initial and Analytic Samples by Conceptual Tempo

Description	n	Percentage of initial sample (%)
Initial sample	138	100.00
Reflective students	51	36.96
Impulsive students	19	13.77
Slow-Inaccurate students	68	49.27
Fast-Accurate students	0	0.00
Final analytic sample (Reflective + Impulsive)	70	50.72

As shown in Table 2, Slow-Inaccurate students constituted the largest descriptive group (49.27%), whereas Reflective and Impulsive students together represented 70 of the 138 participants (50.72%). These 70 students formed the final inferential sample because the research hypothesis specifically addressed differences between the Reflective and Impulsive profiles. The inferential findings therefore apply to these two groups and not to the complete set of MFFT categories.

Research Instruments

Two instruments were used to collect the study data: the Matching Familiar Figures Test (MFFT) for conceptual-tempo classification and a researcher-developed mathematics achievement test.

Matching Familiar Figures Test (MFFT)

Students' conceptual tempo was assessed using the MFFT, which evaluates differences in response speed and response accuracy when individuals select an exact match to a target figure from several visually similar alternatives. Response latency and accuracy jointly represent the speed-accuracy trade-off underlying reflection-impulsivity (Lovett et al., 2020; Barrouillet & Gaillard, 2021).

The MFFT used in this study consisted of 13 visual-discrimination items. The instrument was administered under standardized conditions, and completion time and number of correct responses were recorded separately for each student. This procedure enabled individual response latency and accuracy to be combined during classification. Accurate measurement of both components is important when MFFT performance is used to characterize reflection-impulsivity (Viator et al., 2022).

The operational classification thresholds were derived from the sample distributions of MFFT response latency and accuracy using the median-split procedure applied in the study. The response-latency median was 4 minutes 28 seconds and the accuracy median was 9 correct responses. Students with response times at or above 4 minutes 28 seconds and at least 9 correct responses were classified as Reflective; students with response times below 4 minutes 28 seconds and fewer than 9 correct responses were classified as Impulsive; students with response times at or above 4 minutes 28 seconds and fewer than 9 correct responses were classified as Slow-Inaccurate; and students with response times below 4 minutes 28 seconds and at least 9 correct responses were classified as Fast-Accurate. These thresholds were applied consistently to all 138 MFFT records.

This operationalization combines speed and accuracy rather than treating either indicator independently. The Reflective-Impulsive contrast has been widely used to characterize differences in cognitive processing efficiency and academic performance (Lovett et al., 2020; Tikhomirova et al., 2022; Tikhomirova et al., 2023). Maulana and Siregar (2024) also reported the applicability of the MFFT for assessing reflective and impulsive tendencies among Indonesian secondary-school students.

Although all four profiles were used to describe the initial sample, only Reflective and Impulsive students entered the regression analysis. This distinction between descriptive classification and inferential inclusion was maintained throughout the analysis.

Mathematics Achievement Test

Students' mathematics achievement was assessed using a researcher-developed test consisting of 30 multiple-choice items. The instrument was designed according to the junior high school mathematics curriculum and assessed students' knowledge, understanding, and application of mathematical concepts.

The assessment blueprint mapped the 30 items across four content domains - Numbers and Arithmetic, Algebra, Geometry, and Statistics and Probability - and three cognitive levels: C1 (Remembering), C2 (Understanding), and C3 (Applying). The use of an assessment blueprint supports alignment between content representation, cognitive demand, and instructional objectives (K. K. Allen et al., 2021; Palengka et al., 2022; Cabrera et al., 2023).

Table 3 presents the distribution of test items across content domains and cognitive levels. The blueprint shows that the instrument included both conceptual and procedural mathematics tasks rather than concentrating on a single curriculum domain.

Table 3. Blueprint of the Mathematics Achievement Test

Content domain	Cognitive level	Description of skills assessed	Number of items
Numbers & Arithmetic	C1 - Remembering	Performing basic operations (addition, subtraction, multiplication, and division) and identifying FPB and KPK	5
Numbers & Arithmetic	C2 - Understanding	Interpreting fractions, ratios, and numerical relationships in simple contexts	4
Algebra	C2 - Understanding	Identifying algebraic expressions, variables, and equivalent forms	4
Algebra	C3 - Applying	Solving linear equations, simple systems, and algebraic word problems	4
Geometry	C2 - Understanding	Recognizing properties of plane and solid figures	4
Geometry	C3 - Applying	Calculating perimeter, area, volume, and surface area	4
Statistics & Probability	C2 - Understanding	Interpreting tables, diagrams, mean, median, and mode	3
Statistics & Probability	C3 - Applying	Solving contextual problems involving data interpretation and probability	2
Total			30

Grade-specific versions of the mathematics achievement test were administered to students in Grades VII, VIII, and IX. Each form contained 30 items and followed the same content blueprint, cognitive-level distribution, scoring range, and general assessment structure. The forms were not subjected to formal statistical equating; therefore, the common scoring framework supported the pooled analysis, but cross-grade score comparability was interpreted cautiously.

Validity and Reliability of the Mathematics Achievement Test

Content validity was evaluated through expert judgment involving mathematics education lecturers and experienced mathematics teachers. The experts reviewed the items for relevance, clarity, and alignment with the intended instructional objectives. Expert review remains an established procedure for evaluating content validity in educational assessment research (O. A. & K., 2025).

Following expert review, item analysis was conducted to assess item difficulty and item discrimination. Items with difficulty indices between .30 and .70 and discrimination indices of at least .30 were considered acceptable.

Table 4 summarizes the psychometric criteria applied during test refinement. Of the initial items evaluated, 24 met the specified difficulty criterion and 25 met the discrimination criterion. Items that initially failed to satisfy the specified difficulty or discrimination criteria were revised following item analysis and expert review, then re-evaluated before final administration. After this refinement process, the final test form retained 30 items.

Table 4. Summary of Item Analysis for the Mathematics Achievement Test

Psychometric index	Criteria	Number of items	Decision
Item difficulty (p)	.30 <= p <= .70	24	Retained
	p < .30 or p > .70	6	Revised
Item discrimination (r_it)	r_it >= .30	25	Retained
	r_it < .30	5	Revised and re-evaluated
Final test form	-	30 items	Used in the study

Internal consistency reliability was estimated separately for each grade-specific mathematics achievement test using Cronbach's alpha. Grade-specific reliability estimates were used because the three grades completed different forms, even though the forms shared the same blueprint and scoring structure. Reliability coefficients of approximately .70 or higher are generally considered adequate for achievement measures used in correlational research (Putra & Fitriani, 2022).

As shown in Table 5, Cronbach's alpha coefficients were .78 for Grade VII, .80 for Grade VIII, and .81 for Grade IX, indicating acceptable-to-good internal consistency across the three grade-specific forms. No pooled reliability coefficient was used to infer statistical equivalence among the grade forms.

Table 5. Reliability of Mathematics Achievement Tests by Grade Level

Grade level	Number of items	Cronbach's alpha	Interpretation
VII	30	.78	Acceptable
VIII	30	.80	Good
IX	30	.81	Good

Data Collection Procedures

Data collection was conducted after formal permission had been obtained from the school principal and coordination had been completed with the mathematics teachers at the research site. The researcher then scheduled the MFFT and mathematics achievement test sessions in coordination with the participating classes.

The data-collection process was conducted sequentially. First, the MFFT was administered under standardized conditions. Students responded to the 13 visual-discrimination items, and the researcher recorded each student's completion time and accuracy. These measurements were subsequently used to classify students into the four conceptual-tempo profiles.

Second, the mathematics achievement test was administered in a subsequent session. Students completed 30 multiple-choice items within a standardized time allocation of 100 minutes under the supervision of the researcher and classroom teacher. The same administration procedures were applied consistently to participants within each grade level.

After test administration, all response sheets were checked for completeness. Responses were then scored, coded, and entered into the dataset before statistical analysis.

Ethical Considerations

Formal permission to conduct the study was obtained from the school principal before data collection. Because the participants were minors, informed consent was obtained from parents or legal guardians and student assent was obtained before participation. Participation was voluntary, and students were informed that participation or withdrawal would not affect their academic standing. Identifying information was anonymized, confidentiality was maintained throughout data handling and analysis, and the collected data were used solely for research purposes.

Data Analysis

Data were analyzed using IBM SPSS Statistics version 23. Descriptive statistics were first calculated to summarize the distribution of MFFT profiles and mathematics achievement scores.

The descriptive analysis included frequencies and percentages for all four MFFT classifications. For the Reflective and Impulsive analytic groups, mathematics achievement was summarized using the mean, standard deviation, median, minimum, and maximum.

To examine the association between conceptual tempo and mathematics achievement, a simple linear regression model with dummy coding was employed (Equation 2). This approach is appropriate when the predictor contains two categorical levels and the outcome variable is continuous (Field, 2020).

$$Y = \beta_0 + \beta_1 D + \varepsilon \qquad (2)$$

where Y represents the mathematics achievement score, D is the dummy-coded conceptual-tempo variable (0 = Impulsive, 1 = Reflective), beta0 is the regression intercept, beta1 is the regression coefficient associated with conceptual-tempo membership, and epsilon is the random error term.

Because the predictor was binary, beta0 represents the estimated mean mathematics score for Impulsive students, while beta1 represents the estimated mean difference between Reflective and Impulsive students. The values 0 and 1 served solely as nominal indicators of group membership and did not represent an ordinal ranking of the two cognitive styles. Thus, the dummy-variable regression provides both a formal hypothesis test and a directly interpretable estimate of the between-group difference.

Before hypothesis testing, regression assumptions were examined, including residual normality, homoscedasticity, and the presence of influential observations. These assumptions were assessed using Q-Q plots, residual-versus-fitted plots, and standardized residual values in accordance with established regression guidelines (Field, 2020; Finell et al., 2022).

The regression model was evaluated using R, R^2, adjusted R^2, the model F statistic, the regression coefficient (B), standard error, t statistic, and associated p value. Statistical significance was evaluated at alpha = .05.

The coefficient of determination (R^2) was interpreted as the proportion of observed variance in mathematics achievement statistically associated with Reflective-Impulsive group membership within the analytic sample. It was not interpreted as evidence of a causal proportion of mathematics achievement attributable to cognitive style.

RESULTS AND DISCUSSION

Distribution of Conceptual Tempo Profiles

All 138 students selected through the sampling procedure completed the Matching Familiar Figures Test (MFFT). Based on the combined response-latency and accuracy criteria, 51 students (36.96%) were classified as Reflective, 19 students (13.77%) as Impulsive, 68 students (49.27%) as Slow-Inaccurate, and no students were classified as Fast-Accurate. As reported in Table 2, the Slow-Inaccurate profile constituted the largest proportion of the initial sample, followed by the Reflective and Impulsive profiles.

Figure 3 provides a visual representation of the distribution of the four conceptual-tempo profiles. The figure highlights the predominance of the Slow-Inaccurate group and also distinguishes the 70 Reflective and Impulsive students who constituted the inferential analytic sample.

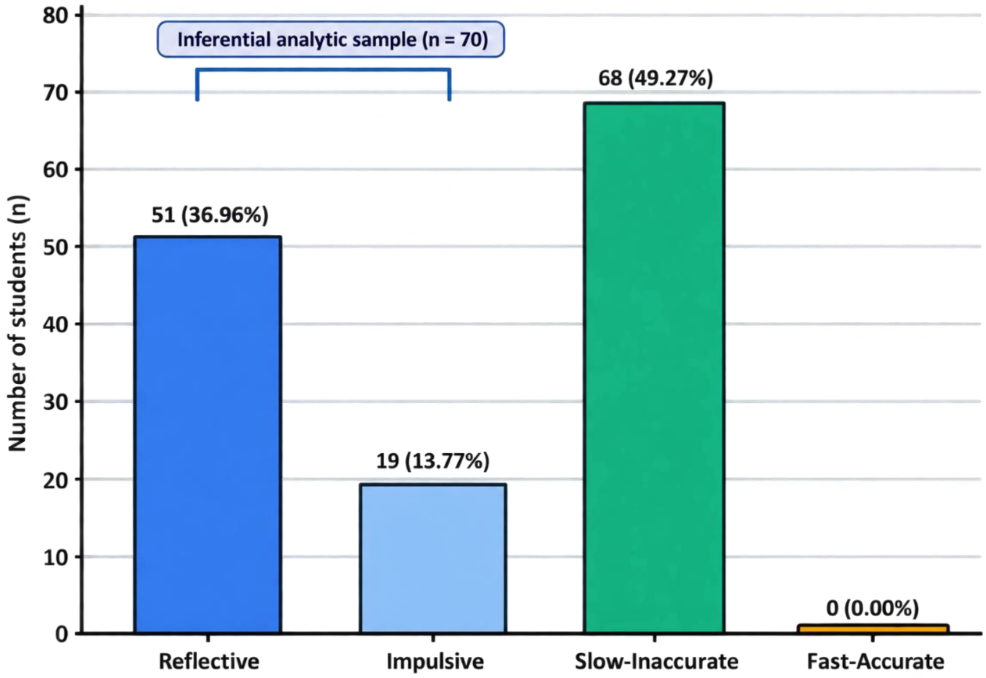

Figure 3. Distribution of students across the four conceptual-tempo profiles identified using the Matching Familiar Figures Test (MFFT). Percentages are calculated from the initial sample of 138 students. Reflective and Impulsive students constituted the final inferential analytic sample (n = 70)

The overall distribution indicates substantial heterogeneity in students' conceptual-tempo characteristics. However, in accordance with the analytical focus of the study, subsequent inferential analyses were restricted to the two contrasting poles of the reflection-impulsivity continuum. Consequently, the final analytic sample consisted of 70 students, comprising 51 Reflective and 19 Impulsive students. The Slow-Inaccurate group was retained in the descriptive classification but was not included in the comparative and regression analyses.

Mathematics Achievement of Reflective and Impulsive Students

Descriptive statistics were examined to characterize mathematics achievement within the two analytic groups. As presented in Table 6, Reflective students achieved a higher mean mathematics score (M = 61.12, SD = 10.84) than Impulsive students (M = 34.88, SD = 9.18), corresponding to an observed mean difference of approximately 26.24 points.

Table 6. Descriptive Statistics of Mathematics Achievement by Cognitive Style

Cognitive style	n	Mean	SD	Median	Minimum	Maximum
Reflective	51	61.12	10.84	59.94	36.63	76.59
Impulsive	19	34.88	9.18	33.30	33.30	63.27

The median scores showed the same overall pattern as the mean scores. Reflective students had a median mathematics score of 59.94, whereas Impulsive students had a median score of 33.30. Scores among Reflective students ranged from 36.63 to 76.59, while scores among Impulsive students ranged from 33.30 to 63.27. Although the observed score ranges partially overlapped, both the mean and median values indicate that mathematics achievement was generally higher among Reflective students.

Figure 4 complements the descriptive statistics in Table 6 by displaying the group means together with ±1 standard deviation error bars. The visual comparison shows a clear separation between the mean mathematics achievement scores of Reflective and Impulsive students while also representing the variability within each group.

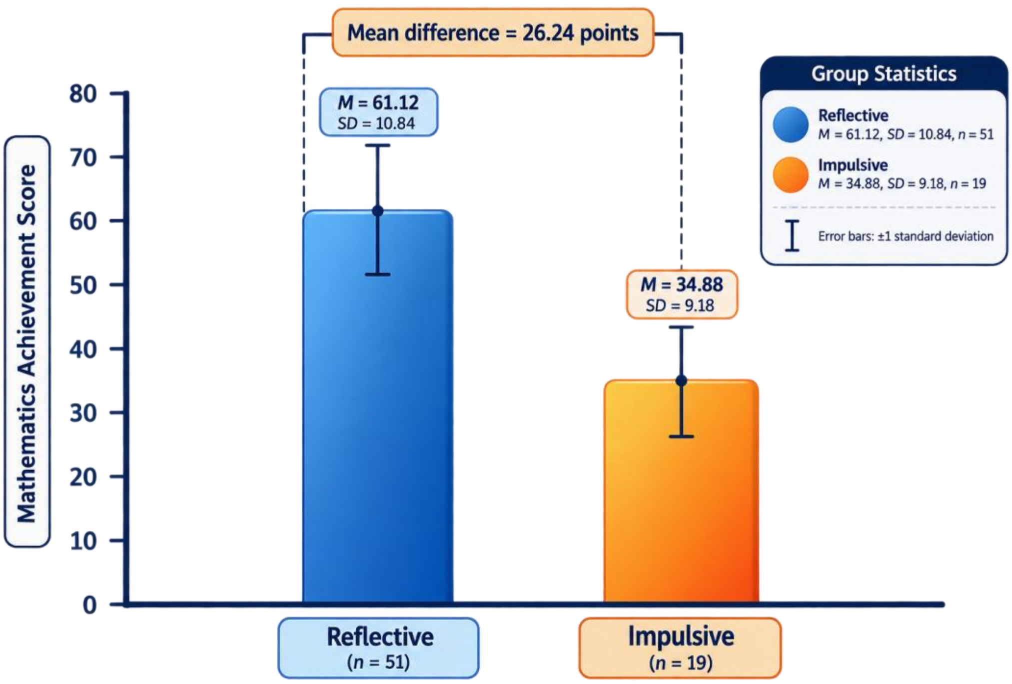

Figure 4. Mean mathematics achievement scores of Reflective and Impulsive students. Error bars represent ±1 standard deviation. Reflective students (n = 51) obtained a mean score of 61.12 (SD = 10.84), whereas Impulsive students (n = 19) obtained a mean score of 34.88 (SD = 9.18).

Table 6 and Figure 4 provide consistent descriptive evidence of a substantial difference in mathematics achievement between the two cognitive-style groups. Inferential analysis was subsequently conducted to determine whether this observed difference was statistically significant.

Regression Analysis and Hypothesis Testing

Prior to hypothesis testing, regression diagnostics were examined. Visual inspection of the Q-Q plot indicated that the residuals were approximately normally distributed, and the residuals-versus-fitted plot showed no pronounced funnel-shaped pattern, indicating no substantial evidence of heteroscedasticity. Standardized residuals did not indicate a major influential outlier. Thus, no serious violation of the assumptions required for the simple regression analysis was identified.

A simple linear regression analysis with dummy coding was conducted to examine the statistical association between cognitive style and mathematics achievement. Cognitive style was coded as 0 for Impulsive students and 1 for Reflective students. The principal regression statistics are summarized in Table 7.

Table 7. Simple Linear Regression of Mathematics Achievement on Cognitive Style

Statistic	Value
R	.751
R^2	.563
Adjusted R^2	.557
F(1, 68)	87.70
Model p	< .001
Intercept (B0)	34.877
Cognitive-style coefficient (B1)	26.238
SE of B1	2.80
t	9.37
p	< .001

As shown in Table 7, the regression model was statistically significant, $F(1, 68) = 87.70$, $p < .001$. The model yielded $R = .751$ and $R^2 = .563$, indicating that 56.3% of the observed variance in mathematics achievement within the Reflective-Impulsive analytic sample was statistically associated with cognitive-style membership. The adjusted R^2 was .557, showing that the proportion of explained variance remained nearly unchanged after adjustment for model complexity.

The regression coefficient for cognitive style was positive and statistically significant ($B = 26.238$, $SE = 2.80$, $t = 9.37$, $p < .001$). Because Impulsive students were coded as 0 and Reflective students as 1, the intercept of 34.877 represents the estimated mean mathematics achievement score for the Impulsive group, whereas the coefficient of 26.238 represents the estimated mean difference between Reflective and Impulsive students.

$$\hat{Y} = 34.877 + 26.238(D)$$

where $D = 0$ for Impulsive students and $D = 1$ for Reflective students. Substituting $D = 0$ yields an estimated mathematics score of 34.877 for Impulsive students, whereas substituting $D = 1$ yields an estimated score of 61.115 for Reflective students. These estimated values correspond closely to the observed group means presented in Table 6.

The convergence of the descriptive statistics in Table 6, the visual comparison in Figure 4, and the inferential results in Table 7 consistently indicates that Reflective students achieved higher mathematics scores than Impulsive students. The statistically significant regression coefficient therefore supports H1 and leads to rejection of H0. Within the Reflective-Impulsive analytic sample, cognitive-style membership was significantly associated with mathematics achievement.

Discussion

Overview of the Main Findings

This study examined differences in mathematics achievement between Reflective and Impulsive students and the statistical association between conceptual tempo and mathematics achievement in a 3T junior high school context. Three findings are particularly important. First, Reflective students achieved substantially higher mathematics scores than Impulsive students. Second, the dummy-coded regression model indicated a statistically significant association between cognitive-style membership and mathematics achievement. Third, the complete MFFT classification revealed considerable heterogeneity in conceptual-tempo profiles, with Slow-Inaccurate students constituting the largest group in the initial sample.

As shown in Table 6 and Figure 4, Reflective students obtained a mean mathematics score of 61.12 (SD = 10.84), compared with 34.88 (SD = 9.18) among Impulsive students. The approximately 26.24-point mean difference was also reflected in the median scores, indicating that the observed difference was not limited to the arithmetic mean. Table 7 further showed that the Reflective-Impulsive distinction was statistically associated with mathematics achievement, $F(1, 68) = 87.70$, $p < .001$, with $R^2 = .563$. Together, these findings support the hypothesis that Reflective students demonstrated higher mathematics achievement than Impulsive students within the analytic sample.

Reflective-Impulsive Differences in Mathematics Achievement

The higher mathematics achievement observed among Reflective students is consistent with the theoretical characteristics of reflective cognitive processing. Reflective learners generally allocate more time to examining task requirements, considering alternative responses, checking intermediate steps, and verifying answers before making a final decision. In contrast, Impulsive learners tend to respond more rapidly and may devote less time to evaluating possible solutions. In mathematics, where successful performance often depends on sequential reasoning, procedural accuracy, and careful verification, these differences in response regulation can be particularly relevant.

The present findings therefore suggest that the achievement difference between the two groups is consistent with the speed-accuracy characteristics underlying conceptual tempo. Reflective students' greater tendency toward deliberate processing may support accuracy in tasks requiring several computational or reasoning steps, whereas rapid responding without sufficient verification may increase the likelihood of conceptual or procedural errors among Impulsive students.

This interpretation aligns with previous studies reporting superior mathematics performance among Reflective learners compared with Impulsive learners in tasks requiring analytical reasoning, accuracy, and multistep problem solving (J. J. Allen et al., 2021; Tikhomirova et al., 2022). Earlier research grounded in Kagan's reflection-impulsivity framework similarly demonstrated that Reflective children tend to exhibit greater response accuracy and more systematic information-processing strategies than Impulsive children (Zelniker & Jeffrey, 1976).

The present study extends this pattern by showing that the Reflective-Impulsive difference is also evident in overall mathematics achievement in a 3T junior high school setting. Importantly, however, the findings should not be interpreted as showing that reflective processing is universally superior in all learning situations. Rather, they indicate that, for the mathematics assessment used in this study, the Reflective group demonstrated a substantially higher level of performance than the Impulsive group.

Recent studies have continued to identify meaningful relationships between cognitive-processing characteristics and students' mathematics performance (K. K. Allen et al., 2021; Palengka et al., 2022). The current findings are therefore consistent with a broader body of evidence indicating that how students regulate speed, accuracy, and response evaluation can be associated with differences in academic performance.

Statistical Association Between Cognitive Style and Mathematics Achievement

The regression analysis provides a complementary interpretation of the descriptive group difference. Because cognitive style was dummy-coded as 0 = Impulsive and 1 = Reflective, the regression coefficient can be interpreted directly as the estimated difference between the two group means.

The coefficient of B = 26.238 indicates that membership in the Reflective group was associated with an estimated mathematics score approximately 26.24 points higher than membership in the Impulsive group. This estimate closely corresponds to the observed descriptive difference between the mean scores of 61.12 and 34.88. The close agreement between the descriptive statistics and the regression coefficient strengthens the internal consistency of the reported results.

The model explained 56.3% of the observed variance in mathematics achievement within the Reflective-Impulsive analytic sample. This value indicates a substantial statistical association within the present dataset, but it should not be interpreted as meaning that conceptual tempo caused 56.3% of students' mathematics achievement. The study employed a correlational, nonexperimental design, and the regression model included only one predictor. Consequently, other individual, instructional, and contextual variables that may contribute to mathematics achievement were not represented in the model.

The R^2 value should therefore be interpreted as the proportion of observed score variance statistically associated with Reflective versus Impulsive group membership among the 70 students included in the inferential analysis. It does not quantify a causal contribution of cognitive style to achievement, nor does it imply that the same proportion would necessarily be observed in other schools or student populations.

This distinction is important because predictive relationships should not be treated as direct causal evidence. In the present study, the appropriate conclusion is that Reflective-Impulsive cognitive-style membership was strongly associated with mathematics achievement within the analytic sample.

Relevance of the 3T Educational Context

A central contribution of this study is its focus on a 3T educational setting. Much of the literature examining reflective-impulsive differences has been developed in educational contexts with relatively greater access to instructional resources. By contrast, rural and under-resourced schools may experience different combinations of learning support, instructional materials, teacher availability, and opportunities for individualized assistance (Rahman et al., 2021; Putra & Fitriani, 2022).

The present findings demonstrate that differences between Reflective and Impulsive students are observable within this underrepresented educational context. This adds contextual evidence to the conceptual-tempo literature and suggests that individual differences in response regulation remain relevant even in settings where students may face broader educational constraints.

However, the study did not compare 3T and non-3T schools and therefore cannot establish that the 3T environment amplifies, moderates, or causes the observed Reflective-Impulsive achievement difference. The contextual contribution of the study lies instead in documenting the association within a setting that has received comparatively less empirical attention.

This distinction is important for maintaining an appropriate level of inference. The results support the applicability of conceptual-tempo research to a 3T junior high school context, but they do not demonstrate that the strength of the association is unique to, or produced by, the 3T environment. Comparative multi-school research would be required to test such contextual moderation directly.

The Slow-Inaccurate Profile as an Important Descriptive Finding

Although the inferential analysis focused on Reflective and Impulsive students, the full MFFT distribution revealed another important finding. Slow-Inaccurate students represented 68 of the 138 participants (49.27%), making this the largest conceptual-tempo profile in the initial sample, whereas no student was classified as Fast-Accurate.

The prevalence of the Slow-Inaccurate profile demonstrates that the initial sample contained substantial variation beyond the two focal groups. These students exhibited the combination of relatively longer response latency and lower accuracy according to the MFFT classification criteria. Because they were not included in the regression analysis, the statistical findings reported for Reflective and Impulsive students should not be generalized to this group.

The existence of a large Slow-Inaccurate group also has theoretical and methodological importance. Research has noted that combinations of response speed and accuracy beyond the traditional Reflective-Impulsive poles require careful interpretation because they may represent different processing patterns rather than simple extensions of reflection or impulsivity (Lovett et al., 2020; Viator et al., 2022).

The present study cannot determine why the Slow-Inaccurate profile was prevalent. Variables such as motivation, self-regulation, prior achievement, working memory, classroom support, or other contextual influences were not measured and therefore should not be presented as explanations for this pattern. Instead, the high proportion of Slow-Inaccurate students should be treated as an empirical finding that generates new questions for future research.

Future studies could explicitly examine whether Slow-Inaccurate students demonstrate distinctive mathematics-learning characteristics and whether psychological, instructional, or contextual factors help explain the combination of extended response time and lower accuracy observed in this group.

Pedagogical Implications

The observed achievement difference between Reflective and Impulsive students has practical implications for mathematics instruction. The findings suggest that teachers may benefit from recognizing differences in how students regulate response speed, evaluate alternatives, and verify solutions. Rather than treating all students as requiring identical problem-solving conditions, instruction can incorporate opportunities that support deliberate and accurate mathematical reasoning.

For example, teachers may provide structured time for students to examine problem requirements, encourage explicit checking of intermediate calculations, ask students to justify solution steps, and model systematic procedures for evaluating alternative strategies. Such practices may be particularly helpful for students who tend to respond quickly without sufficient verification.

For Impulsive students, instructional scaffolds may include prompts such as checking each computational step, identifying the information required before solving, comparing alternative answers, or explaining why a selected solution is reasonable. These strategies are consistent with the goal of improving response regulation rather than simply encouraging students to work more slowly.

Reflective students may also benefit from instructional support. Although deliberate processing may enhance accuracy, excessively extended processing can sometimes reduce efficiency. Therefore, differentiated instruction should aim to balance accuracy and efficiency rather than assuming that slower responding is always preferable.

Recent research has highlighted pedagogical differences associated with reflective and impulsive cognitive styles and the potential relevance of differentiated instruction in analytical learning tasks (Glomb et al., 2024; Susiloningsih et al., 2025). Widodo and Hartati (2024) similarly emphasize differentiated mathematics instruction based on cognitive characteristics.

Nevertheless, the present study did not experimentally evaluate any instructional intervention. The pedagogical recommendations derived from the findings should therefore be interpreted as evidence-informed implications rather than demonstrated treatment effects. Experimental or quasi-experimental studies would be required to establish whether particular instructional strategies improve outcomes for Reflective, Impulsive, or Slow-Inaccurate students.

Limitations and Directions for Future Research

Several limitations should be considered when interpreting the findings. First, the study was conducted in a single 3T junior high school. The findings therefore provide contextualized evidence but should not be generalized automatically to all rural, peripheral, or Indonesian secondary-school populations. Multi-school studies involving different geographic and educational contexts would provide a stronger basis for broader generalization.

Second, the study used a cross-sectional correlational design. Although the regression model identified a statistically significant association, causal direction cannot be established. Longitudinal or experimental research would be needed to determine whether changes in response-regulation characteristics are associated with subsequent changes in mathematics achievement.

Third, the inferential analysis included 51 Reflective and 19 Impulsive students, resulting in unequal group sizes. Moreover, 68 Slow-Inaccurate students were excluded from the inferential comparison, and no Fast-Accurate students were identified. Consequently, the regression findings specifically characterize the Reflective-Impulsive contrast and do not represent all conceptual-tempo profiles observed in the initial sample.

Fourth, grade-specific mathematics achievement test forms were developed using the same blueprint, item structure, cognitive-level distribution, scoring range, and general assessment framework, but no formal statistical equating procedure was conducted across Grades VII, VIII, and IX. Consequently, pooled mathematics scores may partly reflect differences in form difficulty across grade levels. Future studies should consider common-item equating, within-grade standardization, or statistical adjustment for grade level when pooling achievement scores.

Fifth, mathematics achievement was measured using a 30-item multiple-choice assessment. Although the instrument demonstrated acceptable reliability and represented several curriculum domains and cognitive levels, a single assessment format cannot capture the full complexity of mathematical competence. Future studies could incorporate open-ended problem solving, mathematical reasoning tasks, interviews, or classroom observations to provide a more comprehensive assessment of students' mathematical thinking.

Future research should also investigate the large Slow-Inaccurate group identified in this study and examine variables that were not included in the present model, such as self-regulation, learning motivation, working memory, classroom environment, family support, and access to learning resources. Mixed-method and longitudinal designs may be particularly valuable for clarifying how these factors interact with conceptual tempo over time.

Overall, the present study provides evidence that Reflective-Impulsive cognitive-style membership is meaningfully associated with mathematics achievement in a 3T junior high school context. Its principal contribution lies in documenting this relationship within an underrepresented educational setting while simultaneously showing that conceptual-tempo diversity extends beyond the two groups used in the inferential analysis.

CONCLUSIONS

This study demonstrates a clear difference in mathematics achievement between Reflective and Impulsive students in a 3T junior high school context. Reflective students achieved a mean score of 61.12, whereas Impulsive students obtained a mean score of 34.88, corresponding to an observed difference of approximately 26.24 points. The dummy-coded regression model confirmed that this difference was statistically significant, $F(1, 68) = 87.70$, $p < .001$, with $R^2 = .563$. Thus, within the Reflective-Impulsive analytic sample, conceptual-tempo membership was strongly associated with mathematics achievement.

These findings support the theoretical relevance of the reflection-impulsivity dimension in mathematics learning, particularly for tasks that require careful reasoning, accuracy, and verification of solution steps. However, because the study employed a cross-sectional correlational design, the results should not be interpreted as evidence that cognitive style caused the observed achievement difference. Rather, the findings indicate a substantial statistical association between Reflective-Impulsive cognitive tempo and mathematics performance in the present sample.

The study also revealed an important descriptive pattern beyond the two focal groups. Slow-Inaccurate students represented 49.27% of the initial sample, making this the largest conceptual-tempo profile, while no students were classified as Fast-Accurate. This distribution demonstrates that conceptual-tempo diversity in the study setting extends beyond the traditional Reflective-Impulsive contrast and identifies the Slow-Inaccurate profile as an important direction for further investigation.

The principal contribution of this study lies in extending evidence on Reflective-Impulsive differences in mathematics achievement to an underrepresented 3T educational setting while simultaneously documenting the broader distribution of conceptual-tempo profiles. From an instructional perspective, the findings support greater attention to students' regulation of response speed and accuracy. Mathematics instruction may benefit from structured opportunities for deliberate reasoning, verification of intermediate steps, and systematic evaluation of solutions, particularly for students who tend to respond rapidly without sufficient checking. These implications should nevertheless be regarded as evidence-informed recommendations rather than experimentally demonstrated instructional effects.

RECOMMENDATIONS

Future research should extend the present findings in several directions. First, the large proportion of Slow-Inaccurate students warrants focused investigation. Subsequent studies should examine whether this profile is associated with distinctive patterns of mathematics achievement, problem-solving behavior, self-regulation, motivation, working memory, or other learner characteristics. Because these variables were not measured in the present study, they should be examined directly rather than inferred from the current results.

Second, future studies should include all four MFFT conceptual-tempo profiles whenever adequate group sizes are available. Such designs would enable direct comparisons among Reflective, Impulsive, Slow-Inaccurate, and Fast-Accurate students and provide a more complete understanding of how combinations of response speed and accuracy relate to mathematics performance.

Third, broader sampling across multiple 3T and non-3T schools is recommended to determine whether the observed Reflective-Impulsive achievement difference is consistent across educational contexts. Comparative multi-school designs would also allow researchers to investigate whether contextual characteristics such as instructional resources, classroom environment, family support, and access to learning opportunities moderate the relationship between conceptual tempo and mathematics achievement.

Fourth, longitudinal and mixed-method designs are recommended to investigate how conceptual-tempo characteristics and mathematics performance develop over time. Combining quantitative measures with interviews, observations, think-aloud protocols, or analyses of students' written solutions may provide deeper insight into the mechanisms through which response speed, accuracy, and self-monitoring are related to mathematical reasoning.

Finally, future research should use multiple measures of mathematics achievement, including open-ended problem-solving tasks, mathematical reasoning assessments, and performance-based measures in addition to multiple-choice tests. Experimental or quasi-experimental studies could also evaluate whether instructional strategies that promote deliberate reasoning, answer verification, and regulation of response speed produce differential benefits for students with different conceptual-tempo profiles.

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Written parental/guardian consent and child assent were obtained.

Ethical Approval
This research was conducted in accordance with principles of research ethics and academic integrity. All research procedures complied with applicable institutional policies. Participants' privacy and data confidentiality were protected, and research data were used solely for scientific purposes.

Data Availability
The data that support the findings of this study are available from the corresponding author upon reasonable request, subject to the confidentiality and consent conditions applicable to data collected from child participants.

Author Contributions Statement

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
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N R Yulia Ningrum	✓	✓		✓	✓					✓		✓		
Nurhayati	✓		✓			✓	✓	✓		✓	✓			

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

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