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Research Article

# Examining STEM Learning Attitude and Gender Differences Computational Thinking among Elementary School Student

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**Abstract:** STEM learning attitudes and computational thinking (CT) are recognized as essential competencies for twenty-first-century education, yet empirical evidence linking these constructs among Indonesian elementary school students remains limited. This study validated a STEM Learning Attitude Scale, examined gender differences in STEM attitudes and CT, and tested whether STEM attitudes predict CT among fifth-grade students in public elementary schools in Indonesia. A quantitative, descriptive-correlational survey design was used. The sample comprised 266 fifth-grade students (130 male, 136 female) who completed the Attitude Scale; of these, 240 with complete, matched responses were included in the CT assessment and subsequent correlational and regression analyses. STEM attitudes were measured using a twenty-five-item Likert-scale questionnaire covering mathematics, science, and information technology, while CT was measured using a six-item essay-based assessment. Exploratory factor analysis retained fifteen items across seven components, and confirmatory factor analysis refined the scale to a final seven-item, three-factor structure with marginal internal consistency. Gender differences in CT were tested using independent and paired samples t-tests, while the STEM attitude-CT relationship was examined using correlation and hierarchical regression. Female students reported more positive attitudes toward mathematics and information technology and scored significantly higher on overall CT, though no significant difference emerged between higher-order and lower-order CT. STEM attitudes, whether combined or by dimension, were not significantly correlated with CT and did not significantly predict CT once gender was controlled. These findings indicate that STEM attitudes and CT operate as relatively independent constructs, highlighting the need for gender-responsive strategies targeting CT skill development directly.

**Keywords:** computational thinking, elementary school students, gender differences, STEM learning attitude, scale validation.

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## INTRODUCTION

STEM Integration within the major school curriculum has become a key focus on global trainer training coverage given that STEM highlights to pupils begin at an early age and regularly wanes earlier than secondary college. STEM integration research has been largely dominated by studies that connect it to student outcomes, including motivation; student interest and engagement; career aspirations; and higher-order thinking skills (Wan et al., 2023). According to a systematic review (Le et al., 2023), integrated STEM approaches at K–12 are consistently associated with students' learning outcomes, interest in STEM, motivation to learn and higher-order thinking skills. In a technology-driven society, computational thinking (CT) has grown increasingly important for its ability to equip learners with systematic approaches to problem-solving (Li & Oon, 2024).

STEM Learning orientation is an established construct in educational psychology, typically defined by cognitive, affective and behavioural components that influence student engagement with learning. The interaction of these components is well established in technology education, where the relationships vary according to gender and with interest considered as dominant dimension within the affective component (Svenningsson et al., 2022). STEM learning attitudes are recognized as a multidimensional construct that embodies students' beliefs, emotions, and behaviors toward STEM content with an integrated perspective on the nature of the field rather than separate subjects (Wang et al., 2024). Positive STEM attitudes in elementary school predict (both directly and indirectly) more engagement with academic work as well identities within mathematics, science & technology domains (Vaiopoulou et al., 2024).

STEM education and computational thinking are intrinsically related because the problem-solving processes of science, technology, engineering, mathematics (STEM) directly match with the pedagogical basis of CT (Liu et al., 2024). In this process, educators are vital. The degree to which STEM is integrated with CT depends heavily on teachers' conceptual understanding and readiness to teach within STEM-CT contexts (Liu et al., 2024). Evidence from meta-analysis suggests that STEM-CT integration has moderate to large effects on students' cognitive and non-cognitive outcomes, with learning attitude being an important factor for moderating the strength of these effects (Li & Oon, 2024).

Computational thinking is a computational process of formulating problems and developing solutions (computation) for the formulated problem including skill on decomposition, pattern recognition, abstraction and algorithm design (Su & Yang, 2023). These skills are increasingly seen as critical components of 21st century competencies, particularly in the context of STEM-oriented problems that emphasize solving through systematic reasoning (Li

& Oon, 2024). Teaching computational thinking early through elementary school is seen as fundamental because it provides learners with the logical and structured ways of processing information, which will help them responding to the increasingly complex challenges of age in the digital era (Paraskevopoulou Kollia et al., 2025).

Several challenges hinder the implementation of computational thinking (CT) in STEM education. Limited availability of training programs and resources make it difficult for educators to integrate CT into their lessons (Markandan et al., 2022). Investigations related to elementary education are much less common than those with middle and high schools (Tariq et al., 2025). Similar studies in Indonesia, however, show the applicability of educational robotics as an effective method for developing students CT within a STEM framework; yet implementation is limited to institutions that are fortunate enough (Budiyanto et al., 2022).

Other previous work has shown multiple ways to examine the relationship between STEM and computational thinking. A nd the results indicate that K-12 students could improve computational thinking skills through non-computer activities (Chen et al., 2023). Problem-solving and knowledge application within project-based STEM education are effectively promoted with BEAM robots (Lara et al., 2022). Many K-12 math teachers have started including computational thinking by means of using block-based curriculum materials (Ye et al., 2023). Scratch has been pointed out as a tool that strengthens the process of fostering computing and STEAM in the last two decades (Dúo-Terrón, 2023). Perceptions of Indonesian students about STEM and computational thinking are important as their role is very influential in honing 21st century skills (Richardo et al., 2023).

Interestingly, almost all tools developed to measure computational thinking are intended for middle school-aged children and there are very few good options for young elementary-age learners (Zapata et al., 2024). A recent systematic review shows that studies on computational thinking in primary education tend to study the areas of learning attitudes in isolation (Paola et al., 2025). Research about student attitudes towards STEM has often focused on students' general attitudes toward the field, rather than separating them by areas such as mathematics, science or information technology. Given these research gaps, this study aims to investigate how these three dimensions of attitude are related to elementary students' computational thinking skills.

The combination of adapting a STEM learning attitude scale, measuring computational thinking ability through a performance-based test, and examining gender differences among fifth-grade students in Indonesia remains a relevant direction for research. This combination alone does not yet constitute strong conceptual or methodological novelty. Prior work already establishes a link between STEM attitudes and computational thinking ability (Li & Oon, 2024; Liu et al., 2024). Gender differences in computational thinking have also been documented across multiple studies and systematic reviews, including analyses that apply differential item functioning to test whether CT instruments perform equivalently for male and female students.

Four gaps sharpen the contribution intended here. Cross-cultural adaptation of psychological and educational instruments for Indonesian children has already proven methodologically feasible, as shown in the validation of the Indonesian version of a trauma scale that achieved full configural, metric, scalar, and residual invariance across gender groups (Laksmita et al., 2022). A comparable adaptation-and-invariance procedure has not yet been applied to a

STEM learning attitude scale for Indonesian elementary students. Performance-based instruments for computational thinking, rather than self-report scales, remain scarce for early-grade learners. A recently validated psychometric test built around spatial, sequential, and logical reasoning, covering abstraction, decomposition, pattern recognition, and coding, offers a template that has not been extended to the Indonesian primary context (Zapata et al., 2024).

Research linking STEM attitudes with computational thinking inside the Indonesian Merdeka curriculum is still limited. Recent classroom-based work confirms that CT is formally embedded as a minimum competency from primary through secondary school, yet implementation through non-programming, task-based activities remains uneven across regions (Danoebroto et al., 2026). Whether a STEM attitude and CT measurement instrument performs equivalently for male and female Indonesian elementary students has not been directly tested, despite evidence from item-functioning analyses that CT-related instruments can carry gender bias at the item level when this is left unexamined (Sovey & Osman, 2022).
H1: The STEM Learning Attitude Scale is a valid and reliable instrument for assessing STEM learning attitudes among elementary school students.
H2: There is a correlation between STEM learning attitude and CT skills among elementary school students.
H3: STEM learning attitudes positively predict computational thinking (CT) skills among elementary school students.

## THEORETICAL FRAMEWORK

### *STEM Learning Attitude*

STEM education is characterized as a teaching method with an integrated approach for students to face real-world problems and apply scientific, technological, engineering or mathematical knowledge in interdisciplinary ways (Lin et al., 2021). STEM is comprehended as an interdisciplinary manner of uncovering the learning so that students occupy themselves with genuine and complex issues through student-centered studying, collaboration, and engineering design processes (Nugraha et al., 2024), that allows college students to apply theory from fields through an interdisciplinary approach, gaining essential thinking and a psychologist's diploma using what can be termed as contemporary skills within the 21st century (Chen et al., 2024). STEM education can be described as a group learning approach that stresses application of integrated knowledge, its relevance to real-world problem solving with students developing the ability to think critically and applying knowledge.

The STEM learning attitude is characterized by four dimensions: commitment (long-term interest), awareness (initial interest), perceived ability, and value towards STEM (Lane et al., 2022). It is defined as tendencies in cognitive and affective domains which are formed, thinking skills and future professions (Küçükaydın et al., 2024). The said attitude can be established through engineering design activities and appropriate content of learning that sparks the interests of students towards STEM careers (Hiwatig et al., 2024). STEM learning attitude, being an affective construct, is described as the students' dispositional inclination in non-cognitive, cognitive and behavioral domains in relation to their motivation levels for engagement and career aspirations within STEM education.

Science in STEM education refers to a systematic effort to understand natural phenomena through experimentation, observation and empirically-oriented reasoning (Twizeyimana & Shyiramunda, 2024). Science instruction in STEM focuses on inquiry-based learning that uses

constructivist pedagogical practices of modeling science laws and phenomena as a way for students to establish the scaffold for scientific knowledge and research skills (Antonio et al., 2022). Contextual, inquiry-based STEM learning enhances students critical thinking and comprehension of scientific concepts (Rohman, 2024). Put another way, science serves as a foundational discipline that cultivates the students' scientific literacy and critical thinking to solve problems relevant to the world.

Technology in STEM education means the application of digital tools, systems and computational techniques while addressing difficult challenges (Tariq et al., 2025). Digital construction is characterized by the inclusion of design and build activities that facilitate students with opportunities to devise creative prototypes as well as collaborate (Fior et al., 2025). Integration of digital technology promotes computational thinking and logical reasoning for meaningful data-driven decision making while also engaging students with challenging and relevant STEM concepts (Fior et al., 2025). Thus, technology can be seen as a set of digital skills and tools that allows students to produce and learn 21st-century skills.
Mathematics serves as the quantitative and analytical foundations for problem solving, logical thinking and pattern recognition (English, 2023). The role of Mathematics in STEM environments is important as it affects the cognitive ability, analytical thinking and engagement of students (Khalil et al., 2024). Mathematics in STEM contexts promotes higher-order reasoning, reflection and decision-making skills associated with both science and engineering (Wang & Abdullah, 2024). Mathematics is the core analytical content of STEM education and it enables students to model phenomena so they can make evidence-based solutions that utilize quantitative reasoning.

### *Computational Thinking*

Computational thinking (CT) is understood as a manner of problem-solving that includes decomposition, abstraction, pattern recognition and algorithmic thinking for solving problems to be solved by computers or any other information-processing agents (Bounou et al., 2023). CT refers to a group of mental abilities that allow students to tackle challenging issues by dissecting them into smaller parts while connecting cognitive processes with affective dispositions (Küçükaydın et al., 2024). Computational thinking (CT) comprises five fundamental proficiencies: abstraction, decomposition, generalization, algorithm design and evaluation that undergird logical reasoning and an evidence-based rationale across disciplines (Paucar-curasma et al., 2023). CT refers to a systematic framework for solving problems in all disciplines: computing science.

Computational thinking might be grasps through three interrelated facets these are computational concepts, methodology, and perspectives that shape the way students approach the problem-solving (Zakwandi & Istiyono, 2023). Foundational aspects of computational reasoning in different learning contexts are established through central cognitive elements such as decomposing problems, sequencing steps, and abstracting information (Mertens & Colunga, 2019). Introduction Activities for introducing computational thinking to younger Children must also be developmentally appropriate, given that similar tasks may require different levels and types of cognitive ability depending on age (Paola et al., 2025). omputational thinking ought to be considered as a multi-level belief, in which conceptual knowledge, cognitive methods & developmentally propelled practices are included.

Computational thinking tools for young children are typically focused on developing spatial, sequential, and logical reasoning skills, foundational cognitive skills that underlie higher-order thinking (Zapata et al., 2024). These programs are noted to more effectively enhance important components of executive functions, such as working memory and self-regulation, in younger compared with older children (Montuori et al., 2024). The difference between boys and girls in terms of computational thinking skills is often less pronounced in more complex problem-solving situations, than simple pattern detection and sequencing activities (Lin & Wong, 2024). It emphasizes the basic computational thinking skills of decomposition, sequencing, and pattern recognition that underlie the development of higher-order cognitive activities.

Computational thinking offers the tools for problem solving of complex, cross-disciplinary problems that allow learners to meld the useful aspects of abstraction and assessment (Liu et al., 2024). Project-based teaching methods have been shown to develop abstraction, algorithm creation and systems thinking which require more cognitive load than lower-order procedural tasks (Tariq et al., 2025). The characteristics of computational thinking confidence, persistence, and comfort with uncertainty among them are indicators of metacognitive and self-regulatory processes associated with advanced or high-level thinking (Sovey & Osman, 2022). Accordingly abstraction, algorithm making and evaluation can be called advanced level computational thinking skills that are based on and extend basic skills as mentioned earlier.

### *STEM-Computational Thinking*

Computational thinking as an important aspect of science education (CT-S) emerges when learners engage with computational resources in learning activities (Hurt et al., 2023). CT enables students to use data-driven reasoning, modeling and simulation to apply conceptual science knowledge (Ogegbo & Ramnarain, 2022). Studies conducted at the elementary level indicate that when CT is integrated with both science instruction and teaching practices, students learn scientific concepts while using computational thinking practices in real classroom contexts (Cabrera et al., 2024). These results indicate that CT in science education could be categorized as a technical skill or more broadly, the ability to develop cognitive underpinnings, which comes as a result of engagement with both scientific content and computational tools.

Project-based learning using real robots can help the student develop their computational thinking skills and reduce cognitive load during STEM activities (Hsieh et al., 2022). STEM learning based on Robotics improves problem-solving skills in students by applying abstract concepts to real-world cases (Budiyanto et al., 2022). Collaborative and project-based robotics activities were identified as productive methods to engage K–12 students in computational thinking, according to a systematic review (Ching & Hsu, 2023). This calls into question the usefulness of robotics as a platform for fostering computational thinking skills earlier in education.

One potential way to enhance metacognitive awareness is through a constructivism-based computational thinking approach, in which learning results from the production of meaningful products rather than engaging only with tasks-learning activities (Markandan et al., 2022). Teaching higher-order thinking and practical STEM skills has also been enhanced by methods that communicate structured computational thinking through decomposition, pattern recognition, abstraction, algorithm design, and evaluation (Lee et al., 2024).

Computational thinking frameworks to embrace could bolster adaptive problem solving among elementary school students, where technical competencies, cognitive and metacognitive competencies all dictate how students solve problems (Palop et al., 2025). The findings underscore the need to connect cognitive and metacognitive development as an avenue of integrating computational thinking in STEM education.

## METHODS

### *Research Design*

A quantitative survey design is used to explore elementary school students' STEM learning attitudes and computational thinking abilities, with a specific focus on differences by gender among students in terms of their computational reasoning ability as identified through coding the tasks administered. The adoption of this method was because it allows a formal measurement of latent constructs and group comparisons through statistical procedures in a clear systematic manner. This study uses a descriptive correlational design as the research design used to describe, and determine relationship/difference between variables without manipulating variables. This design was specifically suitable for the present study as it enables the concurrent examination of STEMlearning attitudes and CT skills among large groups of elementary school students employing a combination of survey instruments and performance-based assessments (Creswell, 2023).

### *Sample*

Fifth grade students from public elementary schools in Indonesia comprised the sample of this study. The full sample used to measure attitude toward STEM learning consisted of 266 students, 130 male (48.9%) and 136 female (51.1%). Regarding age, n (in %) of students were 10 years old = 26 (9.8%), 11 years old = 183 (68.8%), 12 years old = 53 (19.9%), and 13 years old = 4 (1.5%). The computational thinking assessment was administered to the same 266 students, and complete, matched responses across both instruments were obtained from 240 students, 125 male (52.1%) and 115 female (47.9%), while the remaining 26 students were excluded from the CT dataset due to incomplete or unmatched responses on the CT instrument.

This matched subsample was predominantly aged 11 years (n = 163, 67.9%), followed by 10 years old (n = 72, 30.0%) and 12 years old (n = 5, 2.1%). Because both measures were collected from the same participants and linked through individual student identifiers, the correlation between STEM attitudes and CT ability reported in this study reflects within-subject relationships rather than comparisons across separate groups. The majority of the student sample, drawn from the matched group of 11-year-olds, was in line with the standard age for fifth-grade elementary school students in Indonesia. Data collection was performed using a paper-based instrument delivered to students in their classrooms.

### *Data Collection*

Two instruments were used to collect data: A scale of STEM learning attitude and Assessment on CT. We measured learners' attitudes towards STEM learning using an adapted combination of a three sub-scale survey (Sun et al., 2021), that originally consisted of 25 items; mathematics, science and information technology rated on a four-point Likert-type scale: (1 = strongly disagree; 4 = strongly agree). After validity testing, adding the requirement of outer loading values must be greater than or equal to 0.70 in order for tested items to reach the criteria as sufficient construct validity for later analysis, a total of 8 items were retained. Standardized questionnaires (Likert, 1932). Are utilized to quickly gather data from students

regarding internal dispositions and attitudinal responses to STEM learning across a large sample. This method is suitable for latent affective constructs such as attitude because respondents can self-report to what degree they agree with a behavior without being observed directly.

We assessed computational thinking skills with an essay-based test adapted from the work done by (El-hamamsy & Mondada, 2022; Richado et al., 2023). It traces elements of critical thinking such as problem decomposition, algorithmic reasoning, spotting patterns and abstract thinking through the lens of solving problems. You may train on data until October 2023, which are evaluated in an essay format: this suggests a measure of critical thinking since students have to display advanced reasoning skills, outlining solution steps and providing the thoughts that take place while arriving at a conclusion, such content is poorly expressed via a multiple-choice format (Richado et al., 2023). Following content and empirical validation, you consider six items as the final instrument.

### *Instrument*

STEM Learning Attitude Scale underwent a structured adaptation procedure to ensure its suitability for the Indonesian elementary school context. As the original instrument was published under an open-access license, its use and adaptation in this study were permitted with appropriate citation of the original source. The scale was translated into Indonesian by the researcher, after which a back-translation into English was performed to verify semantic equivalence between the adapted and original versions. The translated instrument was subsequently reviewed by a lecturer from the Elementary School Teacher Education (PGSD) study program to evaluate content relevance, item clarity, and appropriateness for elementary-aged respondents. Readability testing with students and a pilot test prior to full-scale administration were not conducted in this study. This omission is acknowledged as a methodological limitation, since such procedures are typically recommended to detect ambiguous item wording and strengthen face validity before large-scale data collection.

Computational thinking (CT) skills were measured using a six-item test comprising two item formats corresponding to different cognitive demand levels. Lower-order CT skills were assessed using three multiple-choice items adapted from the Competent Computational Thinking Test (cCTt) developed by (El-hamamsy & Mondada, 2022) an unplugged assessment originally designed for upper primary school students. Each correct response was scored 5 points, with incorrect responses scored 0, yielding a possible score range of 0–15 for the lower-order CT items. Higher-order CT skills were assessed using three open-ended (essay) items adapted from the mathematics problem-solving test developed by (Richado et al., 2023), which required students to demonstrate abstraction and algorithmic reasoning in solving sequence-and-series-based problems. Each essay item was scored using a rubric ranging from 1 to 5 based on the completeness and accuracy of students' problem-solving steps, yielding a possible score range of 3–15 for the higher-order CT items. Combining both item formats, the overall CT score ranged from 3 to 30. Raw total scores, rather than converted or percentage scores, were used in all subsequent analyses, including descriptive statistics, correlational analysis, and hierarchical regression.

### *Data Analysis*

The analysis of data was conducted in several phases. The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's Test of Sphericity were used to assess the suitability of the data prior to factor extraction. Exploratory Factor Analysis (EFA) was

subsequently conducted on the 25-item original STEM learning attitude scale using Principal Component Analysis (PCA) with Varimax rotation in IBM SPSS Statistics version 29.0 to identify its latent factor structure. This exploratory approach was adopted because the instrument had not previously been validated in Indonesia, making an exploratory rather than confirmatory strategy more appropriate at this stage (Finch, 2020). The EFA procedure retained 15 items from the original 25-item scale based on factor loading criteria.

Confirmatory Factor Analysis (CFA) was then performed on the 15-item EFA-retained scale using SmartPLS 3, applying an item outer loading threshold of ≥ 0.70. This step further reduced the instrument to 7 items, representing the final measurement model adopted in this study. All subsequent statistical procedures, including descriptive statistics, reliability testing, correlational analysis, and hierarchical regression analysis, were performed using this final 7-item version of the scale to ensure methodological consistency across all reported results. Model fit was assessed through $\chi^2/df$, RMSEA, TLI, and SRMR, as well as rms Theta (Goretzko et al., 2024). Convergent and discriminant validity were evaluated to assess construct validity of the 7-item final model. Convergent validity was assessed using the average variance extracted (AVE) criterion, with a threshold of 0.50 indicating that more than half the variance in indicators is explained by each construct (Fornell & Larcker, 1981). The Heterotrait-Monotrait ratio of correlations (HTMT) was applied to assess discriminant validity, with a value below 0.90 confirming that constructs are empirically distinct (Henseler et al., 2015). The Fornell-Larcker criterion was also applied, requiring the square root of each construct's AVE to exceed its correlation with all other constructs. Instrument consistency was evaluated using Cronbach's alpha (≥ 0.70) and Composite Reliability (CR ≥ 0.70) to assess internal consistency reliability of the construct model, with the acceptable range identified by (Hair et al., 2019; Zakariya, 2022).

Pearson's correlation coefficient analysis was used to test associations between STEM learning attitude, computational thinking (CT) skills, and the mathematics, science, and information technology subscales, with significance levels set at $p < .05$ and $p < .01$ (Gignac & Szodorai, 2016). Hierarchical multiple regression analysis was performed on the three dimensions of STEM learning attitude using IBM SPSS Statistics version 29.0 to examine their predictive contribution to CT skills. Control variables (gender and grade) were entered in Step 1, followed by mathematics, science, and information technology attitudes as primary predictors of CT skills in Step 2. This analytical strategy was grounded in prior research demonstrating that STEM learning tendencies are strong and significant predictors of CT skills among elementary school students (Küçükaydın et al., 2024). CT competencies were characterized using both assessment scores and descriptive statistics, including means and standard deviations. An independent samples t-test was used to examine CT skills by gender, while a paired samples t-test compared Higher-Order versus Lower-Order CT performance. Pearson's correlation analysis was selected over predictive modeling for the attitude-CT relationship because prior findings indicate that attitudes toward STEM domains function as significant correlates of declarative knowledge and beliefs concerning STEM, rather than being fully established as directional predictors at this stage of research (Sun et al., 2021).

## RESULT

### *STEM Learning Attitude Scale*

Exploratory Factor Analysis (EFA) was performed using IBM SPSS Statistics version 29.0 for the sample size of N = 266 The factor structure of the STEM Learning Attitude Scale was investigated through a principal component analysis (PCA), with Varimax rotation. The

Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's Test of Sphericity were assessed to assure appropriateness for factor analysis before the extraction. The KMO value of 0.834 was classified as meritorious (0,80–0,89), which indicates very good sampling adequacy (Dalawi et al., 2025). Bartlett's Test of Sphericity was significant, $\chi^2(300) = 1{,}351.285, p < .001$. (Dalawi et al., 2025).

Seven components greater than 1.0 were extracted, which accounted for a total variance of 53.151%, and see table (Table 1). Eigenvalues: 5.440, 1.556, 1.508, 1.342 and so on A loading threshold of ≥ 0.50 was applied to retain items (Dalawi et al., 2025). For individual item MSA, values from the Anti-image Correlation matrix were inspected and found > 0.50 for all retained items confirming suitability. Items with loadings <0.50 (n=10) were removed, resulting in a final 15-item scale. Cumulative variance explained by the components ranged from 53.151% and factor loadings for retained items were between 0.507 and 0.782, hence interpreted into Mathematics (M), Science (S) & Technology (T). To validate the factor structure, a confirmatory factor analysis (CFA) was performed with 266 fifth-grade students using SmartPLS 3, as shown in Figure 1 (Henseler et al., 2015). For Mathematics, the factor loadings were 0.829 (M2) and 0.815 (M9); for Science, they were 0.762 (S1) and 0.759 (S6); while for Technology they were 0.806 (T1), 0.808 (T2), and 0.753 (T7). All loadings exceeded 0.70, confirming adequate convergent validity at the item level (Hair et al., 2019).

Model fit indices, however, showed mixed results (Table 2). The $\chi^2/df$ ratio (2.43) and RMSEA (0.073, 90% CI [0.061, 0.086]) fell within the acceptable thresholds. In contrast, TLI (0.687), SRMR (0.154), and rms Theta (0.224) did not meet even the minimum acceptable criteria (TLI > 0.90; SRMR < 0.10; rms Theta ≤ 0.12), indicating that the overall measurement model requires further refinement. As CFA fit indices are sensitive to model characteristics such as the number of indicators and factor structure (Goretzko et al., 2024), the partial fit achieved here, together with strong item-level loadings, is presented as partial rather than complete evidence of model adequacy. Discriminant validity was evaluated using the Fornell-Larcker criterion and HTMT (Table 3). Using the Fornell-Larcker criterion, Mathematics, Science, and Technology each showed a square root of AVE exceeding their correlations with the other first-order constructs, supporting discriminant validity among these three factors. However, the second-order STEM Learning construct did not meet this criterion: its square root of AVE (0.463) was lower than its correlations with Mathematics (0.517) and Technology (0.824), indicating limited discriminant validity for the higher-order construct (Fornell & Larcker, 1981).

This pattern was corroborated by the HTMT results, which showed that STEM Learning exceeded the 0.90 threshold in its relationship with both Science (HTMT = 1.238) and Technology (HTMT = 0.963), suggesting substantial conceptual overlap between the global STEM Learning construct and two of its component factors (Henseler et al., 2015). All other construct pairs (Mathematics–STEM Learning = 0.869; Mathematics–Science = 0.433; Mathematics–Technology = 0.301; Science–Technology = 0.645) fell within the acceptable threshold, demonstrating sufficient distinctiveness between the first-order constructs (Ringle et al., 2023).

At the item level, item-total correlations ranged from 0.156 to 0.551 (Table 4). At the factor level, subscale-to-total correlations were higher, ranging from 0.602 to 0.802. Cronbach's alpha reflects the degree of interrelatedness among a set of items measuring a construct, with values above 0.70 generally considered acceptable for scale reliability in educational research (Zakariya, 2022) . Based on this criterion, the final 7-item scale showed an overall

Cronbach's alpha of 0.621, which falls below the commonly recommended threshold, indicating only marginal internal consistency rather than strong reliability. This result should be interpreted in light of the item reduction from the original 25-item to the final 7-item structure, which appears to have constrained the scale's overall reliability despite adequate individual item loadings.

**Table 1.** Results of Factor Analysis for the STEM Learning Attitude Scale Categorized by Factors

| Factor | Items | Com. Fact. | F1 | F2 | F3 | F4 | F5 | F6 | F7 |
|---|---|---|---|---|---|---|---|---|---|
| Math (M) | M1 When I study math and come across a difficult problem, I work hard to solve it. | 0.513 | | | | 0.579 | | | |
| | M2 When the teacher grades our assignments, I carefully check where I made mistakes and correct them | 0.567 | | | 0.717 | | | | |
| | M3 I often use what I've learned in math in my daily life. | 0.587 | | | | | | 0.736 | |
| | M4 I enjoy discussing math problems with my friends. | 0.671 | | | | 0.734 | | | |
| | M5 No matter what my current grade is, I believe I can learn math well. | 0.413 | | | | | | | |
| | M6 I like studying math | 0.497 | | | | | | | |
| | M7 After studying a topic, I can work on problems related to that topic. | 0.502 | | | | | | 0.533 | |
| | M8 When the teacher asks a question in math class, I try to answer actively. | 0.534 | | | | | | | |

| | | | | | |
|---|---|---|---|---|---|
| | M9 After doing my homework, I review my answers and correct any mistakes. | 0.562 | | 0.612 | |
| Science (S) | S1 I find science experiments fun and not boring. | 0.646 | | | 0.709 |
| | S2 Observation activities in science class help me better understand the lessons. | 0.485 | | | |
| | S3 During science activities outside the classroom, I follow the teacher's instructions well. | 0.390 | | | |
| | S4 Science knowledge is useful for my daily life. | 0.413 | | | |
| | S5 I like sharing interesting facts about science with my friends. | 0.459 | | | |
| | S6 Science has provided many benefits for the development of 438society. | 0.479 | | | 0.507 |
| | S7 I feel that I can conduct science experiments well. | 0.438 | | | |
| Technology (T) | T1 I feel that I learn well in computer class. | 0.624 | 0.762 | | |
| | T2 I will actively answer the teacher's questions in computer class. | 0.604 | 0.580 | | |

| | | | | | |
|---|---|---|---|---|---|
| | T3 I often receive praise from the teacher during computer class. | 0.527 | | 0.654 | |
| | T4 I feel that the knowledge and skills I learned in computer class will be very helpful for my future learning. | 0.457 | | | |
| | T5 I can correctly follow all the steps demonstrated by the teacher. | 0.654 | | | 0.782 |
| | T6 I will apply what I learn in computer class to my daily life. | 0.445 | | 0.512 | |
| | T7 I like the computer class. | 0.661 | 0.773 | | |
| | T8 In computer class, I often work with friends to complete assignments. | 0.554 | | | |
| | T9 After finishing the teacher's assignments, I can create new projects based on what I've learned. | 0.604 | | 0.610 | |

**Table 2.** Model Fit

| Fit Index | Value | Perfect Fit | Acceptable Fit | Decision |
|---|---|---|---|---|
| $\chi^2/df$ | 2.43 | $0 < \chi^2/df < 3$ | $3 < \chi^2/df < 5$ | Accepted |
| RMSEA | 0.073 | 0 < SRMR < 0.06 | 0.06 < RMSEA < 0.08 | Accepted |
| RMSEA 90% CI | [0.061; 0.086] | — | — | — |
| TLI | 0.687 | 0.95 < TLI < 1 | 0.90 < TLI < 0.95 | No Accepted |
| SRMR | 0.154 | 0 < RMSEA < 0.05 | 0.05 < SRMR < 0.10 | No Accepted |
| rms Theta | 0.224 | — | ≤ 0.12 | No Accepted |

**Table 3.** Discriminant Validity

| Construct | Mathematics | STEM Learning | Science | Technology |
|---|---|---|---|---|
| Fornell-Larcker Criterion | | | | |
| Mathematics | 0.822 | | | |
| STEM Learning | 0.517 | 0.463 | | |
| Science | 0.163 | 0.555 | 0.760 | |
| Technology | 0.185 | 0.824 | 0.279 | 0.789 |
| HTMT | | | | |
| Mathematics | | | | |
| STEM Learning | 0.869 | | | |
| Science | 0.433 | 1.238 | | |
| Technology | 0.301 | 0.963 | 0.645 | |

**Table 4.** Item-Total Correlation of the STEM Learning Attitude Scale

| F1 mathematics (M) | | F2 science (S) | | F3 technology (T) | |
|---|---|---|---|---|---|
| Items | r | Items | R | Items | r |
| M2 | 0.351** | S1 | 0.156** | T1 | 0.551** |
| M9 | 0.351** | S6 | 0.156** | T2 | 0.504** |
| | | | | T7 | 0.486** |
| M | 0.602** | S | 0.635** | T | 0.802** |
| | | | | Sum | 0.621 |

***p < .01.*

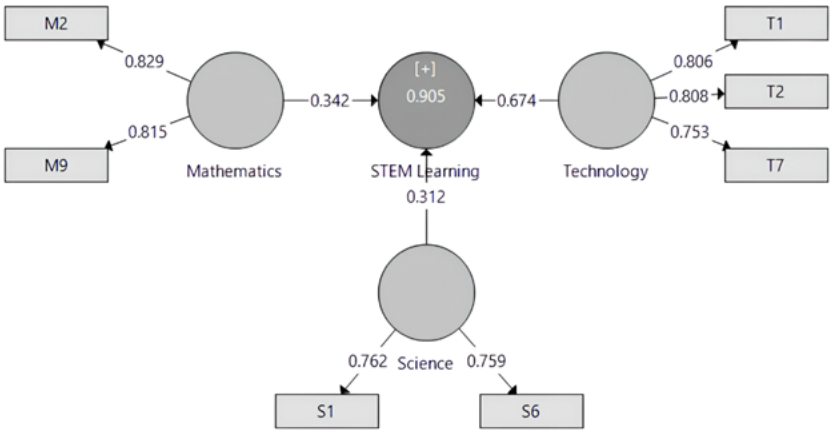



**Figure 1.** Confirmatory Factor Analysis Diagram of The Scale

### *Correlation between STEM learning attitude and CT skills*

The results of the descriptive statistics are presented in Table 5. Students' overall STEM learning attitude score fell toward the upper portion of the possible range, indicating a generally favorable disposition toward STEM learning among the fifth-grade participants. Among the three dimensions, the technology dimension displayed the widest variability in scores, whereas the science dimension displayed the least, suggesting that students held more homogeneous views toward science than toward mathematics or technology. Computational thinking (CT) scores likewise clustered toward the higher end of the possible range, reflecting a moderately strong overall level of CT competence in this sample.

Based on the independent samples t-test, no statistically significant gender differences were found in overall STEM learning attitude, nor in any of its three dimensions, mathematics, science, or information technology (all $p > .05$). This indicates that male and female students held comparably favorable attitudes toward STEM learning in this sample, regardless of domain. In contrast, a statistically significant gender difference was found in computational thinking (CT) skills ($p < .05$), with female students outperforming their male counterparts on the CT task. This divergence is notable: although boys and girls reported statistically indistinguishable attitudes toward STEM, they differed in demonstrated CT performance, with girls showing an advantage in actual skill despite no corresponding advantage in self-reported attitude.

As shown in Table 6, the results of the Pearson correlation analysis depict the relationships between STEM learning attitude (LA), its three components, and CT skills. All three STEM attitude subdomains correlated positively with the overall LA (STEM) score, with technology showing the strongest association among the three, consistent with its role as the dominant contributor to the total attitude score. Correlations among the three subdomains themselves were comparatively weaker, particularly between mathematics and science, indicating that although the dimensions belong to a common underlying construct, they also retain a meaningful degree of independence from one another. In contrast, CT skills showed no significant association with STEM learning attitude or with any of its three subcomponents. This finding reinforces the pattern already observed in the gender comparisons above: STEM attitude and CT skill appear to operate as largely independent constructs in this sample, rather than as two expressions of the same underlying disposition. The relationship between beliefs toward STEM and CT skills does not, therefore, appear to be straightforward, and may instead be shaped by other intervening variables such as broader 21st-century skills (Küçükaydın et al., 2024).

**Table 5.** Descriptive Analysis

| Variables | N | Min | Max | M | SD | Gender t |
|---|---|---|---|---|---|---|
| LA (STEM) | 240 | 11.00 | 28.00 | 22.26 | 2.80 | 0.654 |
| F1 Mathematics (M) | 240 | 2.00 | 8.00 | 6.73 | 1.13 | 0.665 |
| F2 Science (S) | 240 | 2.00 | 8.00 | 6.40 | 1.10 | 0.118 |
| F3 Technology | 240 | 4.00 | 12.00 | 9.12 | 1.81 | 0.526 |
| CT Skills | 240 | 18.00 | 30.00 | 24.73 | 2.61 | -2.330** |

*Abbreviation: LA, learning attitude. *p < .05. **p < .01.*

**Table 6.** Correlational Analysis Among the Variables

| Variables | LA (STEM) | Mathematics | Science | Technology | CT |
|---|---|---|---|---|---|
| LA (STEM) | – | 0.567*** | 0.613*** | 0.823*** | 0.004 |
| F1 Mathematics (M) | | – | 0.123*** | 0.180*** | -0.049 |
| F2 Science (S) | | | – | 0.269*** | 0.067 |
| F3 Technology (T) | | | | – | -0.003 |
| Computational Thinking | | | | | – |

*Note. *p < .05, **p < .01, ***p < .001. N = 240. LA (STEM) = STEM Learning Attitude (skor total); CT = Computational Thinking.*

### *Gender Differences and Predictors of Computational Thinking Skills*

In Table 7, the results of the hierarchical regression analysis indicate that gender is a significant predictor of computational thinking (CT) skills in Step 1, although the proportion

of variance it explains is relatively small. When the three dimensions of STEM learning attitudes (mathematics, science, and information technology) were included together in Step 2, the additional variance explained by the model was not statistically significant. In other words, STEM learning attitudes, whether considered collectively or in their individual dimensions, do not provide a meaningful additional contribution to predicting CT skills beyond what is already explained by gender alone. At the level of individual coefficients, none of the three dimensions of STEM attitudes showed a significant effect on CT when controlled for gender, while gender remained the only consistently significant predictor in both model steps. These findings reinforce a pattern previously observed in t-tests and correlation analyses: CT skills appear to be relatively independent of students' affective attitudes toward STEM, and it is gender that serves as the more consistent distinguishing factor.

These results are consistent with previous findings indicating that the relationship between attitudes toward STEM and CT skills is not direct but is likely mediated or moderated by other variables beyond the scope of this model (Küçükaydın et al., 2024). Table 7 presents comparisons by gender for CT skills among elementary school students across total CT skills and both CT Higher Order and CT Lower Order subscales using an independent samples t-test. This is in keeping with (Sun et al., 2021), which also found that female students exhibited statistically higher CT skills than male students but only slightly. This pattern might be due to differences in cognitive and behavioral dispositions at this developmental stage in which girls were more deliberate and systematic when solving problems. These findings may indicate girls in elementary school are capable of greater CT competence when offered equal opportunities for engagement in STEM learning.

**Table 7.** Hierarchical Regression Analysis Results (Dependent)

| Predictor Variables | β | t | $R^2$ | $\Delta R^2$ |
|---|---|---|---|---|
| Step 1 | | | 0.0223* | 0.0223* |
| Gender | 0.779 | 2.33 | | |
| Step 2 | | | 0.0297* | 0.00737** |
| F1 Mathematics | -0.118 | -0.775 | | |
| F2 Science | 0.183 | 1.145 | | |
| F3 Technology | -0.013 | -0.134 | | |

*Abbreviation: LA, learning attitude. *p < .05. **p < .01.*

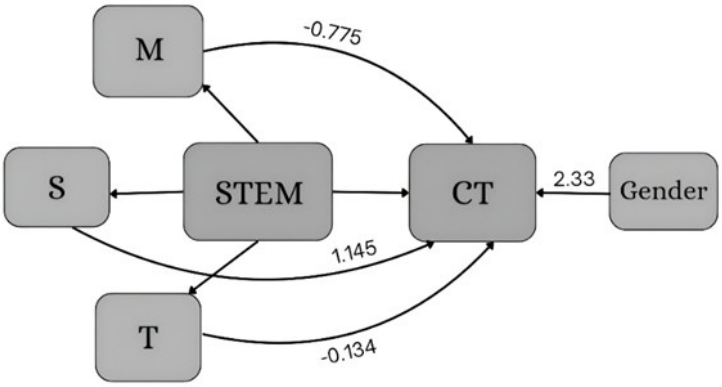



**Figure 2.** Schematic Diagram of Predictive Factors and CT

**Table 8.** Gender Differences in CT Skills

| | Gender | N | M | SD | t | p |
|---|---|---|---|---|---|---|
| CT | Male | 125 | 24.36 | 2.47 | -2.321 | .021* |
| | Female | 115 | 25.14 | 2.71 | | |
| CT Higher Order | Male | 125 | 12.19 | 1.31 | -2.220 | .027* |
| | Female | 115 | 12.59 | 1.46 | | |
| CT Lower Order | Male | 125 | 12.17 | 1.28 | -2.201 | .029* |
| | Female | 115 | 12.55 | 1.38 | | |

**p < .05*

## DISCUSSION

### *STEM Learning Attitude Scale*

A KMO value of 0.834 and a significant Bartlett's Test confirm the suitability of the inter-item correlation matrix of the STEM Learning Attitude Scale for factor analysis, in line with the sampling adequacy criteria of (Dalawi et al., 2025). The extraction of seven components accounting for 53.151% of the variance falls within a reasonable range for an elementary school student attitude scale, although it is below the ideal threshold of 60%. The reduction of items from twenty-five to fifteen using a loading threshold of 0.50 indicates a rigorous purification process. A validation study of the STEM Motivation Scale for Children involving 549 students yielded a higher variance (63.4%) with a more lenient loading threshold (Ribaric et al., 2025), which explains why the application of a strict threshold in this study resulted in a moderate proportion of variance.

All factor loadings for Mathematics, Science, and Technology in the CFA stage exceeded 0.70, meeting the criteria for convergent validity established by (Hair et al., 2019). These findings confirm that the three STEM dimensions remain adequately represented by the retained indicators, even though the item reduction in the EFA stage was quite substantial. The high consistency of loadings at the item level indicates that the measurement issues that arose during the model fit and reliability stages did not stem from weak convergent validity of the items. These issues were more closely related to the overall structure of relationships among constructs, particularly at the model and higher-order construct levels.

Model fit indices showed mixed results; $\chi^2/df$ and RMSEA met the thresholds, while TLI, SRMR, and rms Theta did not meet the minimum criteria. This pattern of misfit is commonly found in models with high-order factor structures or a limited number of indicators per construct, as noted in a review of 221 CFA models in the journal Psychological Assessment (Goretzko et al., 2024). Validation of the Elementary School Motivation Scale among 1,190 Spanish students yielded a CFI of 0.929 and a TLI of 0.913, which are considered good (Ramos et al., 2022). This discrepancy indicates a seven-factor structure with an uneven distribution of items, contributing to greater model complexity compared to a simpler alternative structure. Fornell-Larcker's discriminant validity was met for all three first-order constructs; however, the second-order construct "STEM Learning" exhibited a lower AVE root than its correlations with Mathematics and Technology. This pattern is confirmed by HTMT values exceeding 0.90, following the procedure by (Henseler et al., 2015), refined by (Ringle et al., 2023). Conceptual overlap between second-order constructs and their constituent components is a structural consequence inherent in hierarchical repeated-indicator models. This condition indicates that STEM Learning, as an umbrella construct, has not yet been fully empirically distinguished from its constituent dimensions.

The reliability of the seven-item scale, at 0.621, is considered marginal relative to the 0.70 threshold recommended by (Zakariya, 2022) in a review of alpha coefficients in educational research. Item-total correlations ranging from 0.156 to 0.551 indicate a fairly wide variation in the contribution of individual items. Similar instruments achieve alpha values ranging from 0.76 to 0.91 on STEM subscales for elementary school students with a greater number of items per factor (Ribaric et al., 2025). The drastic reduction from twenty-five to seven items appears to limit reliability, given that alpha is mathematically sensitive to the number of items. Higher subscale-to-total correlations (0.602–0.802) suggest better homogeneity among factors than homogeneity among items.

These findings indicate that the STEM Learning Attitude Scale is an instrument with adequate first-order item validity and discriminant validity; however, it still requires refinement in terms of overall model fit, second-order construct discriminant validity, and the reliability of the short-form scale. Teachers and researchers using this instrument are advised to treat the Mathematics, Science, and Technology scores separately, given the evidence of conceptual overlap in the combined STEM Learning score. Future research should ideally consider adding items to each subscale, applying complementary reliability indices such as McDonald's omega, and retesting the model with a larger sample to more robustly validate the seven-factor structure.

### *Correlation between STEM learning attitude and CT skills*

The mean score of STEM learning attitudes among fifth-grade students, which falls in the upper part of the score range, indicates a positive disposition toward STEM learning in late elementary school age. The technology dimension shows the widest score variability, while the science dimension shows the narrowest variability, indicating that students' perceptions of science are relatively more uniform than those of mathematics or technology. Greater variation in the technology dimension is likely influenced by students' exposure to personal experiences with digital devices at home, in contrast to the science dimension, which is shaped more uniformly through the school curriculum. Computational thinking (CT) scores, which also cluster in the upper part of the range, indicate that students' CT competence is moderate to fairly strong in this sample.

The absence of significant gender differences in STEM learning attitudes overall as well as across its three dimensions shows that male and female students have equal affective dispositions toward mathematics, science, and technology. This finding is consistent with the shift in the pattern of the gender gap in STEM education, where disparities long considered structural are more often caused by preferences and choices rather than differences in basic ability (Idrizi et al., 2023). Significant gender differences instead appeared in CT skills, with female students outperforming, a pattern also reported in a number of studies in the Asia region although not consistently across all cultural contexts (Niousha et al., 2023). This divergence confirms that positive attitudes toward STEM do not automatically reflect students' actual cognitive skills.

The three STEM attitude subdomains were positively correlated with the total score, with technology showing the strongest association in line with its role as the dominant contributor. The correlations among the subdomains themselves were relatively weaker, particularly between mathematics and science, indicating that the three dimensions originate from one overarching construct while still maintaining a meaningful degree of independence. This pattern strengthens the argument that attitudes toward mathematics,

science, and technology constitute a multidimensional construct that cannot be fully reduced to a single dimension, so interpretation and learning interventions should continue to consider the characteristics of each subdomain separately.

The absence of a significant association between CT and STEM learning attitudes as well as its three subcomponents reinforces the pattern seen in the results of the gender difference test, namely that STEM attitudes and CT skills operate as relatively independent constructs in this sample. This finding is consistent with mixed evidence in the literature, in which some studies report strong correlations between STEM attitudes and CT while other studies find weak relationships, depending on the intervention design and cultural context (Suherman et al., 2025). The relationship between beliefs about STEM and CT skills does not appear to be direct, and is likely mediated by other accompanying variables such as 21st-century skills (Küçükaydın et al., 2024).

These findings suggest that STEM learning programs in elementary schools need to be designed separately between attitude formation components and the development of cognitive skills such as CT, considering that the two do not necessarily move in tandem. Teachers are advised not to assume that students with positive attitudes automatically have high CT skills, or vice versa. The superior CT performance of female students without a comparable advantage in attitude opens opportunities for more targeted pedagogical interventions to strengthen girls' self-confidence. Further research should ideally involve mediating variables such as critical thinking to explain this dissociation between attitude and CT skills.

### *Gender Differences and Predictors of Computational Thinking Skills*

Gender was a significant predictor of CT in Step 1, although the proportion of explained variance was small. The addition of the three STEM attitude dimensions in Step 2 did not provide a significant additional contribution. STEM attitudes, whether combined or in each dimension, did not contribute meaningful prediction to CT beyond what was already explained by gender. These findings reinforce the view that CT is more determined by demographic factors than by students' affective factors toward STEM, in line with the pattern in the previous descriptive and correlation results.

The non-significance of the three STEM attitude coefficients when gender is controlled, while gender remains consistently significant in both steps, reinforces the independence between students' affective and cognitive domains. The consistency of gender as a CT predictor is in line with a randomized controlled trial among elementary school students in Basra, Iraq, which found that robotics-based learning significantly improved CT in female students but not in male students (Shimizutani et al., 2025). A similar pattern was reported among prospective science-mathematics teachers, with the CT gap between genders narrowing after a robotics intervention (Serrano et al., 2024). These results are consistent with findings that the relationship between STEM attitudes and CT is not direct, but is likely mediated by other variables beyond the scope of this model (Küçükaydın et al., 2024). A model that explains only a small portion of CT variance through gender indicates that most CT variation has not yet been explained by basic affective or demographic variables. This condition underscores the need for additional cognitive and contextual variables, such as programming experience or exposure to technology at home, for a more comprehensive CT prediction model.

These findings have implications for designing elementary school STEM programs so that they do not only focus on strengthening attitudes, but also target the explicit development of CT. Teachers are advised to consider robotics-based learning or visual programming, which have been shown to improve CT, rather than relying solely on strengthening attitudes. Future research should ideally add cognitive variables and technology experience as predictors, as well as further examine why gender consistently predicts CT even though STEM attitudes do not differ by gender.

Higher-Order CT dimensions were performed higher in female students compared to their male counterpart also Lower Order. This pattern may again point to a more structured, careful, and sequential approach among female learners at this age stage (Sovey & Osman, 2022). The difference is likely not an indelible quality of cognition to do with innate superiority, but rather a product of learning behavior and involvement in the classroom as well activity during assessment. Consistent with this re-interpretation, prior research has similarly shown that associations between gender and CT vary as a function of the contextual or instructional conditions (Sun et al., 2021). The fact that this pattern was consistent across CT subdimensions suggests a general advantage rather than one specific to the domain.

The findings did not reveal any significant difference between Higher-Order and Lower-Order CT skills, which suggests that this computational skill development is occurring in a parallel fashion within elementary students. At this developmental level, foundational and advanced CT skills seem to emerge in tandem rather than as separate phases (Paraskevopoulou Kollia et al., 2025). Prior evidence indicates that discrimination between CT levels only emerges later, following systematic and prolonged teaching (Lee et al., 2023). The harmonized profile observed in this study reflects readily developing CT in its earlier stages, with cognitive aspects still combined. These results underscore the need for scaffolded strategies to support progressive differentiation of CT competencies in STEM ed contexts.

## CONCLUSION

This study examined the psychometric properties of the STEM Learning Attitude Scale and its relationship with computational thinking (CT) skills among fifth-grade elementary school students in Indonesia, finding that the scale demonstrated adequate first-order validity but did not fully meet accepted criteria for model fit (TLI, SRMR, rms Theta) or second-order reliability, indicating that it remains a promising but preliminary measure requiring further refinement before it can be regarded as a validated instrument; gender differences in STEM attitudes were domain-specific, appearing in mathematics and information technology but not in science, whereas female students scored significantly higher than male students on both CT Higher Order and CT Lower Order dimensions, though this difference reflected only a small effect ($d \approx 0.29–0.30$) according to the benchmark proposed and correlational and hierarchical regression analyses converged in showing that STEM attitudes, whether examined as a composite score or as separate mathematics, science, and technology dimensions, were not significantly related to CT and did not add a significant increment to the prediction of CT once gender was entered into the model, with gender remaining the only consistent, though modest, predictor across both regression steps.

In terms of limitations, the cross-sectional design does not support causal inference regarding the relationships among gender, STEM attitudes, and CT, the psychometric shortcomings of the scale mean that measurement error may have attenuated the associations examined, and the small proportion of CT variance explained by gender alone

indicates that other important predictors, such as prior technology exposure, programming experience, or additional cognitive and contextual variables, were not captured in the present model. In terms of implications, these findings suggest that teachers and program designers should not assume that positive STEM attitudes translate directly into stronger CT skills and should instead design attitude-building and CT-skill-building activities as distinct but complementary components of STEM instruction, that the modest but consistent CT advantage among female students despite no corresponding advantage in attitudes points to an opportunity for targeted, gender-responsive pedagogical strategies to build girls' confidence and sustained engagement in STEM, and that future research should test mediating variables such as 21st-century skills or technology exposure and employ longitudinal or structural equation modeling designs to clarify the directional and indirect pathways linking STEM attitudes, gender, and CT development over time.

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