Al-Ishlah: Jurnal Pendidikan
Vol.18, 1 (March, 2026), pp. 1031-1040
ISSN: 2087-9490 EISSN: 2597-940X, DOI: 10.35445/alishlah.v18i1.9354

Ethnomathematics Meets Computational Thinking: Developing a Learning Model for Mathematical Problem-Solving

Eka Sastrawati[1], Andi Gusmaulia Eka Putri[2], Ahmad Faisal Hidayat[3], Yantoro[4], Violita Zahyuni[5]

[1]Universitas Jambi, Jambi, Indonesia; ekasastrawati@unja.ac.id
[2]Universitas Jambi, Jambi, Indonesia; andigusmauliaekaputri@unja.ac.id
[3]Universitas Jambi, Jambi, Indonesia; ahmadfaisalhidayat@unja.ac.id
[4]Universitas Jambi, Jambi, Indonesia; yantoro@unja.ac.id
[5]Universitas Jambi, Jambi, Indonesia; violitazahyuni0692@unja.ac.id

ARTICLE INFO

Keywords:

ethnomathematics;
computational thinking;
mathematical problem-solving;
learning model

Article history:

Received 2026-01-08
Revised 2026-02-23
Accepted 2026-03-31

ABSTRACT

Mathematical problem-solving and computational thinking (CT) are essential competencies in 21st-century mathematics education. This study developed and evaluated an ethnomathematics-based learning model integrated with CT to enhance elementary students' problem-solving skills. Using a Research and Development approach guided by the ADDIE framework, the model incorporated local Jambi cultural artifacts, including traditional batik geometric patterns, architectural designs, and community-based measurement practices. The model was implemented over eight instructional sessions (four weeks) with 30 fifth-grade students. Expert validation was conducted by three specialists using a five-point Likert scale assessing content, instructional design, and language clarity, yielding a high validity index (M = 4.06/5.00; 81.2%). Effectiveness was examined using a one-group pretest–posttest design (without a control group). Mathematical problem-solving was measured through an essay-based test aligned with Polya's stages, while CT was assessed using a rubric-scored written test covering decomposition, pattern recognition, abstraction, and algorithmic thinking (Cronbach's $\alpha > 0.80$). Results showed significant improvements in mathematical problem-solving (pre: M = 68.00, SD = 7.85; post: M = 86.00, SD = 6.92; $p < .001$) and CT (pre: M = 65.15, SD = 8.10; post: M = 83.30, SD = 7.25; $p < .001$), with a large effect size ($d = 2.45$). These findings provide preliminary evidence for integrating ethnomathematics and CT, warranting larger controlled studies to confirm generalizability.

Corresponding Author:
Eka Sastrawati
Universitas Jambi, Jambi, Indonesia; ekasastrawati@unja.ac.id

1. INTRODUCTION

Mathematical problem-solving is widely recognized as a core competence in mathematics education and a fundamental component of 21st-century learning (Mills et al., 2024; Siller & Greefrath, 2020). Problem-solving enables students to construct conceptual understanding, apply logical reasoning, and generate solutions to unfamiliar situations. In this study, mathematical problem-solving is operationalized using Polya's four stages—understanding the problem, devising a plan, carrying out the plan, and evaluating the solution—which emphasize structured reasoning and reflective thinking processes. Despite its importance, empirical evidence suggests that elementary students' problem-solving skills remain relatively low, as mathematics instruction is often dominated by procedural tasks and formula memorization rather than strategic and analytical reasoning (Chen et al., 2023; Huencho & Chandía, 2023).

Alongside problem-solving, contemporary educational discourse highlights the growing importance of computational thinking (CT) as a transversal cognitive competence applicable across disciplines, including mathematics. In mathematics education, CT is commonly conceptualized through four interrelated components: decomposition, pattern recognition, abstraction, and algorithm design (Weintrop et al., 2020; Yadav et al., 2021). Decomposition involves breaking complex problems into manageable parts; pattern recognition identifies regularities or structures; abstraction focuses on essential information while filtering irrelevant details; and algorithm design entails constructing systematic, step-by-step solution procedures. These components conceptually align with Polya's problem-solving stages: decomposition supports problem comprehension, pattern recognition and abstraction facilitate planning, and algorithm design parallels the execution of solution strategies. Meta-analytic evidence indicates that CT-oriented instruction can enhance reasoning and problem-solving performance (Chen et al., 2023; Montuori et al., 2024). However, CT integration in schools often occurs through coding activities or technology-driven interventions, which are often detached from meaningful subject-specific and sociocultural contexts (Relkin et al., 2021; Wang et al., 2022).

In parallel, ethnomathematics positions mathematics as culturally situated knowledge embedded in local practices, artifacts, and community activities (Rosa & Orey, 2023; Orey & Rosa, 2022). By incorporating cultural contexts—such as traditional architectural designs, batik geometric motifs, crafts, and indigenous measurement systems—ethnomathematics-based instruction can make abstract concepts more meaningful and accessible to learners. Research suggests that culturally grounded mathematics learning enhances engagement, conceptual understanding, and critical reflection (Huencho & Chandía, 2023; Tikva & Tambouris, 2021). Nevertheless, many ethnomathematics studies focus primarily on documenting cultural artifacts or developing contextualized teaching materials, rather than constructing structured instructional models that explicitly cultivate higher-order thinking processes.

Although both CT integration and ethnomathematics show promise for improving mathematics learning, they are often treated as separate pedagogical approaches. Studies on CT in mathematics emphasize cognitive and algorithmic reasoning but rarely incorporate cultural contextualization (Looi et al., 2023; Ye et al., 2023). Conversely, ethnomathematics research highlights cultural relevance yet seldom integrates explicit computational thinking frameworks. As a result, limited empirical evidence exists regarding how culturally contextualized mathematical tasks can systematically foster CT processes that directly support structured problem-solving. This gap suggests the need for a coherent instructional model that intentionally integrates cultural grounding with computational reasoning to strengthen elementary students' mathematical problem-solving.

Theoretically, integrating ethnomathematics and CT aligns with constructivist and sociocultural perspectives, which emphasize knowledge construction through meaningful experiences and social interaction (Barendsen & Tolboom, 2021; Yadav et al., 2021). Culturally embedded tasks provide authentic contexts for sense-making, while CT components offer structured cognitive tools for analyzing and solving problems. Such integration has the potential to bridge the gap between contextual relevance and analytical rigor in mathematics learning. However, to date, few studies have developed and empirically validated a structured learning model that systematically integrates ethnomathematics and CT within a clearly articulated pedagogical framework.

To address this gap, the present study develops a structured instructional model integrating ethnomathematics and computational thinking. The model specifies learning syntax, social system, support system, and assessment strategies, embedding CT components—decomposition, pattern recognition, abstraction, and algorithm design—within culturally contextualized mathematical activities. The model is validated by experts and trialed in an elementary classroom to examine its validity, practicality, and preliminary effectiveness in enhancing students' problem-solving skills.

Accordingly, this study seeks to answer the following research questions: 1. How can an ethnomathematics-based learning model integrated with computational thinking be systematically designed for elementary mathematics instruction? 2. To what extent is the developed model valid and practical for classroom implementation? 3. Does the model provide preliminary evidence of effectiveness in improving students' mathematical problem-solving skills? By articulating and empirically examining a structured ethnomathematics–CT learning model, this study contributes a design-based framework and initial effectiveness evidence for culturally responsive, cognitively structured mathematics education.

2. METHODS

This study employed a Research and Development (R&D) approach guided by the ADDIE framework (Analysis, Design, Development, Implementation, and Evaluation) to develop, validate, and conduct a limited field trial of a structured learning model integrating ethnomathematics and computational thinking (CT). The study was designed to produce a theoretically grounded and practically feasible instructional model and to examine its preliminary effectiveness. The evaluation phase used a one-group pretest–posttest design without a control group; therefore, the findings regarding effectiveness are considered preliminary and not intended to establish causal inference.

The development process began with a needs analysis through classroom observation, curriculum review, and interviews with teachers to identify students' difficulties in mathematical problem-solving and the limited integration of culturally contextualized instruction and computational thinking processes. Based on this analysis, a structured learning model was designed by embedding four core CT components—decomposition, pattern recognition, abstraction, and algorithm design—into culturally contextualized mathematical activities. Ethnomathematical contexts were drawn from local Jambi cultural artifacts and systematically mapped onto Grade 5 mathematics topics. Traditional batik geometric motifs were used to support learning about symmetry, transformations, and pattern structures; traditional house architectural designs were connected to geometric shapes, angles, and spatial reasoning; local measurement practices were linked to unit conversion and proportional reasoning; and repetitive ornamental or weaving patterns were used to explore numerical sequences and generalization. This mapping ensured alignment between cultural context, mathematical content, and CT processes.

The structured components of the learning model include instructional syntax, teacher and student roles, learning resources, CT embedding, and assessment strategies, as summarized in Table 1.

Table 1. Components of the Ethnomathematics–Computational Thinking Learning Model

Phase (Syntax)	Teacher Role	Student Role	Learning Resources	CT Embedded	Assessment Focus
Cultural Problem Orientation	Present contextual cultural problem and guide inquiry	Observe, identify key information	Images, videos, real cultural artifacts	Decomposition	Diagnostic questioning
Problem Decomposition	Scaffold breaking down complex problems	Identify sub-problems	Structured worksheets	Decomposition	Formative checklist
Pattern Exploration	Facilitate identification of regularities	Detect and describe patterns	Batik/architecture visuals	Pattern recognition	Worksheet analysis
Abstraction and Modeling	Guide generalization into mathematical form	Formulate mathematical representation	Guided prompts	Abstraction	Rubric-based evaluation

Phase (Syntax)	Teacher Role	Student Role	Learning Resources	CT Embedded	Assessment Focus
Algorithm Design	Support step-by-step solution planning	Construct systematic procedures	Problem-solving sheets	Algorithm design	Polya-aligned rubric
Reflection and Evaluation	Facilitate reflective discussion	Evaluate solution accuracy and reasoning	Reflection journal	Integrated CT processes	Reflective assessment

The study was conducted in one public elementary school in Jambi City, Indonesia. The school was purposively selected because it integrates local cultural elements in instruction and represents a typical urban public elementary school context. Participants included 30 fifth-grade students (aged 10–11) from one intact classroom and one mathematics teacher with 8 years of teaching experience. Inclusion criteria included enrolment in Grade 5, regular attendance during the intervention period, and participation in regular classroom instruction without specialized parallel curriculum modifications. The sample size reflects a limited field trial typical of R&D studies aimed at evaluating feasibility, validity, and preliminary effectiveness rather than broad generalization.

The intervention was implemented over eight instructional sessions across four weeks. Data collection involved pre-test and post-test measures of mathematical problem-solving and computational thinking, expert validation instruments, and practicality questionnaires administered to both teachers and students after implementation.

Mathematical problem-solving was assessed using six open-ended essay items aligned with Polya's four stages: understanding the problem, devising a plan, carrying out the plan, and evaluating the solution. Responses were scored using an analytic rubric on a four-point scale per stage and converted to a 100-point scale. Content validity was evaluated using Aiken's V, with coefficients ranging from 0.84 to 0.92, indicating strong content relevance. Because scoring involved subjective judgment, two independent raters evaluated student responses, and inter-rater reliability analysis yielded an intraclass correlation coefficient (ICC) of 0.87. Internal consistency reliability was acceptable, with Cronbach's alpha of 0.82.

Computational thinking was measured using a 12-item structured-response test assessing decomposition, pattern recognition, abstraction, and algorithm design, with three items per component. Items were adapted from established computational thinking assessment frameworks and contextualized within mathematical and cultural problem situations. Content validity was examined using a Content Validity Index (CVI), yielding an overall index of 0.88. Internal consistency reliability was 0.85, indicating satisfactory measurement stability. Example tasks required students to design step-by-step procedures for solving pattern-based cultural problems or to generalize structural relationships found in batik motifs.

Practicality was evaluated through teacher and student questionnaires using a five-point Likert scale. The teacher instrument consisted of 18 items addressing instructional clarity, feasibility, time allocation, student engagement, and clarity of CT integration. The student questionnaire consisted of 15 items addressing engagement, comprehensibility, cultural relevance, and perceived usefulness. Reliability analysis indicated high internal consistency (teacher $\alpha = 0.91$; student $\alpha = 0.88$).

Data analysis combined descriptive and inferential procedures. Expert validation and practicality responses were analyzed using mean scores and percentage indices. For effectiveness analysis, normality assumption testing was conducted before inferential analysis. If assumptions were met, paired-samples t-tests were used to compare pre-test and post-test scores; if assumptions were violated, a nonparametric alternative (Wilcoxon signed-rank test) was planned. Effect sizes appropriate for paired designs were calculated, along with confidence intervals, to provide an estimate of practical significance. Because the study employed a one-group pretest–posttest design without a control group, the results are interpreted as evidence of preliminary effectiveness within the context of a limited field trial.

Ethical considerations were addressed by obtaining formal permission from the school administration and informed consent from teachers, students, and parents. Participation was voluntary, and data were anonymized and reported in aggregate form to ensure confidentiality.

3. FINDINGS AND DISCUSSION

3.1 Findings

The findings are presented in four sections: (1) expert validation results, (2) practicality evaluation, (3) preliminary effectiveness analysis, and (4) learning process evidence based on classroom observations and student work. The expert validation instrument consisted of 24 items rated on a five-point Likert scale (1 = very poor to 5 = very good), covering three dimensions: content relevance (8 items), instructional design coherence (10 items), and language clarity (6 items). Based on the predetermined criteria, mean scores ≥ 4.00 (≥ 80%) were categorized as "very valid," 3.00–3.99 as "valid," and below 3.00 as requiring major revision. The overall validity mean score was 4.06 (81.2%), indicating very high validity. Dimension-level results are presented in Table 2.

Table 2. Expert Validation Results by Dimension

Dimension	Items (n)	Mean	Percentage (%)	Category
Content relevance	8	4.05	81.0	Very Valid
Instructional design coherence	10	4.08	81.6	Very Valid
Language clarity	6	4.04	80.8	Very Valid
Overall	24	4.06	81.2	Very Valid

Content validity analysis using Aiken's V indicated coefficients ranging from 0.84 to 0.92 across items, confirming strong agreement among validators. Minor revisions were suggested, mainly to simplify worksheet instructions and clarify problem statements, and were implemented before field testing.

Practicality was evaluated using teacher (18 items) and student (15 items) questionnaires, both on a five-point Likert scale. A percentage ≥ 85% was categorized as "very practical." The teacher questionnaire yielded an overall mean of 4.60 (92.0%), and the student questionnaire yielded 4.50 (90.0%), both of which were categorized as very practical. Detailed results are shown in Table 3.

Table 3. Practicality Results by Dimension

Respondent	Dimension	Mean	Percentage (%)	Category
Teacher	Instructional clarity	4.65	93.0	Very Practical
Teacher	Feasibility & time management	4.55	91.0	Very Practical
Teacher	Student engagement	4.60	92.0	Very Practical
Student	Engagement & interest	4.52	90.4	Very Practical
Student	Clarity of tasks	4.48	89.6	Very Practical
Student	Cultural relevance	4.50	90.0	Very Practical

These findings indicate that the learning model was perceived as feasible, clearly structured, and engaging within authentic classroom conditions.

Preliminary effectiveness was examined using a one-group pretest–posttest design. Because no control group was included, the findings are considered preliminary and contextualized within a limited field trial. Normality assumptions were satisfied based on Shapiro–Wilk tests ($p > .05$), allowing the use of paired-samples t-tests.

For mathematical problem-solving, mean scores increased from 68.00 (SD = 7.85) to 86.00 (SD = 6.92). The paired-samples t-test revealed a statistically significant improvement, $t(29) = 12.47$, $p < .001$ (two-tailed). The 95% confidence interval for the mean difference ranged from 15.05 to 20.95. The effect size for paired samples was very large (d = 2.45; 95% CI [1.80, 3.10]). Descriptive results are shown in Table 4.

Table 4. Pretest–Posttest Results for Mathematical Problem-Solving

Measure	Pretest Mean (SD)	Posttest Mean (SD)	Mean Difference	t(29)	p-value	95% CI of Difference
Problem-solving	68.00 (7.85)	86.00 (6.92)	18.00	12.47	< .001	[15.05, 20.95]

For computational thinking (CT), the total score increased from 65.15 (SD = 8.10) to 83.30 (SD = 7.25), t(29) = 11.32, p < .001, with a 95% confidence interval for the mean difference of [14.70, 21.60]. Improvements were observed across all four CT components, as shown in Table 5.

Table 5. Pretest–Posttest Results for Computational Thinking

CT Component	Pretest Mean (SD)	Posttest Mean (SD)	Mean Gain
Decomposition	65.20 (8.30)	84.60 (7.10)	19.40
Pattern recognition	67.10 (7.90)	82.30 (7.40)	15.20
Abstraction	64.80 (8.40)	80.90 (7.80)	16.10
Algorithm design	63.50 (8.10)	85.40 (6.90)	21.90
CT Total	65.15 (8.10)	83.30 (7.25)	18.15

The largest gains were observed in algorithm design and decomposition, suggesting that the structured instructional phases particularly supported systematic reasoning and step-by-step solution construction.

Although the effect size for problem-solving was very large (d = 2.45), this magnitude should be interpreted cautiously. The one-group pretest–posttest design may inflate effect sizes due to testing effects, novelty effects associated with a new instructional approach, the relatively short intervention duration (eight sessions), and the absence of a comparison group. Therefore, the findings should be considered evidence of preliminary effectiveness rather than definitive causal impact.

To complement quantitative results, classroom observations and student work were coded using structured observation sheets aligned with the four CT components. Representative patterns are presented in Table 6.

Table 6. Observed Computational Thinking Behaviors During Implementation

CT Component	Observed Behavior	Evidence from Student Work
Decomposition	Breaking complex cultural problems into smaller parts	Students divided batik area tasks into unit tiles before calculating totals
Pattern recognition	Identifying structural repetition in motifs	Students described rotational and reflective symmetry in batik designs
Abstraction	Translating contextual problems into mathematical representation	Students modeled traditional roof shapes as composite geometric figures
Algorithm design	Constructing structured solution procedures	Students listed step-by-step unit conversion processes in measurement tasks

These qualitative findings provide process-level evidence that students increasingly demonstrated structured computational thinking behaviors during culturally contextualized mathematical problem-solving activities.

Overall, the results indicate that the developed ethnomathematics–computational thinking learning model is valid and practical, and provide preliminary evidence of improving mathematical problem-solving and computational thinking skills within a limited field trial context. Further research with controlled experimental designs and larger samples is necessary to confirm the robustness and generalizability of these findings.

3.2 Discussion

This study aimed to develop and conduct a limited field trial of a structured learning model integrating ethnomathematics and computational thinking (CT) to enhance elementary students' mathematical problem-solving skills. The findings indicate that the developed model is valid and practical and demonstrates preliminary effectiveness. Rather than merely attributing improvement to contextualized learning, it is important to explain the mechanisms through which cultural grounding and computational thinking processes may have supported students' problem-solving development.

The integration of ethnomathematics provided meaningful cultural contexts—such as batik geometric motifs, traditional architectural structures, and local measurement practices—that functioned as cognitive entry points for abstraction and pattern recognition. Cultural artifacts served not only as motivational tools but as epistemic resources through which mathematical structures became visible. When students analyzed repeating motifs in batik patterns, they identified regularities and invariants before generalizing them mathematically. This process reflects abstraction emerging from situated experience rather than from purely symbolic manipulation. Such contextual grounding aligns with the principles of ethnomathematics, which position mathematical knowledge as embedded in cultural practices (Rosa & Orey, 2023; Orey & Rosa, 2022). Prior studies have shown that culturally contextualized mathematics learning enhances engagement and conceptual understanding (Huencho & Chandía, 2023; Tikva & Tambouris, 2021), yet many did not explicitly articulate how these contexts cultivate structured higher-order reasoning.

The incorporation of computational thinking complemented cultural contextualization by providing systematic cognitive scaffolding. CT in mathematics is commonly framed in terms of decomposition, pattern recognition, abstraction, and algorithm design (Weintrop et al., 2020; Yadav et al., 2021). These processes closely align with Polya's stages of problem-solving. Decomposition supports understanding complex problems by breaking them into manageable components. Pattern recognition and abstraction facilitate devising a solution plan by identifying structural relationships. Algorithm design parallels the execution of a plan through structured, step-by-step procedures. In this model, CT did not function as a technology-driven add-on but as a cognitive organizer embedded within culturally meaningful tasks. Empirical literature indicates that CT-oriented instruction can strengthen logical reasoning and structured problem-solving (Chen et al., 2023; Montuori et al., 2024). However, many CT interventions emphasize coding or digital tools (Looi et al., 2023; Ye et al., 2023), often detached from sociocultural meaning-making. By grounding CT processes in local cultural contexts, this study demonstrates a complementary relationship between cultural relevance and algorithmic reasoning.

Theoretically, this integration can be understood through constructivist and sociocultural learning perspectives. Constructivism emphasizes that knowledge is actively constructed through meaningful engagement rather than passively received. In this study, students constructed mathematical understanding by analyzing culturally situated patterns and modeling them mathematically. Sociocultural theory further explains that learning is mediated by cultural tools and social interaction (Yadav et al., 2021). Cultural artifacts in the classroom functioned as mediational tools, enabling students to negotiate meaning collaboratively while engaging in structured reasoning. In this sense, the model connects culturally responsive pedagogy with problem-solving theory, using Polya's framework as a structural backbone and CT as the operational cognitive mechanism.

Compared with previous research, this study offers a distinct contribution. Ethnomathematics-only interventions have emphasized cultural documentation or the development of contextual material (Huencho & Chandía, 2023; Tikva & Tambouris, 2021), but often lacked explicit alignment with systematic cognitive frameworks. Conversely, CT-focused mathematics interventions have demonstrated improvements in reasoning (Chen et al., 2023; Ye et al., 2023), but they often rely on digital or coding-based environments and pay limited attention to cultural grounding. The present study differs by operationalizing the integration of ethnomathematics and CT within a clearly structured instructional model specifying syntax, teacher roles, student roles, support systems, and assessment strategies. Thus, the novelty lies not merely in combining two approaches but in articulating and validating a coherent pedagogical design that aligns cultural context, computational processes, and problem-solving theory.

Although the statistical findings indicate substantial improvement and a very large effect size, this magnitude must be interpreted cautiously. The one-group pretest–posttest design is susceptible to testing effects, novelty effects associated with exposure to a new instructional model, and short-duration intervention influences. Without a control group, it is not possible to attribute gains exclusively to the intervention. Therefore, the findings represent preliminary effectiveness within the scope of a limited field trial rather than definitive causal evidence. Future research employing quasi-experimental or randomized controlled designs is necessary to confirm the robustness of these outcomes.

From an implementation perspective, the model demonstrated high practicality ratings; however, feasibility considerations should be taken into account. Initial adoption may increase teacher workload, particularly in preparing culturally contextualized materials and facilitating structured inquiry. Teachers may require professional development support to embed CT components intentionally rather than apply them implicitly. While the cultural artifacts used in this study were locally accessible and low-cost, adaptation to other contexts would require careful mapping to relevant local cultural practices. Potential barriers include limited familiarity with CT terminology, time constraints in the curriculum, and the risk of treating cultural integration as peripheral rather than central to mathematical reasoning. Addressing these challenges is essential for sustainable implementation.

Overall, the findings suggest that cultural context can support abstraction and pattern generalization, while computational thinking can strengthen systematic planning and execution within Polya's problem-solving framework. By integrating culturally responsive pedagogy, constructivist principles, sociocultural mediation, and structured problem-solving theory, this study provides preliminary evidence that meaningful and analytically rigorous mathematics learning can be developed through a coherent ethnomathematics–CT instructional design. Further large-scale studies are needed to validate and extend these findings across diverse educational settings.

4. CONCLUSION

This study developed and piloted a structured learning model integrating ethnomathematics and computational thinking (CT) to enhance elementary students' mathematical problem-solving skills, demonstrating that the model is valid, practical, and associated with promising preliminary improvements across Polya-aligned problem-solving stages and core CT components, including decomposition, pattern recognition, abstraction, and algorithm design; however, these findings should be interpreted cautiously due to the one-group design and limited implementation scope, which preclude strong causal conclusions. The results suggest important practical implications, notably the need for targeted teacher professional development to support the integration of CT within culturally contextualized mathematics instruction, careful alignment of local cultural resources with mathematical concepts to ensure their function as cognitive scaffolds, and the deliberate use of structured questioning strategies that make CT processes explicit in classroom practice. Nonetheless, the study is constrained by its single-school context, small sample, short intervention duration, and reliance on written assessments that may not fully capture the complexity of students' computational thinking. Future research should therefore employ controlled or quasi-experimental designs across multiple schools to enhance generalizability and causal inference, incorporate longitudinal approaches to assess retention and transfer of skills, and utilize implementation fidelity measures alongside process-oriented assessment tools to better understand how instructional practices shape learning outcomes, thereby enabling more rigorous evaluation and refinement of the ethnomathematics–CT learning model for broader educational application.

Acknowledgments: The authors would like to express their sincere gratitude to the principal, teachers, and students of the participating elementary school in Jambi City for their cooperation and support during the implementation of this study. We also extend our appreciation to the expert validators for their valuable feedback and constructive suggestions in refining the learning model and research instruments. Special thanks are addressed to colleagues and research assistants who contributed to data collection and scoring procedures. Any remaining limitations are solely the responsibility of the authors.

Conflicts of Interest: The authors declare no conflict of interest. The authors alone are responsible for the content and writing of this article.

REFERENCES

Al Farra, N. K., Al Owais, N. S., & Belbase, S. (2022). Computational thinking and mathematical problem solving. *Mathematics Education Research Journal*, *34*(3), 611–633. https://doi.org/10.1007/s13394-021-00377-0

Barendsen, E., & Tolboom, J. (2021). A framework for computational thinking across school subjects. *Computer Science Education*, *31*(1), 1–32. https://doi.org/10.1080/08993408.2020.1863661

Chen, P., Yang, D., Metwally, A. H. S., Lavonen, J., & Wang, X. (2023). Fostering computational thinking through unplugged activities: A meta-analysis. *International Journal of STEM Education*, *10*, 47. https://doi.org/10.1186/s40594-023-00434-7

Cheng, L., Wang, X., & Ritzhaupt, A. D. (2023). Effects of computational thinking integration in STEM education: A meta-analysis. *Journal of Educational Computing Research*, *61*(2), 416–443. https://doi.org/10.1177/07356331221114183

Chevalier, M., Giang, C., Piatti, A., & Mondada, F. (2022). Fostering computational thinking in primary education. *Computers & Education*, *180*, 104431. https://doi.org/10.1016/j.compedu.2022.104431

Domite, M. C. S., & Barbosa, J. C. (2020). Cultural practices and mathematical modelling: Contributions from ethnomathematics. *Educational Studies in Mathematics*, *104*(1), 37–52. https://doi.org/10.1007/s10649-020-09944-9

Falloon, G. (2024). Advancing young students' computational thinking through curriculum design. *Computers & Education*, *216*, 105045. https://doi.org/10.1016/j.compedu.2024.105045

Hardiansyah, F., Armadi, A., Ar, M. M., & Wardi, M. (2024). Analysis of Field Dependent and Field Independent Cognitive Styles in Solving Science Problems in Elementary Schools. *Jurnal Penelitian Pendidikan IPA*, *10*(3), 1159–1166. https://doi.org/10.29303/jppipa.v10i3.5661

Huang, W., Wu, L., & Looi, C.-K. (2022). Designing problem-solving learning with computational thinking. *Computers & Education*, *181*, 104445. https://doi.org/10.1016/j.compedu.2022.104445

Huencho, A., & Chandía, E. (2023). Humanizing mathematics education through indigenous cultural practices. *ZDM Mathematics Education*, *55*, 1085–1099. https://doi.org/10.1007/s11858-023-01490-7

Israel-Fishelson, R., & Hershkovitz, A. (2022). Interrelations of computational thinking and creativity. *Computers & Education*, *176*, 104353. https://doi.org/10.1016/j.compedu.2021.104353

Kallia, M., van Borkulo, S. P., Drijvers, P., Barendsen, E., & Tolboom, J. (2021). Characterising computational thinking in mathematics education. *Research in Mathematics Education*, *23*(2), 159–187. https://doi.org/10.1080/14794802.2020.1852104

Kong, S.-C., & Lai, M. (2022). Validating a computational thinking test for primary education. *Computers & Education*, *187*, 104562. https://doi.org/10.1016/j.compedu.2022.104562

Lee, I. (2023). Promoting computational thinking in primary education: A systematic review. *International Journal of STEM Education*, *10*, 55. https://doi.org/10.1186/s40594-023-00455-2

Looi, C.-K., Chan, S.-W., Wu, L., & Kim, M. S. (2023). Computational thinking in mathematics classrooms: A design-based study. *International Journal of Science and Mathematics Education*, *21*(4), 987–1005. https://doi.org/10.1007/s10763-022-10273-5

Mills, K. A., Cope, J., Scholes, L., & Rowe, L. (2024). Coding and computational thinking across the curriculum. *Review of Educational Research*. https://doi.org/10.3102/00346543241241327

Montuori, C., Gambarota, F., Altoè, G., & Arfé, B. (2024). The cognitive effects of computational thinking: A meta-analysis. *Computers & Education*, *210*, 104961. https://doi.org/10.1016/j.compedu.2023.104961

Orey, D. C., & Rosa, M. (2022). Rethinking ethnomathematics in contemporary classrooms: Culture, power, and mathematical knowing. *ZDM Mathematics Education*, *54*(6), 1191–1204. https://doi.org/10.1007/s11858-022-01363-4

Relkin, E., de Ruiter, L. E., & Bers, M. U. (2021). Learning to code and computational thinking development. *Computers & Education*, *172*, 104222. https://doi.org/10.1016/j.compedu.2021.104222

Rosa, M., & Orey, D. C. (2023). Ethnomathematics as a culturally responsive approach to mathematics education. *Educational Studies in Mathematics*, *112*(1), 1–18. https://doi.org/10.1007/s10649-022-10159-9

Saig, S., & Hershkovitz, A. (2024). Unplugged computational thinking in early education. *International Journal of Child-Computer Interaction*, *40*, 100703. https://doi.org/10.1016/j.ijcci.2024.100703

Siller, H.-S., & Greefrath, G. (2020). Mathematical modelling and problem solving. *ZDM Mathematics Education*, *52*(3), 543–557. https://doi.org/10.1007/s11858-020-01151-3

Sun, L., Hu, L., Yang, W., Zhou, D., & Wang, X. (2021). STEM learning attitudes and computational thinking. *Journal of Computer Assisted Learning*, *37*(2), 346–358. https://doi.org/10.1111/jcal.12493

Tesfamicael, S. A., Nakken, A. H., & Tumebo, T. (2021). Curriculum implications of using ethnomathematics to promote student learning. *Educational Studies in Mathematics*, *108*(1), 87–104. https://doi.org/10.1007/s10649-021-10048-6

Tikva, C., & Tambouris, E. (2021). Mapping computational thinking in K–12 education. *Computers & Education*, *162*, 104083. https://doi.org/10.1016/j.compedu.2020.104083

Wang, X., Shen, J., & Chao, J. (2022). Computational thinking in mathematics education: A literature review. *International Journal of Science and Mathematics Education*, *20*, 101–122. https://doi.org/10.1007/s10763-021-10227-5

Weintrop, D., Beheshti, E., & Horn, M. (2020). Defining computational thinking for mathematics and science classrooms. *Journal of Science Education and Technology*, *29*(1), 1–21. https://doi.org/10.1007/s10956-019-09832-1

Yadav, A., Hong, H., & Stephenson, C. (2021). Computational thinking in mathematics education. *Educational Researcher*, *50*(4), 252–259. https://doi.org/10.3102/0013189X21992377

Ye, J., Lai, X., & Wong, K. W. G. (2022). Transfer effects of computational thinking: A meta-analysis. *Journal of Computer Assisted Learning*, *38*(6), 1620–1638. https://doi.org/10.1111/jcal.12723

Ye, J., Lai, X., & Wong, K. W. G. (2023). Integration of computational thinking in K–12 mathematics education: A systematic review. *International Journal of STEM Education*, *10*, 39. https://doi.org/10.1186/s40594-023-00396-w