Pyramid: Journal of Mathematical Sciences
Vol. 1, 1 (Januari, 2026), pp. 31-43
ISSN: xxxx-xxxx EISSN: xxxx-xxxx

Which Computational Thinking Components Are Emphasized in Science and Mathematics Education? A Bibliometric and Thematic Mapping Study

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ARTICLE INFO

Keywords:

Computational Thinking;

Mathematics Education;

Science Education

Article history:

Received 2026-01-08
Revised 2026-01-26
Accepted 2026-01-31

ABSTRACT

Computational thinking (CT) has become a key competency in contemporary science and mathematics education, yet prior research often conceptualizes CT as a uniform construct with limited attention to disciplinary differences. This study aims to systematically map how CT components are emphasized across science/STEM and mathematics education in order to clarify domain-specific patterns and research directions. A bibliometric and thematic mapping approach was employed using peer-reviewed publications retrieved from the Dimensions AI database. Following PRISMA 2020 guidelines, 421 articles were included in the final dataset. Bibliometric analysis was conducted to examine publication trends and domain distribution, while co-word analysis and thematic mapping using VOSviewer were applied to identify thematic structures and the relative prominence of CT components across domains. The findings reveal six major thematic clusters representing conceptual problem solving, classroom pedagogy, technology and artificial intelligence, core CT components, programming and digital tools, and learning outcomes and affective dimensions. Comparative analysis shows distinct domain-responsive emphases: science/STEM education prioritizes algorithmic procedures, modeling and simulation, and data-oriented practices, whereas mathematics education more strongly emphasizes abstraction, generalization, pattern recognition, and formal algorithmic reasoning. These results indicate that CT should be conceptualized as a discipline-responsive construct rather than a generic set of skills. The study concludes by highlighting implications for curriculum design, teacher education, and assessment practices, and by identifying gaps for future research on the integration of computational thinking in domain-sensitive ways.

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1. INTRODUCTION

Computational thinking (CT) has been widely recognized as one of the key competencies of the 21st century that is relevant across disciplines, particularly in science and mathematics education. Various studies show that CT functions not only as a computational skill, but also as a way of thinking that supports complex problem-solving, scientific reasoning, and the development of mathematical thinking (Grover & Pea, 2018; Shute et al., 2017). The integration of CT in science and mathematics learning allows students to build models, simulate, and represent thought processes algorithmically, thereby strengthening conceptual understanding and evidence-based reasoning skills (Li et al., 2020; Weintrop et al., 2015). The global policy framework also places CT as part of the digital literacy and STEM agenda, in line with the increasing role of artificial intelligence and computing technology in education and the world of work (OECD, 2023; UNESCO, 2023). The emphasis emphasized that strengthening CT in science and mathematics education is not just a pedagogical innovation, but a strategic need to prepare students to face the demands of the digital and data-based era.

The theoretical framework of CT generally views CT as a multidimensional construct consisting of several main components, such as decomposition, pattern recognition, abstraction, algorithmic thinking, debugging, and generalization. Brennan & Resnick (2012) propose a framework that emphasizes computational practices, concepts, and perspectives, while Shute et al. (2017) group CT into a set of cognitive skills that include decomposition, abstraction, and algorithm design. Wing (2017) (2006) defines CT as a thought process in formulating problems and their solutions so that they can be executed by information processing agents, while Brennan & Resnick (2012) highlight the role of practices such as debugging and modularization in the development of CT. These differences in definitions and frameworks suggest that CT is not understood as a single skill, but rather as a collection of interrelated components and can emerge with different emphasis depending on the context of the discipline and the learning objectives. This perspective reinforces the importance of examining specifically the components of CT emphasized in science and mathematics education, rather than treating CT as a homogeneous construct.

The integration of computational thinking in science education is generally realized through modeling, simulation, inquiry-based investigation, and data analysis activities, which allow students to represent natural phenomena and test hypotheses computationally (Weintrop et al., 2021). The approach encourages the use of abstraction to represent complex systems, decomposition to break down phenomena into subprocesses, as well as algorithmic thinking to design exploration and simulation procedures (Moon et al., 2023; Sengupta et al., 2018). The focus of CT in science is often related to scientific modeling, data-driven inquiry, and computational experimentation, thus positioning CT as a means to strengthen evidence-based reasoning and understanding causality (Berland & Wilensky, 2015). Meanwhile, the integration of computational thinking in mathematics education shows different characteristics, with a strong emphasis on algorithmic reasoning, patterning, and abstraction as the core of mathematical activities. The approach is reflected in the use of algorithmic procedures, pattern generalization, and symbolic representations to construct and test mathematical structures (Sinclair & de Freitas, 2019). Research shows that CT in mathematics is often associated with strengthening concept understanding, the development of algebraic thinking, and the ability to represent relationships through algorithmic structures (Grover, 2019; Li, 2023). The difference in epistemological character between science and mathematics indicates that both domains have the potential to emphasize different components of CT, so specific cross-domain analysis is important for understanding such emphasis patterns.

Kajian bibliometrik mengenai computational thinking dalam pendidikan telah menunjukkan a significant increase in the number of publications and the diversity of themes, both at a general level and in specific contexts such as mathematics, science, and STEM. A number of studies have mapped

CT trends across domains or focused on one specific area, such as mathematics education or specific learning approaches (Muhammad et al., 2024; Romandoni et al., 2025). Other bibliometric studies also highlight the integration of CT in science education or in STEM and project-based learning frameworks, but such analyses generally still place CT as a global construct without systematic mapping of its components (Maharani et al., 2023; Romandoni et al., 2025). The focus of existing bibliometric studies tends to emphasize publication trends, author collaboration, and the evolution of themes in general, while explicit analysis of the emphasis on each component of CT, such as decomposition, abstraction, or debugging, is still relatively limited. The evidence suggests that there have not been many studies that have specifically mapped the emphasis of CT components in the context of science and mathematics education in a comparative manner. This gap indicates an important research gap, particularly to understand how domain characters affect the distribution and dominance of CT components in the literature.

This study aims to systematically map the most emphasized CT components in the science and mathematics education literature through bibliometric and thematic mapping approaches. This analysis was specifically directed to identify differences in emphasis of CT components between the domains of science and mathematics, as well as to uncover thematic clusters associated with each component. The main contribution of this research lies in providing an evidence-based picture of the dominance and marginalization of CT components in two main STEM domains, thus enriching the theoretical understanding of the domain-specific character of CT. The research findings are also expected to be the basis for the next research agenda and the development of more balanced pedagogical practices in integrating CT components. These objectives and contributions were formulated operationally through a series of research questions that focused on dominance, cross-domain differences, thematic clusters, and CT components that are still underrepresented in the literature.

2. METHODS

This study adopted a bibliometric and thematic mapping approach to examine the emphasis of computational thinking (CT) components in science/STEM and mathematics education. This approach was selected because it enables quantitative identification of publication patterns and qualitative–quantitative exploration of conceptual relationships through keyword co-occurrence and thematic clustering. The design is appropriate for capturing dominant CT components, cross-domain differences, and research gaps, thereby supporting a domain-sensitive interpretation of CT integration in the literature. The data were retrieved from the Dimensions AI database, which provides broad coverage of education and STEM-related publications and offers comprehensive metadata suitable for large-scale bibliometric analysis. The use of Dimensions AI was motivated by its multidisciplinary indexing capacity and its support for advanced bibliometric mapping, enabling systematic identification of publication trends and thematic structures across science/STEM and mathematics education.

The search strategy was constructed to capture studies that explicitly operationalized core computational thinking components within science and mathematics education contexts. The following Boolean query was applied: (Decomposition OR "Pattern Recognition" OR Abstraction OR Algorithms) AND ("science education" OR "mathematics education"). This query was designed to retrieve publications that directly addressed CT components while ensuring domain relevance. The search was restricted to peer-reviewed publications to maintain academic rigor. Study selection followed the PRISMA 2020 guidelines. The initial search identified 523 records from the Dimensions AI database. Prior to screening, 68 records were removed due to ineligibility identified by automation tools, incomplete metadata, or inappropriate document types. The remaining 455 records were screened based on titles and abstracts, resulting in the exclusion of 34 records that were not relevant to computational thinking components or did not address science or mathematics education contexts. A total of 421 reports were subsequently sought for retrieval and assessed for eligibility through full-text examination. All reports were successfully retrieved, and no additional exclusions were made at the full-text stage, as all retrieved studies met the predefined inclusion criteria. Consequently, 421 studies were included in the final bibliometric and thematic analysis. A summary of the study selection process is presented in Table 1.

Table 1. Data Collection Flow

PRISMA 2020 Stage	Description	n
Identification	Records identified from Dimensions AI database	523
	Records removed before screening (automation tools, incomplete metadata, inappropriate document types)	68
Screening	Records screened (title and abstract)	455
	Records excluded after title and abstract screening (not relevant to CT components or science/mathematics education)	34
Eligibility	Reports sought for retrieval (full-text assessment)	421
	Reports not retrieved	0
	Reports excluded after full-text assessment (did not meet inclusion criteria)	0
Included	Studies included in the final bibliometric and thematic analysis	**421**

The inclusion criteria comprised studies conducted in educational contexts that explicitly addressed one or more computational thinking components and were situated within science/STEM education or mathematics education. Studies were excluded if they were not focused on educational settings or did not explicitly engage with computational thinking components relevant to the target domains. The final dataset of 421 studies was analyzed using a combination of bibliometric techniques and thematic mapping procedures. Bibliometric analysis was conducted to identify overall publication patterns, temporal trends, and domain distribution between science/STEM and mathematics education. Co-word analysis was employed to examine relationships among keywords representing CT components and instructional contexts, enabling identification of conceptual linkages and relative prominence of specific CT components within each domain. Thematic mapping was applied to cluster related keywords and to distinguish between core and extended CT components across domains, thereby facilitating systematic comparison of how CT is operationalized in science/STEM and mathematics education. All analyses and network visualizations were conducted using bibliometric software, including VOSviewer, to generate keyword co-occurrence networks and thematic clusters. The dataset was further disaggregated by domain to support comparative analysis of CT component emphasis between science/STEM and mathematics education.

3. FINDINGS AND DISCUSSION

3.1. Descriptive Characteristics of the Dataset

The dataset analyzed in this study consisted of 421 publications obtained from the Dimensions database after going through the selection stage based on the PRISMA protocol. All documents meet the inclusion criteria and represent research on computational thinking in the context of science and mathematics education. The publications in this corpus cover the period 2022–2026, which describe the latest developments in computational thinking research in education. The number of publications shows a consistent increase from year to year, with a peak in 2025 (n = 191). The number of publications in previous years was recorded at 95 documents in 2024, 71 documents in 2023, and 57 documents in 2022. The 2026 data (n = 7) reflects partial coverage at the beginning of the year. This growth trend is shown in Figure 1, which shows the increasing attention of researchers to the integration of computational thinking in science and mathematics education.

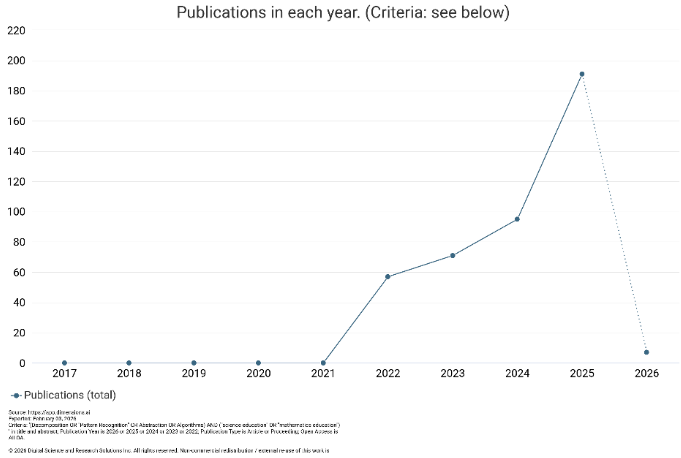

Figure 1. Publication Trends

Most of the documents in the dataset were journal articles (n = 395; 93.8%), while conference proceedings (n = 26; 6.2%) made up a smaller proportion. This composition shows that the study of computational thinking in education has developed mainly through the publication of reputable journals, while proceedings serve as a medium for initial dissemination and discussion of research findings. Publications come from a variety of journals and proceedings focusing on mathematics education, science education, STEM education, and educational technology. This diversity of sources reflects the cross-disciplinary nature of computational thinking as well as the involvement of the mathematics and science education communities in its development and implementation.

3.2. Domain Distribution: Science/STEM and Mathematics

As the main basis for comparison, this study distinguishes publications based on two domains, namely science/STEM education and mathematics education. Of the total studies analyzed, there were 158 publications in the science/STEM domain and 234 publications in the mathematics domain. This is presented in Table 1 below.

Table 2. Comparison of CT Codes in Mathematics Education and Science Education

CT Components	Science Education (n=158)	Mathematics Education (n=234)
Algorithm	119 (75,32%)	135 (57,69%)
Abstraction	36 (22,78%)	108 (46,15%)
Decomposition	22 (13,92%)	55 (23,50%)
Pattern Recognition	12 (7,59%)	44 (18,80%)

These findings show that research related to computational thinking (CT) is more commonly reported in the context of mathematics education than science/STEM education. Proportionally, the mathematics domain accounted for about 59.7% of the total publications, while the science/STEM domain accounted for about 40.3%. This distribution indicates that mathematics is becoming a more dominant context in the implementation and study of CT, thus providing a solid basis for conducting comparative analysis between domains. The difference in the number and proportion of publications is the main justification for comparing the characteristics of the integration of CT components between science/STEM education and mathematics education, both in terms of component focus, learning approach, and tendency to report research results.

Based on these data, it can be seen that there is a difference in the emphasis on the computational thinking (CT) component between science education and mathematics education. In science education, the most dominant component is Algorithms (75.32%), which shows that CT is more widely used for the development of procedural steps, phenomenon modeling, and computational simulations in understanding the laws of nature and solving process-based problems. Meanwhile, other components such as Abstraction and Decomposition appear in relatively smaller proportions than in the mathematical domain. In contrast, in mathematics education, although Algorithms remain the highest component (57.69%), there is a much stronger emphasis on Abstraction (46.15%), which reflects the characteristics of mathematics that rely heavily on simplifying complex problems into symbolic models and logical structures. In addition, Decomposition (23.50%) and Pattern Recognition (18.80%) also appeared more significantly, almost double in percentage terms compared to science education, suggesting that mathematics education tends to explore the spectrum of CT components more comprehensively, particularly in solving numerical or graphical problems and identifying pattern regularity.

3.3. Thematic Clusters of Computational Thinking Research

A co-word mapping using VOSviewer resulted in 43 items grouped into six main thematic clusters, which are visualized in different colors in Figure 2. Each color represents a relatively coherent and interconnected thematic focus in the literature. These color differences help identify how computational thinking (CT) is associated with conceptual, pedagogical, technological, and learning outcomes. The density and size of nodes indicate the degree of occurrence and relative role of a concept in the network. Thus, this visualization provides a basis for understanding the thematic structure of CT research in science and mathematics education.

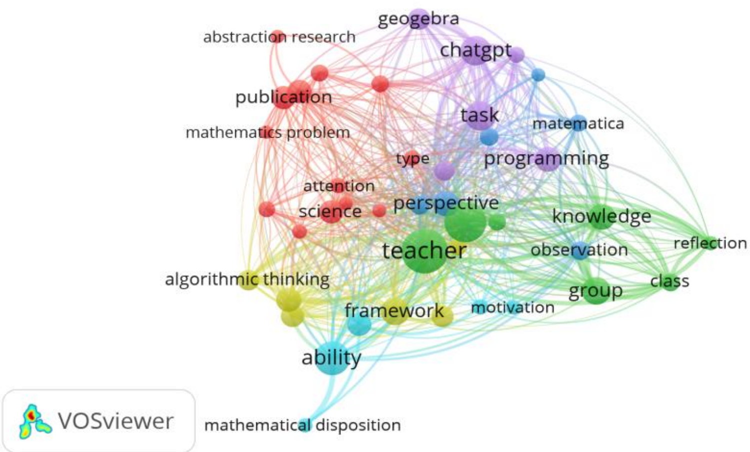

Figure 2. Co-word Mapping

Cluster 1, which is marked in red, represents a strong conceptual and problem-based theme in the context of mathematics and science. This cluster includes terms such as abstraction research, algorithm, mathematical problem, and science, which show the relationship of CT to problem-solving and concept development. The dominance of terms related to mathematical problems indicates that CT is often positioned as a framework for solving formal representation-based problems. The presence of algorithms and abstraction confirms the role of these two components in building procedures and simplifying concepts. This cluster reflects CT's strong orientation on conceptual and problem solving aspects. Cluster 2, visualized in green, focuses on the pedagogical dimension and classroom practice. Keywords such as class, group, knowledge, practice, reflection, and teacher show that CT is widely studied in the context of classroom interaction and collaborative learning. The strong relationship between the teacher and the group confirms the role of the teacher as a facilitator in the development of CT. The presence of reflection indicates that reflective and metacognitive processes are an important part of the implementation of CT. This cluster places CT as part of pedagogical practice, not just as an individual skill.

Cluster 3, which is marked in blue, represents the integration of technology and artificial intelligence in learning. This cluster includes terms such as artificial intelligence, mathematica, observation, and perspective. This theme shows that CT is increasingly associated with the use of software and computing systems in supporting the exploration of concepts. The relationship with observation shows that technology is often used to facilitate observation and analysis. This cluster reflects a shift in the literature towards the use of technology as an important context in the development of CT. Cluster 4, visualized in yellow, explicitly contains the core components of computational thinking. Terms such as algorithmic thinking, decomposition, and pattern recognition appear along with critical thinking and frameworks. This cluster shows that the study not only identifies the components of CT separately, but also links them to a broader conceptual framework. The association with critical thinking shows that CT is often positioned as part of higher thinking skills. This cluster represents a major theoretical foundation in the CT literature.

Cluster 5, which is marked in purple, highlights the integration of CT with digital programming and tools. Keywords such as chatgpt, debugging, geogebra, programming, and tasks indicate a focus on computing environments and technology-based tasks. The presence of debugging signifies the importance of iterative processes and error correction in CT learning. The integration of geogebra and programming confirms the role of digital tools in the context of mathematics and STEM. This cluster reflects the latest developments in CT research that are increasingly connected to learning technologies and generative AI. Cluster 6, visualized in light blue/turquoise, represents the dimensions of learning outcomes and affective aspects. This cluster includes terms such as ability, computational thinking, effectiveness, mathematical disposition, and motivation. This focus shows that CT is also studied in relation to student abilities and learning effectiveness. The presence of motivation and mathematical disposition indicates attention to students' attitudes and affective responses to CT-based learning. This cluster expands the scope of CT as an impact construct on the cognitive and affective dimensions.

The structure of these six clusters shows that CT research in science and mathematics education develops in several interconnected focuses, ranging from conceptual, pedagogical, technological, to learning outcomes. The core components of CT do not appear in isolation, but are integrated with classroom practice and the use of technology. This pattern provides a conceptual foundation for interpreting the different emphasis of CT components in each domain. Therefore, these thematic findings form the basis for further analysis of the core components and expansion components of CT in the next section. The analysis linked the thematic map to the quantitative distribution of CT components in science and mathematics education.

3.4. Core and Extended Computational Thinking Components Across Domains

This section integrates the analysis of core computational thinking (CT) components with extended, practice-oriented CT components to capture both the conceptual and operational use of CT across science/STEM and mathematics education. Consistent with the theoretical framework presented in the introduction, the core CT components examined in this study include decomposition, pattern recognition, abstraction, and algorithmic thinking. In addition, extended CT components were identified to reflect domain-specific practices, including modeling and simulation, data analysis, debugging, and generalization. Based on the dataset, algorithmic thinking emerges as the most frequently emphasized core component in both domains. In science/STEM education (n = 158), algorithmic thinking is reported in 119 publications (75.32%), indicating a strong focus on procedural reasoning, step-by-step problem solving, and the use of algorithms to support modeling, experimentation, and computational simulations. In mathematics education (n = 234), algorithmic thinking is also dominant, appearing in 135 publications (57.69%), although its relative proportion is lower than in science/STEM.

Substantial domain differences are observed in the emphasis on abstraction. In mathematics education, abstraction is highlighted in 108 publications (46.15%), compared with only 36 publications (22.78%) in science/STEM. This pattern reflects the central role of abstraction in mathematics, where learners frequently transform concrete situations into symbolic representations and formal mathematical structures. Decomposition and pattern recognition also show stronger emphasis in mathematics education. Decomposition appears in 55 mathematics publications (23.50%), compared with 22 publications (13.92%) in science/STEM. Pattern recognition is reported in 44 mathematics publications (18.80%), while only 12 science/STEM publications (7.59%) emphasize this component. These findings suggest that mathematics education more consistently engages learners in breaking down complex problems and identifying structural regularities in numerical, graphical, and algebraic contexts.

Beyond the four core components, extended CT components reveal clear domain-specific patterns. In science/STEM education, components related to modeling and simulation as well as data analysis are more prominent, reflecting the empirical and inquiry-oriented nature of scientific learning. These components support the use of computational representations to model dynamic systems, test hypotheses, and analyze experimental or observational data. In contrast, mathematics education more frequently emphasizes extended components associated with generalization, symbolic manipulation, and formal reasoning, which align with the higher emphasis on abstraction, decomposition, and pattern recognition.

To further support the interpretation of these domain-specific emphases, Table X summarizes the thematic mapping of CT components based on prior literature. The table highlights that modeling and simulation and data analysis are more strongly associated with science/STEM contexts, whereas abstraction, algorithmic thinking, pattern recognition, debugging, and generalization are more strongly emphasized in mathematics education. This synthesis reinforces the quantitative findings by situating them within established theoretical and empirical frameworks.

Table 3. Thematic mapping of computational thinking components across domains

CT Component	Field	Thematic Justification from the Literature
Modeling & Simulation	**Science/STEM**	Science learning uses *agent-based modeling*, phenomenon simulation, and dynamic system representation (Sengupta et al., 2013; Weintrop, 2016)
Data Analysis	**Science/STEM**	Emphasis on experimental data analysis, scientific inquiry, and data-driven reasoning (Li et al., 2020)
Decomposition	Science/STEM	Complex science problems are often broken down into subprocesses (e.g. ecological systems, physics, or chemical processes) (Rijke et al., 2018; Ritschel et al., 2022)
Algorithmic Thinking	**Mathematics**	Emphasis on formal rules-based procedures, algorithmic steps, and reasoning (Angeli, 2022; Borkulo et al., 2021)
Abstraction	**Mathematics**	Mathematical abstraction through symbolization, generalization, and formal structure (Boonstra et al., 2023; Cetin, 2017; Wing, 2017)
Pattern Recognition	**Mathematics**	Numerical pattern identification, function, and relationship identification activities (Taufik et al., 2024)

Debugging	Mathematics (more limited)	It appears more often in the context of mathematical programming or coding-based tasks than in the context of pure science (Brennan & Resnick, 2012)
Generalization	Mathematics	The process of generalization from specific cases to formal forms is a strong characteristic of mathematical thinking (Shute et al., 2017)

Overall, the combined analysis of core and extended CT components indicates that while algorithmic thinking serves as a shared foundation across both domains, mathematics education places stronger emphasis on abstraction, decomposition, and pattern recognition. In contrast, science/STEM education prioritizes procedural and algorithmic aspects of CT, supported by extended components related to modeling, simulation, and data analysis. This integrated perspective strengthens theoretical consistency while capturing meaningful differences in how CT is operationalized across science and mathematics education.

Discussion

This study aimed to map and compare the emphasis of computational thinking (CT) components in science/STEM and mathematics education using a bibliometric and thematic mapping approach. The findings provide clear evidence that CT is operationalized differently across the two domains, supporting the view that CT should not be treated as a unitary construct but rather as a set of interrelated components whose prominence varies by disciplinary context. In response to RQ1, the results indicate that science/STEM education places a strong emphasis on algorithmic thinking, which appears as the most dominant core component. This prominence reflects the procedural and process-oriented nature of scientific practices, where learners are often required to follow stepwise procedures, implement computational models, and run simulations to explore scientific phenomena. The strong presence of extended components such as modeling and simulation and data analysis further reinforces this interpretation. These components align closely with inquiry-based learning and empirical investigation, where computational tools are used to represent dynamic systems, test hypotheses, and interpret experimental data (Li et al., 2020; Sengupta et al., 2018; Weintrop, 2016). The findings thus suggest that CT in science/STEM is primarily enacted as a means to support procedural modeling and data-driven inquiry.

Addressing RQ2, the analysis shows that while algorithmic thinking also remains prominent in mathematics education, the domain places substantially greater emphasis on abstraction, along with higher levels of decomposition and pattern recognition. This pattern is consistent with the epistemic nature of mathematics, which relies heavily on symbolic representation, generalization, and the identification of underlying structures across different problem contexts. The strong role of abstraction observed in this study echoes prior work highlighting abstraction as a central feature of mathematical thinking and computational thinking in mathematics classrooms (Grover, 2019; Kallia et al., 2021). Similarly, the higher presence of decomposition and pattern recognition suggests that mathematical CT practices more frequently involve breaking down complex problems and identifying regularities in numerical, algebraic, or graphical representations.

With respect to RQ3, the comparative analysis demonstrates a clear differentiation in how CT components are emphasized across domains. Science/STEM education tends to prioritize the procedural and operational dimensions of CT, supported by extended components related to modeling, simulation, and data analysis. In contrast, mathematics education places stronger emphasis on representational and structural dimensions of CT, particularly abstraction, pattern recognition, and decomposition. These differences indicate that CT is shaped by the epistemological and pedagogical demands of each discipline. Rather than reflecting inconsistent use of CT, the observed patterns suggest that CT is adapted to serve domain-specific goals, with science emphasizing dynamic system modeling and empirical reasoning, and mathematics emphasizing formal structure, generalization, and symbolic reasoning.

From a theoretical perspective, these findings support frameworks that conceptualize CT as a multi-component construct with both core and domain-specific elements (Brennan & Resnick, 2012; Wing, 2017). The results further extend this perspective by providing empirical bibliometric evidence that different educational domains systematically privilege different subsets of CT components. This reinforces the importance of moving beyond generic definitions of CT when designing curricula and assessments, and instead aligning CT components with disciplinary practices and learning goals. In terms of practical implications, the results suggest that instructional designs for CT should be tailored to disciplinary contexts. For science/STEM education, learning activities that integrate computational modeling, simulation, and data analysis may be particularly effective for fostering CT in ways that align with scientific inquiry. For mathematics education, tasks that foreground abstraction, pattern recognition, and decomposition may better support the development of CT in ways that are congruent with mathematical reasoning and structure. Such alignment may enhance both conceptual coherence and instructional effectiveness.

Finally, the study also highlights areas for future research. Components such as debugging and certain forms of generalization appear less frequently across both domains, suggesting potential gaps in how these aspects of CT are integrated into science and mathematics education. Future studies could explore how these underrepresented components might be more systematically incorporated into curricula and how their inclusion affects student learning outcomes. In addition, the use of advanced bibliometric tools, such as co-word analysis and clustering techniques, may further refine component-level mapping and provide deeper insights into the evolving conceptual structure of CT across disciplines.

4. CONCLUSION

This study shows that computational thinking (CT) in education has developed into a discipline-embedded construct rather than a uniform set of generic skills. Across the reviewed studies, a common core of CT components—such as decomposition, abstraction, algorithmic thinking, pattern recognition, and debugging—emerges in both mathematics and science/STEM education, while extended components, particularly modeling & simulation and data analysis, are more prominently emphasized in science/STEM contexts. The results further indicate clear domain-specific patterns of CT integration: mathematics education tends to foreground abstraction, formal procedures, generalization, and symbolic reasoning, whereas science/STEM education prioritizes system-based modeling, simulation, and empirical data analysis to support reasoning about dynamic and complex phenomena. In addition, CT assessment practices remain largely task-based and performance-oriented, with limited use of standardized and validated instruments, especially within mathematics education, highlighting an important methodological gap in the field. Taken together, these findings suggest that CT should be conceptualized as a context-sensitive and discipline-responsive framework rather than a one-size-fits-all construct. Future research is therefore encouraged to develop domain-sensitive CT assessment tools, explore systematic integration of extended CT components within mathematics curricula, and employ longitudinal and design-based approaches to better understand how different CT integration models influence both disciplinary learning outcomes and the development of transferable computational thinking competencies.

Acknowledgments: The authors acknowledge the administrative and technical support provided by colleagues and institutional staff in facilitating data access, database retrieval, and bibliometric data processing. The authors also acknowledge the use of bibliometric software tools for data visualization and thematic mapping.

Conflicts of Interest: The authors declare no conflict of interest.

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