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Mapping Computational Thinking in STEM Education: A Bibliometric Study

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Abstract. The study aimed to explore the intellectual landscape of computational thinking (CT) in K–12 science, technology, engineering and mathematics (STEM) education by identifying dominant research themes, influential publications and evolving trends. It sought to consolidate fragmented scholarship and provide a structured overview to guide future research and practice in CT integration in STEM contexts. A bibliometric analysis, using VOSviewer software, was conducted on 1 018 peer-reviewed articles that had been published between 2007 and 2025 and were indexed in the Scopus database. The results reveal three major thematic clusters: (1) Pedagogical innovations and learning environments; (2) Theoretical foundations and disciplinary integration; and (3) Design frameworks and learning challenges. Co-word analysis shows a growing emphasis on block-based programming, robotics and teacher professional development. The findings inform curriculum developers, teacher educators and policymakers where to focus efforts, particularly in designing inclusive, interdisciplinary and assessment-rich CT experiences for diverse STEM learners. This study is among the first comprehensive bibliometric analyses to map the CT–STEM research interface. It offers a data-driven synthesis of intellectual trends, highlights key gaps and sets the stage for future empirical and theoretical contributions in CT education.

Keywords: bibliometric analysis; computational thinking; K–12 education; STEM education; quality education

1. Introduction

The rapidly changing world requires a particular set of skills for workforce development. The increasing demand for a technologically literate workforce in the digital age has made computational thinking (CT) an essential competency in 21st-century education. Wing (2006) articulates that CT is a basic skill everyone needs. It is not exclusive to computer scientists. It involves a set of cognitive abilities that includes problem decomposition, abstraction, algorithmic thinking

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and logical reasoning. CT has evolved from a niche topic in computer science education to a cross-disciplinary framework that influences how learning has taken place across science, technology, engineering and mathematics (STEM) domains over the last two decades (Shute et al., 2017; Weintrop et al., 2016).

The integration of CT in STEM education is rooted in its ability to foster higher-order thinking, support inquiry-based learning and prepare students to navigate complex, data-rich environments. CT is a skill that is seen to provide multiple benefits both to scholars and educators. In addition, scholars and educators increasingly recognise that integrating CT into STEM learning environments can cultivate creativity, enhance scientific modelling and deepen understanding of disciplinary content (Grover & Pea, 2013; Sengupta et al., 2013). CT is not only about learning to code; it also involves learning to think computationally to solve real-world problems, design systems and understand human behaviour through the lens of algorithmic processes (diSessa, 2018; Wing, 2006).

On a larger scale, there are several national and international educational frameworks that have started to embed CT in their science and mathematics standards, which promotes a steady increase in the perceived relevance of CT. The Next Generation Science Standards in the United States, for instance, emphasises CT as a crosscutting concept that should be integrated, from the early grades, into learning experiences of students (National Research Council, 2013). Similarly, international curricula and policy efforts have responded by incorporating CT into both formal and informal learning settings, thereby highlighting its foundational role in building STEM literacy and digital citizenship (Czerkawski & Lyman, 2015; Voogt et al., 2015).

Due to increasing popularity, many scholars have become interested in conducting research on CT, which spans across various domains, including curriculum development, teaching pedagogies, professional development of teachers, learning technologies and assessment techniques (Israel & Lash, 2020; Yadav et al., 2016). Innovations such as block-based programming tools, robotics kits, unplugged activities and game-based learning environments have provided new entry points for CT instruction at all levels of education (Basu et al., 2016; Eguchi, 2016). Furthermore, research has explored the cognitive dimensions of CT, its role in developing scientific reasoning and sociocultural challenges related to equitable implementation in diverse classroom contexts (Lodi & Martini, 2021; Taylor & Baek, 2019).

Despite the increasing number of studies on CT, there are persistent gaps in the field. Research has often been domain-specific or tool-driven, which makes it difficult to identify unifying trends, foundational theories and shared challenges in CT research in STEM education. Systematic literature reviews have attempted to classify research, but few have taken a holistic view of the intellectual structure of the field. Without such mapping, stakeholders, including educators, researchers and policymakers, lack a comprehensive understanding of how CT in STEM education has evolved and what future directions are most promising.

To address this gap, this study employed a bibliometric analysis to explore the intellectual landscape of CT in K–12 STEM education. This study employed bibliometric analysis because it offers a quantitative lens for investigating scholarly documents by analysing citation patterns, thematic co-occurences and author collaborations (Zupic & Čater, 2015). Unlike narrative reviews, which often rely in subject interpretation, bibliometric approaches provide a data-driven way to trace the development of a field, identify influential works and visualise relationships among research topics and communities (van Eck & Waltman, 2014).

This study focused on key bibliometric techniques, namely bibliographic coupling and co-word analysis, to map the conceptual, intellectual and thematic patterns that define the field. Bibliographic coupling identifies current thematic clusters based on shared references. Co-word analysis reveals conceptual linkages by analysing keyword co-occurrence across publications. Collectively, these approaches offer a rich and multidimensional perspective on how CT is theorised, applied and operationalised in K–12 STEM education research. The decision to focus on Scopus-indexed literature ensured a broad yet high-quality dataset, given the comprehensive coverage of peer-reviewed journals of Scopus across education, computer science and interdisciplinary fields. This methodological choice was crucial for generating reliable insights that reflect both disciplinary depth and topical breadth.

By investigating over a thousand relevant publications spanning nearly two decades, this study aimed to answer the following overarching questions: What are the major intellectual contributions shaping CT in K–12 STEM education? What conceptual frameworks and pedagogical trends dominate the discourse? How has research evolved over time, and what are the emerging frontiers? Addressing these questions provides both theoretical and practical value: it not only synthesises what is known but also highlights areas that require further exploration and investment.

This bibliometric study contributes to the consolidation of fragmented research, illuminates interdisciplinary linkages and supports strategic decision-making in curriculum development, teacher training and educational technology design. As CT continues to gain traction globally, an informed understanding of its scholarly trajectory will be critical for guiding inclusive, innovative and evidence-based practices in STEM education.

2. Literature Review

CT has emerged as a vital competency in 21st-century education, particularly in the context of STEM. Scholars agree that CT fosters essential skills such as abstraction, decomposition and algorithmic thinking, which are crucial for problem-solving across disciplines. As a result, education systems worldwide are integrating CT into K–12 STEM curricula to cultivate technologically literate students who are equipped for complex, data-driven futures.

The literature promotes a variety of conceptualisation and implementation strategies with regard to CT. Other research strengthens the significance of CT, particularly in STEM education. Aulia et al. (2025) conducted a systematic review that emphasised the growing prevalence of CT in STEM education, while noting significant gaps, particularly in understanding long-term impacts. Complementing this, Novia et al. (2025) stress the need for clearer definitions and robust instructional frameworks, especially those that promote inclusive practices. These reviews collectively underscore that, while enthusiasm for CT is widespread, pedagogical consistency remains elusive.

Teacher preparedness is one of the emerging challenges faced by CT. Teachers, as the implementers of CT, must be equipped with the skills needed for the successful implementation and execution of CT in classrooms. Melumad and Yun (2025) highlight the exploratory nature of efforts to integrate CT in pre-service science teacher education. Their work advocates for holistic approaches that align CT with modern education standards, including the integration of unplugged activities and cross-disciplinary strategies. Similarly, Grover and Pea (2013) outline foundational gaps in our understanding of what students should learn from CT curricula and call for research on assessment strategies, learning progressions and attitudes towards computing.

Meanwhile, Lee and Lee (2021), from a disciplinary perspective, propose a framework for integrating CT in STEM that connects classroom practices to professional competencies. This study strengthens the idea that CT in STEM education promotes better learning experiences. This aligns with the view of Tanjung et al. (2023), who emphasise the importance of decomposing CT into learnable stages in science education. However, both studies acknowledge the absence of robust models that link CT with specific content areas such as physics, biology or engineering – an area ripe for future inquiry.

Pedagogically, game-based and constructivist approaches are prominent. The efficacy of gamification in promoting student engagement and critical thinking is highlighted by the studies of Triantafyllou et al. (2025) and Bortz et al. (2019). These approaches align with constructivist theories that posit learning as an active, exploratory process, especially when paired with programming environments such as Scratch. However, Hsu et al. (2018) observed that many of the instructions pertaining to CT remain confined to programming; they call for broader conceptual frameworks and differentiated methods that are tailored to cognitive development levels.

Another persistent concern is the lack of assessment tools. Tang et al. (2020) and Li et al. (2020) identify gaps in evaluating CT competencies, particularly in connection with disciplinary learning outcomes. As CT continues to evolve beyond its computing origins, researchers emphasise the importance of developing assessments that capture both the process and outcomes of CT-infused instruction. The literature reveals both convergence and fragmentation. While the value of CT in K–12 STEM education is well recognised, efforts to define, teach and evaluate it vary widely. Future research must address theoretical clarity, scalable models for teacher training and empirically validated assessment frameworks. These steps are essential to ensure that CT integration moves from innovative pilots to sustainable, system-wide practice.

3. Methodology

3.1 Bibliometric Analysis

This study used a bibliometric analysis to critically explore the intellectual landscape of CT in STEM education. Through this technique and by mapping citation relationships, patterns of author collaboration and co-word structures, an extensive understanding of scholarly literature was attained (van Eck & Waltman, 2014). In contrast to traditional systematic literature reviews, bibliometric analysis enables a clear visualisation of knowledge structures and the identification of influential research themes and emerging areas in the field.

This study used data from the Scopus database, which was purposively selected as the source of bibliometric data because it has broad coverage of peer-reviewed journals across various education and technology disciplines. Articles that were believed to be important for this research were identified and selected using a targeted search strategy, to ensure they aligned with the study scope on the integration of CT in STEM education. Data refining and cleaning were done before bibliometric techniques were applied to view document relationships and conceptual linkages. The study used two core bibliometric techniques to achieve the objectives of the study:

1. Bibliographic coupling examines the degree of similarity between publications based on shared references. When two documents cite the same sources, it suggests thematic or methodological commonality (Kessler, 1963). Bibliographic coupling is particularly effective for identifying current research fronts and thematic clusters because it connects newer publications that may not yet have accrued significant citations (Zupic & Čater, 2015). This approach is essential for capturing contemporary discussions and mapping how different studies converge around shared intellectual foundations in CT education.

2. Co-word analysis investigates the co-occurrence patterns of keywords drawn from article titles and abstracts to identify conceptual relationships and trends. By examining how frequently terms appear together, co-word analysis reveals the semantic structure of the field and highlights emerging themes, dominant research areas and their interconnections (Callon et al., 1983). It is particularly useful for tracking the evolution of research discourse and identifying future directions in CT scholarship (Tan Luc et al., 2022).

The dataset was analysed using the VOSviewer software. VOSviewer software is a powerful tool for constructing and visualising bibliometric networks. The software was used to generate the visual maps for documents, authors and keywords, to reveal distinct research clusters and conceptual linkages in the literature. These visualisations offer insight into the intellectual structure of the field and its interdisciplinary connections across science, technology and education domains.

Through this methodological framework, the study provides a rigorous and data-driven perspective on the development, trends and knowledge architecture of CT in K–12 STEM education. The findings serve to not only summarise the state of the field but also to inform future empirical inquiries, curriculum design and policymaking in the context of computational education.

3.2 Search Strategy and Data Collection

The bibliographic data for this study were extracted from the Scopus database on 8 July 2025 using a refined Boolean search strategy targeting title and abstract text data relevant to differentiated instruction in higher education (Table 1).

Table 1: Search string used for database search

Keyword	Justification
"Computational thinking"	This helped in identifying literature relating to CT
"Science education" OR "science teaching" OR "science learning" OR "STEM education"	This helped in identifying literature on STEM education

The Scopus database was selected because of its rigorous indexing standards, wide disciplinary coverage and reputation for high-quality, peer-reviewed content. In 2025, Scopus included over 100 million records across more than 24 000 active titles in diverse fields, including education, computer science and STEM disciplines, which made it one of the most authoritative sources for bibliometric research (Feldner, 2025). Unlike platforms with broader but less curated coverage, Scopus maintains strict inclusion criteria and indexing protocols, thereby ensuring the reliability and scholarly relevance of retrieved publications. Its detailed metadata and citation tracking capabilities allow for robust analyses of publication trends, authorship networks and thematic evolution – key components of mapping the intellectual structure of emerging research domains such as CT in K–12 STEM education (Baas et al., 2020).

This study included only peer-reviewed journal articles published between 2007 and 2025, because 2007 was the year CT started receiving widespread scholarly attention after the publication of Wing's seminal work. Only articles written in English were retained, to ensure consistency in keyword extraction and interpretation. Book chapters, books, editorial notes, conference proceedings, dissertations and grey literature were excluded, to maintain data standardisation and peer-review integrity (Mingers & Leydesdorff, 2015). Additionally, only Scopus-indexed articles categorised under relevant subject areas (education, computer science, engineering and social sciences) were included, because these directly align with CT integration in STEM contexts.

4. Results and Findings

4.1 Descriptive Analysis

A total of 1 018 documents covering the period from 2007 to 2025 and related to CT in STEM education were retrieved from the Scopus database. These publications had collectively received 11 010 citations, with an average of 16.73 citations per article and an H-index of 21, which indicates a steadily growing but still emerging area of scholarly interest.

As illustrated in Figure 1, the annual publication output had increased significantly over the period, from just 1 document in 2007 to a peak of 151 documents in 2024, which was the most prolific year to date. The growth trend becomes more pronounced from 2016 onward, with notable increases in 2020, 2021, and 2023.

Although the number of publications appears to decline in 2025 (with 80 documents recorded), this is probably because the year was not over when data were collected, and additional publications may not yet have been fully indexed in the database. The rising trajectory highlights the expanding importance of CT in STEM education, and the way researchers increasingly explored its role in problem-solving, critical thinking and digital literacy across diverse education contexts.

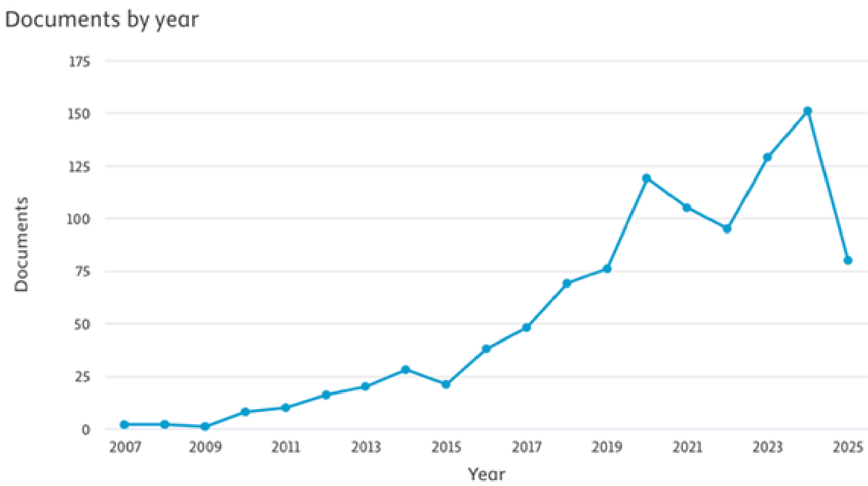

Figure 1: Number of publications on CT in STEM education

4.2 Bibliographic Coupling Analysis

From the initial dataset of 1 018 documents retrieved from the database, 60 documents met the threshold criterion of having at least 38 cited references. After further refinement, 54 documents representing the most interconnected publications were retained for analysis. Multiple threshold values were tested to ensure the formation of robust and well-balanced clusters, leading to an ultimate selection of a value that avoids overly simplistic or excessively complex visualisations. The final threshold provided optimal clarity and thematic coherence of the the bibliographic coupling network.

The analysis reveals that the three most strongly coupled publications are Ogegbo and Ramnarain (2022), with 51 citations; Wang et al. (2022), with 103 citations; and Román-González et al. (2017), with 581 citations. Table 2 presents the top 10 documents with the highest total link strength, which indicates the cumulative strength of connection of a publication to other documents (van Eck & Waltman, 2014).

Table 2: Top 10 documents with the highest total link strength

Documents	Citation	Total link strength
Ogegbo, A. A., & Ramnarain, U. (2022). A systematic review of computational thinking in science classrooms. *Studies in Science Education, 58*(2), 203–230). https://doi.org/10.1080/03057267.2021.1963580	51	181
Wang, C., Shen, J., & Chao, J. (2022). Integrating computational thinking in STEM education: A literature review. *International Journal of Science and Mathematics Education, 20*, 1949–1972. https://doi.org/10.1007/s10763-021-10227-5	103	167
Román-González, M., Pérez-González, J. C., & Jiménez-Fernández, C. (2017). Which cognitive abilities underlie computational thinking? Criterion validity of the Computational Thinking Test. *Computers in Human Behavior, 72*, 678–691. https://doi.org/10.1016/j.chb.2016.08.047	581	165
Weintrop, D., Beheshti, E., Horn, M., Orton, K., Jona, K., Trouille, L., & Wilensky, U. (2016). Defining computational thinking for mathematics and science classrooms. *Journal of Science Education and Technology, 25*(1), 127–147. https://doi.org/10.1007/s10956-015-9581-5	1 067	161
Román-González, M., Pérez-González, J. C., Moreno-León, J., & Robles, G. (2018). Extending the nomological network of computational thinking with non-cognitive factors. *Computers in Human Behavior, 80*, 441–459. https://doi.org/10.1016/j.chb.2017.09.030	94	151
Sands, P., Yadav, A., & Good, J. (2018). Computational thinking in K–12: In-service teacher perceptions of computational thinking. In M. S. Khine (Eds.), *Computational thinking in the STEM disciplines: Foundations and research highlights* (pp. 151–164). Springer International Publishing. https://doi.org/10.1007/978-3-319-93566-9_8	53	151
Sengupta, P., Dickes, A., & Farris, A. (2018). Toward a phenomenology of computational thinking in STEM education. In M. S. Khine (Eds.) *Computational thinking in the STEM disciplines: Foundations and research highlights* (pp. 49–72). Springer International Publishing. https://doi.org/10.1007/978-3-319-93566-9_4	76	150
Lodi, M., & Martini, S. (2021). Computational thinking, between Papert and Wing. *Science and Education, 30*(4), 883–908. https://doi.org/10.1007/s11191-021-00202-5	129	144

Ioannou, A., & Makridou, E. (2018). Exploring the potentials of educational robotics in the development of computational thinking: A summary of current research and practical proposal for future work. *Education and Information Technologies, 23*(6), 2531–2544. https://doi.org/10.1007/s10639-018-9729-z	142	141
Sengupta, P., Kinnebrew, J. S., Basu, S., Biswas, G., & Clark, D. (2013). Integrating computational thinking with K–12 science education using agent-based computation: A theoretical framework. *Education and Information Technologies, 18*(2), 351–380. https://doi.org/10.1007/s10639-012-9240-x	441	140

Bibliographic coupling is based on network visualisation and analysis produced three distinct clusters. Figure 2 shows the network structure of bibliographic coupling analysis. Each cluster was labelled and characterised according to representative publications through the authors' inductive interpretation and understanding of the three clusters.

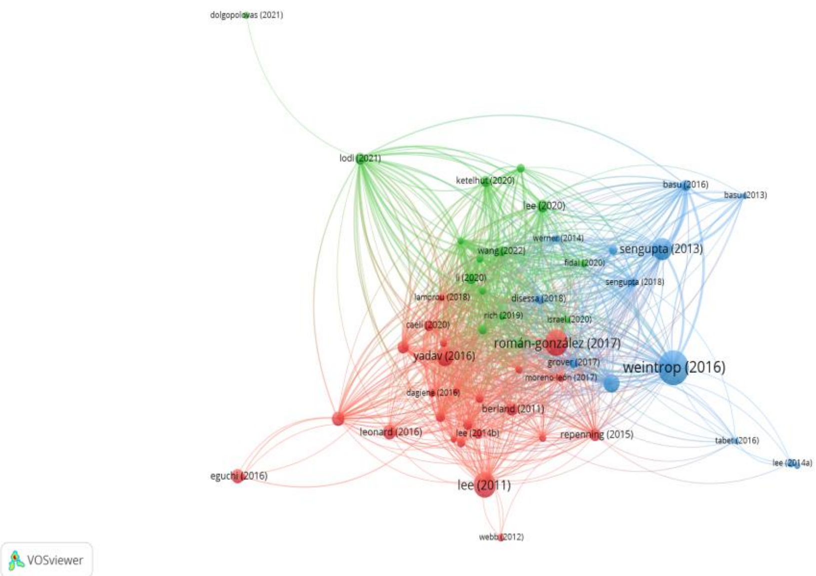

Figure 2: Bibliographic coupling analysis of CT in STEM education

Cluster 1 (red): This cluster is labelled Pedagogical Innovations and Learning Environments in Computational Thinking. This cluster emphasises the integration of CT in STEM education through different teaching pedagogies and learning environments. It highlights that CT can be incorporated in STEM teaching through various teaching strategies. Studies demonstrate that robotics (Eguchi, 2016; Leonard et al., 2016), game-based learning (Berland & Lee, 2011; Repenning et al., 2015), and unplugged activities (Caeli & Yadav, 2020) foster engagement and conceptual understanding. Research also emphasises teacher preparation (Jaipal-Jamani & Angeli, 2017; Lamprou & Repenning, 2018), assessment models (Román-González et al., 2017), and gender dynamics in collaborative CT tasks (Ardito et al., 2020; Taylor & Baek, 2019). Collectively, these works explored how CT is taught, measured and scaled—underscoring its interdisciplinary potential and the importance of contextualised, inclusive and innovative instructional approaches in science education.

Cluster 2 (green): Theoretical Foundations and Disciplinary Integration of Computational Thinking in STEM is the label of the second cluster. This cluster challenges the foundational, interdisciplinary and cognitive dimensions of CT in STEM education. Several studies promote CT as a mode of scientific inquiry rather than mere coding and emphasises CT as a cognitive process with problem-solving and debugging trajectories (Li et al., 2020; Rich et al., 2019).

CT is explored through disciplinary lenses, particularly science and mathematics, to highlight its conceptual integration and epistemological alignment (Israel & Lash, 2020; I. Lee et al., 2020; Luo et al., 2020). Reviews emphasise teacher beliefs (Sands et al., 2018), professional development (Ketelhut et al., 2020) and unplugged approaches (Huang & Looi, 2020). Collectively, the cluster deepens our understanding of CT as a pedagogical and cognitive construct and reinforces its relevance across disciplines and education contexts.

Cluster 3 (blue): Lastly, Cluster 3 is named Design Frameworks and Learning Challenges in Computational Thinking Integration. This cluster focuses on how to effectively design learning environments to uncover cognitive challenges students face when engaging in CT in K–12 STEM settings. Central themes include debugging strategies (Lee et al., 2014), CT-based science integration (Sengupta et al., 2013), and scaffolding student thinking using blended and game-based models (Grover et al., 2015; Werner et al., 2014).

Several studies present learning frameworks informed by agent-based modelling, hypothesis-driven analytics and constructivist pedagogy (Basu et al., 2016; Grover, 2017). Theoretical expansions propose CT as a literacy (diSessa, 2018) and epistemic practice in STEM (Weintrop et al., 2016). This body of work bridges theory and practice by emphasising both pedagogical design and students' conceptual difficulties when applying CT in science and computing education.

Table 3 summarises the bibliographic coupling analysis by presenting its clusters, cluster labels, number of articles and representative publications.

Table 3: Bibliographic coupling clusters on CT in STEM education

Cluster	Cluster label	Number of articles	Representative publications
1 (red)	Pedagogical Innovations and Learning Environments in Computational Thinking	26	Eguchi (2016); Jaipal-Jamani and Angeli (2017); Lee et al. (2011); Leonard et al. (2016); Román-González et al. (2017); Yadav et al. (2016)
2 (green)	Theoretical Foundations and Disciplinary Integration of Computational Thinking in STEM	15	Ketelhut et al. (2020); Li et al. (2020); Lodi and Martini (2021); Wang et al. (2022)
3 (blue)	Design Frameworks and Learning Challenges in Computational Thinking Integration	13	Basu et al. (2016); diSessa, (2018); Grover et al. (2015); Grover et al. (2017); Sengupta et al. (2013); Weintrop et al. (2016)

The three thematic clusters identified in this study generate key pedagogical and policy implications. First, the cluster on Pedagogical Innovations and Learning Environments underscores that classroom-level integration of CT requires intentional instructional design and differentiated learning environments. This suggests that policymakers and curriculum developers should prioritise professional development that equips teachers not only with tools (e.g., robotics, block-based programming) but also with pedagogical repertoires for scaffolding decomposition, abstraction and debugging in real inquiry contexts.

Second, the cluster on Theoretical Foundations and Disciplinary Integration indicates that CT must be positioned as a cross-disciplinary cognitive practice rather than a purely coding-oriented skill. Policymakers should, therefore, embed CT as a core literacy across science and mathematics standards, comparable to modelling or argumentation, not as an optional elective. Finally, the cluster on Design Frameworks and Learning Challenges reveals persistent difficulties experienced by learners, which points to the need for policy mechanisms that support sustained teacher mentoring, iterative curriculum experimentation and evidence-based assessment frameworks. Rather than episodic pilot projects, CT integration should be approached as a long-term system initiative that invests in sustained capacity-building, monitoring and feedback loops across grade levels.

4.3 Co-Word Analysis

From 3 720 keywords extracted from titles and abstracts, 64 met the minimum threshold of 16 occurrences, forming three clusters. The analysis shows that the keywords with the highest occurrence were computational thinking (587), computational thinkings (467), computer science education (390), students (331), and education computing (317). Table 4 summarises the top 15 co-occurring keywords, their number of occurrences, and relevance.

Table 4: Top 15 keywords in the co-occurrence of keyword analysis

Ranking	Keyword	Occurrences	Total link strength
1	Computational thinking	587	2 433
2	Computational thinkings	467	2 856
3	Computer science education	390	1 906
4	Students	331	2 092
5	Education computing	317	2 034
6	Engineering education	209	1 469
7	Curricula	169	1 152
8	Teaching	153	1 048
9	STEM education	138	565
10	Science education	107	494
11	Education	87	548
12	Computer programming	73	496
13	STEM	63	453
14	Teachers	58	403
15	e-learning	54	367

Figure 3 presents a network map of the co-word analysis. The map produced three clusters, which were classified and labelled according to the authors' inductive interpretation of the occurring words.

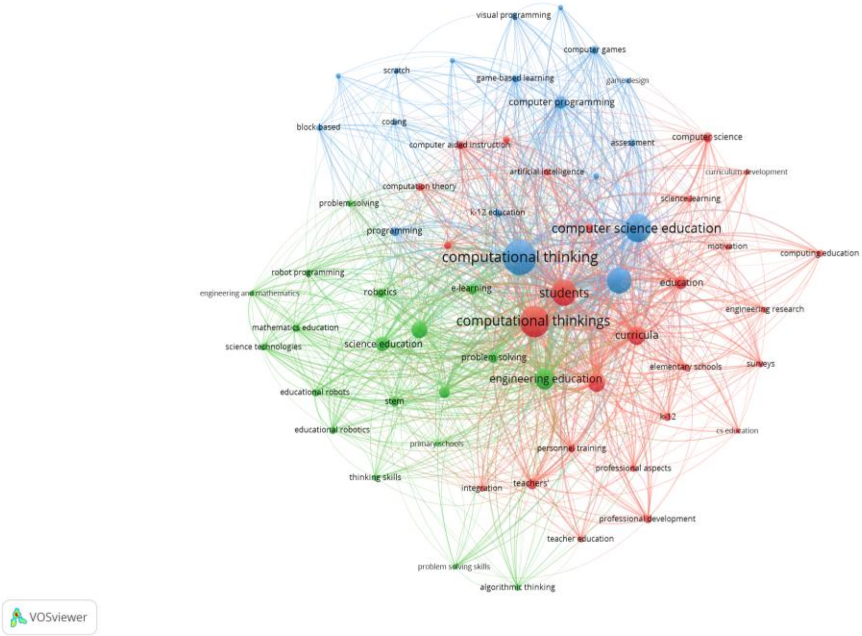

Figure 3: Co-word analysis of CT in STEM education

Cluster 1 (red): With 27 keywords, this cluster is labelled Pedagogical Foundations and Professional Practices in Computational Thinking Integration. This cluster explains the need to equip educators with the necessary skills, competencies and support systems to effectively incorporate CT in STEM education. Many studies highlight how instructional design, teacher training and systemic support shape the effectiveness of CT initiatives, particularly when aligned with constructivist frameworks and adaptive learning technologies (Li et al., 2025; Kim et al., 2025).

The interplay between motivation, cognitive scaffolding and personalised instruction reveals a shift towards learner-centred approaches, which is bolstered by artificial intelligence (AI) and data-informed systems (Tan et al., 2024). Despite these advances, research still identifies limitations in long-term teacher efficacy and sustainability in marginalised contexts (Alfaro-Ponce et al., 2023). This cluster, thus, contributes to a broader understanding of CT as more than technical skill-building; it is a pedagogical innovation that requires interdisciplinary collaboration, professional empowerment and responsive education systems.

Cluster 2 (green): The second cluster, which is labelled Robotics-Enhanced Thinking and Problem-Solving in STEM Education, comprises 19 keywords that centre on the integration of robotics, coding and algorithmic thinking as tools for enhancing cognitive and problem-solving abilities in STEM learning, especially in primary and early secondary education. Recent studies emphasise how robotics-based interventions promote hands-on engagement, foster curiosity and strengthen logical reasoning through iterative design and debugging processes (Olamilekan, 2025). Research also underscores the synergy between e-learning platforms and physical computing devices. This synergy supports inclusive access and differentiated instruction in science and mathematics education

(Alrashidi, 2023). Moreover, the development of thinking skills, especially in algorithmic reasoning and computational problem-solving, is increasingly framed as essential for foundational STEM literacy (Jacob & Warschauer, 2018). Despite increasing adoption, the field still grapples with scalable models and curriculum alignment, especially in diverse classroom settings. This cluster contributes a forward-looking perspective on the way robotics and digital tools are reshaping the pedagogical landscape and cognitive development in STEM education.

Cluster 3 (blue): The last cluster comprises 18 keywords and is titled Block-Based Programming and Game-Oriented Approaches in K–12 Computing Education. This cluster explores the intersection of block-based programming, visual learning environments and game-based pedagogies as transformative tools in K−12 computing education. Recent studies show that platforms such as Scratch and other visual programming tools lower entry barriers and foster student creativity, especially in middle school settings (Arora et al., 2023). The integration of game design and coding enhances engagement while reinforcing core CT skills, thereby making programming more accessible and meaningful (Ma et al., 2023).

This approach supports experiential and iterative learning, which involve students building problem-solving skills through real-time feedback and playful experimentation. Moreover, emerging research is refining assessment strategies to evaluate not only technical proficiency but also logical structuring and conceptual understanding in these environments (El-Hamamsy et al., 2023). As block-based programming continues to evolve, this cluster highlights its critical role in democratising computer science education and shaping the next wave of computationally literate learners. Table 5 summarises the co-word analysis represented by cluster label, number of keywords and representative keywords.

Table 5: Co-word analysis on CT in STEM education

Cluster No. and colour	Cluster label	Number of keywords	Representative keywords
1 (red)	Pedagogical Foundations and Professional Practices in Computational Thinking Integration	27	computational thinkings; students; curricula; teaching
2 (green)	Robotics-Enhanced Thinking and Problem-Solving in STEM Education	19	stem education; engineering education; science education; e-learning; robotics
3 (blue)	Block-Based Programming and Game-Oriented Approaches in K–12 Computing Education	18	computational computing; computer science education; education computing; computer programming

5. Discussion

This section explains the important research streams that shape CT in STEM education, as identified by bibliographic coupling and co-word analyses. Critically, it synthesises emerging directions, conceptual gaps and methodological opportunities.

5.1 Accelerating Scholarly Interest and Research Expansion

Analysis of the bibliometric trajectory of CT in STEM education indicates that there has been a sharp increase in scholarly attention being paid to CT over the past decade. The highest publication output was recorded in 2024, which clearly explains that its rapid increase aligns with global education shifts that emphasise digital literacy, interdisciplinary learning and 21st-century competencies. The growing number of publications suggests that CT has evolved from a niche topic to a central pillar in K–12 STEM discourse, particularly as technology-enhanced learning environments gain traction (Shute et al., 2017; Weintrop et al., 2016).

While citation rates peaked in 2020, possibly reflecting foundational contributions during the pandemic-driven edtech boom, the subsequent decline in citations in spite of publication growth may indicate a fragmentation of research themes or delayed citation accumulation for recent works. The high H-index (21) affirms a core group of influential publications shaping the field. The continued expansion of the field signals a robust intellectual movement towards reimagining pedagogy, curriculum and assessment through computational frameworks (Grover et al., 2015; Sengupta et al., 2013).

5.2 Foundational Theories and Epistemic Anchors of Computational Thinking

Bibliographic coupling analysis was used to map the collection of influential works that continue to shape the epistemological and theoretical foundations of CT in STEM education. Wing's (2006) articulation of CT as a fundamental literacy, Papert's (1980) constructionist vision, and Weintrop et al.'s (2016) disciplinary framework collectively anchor this field in both cognitive science and education theory. The large number of citations and total link strength values of these scholars reflect their enduring influence across various scholarly clusters.

Importantly, these works do not merely promote CT as a coding skill but position it as a way of thinking, intersecting problem-solving, systems analysis and algorithmic reasoning (Barr & Stephenson, 2011; Shute et al., 2017). The prominence of studies on science integration (Sengupta et al., 2013), blended learning (Grover et al., 2015), and curriculum development (NGSS, 2013) underscores the transdisciplinary relevance of CT. This cluster of influential literature points to a mature, theory-driven discourse and lays the groundwork for empirical validation, curricular innovation and broader adoption of CT as an education imperative across STEM domains.

For example, in Cluster 1, Román-González et al. (2017) represents a highly cited empirical anchor that operationalises and validates CT assessment, and shapes much of the subsequent work on how CT development is measured in school-based environments. In Cluster 2, Li et al. (2020) illustrate the theoretical turn that reframes CT primarily as a cognitive practice rather than a coding skill, thereby influencing how CT is positioned in mathematics and science standards. Meanwhile, Cluster 3 is strongly represented by Sengupta et al. (2013), whose agent-based modelling framework demonstrates how CT can be enacted through scientific modelling and data-rich inquiry. These highly cited works illuminate how the clusters are not merely algorithmically derived groupings, but also represent major intellectual pathways through which CT scholarship has evolved and been operationalised in practice.

While Wing (2006), Papert (1980) and Weintrop et al. (2016) remain the intellectual anchors of the field, their influence has evolved in distinct ways over time. Papert's constructionism initially framed computing as a vehicle for learning through making, which laid the philosophical groundwork for the surge of robotics- and game-based designs found in Cluster 1. Wing's (2006) argument that CT is a fundamental literacy for all learners catalysed the shift from CS-centric 'coding skill' to a broader K–12 educational agenda, and this perspective now underpins many policy documents, standards and curricular frameworks internationally.

Meanwhile, Weintrop et al.'s (2016) disciplinary articulation of CT provided a pragmatic bridge between theory and classroom practice, particularly in science and mathematics. More recent publications have built on these foundations by moving towards measurement, progression models and equity-oriented CT approaches, suggesting that, while the early works remain conceptual cornerstones, current research is increasingly focused on operationalising CT in real-world learning systems. This shift indicates a maturation of the field—from advocating for the importance of CT towards concretising how CT is taught, assessed and institutionalised across educational systems.

5.3 Practical Curriculum Applications of CT in STEM Education

The clusters point to practical examples of how CT can be embedded in STEM learning. For instance, robotics tasks (Cluster 1) can be used in engineering or physical science units, where students iteratively test and debug drive-train designs and make algorithmic reasoning explicit through sensor-based control. Block-based programming tools (Cluster 3) such as Scratch or MakeCode can support mathematics learning by requiring students to model patterns, sequences and functions through programmable simulations.

Agent-based modelling (Cluster 3), as demonstrated in Sengupta et al. (2013), can be used in environmental science units where students can build computational models of population interactions or ecosystem dynamics, thereby connecting domain-specific knowledge with computational representations. These examples indicate that CT integration is not limited to coding electives; rather, it can be embedded in core disciplinary learning targets, thereby supporting curriculum developers by aligning CT with existing STEM curricular outcomes.

6. Conclusion

This study analysed the intellectual and conceptual development of CT in STEM education and provides a systematic and data-driven exploration of CT in STEM education from 2007 to 2025. Analysis of the data shows a significant increase in research publications, which reflect the increasing popularity of CT in STEM education. Three major research clusters, namely (1) Pedagogical innovations and learning environments, (2) Theoretical foundations and disciplinary integration; and (3) Design frameworks and learning challenges, were analysed using bibliographic coupling technique. These clusters underscore the multidimensional character of CT, as a cognitive process, instructional approach and epistemic tool in STEM contexts. In addition, co-word analysis exposes evolving themes, including teacher professional development, robotics-based problem-solving and block-based programming environments, and emphasise the interdisciplinary and practice-oriented nature of CT research further. The findings affirm that CT is no longer confined to computer science; rather, it is a unifying literacy with implications for scientific reasoning, mathematical thinking and inclusive pedagogy.

Beyond mapping knowledge structures, this study offers critical insights for shaping future directions in both research and practice. The field is moving towards contextualised, equity-driven and integrative approaches to CT education, by prioritising not only technical skill development but also creativity, collaboration and real-world problem-solving. However, challenges remain in terms of curriculum coherence, scalable assessment models and sustained teacher capacity-building. This analysis lays the groundwork for more targeted empirical investigations and policy innovations. By clarifying the current state of knowledge and identifying gaps, it serves as a strategic resource for educators, researchers and policymakers who are committed to embedding CT meaningfully in the fabric of STEM education.

This study was limited by its reliance on Scopus as the sole bibliographic source. While Scopus provides extensive coverage and rigorous indexing standards, it does not capture all high-quality publications, particularly not those indexed exclusively in ERIC or Web of Science. Consequently, some relevant studies may not have been included in the dataset. In addition, bibliometric techniques are inherently quantitative, and although they reveal structural patterns, they cannot fully capture the contextual depth, epistemic nuance and pedagogical complexity embedded in individual CT integration studies. Future bibliometric work could adopt a multi-database strategy and combine bibliometric mapping with qualitative content analysis to deepen interpretive insight.

Looking ahead, the field is poised to intersect more deeply with emerging education priorities such as AI, data science and ethical computing. Future CT scholarship could explore how AI-assisted learning environments can support adaptive scaffolding, automated assessment and personalised debugging feedback. Similarly, data science thinking, such as data modelling, statistical reasoning and visualisation, can serve as a powerful extension of CT in STEM domains, particularly as students engage with real-world datasets. Finally, there is a pressing need for equity-driven CT research that foregrounds access, cultural responsiveness, gender dynamics and the participation of underserved groups. Prioritising these directions will ensure that CT integration does not only scale, but also becomes more inclusive, future-ready and socially just.

7. Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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