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MAPPING THE EVOLUTION OF COMPUTATIONAL THINKING IN EARLY CHILDHOOD EDUCATION: A BIBLIOMETRIC ANALYSIS OF RESEARCH TRENDS (2010-2023)

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Abstract

This bibliometric study analyses the intellectual landscape of computational thinking (CT) research in early childhood education, based on 161 Scopus-indexed publications from 2010 to 2023. Using co-occurrence analysis, citation mapping, and network visualisation, the study identifies key trends, influential contributions, and thematic priorities. The findings show a marked increase in research output, especially after 2019, reflecting the field's transition to a more established domain. Research is primarily concentrated in high-impact countries like the United States and Greece, with limited international collaboration. Five major research clusters were identified, focusing on robotics, technology integration in preschools, and assessment methods. Temporal analysis reveals a shift post-2020 toward developing context-appropriate implementation strategies, including "unplugged" methods and standardised assessment frameworks. These findings highlight the disparity between high-resource contexts driving research and underrepresented regions, stressing the need for contextually relevant models. In particular, "unplugged" CT methods emerge as an equity pathway, offering scalable solutions for diverse educational settings, especially in Southeast Asia.

Keywords: Minecraft, STEM Education, Sustainable Development Goals, Game-based Learning

1. Introduction

Computational thinking (CT) has emerged as a critical competency for navigating the increasingly digitised landscape of 21st-century problem-solving. Originally rooted in computer science, CT now influences diverse disciplines, including mathematics, engineering, and the creative arts (Wing, 2006; Bers et al., 2014). Defined as the ability to decompose complex problems, recognise patterns, and design algorithmic solutions (Barr et al., 2011), CT equips learners with systematic reasoning skills essential for technological literacy. While the integration of CT into K-12 education has gained substantial momentum globally, its application in early childhood education (ECE)—a formative period for cognitive and socioemotional development—remains comparatively underdeveloped, particularly in low- and middle-income countries (Adanır et al., 2023). This gap is especially evident in Southeast Asian nations, where countries like Vietnam and Thailand are actively implementing national STEM and coding curricula. This creates an urgent need for evidence-based guidance on effective and equitable implementation strategies.

The early childhood period (ages 3-8) represents a critical developmental window for cultivating foundational reasoning skills. Bers (2018) reconceptualises CT in ECE as a "playground for learning," where age-appropriate tools, such as tangible robotics kits (e.g., KIBO) and narrative-based programming environments (e.g., ScratchJr), foster skills in sequencing, debugging, and abstraction within developmentally appropriate frameworks.

Empirical evidence increasingly demonstrates that well-implemented CT activities enhance not only logical reasoning but also creativity, collaboration, and problem-solving abilities in young learners. For instance, Sullivan and Bers (2016) documented significant improvements in sequencing and problem-solving capabilities among preschoolers exposed to an 8-week robotics curriculum, compared to peers in traditional educational settings.

Despite this promising trajectory, several challenges remain in establishing CT as a core component of early learning. First, conceptual boundaries are often contested, with educators frequently conflating CT with coding proficiency, rather than recognising it as a broader cognitive framework (Yadav et al., 2017). Second, assessment approaches lack developmental validity for young learners, often relying on observational rubrics rather than standardised, age-appropriate metrics (Relkin and Bers, 2021). Third, socioeconomic disparities constrain equitable access to CT resources. High-income countries leverage sophisticated robotics laboratories, while under-resourced regions depend primarily on low-cost, unplugged activities (Zeng et al., 2023).

The rapid proliferation of research on CT in ECE has created a fragmented and challenging knowledge landscape. While narrative reviews have examined qualitative aspects of CT implementation (Su and Yang, 2023), and bibliometric analyses have mapped CT research in broader K-12 contexts (Adanır et al., 2023), a systematic quantitative mapping of the intellectual structure focusing specifically on CT in ECE is notably absent. This gap is critical, as understanding the evolution, geographic distribution, and thematic priorities of this emerging field is essential for informing evidence-based policy, practice, and research agendas.

Bibliometric analysis offers a valuable methodological approach for addressing this gap by providing quantitative insights into the structural and dynamic characteristics of scientific fields (Zupic and Čater, 2015). As an emerging interdisciplinary domain, CT in ECE benefits from bibliometric mapping to reveal collaboration networks, identify influential contributions, and track thematic evolution over time. This approach aligns with Science Mapping Theory (Börner et al., 2003), which posits that quantitative analysis of publication patterns can reveal the cognitive structure and social organisation of scientific fields.

This study leverages the Scopus database for its comprehensive coverage of both journal articles and conference proceedings, with the latter being particularly significant in educational technology research. Unlike Web of Science, Scopus indexes approximately 70% more education-focused journals, including publications from non-Western contexts, providing greater representation of diverse approaches to CT integration (Baas et al., 2020). Through a systematic analysis of 161 publications spanning 2010-2023, this study addresses three interrelated research questions:

- **RQ1**: How has CT research in ECE evolved temporally and geographically, and what patterns emerge in productivity and growth rates across regions?
- **RQ2**: Which countries and journals have most significantly shaped the intellectual structure of the field, and what is the position and presence of Southeast Asian researchers within that structure?
- **RQ3**: What thematic clusters define the research landscape of CT in ECE, and how have these priorities shifted in response to educational challenges, particularly before and after 2020?

By systematically mapping the intellectual landscape of CT in ECE, this study aims to provide a comprehensive understanding of current research trends, identify critical gaps in knowledge production, and offer strategic guidance for research, policy, and practice. The findings will be particularly valuable for addressing geographic and resource disparities in CT integration, informing curriculum development for early childhood educators, and establishing research priorities that align with the developmental needs of young learners in diverse contexts.

2. Literature Review

2.1 Conceptual Foundations of Computational Thinking in Early Childhood Education

CT has evolved from a discipline-specific construct into a foundational competency that transcends traditional subject boundaries. Originally conceptualised by Wing (2006) as a problem-solving approach rooted in computer science principles, CT has undergone significant theoretical refinement as it extends into early educational contexts. In their seminal framework, Barr et al. (2011) defined CT as encompassing four core dimensions: decomposition, pattern recognition, abstraction, and algorithm design. This framework has been highly influential in guiding curriculum development across educational levels, though its application in early childhood settings necessitates substantial developmental adaptation.

For early childhood contexts, Bers (2018) reconceptualised CT as a “playground for learning,” emphasising developmentally appropriate engagement with computational concepts through playful interaction rather than abstract instruction. This perspective aligns with constructivist learning theories (Piaget, 1970) and sociocultural approaches (Vygotsky, 1978), positioning CT as an extension of children’s natural problem-solving processes, rather than an imposed skill set. Sullivan and Bers (2016) further refined this conceptualisation by demonstrating how tangible interfaces facilitate the development of computational competencies through embodied learning experiences. Their longitudinal studies documented significant gains in sequential thinking (d = 0.74) among preschool populations.

Despite this theoretical evolution, significant ambiguity remains regarding the precise boundaries of CT in early childhood contexts. Yadav et al. (2017) identified a troubling trend in which educators often conflate CT with coding proficiency, neglecting its broader cognitive dimensions. This conceptual confusion has practical consequences for curriculum design, assessment practices, and resource allocation, particularly in resource-constrained educational environments. Recent work by Relkin et al. (2021) attempts to address this ambiguity by establishing developmentally validated assessment frameworks specifically calibrated for young learners, though their implementation remains limited, primarily to high-income educational settings.

2.2 Pedagogical Approaches and Implementations

The pedagogical landscape for introducing CT in early childhood settings has evolved along two primary trajectories, distinguished by their technological requirements and implementation modalities.

2.2.1 Pedagogical Approaches and Implementations

Robotics-based interventions constitute the most extensively researched approach to CT integration in early childhood settings. Programmable platforms such as KIBO (Bers, 2018), Bee-Bot (Papadakis, 2020), and Code-a-pillar (Sullivan and Bers, 2019) leverage tangible interfaces that align with young children’s developmental needs. These tools support concrete operational thinking by making abstract computational concepts physically manipulable. A systematic review by Bakala et al. (2021) identified 24 empirical studies of robotics-based CT interventions for children ages 3-8, with effect sizes ranging from moderate to large for improvements in sequential thinking (d = 0.58-0.92) and logical reasoning (d = 0.43-0.77).

Screen-based programming environments represent a complementary approach, with ScratchJr emerging as the most thoroughly evaluated platform for early learners. Portelance and Bers (2014) documented significant improvements in spatial reasoning (d = 0.62) and pattern recognition (d = 0.47) among children aged 4-6 following structured engagement with block-based programming activities. However, despite promising efficacy data, significant implementation barriers persist. The high cost of robotics kits makes widespread adoption prohibitive in many educational contexts (Papadakis, 2020), while screen-based solutions raise developmental concerns regarding appropriate technology exposure for young children (Strasburger and Hogan, 2013).

2.2.2 Unplugged Approaches

In response to both resource constraints and developmental considerations, researchers have developed an expanding repertoire of "unplugged" CT activities requiring minimal technological infrastructure. Zeng et al. (2023) systematically evaluated paper-based pattern recognition tasks in kindergarten settings across diverse socioeconomic contexts, documenting significant improvements in algorithmic thinking regardless of prior technological exposure. Similarly, Relkin et al. (2020) reported comparable efficacy between unplugged storytelling activities and robotics-based interventions for developing computational sequence recognition (no significant difference, p = .74), suggesting potential for cost-effective implementation.

The pedagogical literature reveals a complex efficacy landscape, with both plugged and unplugged approaches demonstrating measurable benefits under appropriate implementation conditions. However, methodological limitations constrain generalisability, with most studies utilising small sample sizes (median N = 42 across reviewed studies), brief intervention periods (typically 4-8 weeks), and researcher-implemented rather than teacher-implemented protocols (Bakala et al., 2021). Additionally, the predominance of studies from high-income educational contexts (87% of empirical research identified by Su and Yang, 2023) raises significant questions regarding cross-cultural validity and implementation feasibility in diverse settings.

2.3 Assessment Frameworks and Equity Considerations

The assessment of CT competencies in early childhood presents distinct methodological challenges due to developmental considerations, linguistic capabilities, and the abstract nature of computational concepts. Current assessment approaches can be grouped into three primary categories, each with specific limitations (Zapata-Cáceres et al., 2020).

Task-based assessments, such as puzzle completion and sequence recognition, provide concrete measures of specific computational skills but may lack ecological validity when detached from authentic learning contexts. Observational protocols, including the Positive Technological Development framework (Bers, 2018) and CT-STEM instruments (Relkin and Bers, 2021), offer rich contextual data but are hindered by reliability concerns and resource-intensive implementation. Artifact analysis methods, which examine children's computational products (e.g., Scratch programmes, robot command sequences), often lack standardised scoring criteria, limiting cross-context comparability (Bakala et al., 2021).

Recently developed validated instruments address some of these limitations. The Computational Thinking Test for Beginners (Zapata-Cáceres et al., 2020) demonstrates strong psychometric properties (α = .82-.89) across linguistically diverse populations, while TechCheck (Relkin and Bers, 2021) is specifically designed for early childhood populations with developmentally appropriate items. However, these instruments remain underutilised, with only 18% of empirical studies identified by Su and Yang (2023) employing standardised assessment measures.

Equity considerations intersect with assessment challenges, particularly regarding geographic disparities in research production and implementation. CT initiatives are largely concentrated in high-resource educational environments in North America, Western Europe, and East Asia (Bakala et al., 2021), creating significant knowledge gaps on strategies suitable for diverse socioeconomic contexts. Although some studies address gender disparities in early STEM engagement (Sullivan and Bers, 2013; Bers et al., 2019), evidence for supporting children with disabilities or from marginalised communities is limited.

The reliance on commercial technological platforms exacerbates equity concerns. Rosario and Rosas (2019) documented sharp increases in educational robotics costs, creating substantial barriers to adoption in resource-constrained settings. These economic constraints underscore the need for research into culturally appropriate, low-cost implementation strategies to ensure that CT becomes a universal competency rather than an educational privilege.

2.4 Research Gaps and Methodological Limitations

Despite the growing literature, critical gaps remain in CT research within early childhood contexts. Geographic representation is highly imbalanced, with limited contributions from Africa, South Asia, and Latin America, leading to significant knowledge gaps regarding culturally responsive implementation strategies (Zeng et al., 2023). Collaboration patterns reveal fragmentation, with 72% of CT publications involving single-institution authorship, limiting cross-institutional knowledge transfer (Su and Yang, 2023). Methodologically, the field is dominated by short-term studies focusing on immediate outcomes, with few longitudinal investigations. For example, Bakala et al. (2021) found the median intervention duration in empirical studies was just 6.4 weeks, with only three studies examining outcomes beyond six months. This short timeframe limits understanding of how early CT experiences impact long-term academic and cognitive development. Furthermore, assessment approaches often lack validation across diverse populations, with reliance on researcher-developed measures rather than standardized instruments, complicating cross-study comparisons and meta-analytic synthesis (Zapata-Cáceres et al., 2020). These gaps highlight the importance of bibliometric approaches in mapping research trends, collaboration networks, and thematic evolution. By quantitatively analysing publication patterns, citation structures, and keyword co-occurrences, bibliometric analysis offers strategic insights into the intellectual development of CT research in early childhood contexts, identifying both productive areas and critical gaps for further investigation.

3. Method

This study employed a systematic bibliometric analysis to examine research trends and the intellectual structure of CT within early childhood education (ECE). Bibliometric analysis provides a quantitative and systematic approach to studying publication patterns, citation networks, and thematic evolution within scientific domains (Donthu et al., 2021; Zupic and Čater, 2015). This methodology enables researchers to identify influential contributions, map collaboration networks, and track the temporal development of research priorities through statistical analysis of publication metadata.

3.1 Data Source Selection

The Scopus database was selected as the primary data source for this study based on four critical considerations. First, Scopus offers comprehensive multidisciplinary coverage with over 25,000 indexed sources, including both journal articles and conference proceedings, the latter being particularly significant in educational technology research. Second, Scopus provides robust metadata export capabilities essential for bibliometric analysis, including complete citation information, institutional affiliations, and keyword classifications. Third, unlike Web of Science, Scopus indexes approximately 70% more education-focused journals, providing greater representation of research from diverse geographical contexts (Baas et al., 2020). Fourth, Scopus implements rigorous quality control processes for indexed publications, ensuring the scientific integrity of the analysed corpus (Falagas et al., 2008).

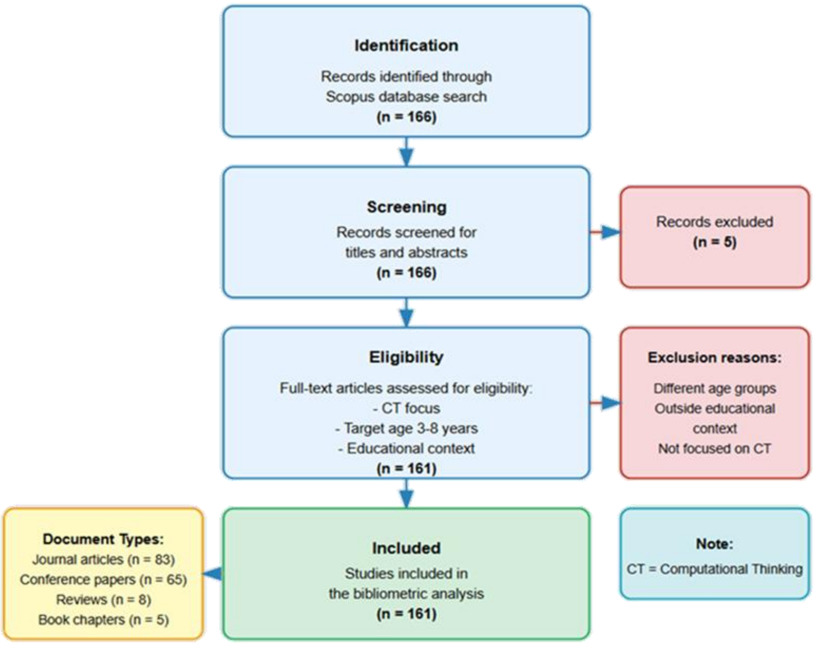
3.2 Search Strategy and Study Selection

A systematic search strategy was developed following established guidelines for bibliometric reviews in educational research (Ha et al., 2020). Keywords related to computational thinking were combined with terms associated with early childhood educational contexts using Boolean operators. The final search string was constructed to maximise precision while maintaining adequate sensitivity:

KEY ((“computational thinking”)) AND KEY ((“early childhood” OR “young child*” OR “early years” OR “preschool*” OR “pre-school*” OR “kindergarten*” OR “pre-k*” OR “infant*” OR “nursery school” OR “pre-primary” OR “pre-elementary”)) AND PUBYEAR < 2024 AND (LIMIT-TO (DOCTYPE, “ar”) OR LIMIT-TO (DOCTYPE, “cp”) OR LIMIT-TO (DOCTYPE, “re”) OR LIMIT-TO (DOCTYPE, “ch”))

The approach more effectively identifies publications where computational thinking is a central research focus, as opposed to those where it is only an incidental mention. The document types were limited to articles, reviews, conference papers, and book chapters to ensure scholarly quality and exclude less substantial formats, such as editorials and letters. The search was temporally bounded from the inception of the database through December 2023, with data extraction conducted on January 10, 2024.

Figure 1: PRISMA Flow Diagram Detailing Steps to Identify and Screen (Author’s adopted from Moher et al., 2009)



The initial search yielded 166 documents. Following established bibliometric protocols (Aria and Cuccurullo, 2017), a systematic screening process was implemented to ensure the relevance of the corpus (see the PRISMA diagram in Figure 1). Two researchers independently evaluated titles and abstracts based on pre-established inclusion criteria: (1) an explicit focus on computational thinking; (2) the target population being within the early childhood age range (under 6 years); and (3) an educational context or intervention. Five documents were excluded for failing to meet these criteria, typically addressing different age groups or educational levels. The final dataset comprised 161 documents: 83 journal articles (51.6%), 65 conference papers (40.4%), 8 reviews (5.0%), and 5 book chapters (3.1%).

3.3 Analytical Procedures

The analytical framework integrated complementary software tools to maximise methodological rigor. Biblioshiny (v.3.1.4), a web interface for the R-based Bibliometrix package, provided comprehensive bibliometric analysis capabilities, including performance metrics, citation analysis, and thematic mapping (Aria and Cuccurullo, 2017). VOSviewer (v.1.6.18) offered specialised visualisation functionality for network analysis and cluster identification (Van Eck and Waltman, 2010). This combination of analytical platforms is well-established in educational research bibliometrics and enables both statistical rigor and interpretive visualisation.

3.4 Methodological Limitations

While methodologically robust, this bibliometric approach entails certain limitations that require acknowledgment. First, the exclusive reliance on Scopus potentially underrepresents research published in non-indexed sources, particularly from developing regions. Second, bibliometric analysis captures formal scholarly communication but may not reflect practical innovations documented through non-academic channels. Third, citation metrics reflect visibility and influence but do not directly measure research quality or methodological rigor. Fourth, the two-year citation window for recent publications (2021-2023) may inadequately capture their eventual impact due to citation lag effects.

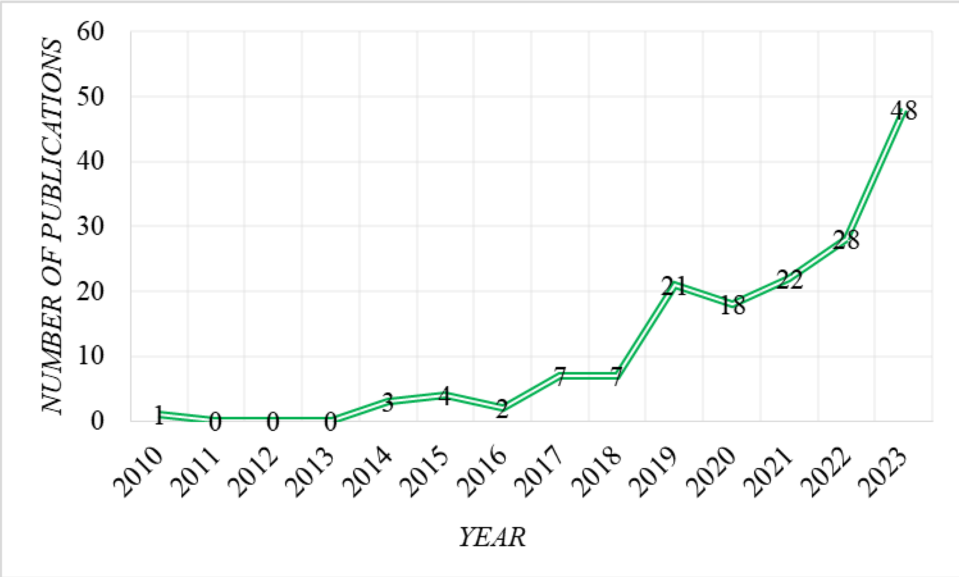
To mitigate these limitations, the results are interpreted with appropriate caution, emphasising patterns and trends rather than absolute metrics. Additionally, the discussion contextualises bibliometric findings within the broader literature to provide a more comprehensive understanding of the field's development.

4. Results

4.1 Temporal and Geographic Evolution of Research Output

Analysis of publication patterns reveals distinct developmental phases in CT research within ECE. Figure 2 illustrates the annual distribution of publications from 2010 to 2023, showing a clear inflection point in research productivity.

Figure 2: Number of Publications Over the Years



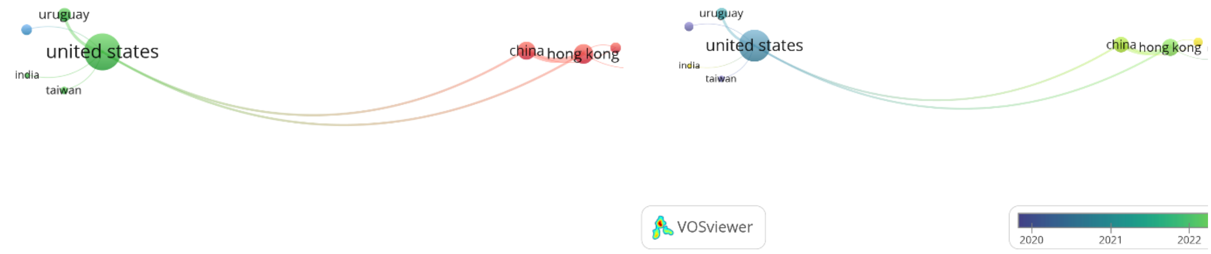
The longitudinal trajectory of research can be characterised by two distinct phases:

- **Emergence Phase (2010-2018)**: This initial period represents the nascent stage of CT research in ECE, with only 24 publications over eight years (14.9% of the total corpus). Annual output remained consistently low, ranging from 0 to 7 publications, reflecting limited research attention to computational concepts in early learning contexts. The field's inaugural contribution emerged in 2010 with Bers' publication, *The TangibleK Robotics Program: Applied Computational Thinking for Young Children*, in *Early Childhood Research and Practice*, establishing foundational approaches to robotics-based CT integration.
- **Expansion Phase (2019-2023)**: This period witnessed substantial acceleration in research productivity, with 137 publications representing 85.1% of the total corpus. Annual output increased dramatically from 21 publications in 2019 to 48 in 2023, representing a 129% growth rate over this four-year interval. This acceleration corresponds with global educational policy initiatives promoting early digital literacy, including the European Commission's Digital Education Action Plan (2019) and the USA' expansion of CS4All initiatives to include early childhood contexts.

The Compound Annual Growth Rate (CAGR) for publications during the expansion phase was 22.9%, substantially exceeding the 6.2% growth rate for educational research broadly during the same period (Scopus benchmark), as well as the 14.3% growth rate for general CT research across all educational levels. This differential growth pattern suggests intensified scholarly attention to ECE contexts specifically, rather than merely reflecting broader trends in computational research.

The network visualisation of international collaboration (Figures 3a and 3b) identifies three distinct collaboration clusters, differentiated by colour. The USA constitutes the most interconnected node, with 48 co-authorship connections, 6 international links, and a total link strength of 13, indicating both extensive and intensive collaborative relationships. Hong Kong and China demonstrate robust regional collaboration, with link strengths of 12 and 11, respectively, suggesting established research partnerships between these proximate educational systems. The network visualisation further reveals emerging collaborative relationships involving India and Australia, with publications first appearing in 2023, indicating the geographical expansion of the research community

Figure 3a and 3b: Mapping of the distribution of international countries/regions collaborations



4.2 Intellectual Impact and Scientific Leadership

Considerable variation in citation impact is evident across geographic regions (Table 1). The USA demonstrates the highest absolute impact, with 1,188 total citations, averaging 51.7 citations per article. Cyprus achieves the highest per-article impact, with 52.0 citations, despite its lower overall output (4 publications). Finland presents a distinctive impact profile, with 90 citations concentrated in a single highly influential publication, emphasising quality rather than quantity in research contribution. These disparities in citation metrics suggest a significant concentration of influence within specific research centres rather than a broad distribution across the field.

Table 1: Top ten impactful countries/regions

Rank	Country/regions	Total citations	Average Article Citations
1	USA	1188	51.7
2	GREECE	436	33.5
3	CYPRUS	208	52
4	HONG KONG	105	10.5
5	FINLAND	90	90
6	SPAIN	77	9.6
7	CHINA	53	6.6
8	URUGUAY	48	16
9	TURKEY	43	8.6
10	UNITED KINGDOM	26	13

Table 2 below presents impact metrics for the most influential publication sources in the corpus. *Education and Information Technologies* leads with an h-index of 5, accumulating 109 citations across 8 publications since its first CT-ECE publication in 2018. *The International Journal of Child-Computer Interaction* demonstrates exceptional citation efficiency, amassing 208 citations from 6 publications (an average of 34.7 citations per article), despite its recent entry into the field (first publication in 2019). Notably, conference proceedings constitute two of the top five most influential sources, with the IEEE Global Engineering Education Conference demonstrating particular impact (h-index 4, 112 citations). This distribution highlights the significant role of conference publications in shaping this emerging field, a pattern distinctive from many educational research domains where journal articles typically predominate.

Table 2: Journals/proceedings with the most significant impact

Rank	Journal/ Proceeding	Scopus H_index	Total citations	Number of publications	Year of first publication
1	Education and Information Technologies	5	109	8	2018
2	ACM International Conference Proceeding Series	4	58	10	2015
3	IEEE Global Engineering Education Conference	4	112	5	2018
4	International Journal of Child-Computer Interaction	4	208	6	2019
5	Computers and Education	3	172	3	2019
6	16th International Conference on Cognition and Exploratory Learning in the Digital Age	2	8	2	2019
7	AIP Conference Proceedings	2	9	2	2019
8	British Journal of Educational Technology	2	35	2	2022
9	Conference On Human Factors in Computing Systems	2	28	3	2016
10	Early Childhood Education Journal	2	27	2	2022

4.3 Thematic Structure and Conceptual Evolution

Keyword co-occurrence analysis identified five distinct thematic clusters representing specialised research domains within CT-ECE (Figure 4). Each cluster was examined for internal coherence, external boundaries, and conceptual focus:

Cluster 1 (Red): Robotics and Cognitive Development

This cluster emphasises technology-mediated approaches to CT integration, focusing specifically on educational robotics as tools for cognitive development. Key terms within this cluster include “educational robots,” “robotics,” “young children,” “problem-solving,” and “cognitive development.” This research stream explores how tangible interaction with programmable devices facilitates specific cognitive processes, particularly focusing on problem decomposition and sequential reasoning development in children aged 4-7 years.

Cluster 2 (Green): Technology Integration in Preschool Education

This cluster addresses pedagogical and curricular aspects of technology integration within preschool contexts. Central keywords include “preschool,” “preschool education,” “kindergarten,” “technology,” “robot programming,” and “sequencing ability.” Research within this cluster emphasises practical implementation concerns, including classroom management strategies, teacher professional development needs, and curricular alignment considerations specific to formalised preschool settings.

Cluster 3 (Blue): Educational Robotics for Mathematical Development

This research stream explores the intersection of educational robotics, algorithmic thinking, and mathematical education. Keywords include “educational robotics,” “algorithmic thinking,” “mathematics education,” and “digital literacy.” Publications within this cluster examine how computational activities create concrete pathways for abstract mathematical concept development, particularly focusing on spatial reasoning, pattern recognition, and foundational numeracy.

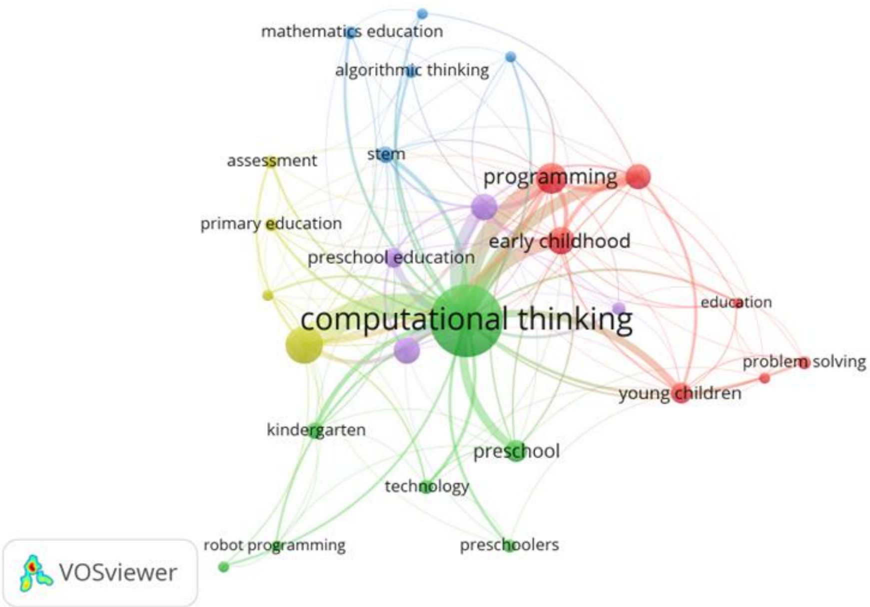
Cluster 4 (Yellow): Assessment of Unplugged Computational Thinking

This cluster focuses on evaluation methodologies for computational thinking, particularly emphasising unplugged (non-screen) approaches. Key terms include “early childhood education,” “assessment,” “preschoolers,” and “unplugged.” This research domain addresses the methodological challenges of measuring abstract computational competencies in developmentally appropriate ways without technological mediation, with particular emphasis on observational protocols and performance-based assessments.

Cluster 5 (Purple): Coding Tools for STEM Integration

This cluster examines specific programming environments and their integration with broader STEM education initiatives. Keywords include “coding,” “STEM,” “primary education,” and “ScratchJr.” Research in this domain investigates how introductory programming experiences through platforms like ScratchJr can serve as vehicles for integrated STEM learning, emphasising the transfer of computational concepts to broader scientific and mathematical domains

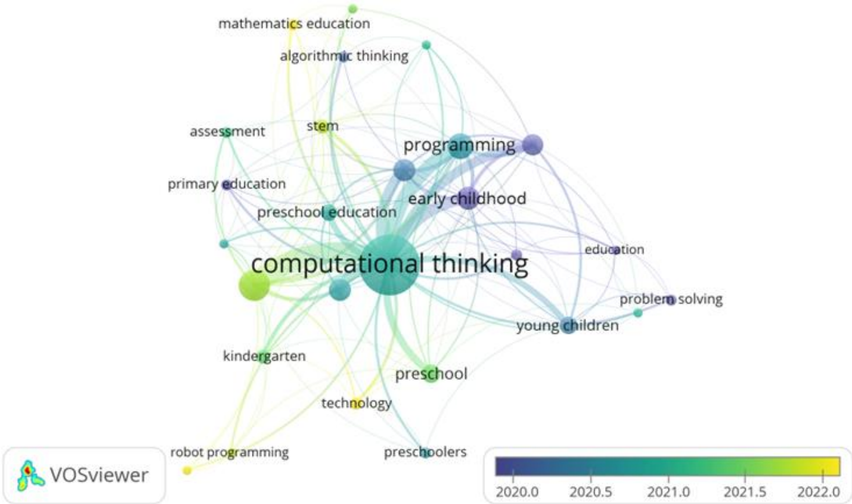
Figure 4: Map of the 27 author’s keywords appearing at least four times



Network visualisation reveals substantial interconnection between clusters, with particularly strong linkages between Clusters 1 (Robotics) and 2 (Preschool Integration), suggesting conceptual overlaps and methodological similarities. The relatively peripheral position of Cluster 5 (Coding/STEM) indicates a somewhat distinct research community with fewer connections to the core robotics-focused literature.

Temporal analysis of keyword distribution (Figure 4) reveals evolutionary patterns in research priorities. The visualisation demonstrates a chronological progression from foundational conceptual work (darker blue) toward more recent applied research directions (yellow). Research on “STEM,” “mathematics education,” “robot programming,” and “technology” clusters predominantly in the 2020-2022 period, indicating a recent shift toward integrated disciplinary approaches and practical technological implementations.

Figure 5: Temporal distribution map of 27 authors’ keywords appearing at least four times



This temporal pattern suggests a maturation sequence, where initial research established conceptual frameworks and proof-of-concept studies, followed by more recent work addressing practical implementation challenges, assessment methodologies, and curricular integration strategies. Notably, research on “assessment” emerged prominently after 2020, indicating growing attention to evaluation frameworks as the field progressed from theoretical conceptualisation to practical implementation and outcome measurement.

5. Discussion

This bibliometric analysis offers a detailed mapping of CT research in ECE, highlighting key trends in productivity, impact, collaboration, and thematic development from 2010 to 2023. The findings underscore the substantial growth of this interdisciplinary field, while also identifying structural challenges that may hinder its equitable progress across diverse educational contexts.

5.1 Geographic Disparities in Research Production and Impact

The bibliometric evidence reveals a substantial geographic concentration of research production and scholarly influence, a pattern documented in broader educational technology research where the isolation of developing regions is a persistent challenge. This issue is particularly acute in Southeast Asia. As Duong et al. (2024) pointed out, although research interest in early childhood STEM education has surged, the presence of ASEAN scholars remains modest in the global landscape, and ineffective collaboration hinders the region's collective influence. Our findings in the specific sub-field of computational thinking strongly corroborate this trend. The data shows a significant concentration of research in high-resource nations like the USA and Greece, coupled with a low overall multiple-country publication ratio of 13.2%, which underscores the concerning fragmentation along geographic lines. This structural imbalance means the global discourse on CT in early childhood is largely being shaped without significant input from the ASEAN region, creating a risk that pedagogical models are developed based on high-resource contexts while overlooking the unique needs and scalable solutions—such as the 'unplugged' equity pathway—critical for sustainable implementation within Southeast Asia.

5.2 Thematic Evolution and Conceptual Development

The thematic evolution of CT research in ECE is not a random progression but follows a logical trajectory, reflecting the maturation of a scientific discipline. The five distinct research clusters identified in our analysis mark the key phases of this story: a journey from foundational, tool-based explorations toward more integrated, equitable, and context-aware pedagogical models.

The field's initial phase was dominated by a tool-centric approach, with robotics-focused research (Clusters 1 and 3) serving as the primary vehicle for introducing CT concepts. This emphasis on tangible programming environments was developmentally appropriate, aligning with children's need for concrete operational thinking (Piaget, 1970) and reflecting a constructionist "learning-by-making" ethos. The exceptional influence of robotics-centred publications from pioneers like Bers (2018) and Papadakis (2020) established this paradigm. However, while developmentally sound, this reliance on expensive hardware created an inherent equity challenge due to the significant resource requirements, setting the stage for a necessary evolution.

A significant pivot in research priorities occurred post-2020, driven by a growing focus on equity and practical implementation. The emergence of "unplugged" research (Cluster 4), which utilises minimal technological infrastructure, represents a direct and innovative response to the access and cost barriers of the robotics era. This shift, accelerated by the global educational disruptions of the COVID-19 pandemic and the corresponding interest in accessible, resilient educational technologies (Rapanta et al., 2020), offered more equitable pathways for CT competency development. The concurrent rise of "assessment" as a prominent keyword signifies the field's maturation from proof-of-concept studies toward developing rigorous, standardised methods for measuring learning outcomes.

The most recent phase in this evolution points toward an emerging frontier of transdisciplinary integration. The increasing prominence of research connecting CT with mathematics education and broader STEM frameworks (Clusters 3 and 5) suggests a growing recognition of CT as a fundamental literacy rather than an isolated skill domain. This aligns with contemporary curricular approaches that emphasise connected learning experiences (Bers et al., 2014). However, the relative peripherality of this research in the network visualisation indicates that STEM integration remains an emerging—rather than fully established—research direction, signalling a key area for future inquiry as the field continues to evolve.

5.3 Methodological Priorities and Research Gaps

Our analysis reveals significant methodological concentrations and corresponding gaps within the literature. The predominance of conference proceedings among high-impact publication venues (3 of the top 5 sources) reflects the field's technological orientation and rapid development pace, but it potentially limits the methodological depth and theoretical elaboration typically associated with journal publications. This reliance on conference dissemination mirrors patterns in other emerging educational technology domains, where rapid knowledge circulation often takes precedence over extended empirical validation (Donthu et al., 2021).

Assessment methodologies constitute a critical research domain requiring further development. While Zapata-Caceres et al.'s (2020) computational thinking test demonstrates significant within-field influence (LC/GC ratio = 15%), the overall corpus reveals limited attention to psychometrically validated assessment instruments. This gap limits the capacity for comparative evaluation across interventions and educational contexts, constraining evidence-based decision-making by practitioners and policymakers.
Longitudinal research remains notably underrepresented, with most studies examining short-term outcomes rather than developmental trajectories. This temporal limitation, common in emerging fields, constrains understanding of how early computational experiences influence subsequent academic development and cognitive growth. Future research would benefit from extended time horizons that could capture developmental continuity between early childhood CT experiences and later educational outcomes.

5.4 Implications for Policy and Practice for ASEAN countries

To directly address the challenges of geographic disparity and the relative absence of ASEAN nations highlighted in Section 5.1, the findings offer the following strategic implications. The strategic value of CT in ECE aligned with the national education policies of ASEAN member states. For instance, in Vietnam, the government's Directive 16/CT-TTg emphasises the need to reform educational methods to meet the demands of the Fourth Industrial Revolution, a goal that requires scalable solutions beyond resource-intensive labs (Prime Minister, 2017). Similarly, Thailand's ambitious 'Coding for All' policy (The Government Public Relations Department, 2022), which aims to make coding a basic literacy, can be significantly accelerated by using unplugged activities to build foundational concepts across all schools, regardless of their technological infrastructure. This approach also directly supports the vision of the Malaysia Digital Economy Blueprint (MyDIGITAL) to cultivate a digitally-competent talent pool from an early age (Economic Planning Unit, Prime Minister's Department, 2021) and aligns with the core principles of Singapore's National AI Strategy (Smart Nation and Digital Government Office, 2019). This broad alignment across diverse national strategies underscores a shared regional recognition of the need for foundational digital skills, for which the proposed models offer a universally applicable starting point.

The emergence of "unplugged" research, identified as a distinct thematic cluster post-2020, is not merely a methodological curiosity but a vital strategic response to the global challenge of educational equity. This approach holds exceptional promise for the diverse socioeconomic landscape of ASEAN member states, offering a viable pathway to democratise CT. It directly addresses the economic and infrastructural barriers, such as the high cost of robotics platforms, that pose significant challenges to implementing technology-based approaches in the region.

This "equity pathway" is particularly salient for ASEAN for several reasons. First, it bypasses the significant cost barrier of expensive robotics kits or digital devices, a major constraint for education systems with limited budgets. Second, unplugged methods promote inclusivity by ensuring that children in both rural and urban areas, regardless of their access to reliable electricity or the internet, have the opportunity to develop foundational skills. Most importantly, unplugged activities are highly flexible for cultural adaptation and localisation. For instance, algorithmic thinking can be taught by sequencing local folktales in Vietnam or the Philippines, while pattern recognition can be explored using traditional batik patterns from Indonesia or weaving designs from Laos. This cultural integration not only makes learning more relevant and engaging but also aligns with the need for culturally adaptable resources.

From a practical standpoint, implementing unplugged methods offers a feasible roadmap for building teacher capacity, as it lowers the barrier for educators who may have "technology anxiety," focusing them on the pedagogy of CT rather than on complex hardware. Furthermore, this should not be viewed as an all-or-nothing solution but as a foundational step within a flexible "hybrid" model. In this model, students can first master core concepts through tangible, low-cost activities before applying them in digital environments like ScratchJr, as and when resources become available. This hybrid model offers a practical roadmap for ASEAN educators, allowing them to build foundational skills universally through unplugged methods while strategically introducing digital tools like ScratchJr or KIBO in schools with better infrastructure, thereby bridging the digital divide. Therefore, we strongly recommend that education policymakers in ASEAN prioritise the development and dissemination of open-source, culturally adaptable "unplugged" CT resource kits and teacher training modules. Investing in these low-cost, high-impact resources is a strategic imperative to build foundational digital literacy equitably across the region and to ensure that all children are prepared for an increasingly digital future.

The persistent finding that educators often conflate CT with coding proficiency underscores a critical need to reorient teacher training. Professional development programmes should shift focus from mastering specific technological tools to developing deep pedagogical content knowledge of CT itself. Training should equip educators with the skills to teach computational concepts through accessible, unplugged methods first. This approach helps mitigate "technology anxiety" and empowers teachers to focus on the cognitive processes underlying CT, making them more adaptable to various teaching tools and contexts in the future. Investment in such targeted teacher preparation is a critical lever for ensuring effective and developmentally appropriate CT integration at scale.

5.5 Limitations and Future Research Directions

While comprehensive, this bibliometric analysis has inherent limitations. The exclusive use of Scopus may underrepresent contributions from regions with limited indexing coverage, particularly Africa and parts of Latin America. Future studies should incorporate regional databases to capture locally published research not indexed globally. The focus on quantitative publication metrics, though methodologically necessary, does not assess research quality or methodological rigor. Future reviews should complement bibliometric approaches with qualitative content analysis to evaluate methodological soundness and theoretical depth. Citation metrics for recent publications (2021-2023) should be interpreted cautiously due to limited citation accumulation. Longitudinal citation tracking would provide a more accurate assessment of emerging influential contributions. Future research should prioritise three critical directions: (1) longitudinal studies examining developmental trajectories from early CT experiences through subsequent educational stages; (2) comparative analyses of resource-intensive versus resource-efficient implementation approaches across diverse socioeconomic contexts; and (3) expanded investigations into unplugged methodologies with potential for broad implementation in resource-constrained settings.

6. Conclusion

This bibliometric analysis delineates the evolving intellectual landscape of computational thinking research in early childhood education, identifying significant growth in productivity, citation impact patterns, collaboration networks, and thematic priorities. The field has demonstrated remarkable expansion, with a 129% growth rate between 2019-2023, reflecting increased global engagement with early computational development.

Five distinct research clusters were identified, highlighting specialised domains focused on robotics integration, preschool implementation, mathematics connections, assessment approaches, and STEM integration. Temporal analysis revealed shifts from foundational conceptualisation toward practical implementation considerations, with post-2020 research particularly emphasising accessible methodologies and cross-disciplinary integration.

However, significant geographic disparities persist, with research production concentrated in high-income nations, limited international collaboration, and the potential marginalisation of non-Western approaches. These structural inequities risk reinforcing existing educational disparities unless systematically addressed through targeted policy interventions and strategic research investments.

To democratise computational thinking as a universal competency, rather than a privileged resource, three actionable pathways emerge: (1) investing in targeted teacher preparation programmes that emphasise developmentally appropriate, culturally responsive pedagogies; (2) developing and disseminating open-source, adaptable resources that function effectively across diverse resource environments; and (3) fostering intentional cross-border research partnerships to accelerate knowledge exchange and methodological innovation. By synthesising productivity metrics, citation patterns, and thematic evolution, this analysis offers a strategic roadmap for researchers, policymakers, and practitioners seeking to advance computational thinking as an accessible competency for all young learners. By embracing these equity-focused approaches, particularly the promotion of culturally-adapted unplugged and hybrid models, nations within Southeast Asia and beyond can ensure that early computational experiences serve as a foundation for inclusive participation in increasingly digital societies.

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