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Trends and Impacts of Artificial Intelligence Application in the Development of Computational Thinking Skills

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Abstract. This study aims to provide a descriptive and bibliometric analysis of the trend of artificial intelligence (AI) application in the development of computational thinking (CT) skills in publications from 2007 to 2024. A total of 191 articles were obtained from Scopus database with certain keywords, and analyzed using Biblioshiny and VOSviewer. The results show that publications fluctuated in 2007–2014, then increased sharply since 2019, with a compound annual growth rate (CAGR) of 22.8% in the period 2019–2024. Early publications received the highest number of citations, such as in 2007 (18 citations), while recent studies show a more even distribution of citations, reflecting a shift from basic to applied research. This analysis highlights the important role of AI in enhancing CT development through learning strategies, educational technology, and cross-disciplines. The impact of AI implementation is seen in various aspects of education, such as learning strategies, educational media, and the relationship between CT and other skills. These findings demonstrate the importance of leveraging AI to support the development of CT in education, which can improve the quality of learning and enrich educational experiences globally.

Keywords: Artificial Intelligence, Computational Thinking, Education, Bibliometric analysis, Biblioshiny Package, R Programming, Thematic analysis.

1. Introduction

Computational Thinking (CT) is one of the problem-solving techniques that is a popular topic in education (Chen *et al.*, 2023; Ogegbo & Ramnarain, 2021). CT is a framework for analyzing problems from a computational perspective (Piatti *et al.*, 2022). CT is recognized as a fundamental concept in computer science in the form of a set of cognitive skills that allow someone to identify patterns, solve complex problems and divide them into small steps, organize and create a series of systematic steps to provide solutions, and build data representations through simulations (Azizah *et al.*, 2022, Rodríguez del Rey *et al.*, 2021; Abar *et al.*, 2021). CT is an important skill that includes systematic problem solving, which is needed to work in the digital world. In the era of industry 4.0, the trend of thinking in the world of education is also required to be able to adapt to these challenges, for this reason the concept of CT thinking is present to answer this challenge (Udvaros *et al.*, 2023).

However, currently, students' CT abilities are known to be still low (Esteve-Mon *et al.*, 2020; Harangus & Katai, 2020; Rahman *et al.*, 2023; Al Husaeni *et al.*, 2023). There is a gap in the educational environment where CT abilities are still relatively weak, even when countries around the world are launching reforms to incorporate computational thinking integration into education (Jalinus *et al.*, 2023). Of course, this is in contrast to the need for CT abilities that students must have. CT is an ability that has been considered by the OECD and is included in the PISA 2021 identification questions. CT is one of the important abilities that students must have to overcome the challenges of the 21st century. CT abilities can support various aspects of 21st century competencies such as critical thinking, creativity, and problem solving (Christensen, 2023). CT skills are very important for students to have to help them solve complex problems in a structured manner, by mastering CT skills, students will be better prepared to survive and compete in the future era (Angraini & Muhammad, 2023). Therefore, considering its importance, CT is now considered a skill that must be developed early on in elementary education (Wang *et al.*, 2024; Alonso-García *et al.*, 2024).

In the last decade, theoretical and empirical studies on CT have experienced rapid development. There have been many discussions on the definition, conceptual framework, and various models of CT. In addition, there have been ongoing efforts to design and implement methods to develop and evaluate CT skills. Several studies aim to examine the general definition of CT and how CT is applied, along with effective strategies to improve CT education (Li *et al.*, 2024a; Kong *et al.*, 2024; Küçükaydın, 2024). Previous studies on the comparison of CT skills with other competencies such as critical thinking, creative thinking, and other problem-solving skills (Suherman & Vidákovich, 2024; Chen & Chung, 2024; Yang, 2024; Aytekin, & Topçu, 2024). We also found several previous studies regarding the development of CT instruments (Na *et al.*, 2024; Li *et al.*, 2024b; Rahman *et al.*, 2023; Zhang *et al.*, 2024a; Metin *et al.*, 2024a). There are several previous studies that examine affective factors, both intrinsic and extrinsic influences such as motivation, self-efficacy, regulated learning, and habits that influence CT (Suherman & Vidákovich, 2024; Chen & Huang, 2024; Kong & Wang, 2024; Yurdakök, E. A., & Kalelioğlu, 2024; Pellas, 2024; Guo *et al.*, 2024; Wu *et al.*, 2024) and the integration of learning aids or media used to improve CT (Louka & Papadakis, 2024; Zurnacı & Turan, 2024; Zhang *et al.*, 2024b; Lee *et al.*, 2024; Pan *et al.*, 2024; Metin *et al.*, 2024b).

In addition, we found that there are quite a few previous studies that have conducted theoretical studies on the effects of CT, teacher competence, and other tools that can improve CT skills (Wang & Xie, 2024; Montuori *et al.*, 2023; Mills *et al.*, 2024; Hu, 2024; Wang *et al.*, 2024; Saad & Zainudin, 2024; Irawan *et al.*, 2024). Theoretical studies on CT have also developed according to the development of technology that occurs. In the era of the industrial revolution 4.0, technological developments have increased rapidly. Previous research on CT combined with automation technologies such as the Internet of Things (IoT), artificial intelligence (AI), and big data has also begun to be of interest. There is previous research that connects AI and CT (Muthmainnah *et al.*, 2024; Weng *et al.*, 2024; Moreno-León *et al.*, 2024).

As an effort to correlate the findings of the preliminary study conducted and guide future research efforts, it is necessary to conduct research on a comprehensive review of recent CT studies. This is done because studies of CT research trends analysis of this kind are still limited (Chen *et al.*, 2023), especially those that combine several research trend analysis tools such as bibliometric analysis. Basically, there have been several previous studies that analyze CT research trends with bibliometric analysis. We found 29 documents in the Scopus Database (https://www.scopus.com/) that analyzed previous research trends on CT with bibliometric analysis, including research on trends in bibliometric analysis of CT on mathematical problem-solving (Irawan & Herman, 2023; Susanti, 2024; Irawan *et al.*, 2024), trends in CT of elementary school students in the past ten years in China (Chen *et al.*, 2024), trends in core content of research on improving computational thinking (Chen & Nguyen, 2024), research trends in K-5 CT education (Adanır *et al.*, 2024), and trends in bibliometric analysis of computational thinking research in physics (Irwandani *et al.*, 2023).

Although several bibliometric analyses have been conducted on general CT topics, there is a lack of comprehensive bibliometric studies that specifically examine the relationship between AI and CT in education. Existing studies rarely explore how AI technologies (e.g., machine learning, NLP) are thematically and methodologically embedded in CT research. Furthermore, impact metrics such as publication growth rate, citation trajectories, and thematic evolutions related to AI-CT integration are under-explored. Therefore, this study addresses this gap by offering a detailed bibliometric and thematic analysis of AI-based CT research trends from 2007 to 2024, using the combined tools Biblioshiny and VOSviewer for a more comprehensive mapping.

However, based on these studies, there has been no research that analyzes the trends and impacts of AI implementation in developing CT in education. Therefore, this study was conducted with the aim of providing a descriptive and bibliometric analysis of research trends and the impacts of AI implementation in developing CT capabilities. We conducted an analysis of Scopus-indexed CT research with a publication range from 2007 to 2024 with a focus on identifying the current status, research developments, themes and main focuses of research on CT, affiliations and contributing institutions, and leading authors in CT research in that period. The novelty of this study is (i) analysis of trends and the impact of AI implementation in developing CT in education, (ii) analysis of CT trends by combining two bibliometric analysis tools, namely VOSviewer and Biblioshiny Package R Programming, and (iii) use of thematic analysis. This study is expected to provide an overview of further research in studying AI for developing CT Skills.

2. Theoretical Framework

2.1. *Definition of CT*

CT is a set of cognitive skills that enable educators to identify patterns, solve complex problems by breaking them down into smaller parts, organize and design systematic steps to provide solutions, and build data representations through simulations (Azizah *et al.*, 2022, Rodríguez del Rey *et al.*, 2021; Abar *et al.*, 2021). In addition, CT has also been integrated into the curriculum with policy documents including ISTE Computational Thinking Competencies 2024 (https://iste.org/standards/computational-thinking-competencies), The Decoding Approach to CT Integration – MIT Education Arcade (2024), and 2024 National Educational Technology Plan (NETP) – U.S. Department of Education. The Programme for International Student Assessment (PISA) 2021 defines CT as the ability to support abstraction, algorithmic thinking, decomposition, and generalization. CT involves problem-solving methods, system design, and understanding of behavior, abstraction, and decomposition in solving certain problems (Wang *et al.*, 2023).

In the latest literature of 2023–2025, CT is understood more broadly and multidimensionally. Gasaymeh and AlMohtadi (2024) define CT as a combination of algorithmic, metacognitive, and adaptive abilities in solving problems, while Dehbozorgi *et al.* (2024) emphasize the role of CT in social engineering and project-based curriculum. Snake-Beings *et al.* (2023) propose a sociomaterial approach, "Computational Thing-Kin" that extends CT to non-human entities. Hurt *et al.* (2023) position CT as an iterative scientific modelling competence. A holistic perspective emerges from Palop *et al.* (2025) which includes affective, ethical, and cultural dimensions. Chesterman (2023) states that CT is a form of cognitive resilience in dealing with digital information. Lin and Wong (2024) highlighted gender differences in CT as an impact of structural bias. Bilbao *et al.* (2024) showed the role of CT in connecting symbolic and algorithmic mathematics, while Meza *et al.* (2024) emphasized the importance of measuring CT through Bebras-based assessments. This synthesis suggests that CT is now understood not only as a technical skill but also as a social, affective, and reflective competency that continues to evolve with technological advances and the needs of 21st-century education.

2.2. *Component of CT*

Mueller *et al.* (2017) formulated four components in CT, namely algorithm, decomposition, pattern recognition, and abstraction. Algorithm is the ability to arrange steps in a structured, critical, and logical manner. Decomposition is the skill in analyzing the whole task by dividing it into small, detailed tasks. Pattern recognition, which is the ability to recognize the differences and similarities of problem patterns that have been found, with the hope of helping to make a prediction. Meanwhile, abstraction is the ability to select relevant information to draw conclusions and use that information in solving the problems faced.

2.3. *Review of Studies Concerning CT*

The study is a growing topic for CT research that is shown as an effort by previous researchers. Alonso-García *et al.* (2024) explored the application and impact of educational robotics on computational thinking in early childhood education. The study found that educational robotics emerged as a powerful tool for comprehensive skill development, significantly impacting mathematics learning and language acquisition. This study suggests the need for additional research to support the findings and offers strong evidence supporting the efficacy of robotics in enhancing computational thinking in early childhood education. The study underscores the importance of structured intervention procedures and clear assessment methods to effectively evaluate the impact of robotics activities on computational thinking (Alonso-García *et al.*, 2024).

Yeni *et al.* (2024) conducted a systematic review to analyze in which K-12 subjects CT is integrated, learning objectives, level of CT integration, teaching strategies, technologies and tools used, assessment strategies, research design, and educational stage of participants. The study conducted by Yeni *et al.* (2024) used SLR and Meta-Analysis with the PRISMA 2020 workflow, which consists of the Identification, Screening, and Inclusion stages. The study found that more than two-thirds of CT integration studies focused mostly on science and mathematics; the majority of studies implemented CT at a substitution level rather than achieving transformational impact; active learning was a commonly mentioned teaching strategy, with block-based language and physical devices being the tools frequently used; and in terms of assessment, the main emphasis was on evaluating attitudes toward technology or learning contexts, rather than developing valid and reliable assessment instruments (Yeni *et al.*, 2024).

In addition, Torres-Torres *et al.* (2024) analyzed Didactic Strategies (DS) and examined whether they incorporate the so-called "minimum actions" (MA) proposed in this article as a strategy to integrate girls into CT. Their study found that girls do not lack competence compared to boys in the CT learning process. They only sometimes approach the coding process differently and/or have different perspectives on coding that should be learned, nurtured, and encouraged.

Triantafyllou *et al.* (2024) synthesize knowledge about gamification and computational thinking to improve education for the benefit of students. The research conducted by Triantafyllou *et al.* (2024) states that the learning theory presented is the basis for how students acquire knowledge, and relevant studies in the field of gamification and computational thinking show some initial positive results from some early research efforts that require further examination. The use of appropriate game mechanics and elements, such as well-designed STEM applications, can attract students' interest in learning through games and motivate them to develop computational thinking and problem-solving skills.

2.4. *Application of Artificial Intelligence in Education*

The development of AI technology, especially machine learning (ML), has made a major contribution to the transformation of education, especially in terms of learning personalization, automated assessment, and the development of high-level thinking skills such as CT. Several recent studies in 2025 show that the application of ML is not only used in the technical realm but has begun to touch on the cognitive, affective, and pedagogical aspects of the learning process.

Sun (2025) developed a personalized learning path based on the SSA-LSTM model for English language learners, showing how ML can adjust learning content based on individual profiles and progress. Li *et al.* (2025) used AI-based eye-tracking technology in mobile devices to build a predictive model of Alzheimer's disease, opening up opportunities for the development of cognition-based assessments in education. Meanwhile, Chu and Kurup (2025) conveyed the urgency of utilizing ML in geriatric anesthesia education, expanding the scope of AI application to the training of medical professionals.

Another study by Kim *et al.* (2025) designed an educational dataset based on constructivist principles to improve AI literacy, demonstrating an approach that integrates learning theory with technology. Pang *et al.* (2025) applied multi-machine learning to assess the quality of martial arts movements, which has the potential to be used in AI-based physical education. In the context of elementary education, Jafarian and Kramer (2025) showed that AI-assisted audio learning can improve students' motivation and engagement in reading, which contributes to academic achievement.

However, although the application of ML in education has been widely developed, there are still methodological challenges in building a consistent integration framework between technology and learning theory. Studies such as those conducted by Ng *et al.* (2025) and Kohnke & Moorhouse (2025) show that although GenAI (Generative AI) brings new opportunities in emotional and creative teaching, its integration requires appropriate school strategies and teacher adaptation. Therefore, the development of a more solid conceptual framework is needed to bridge the potential of AI technology with deep pedagogical principles.

2.5. *AI integration in CT skills development*

The integration of AI in developing CT skills has become an important focus in educational research. Although many studies have explored the relationship between AI and CT (Bayaga, 2024; Tariq *et al.*, 2024, Wang and Wang, 2024; Weng *et al.*, 2024; Hooshyar & Druzdzel, 2024; Ameen *et al.*, 2024; Kaleem *et al.*, 2024), there is still a lack of critical analysis of how AI, especially technologies such as machine learning, systematically supports CT development in various educational contexts. The results of the thematic analysis in this study indicate that keywords such as computational thinking, computer programming, primary schools, and programming profession have experienced significant growth in AI-CT studies. However, the AI technologies used, such as machine learning, are still classified as general basic themes, without in-depth conceptual development.

The use of AI in the context of CT is generally found in several application fields, such as computing education, assessment, computer science education, and curriculum design. The learning materials used include image recognition technology, image enhancement, and learning algorithms. The dominant learning strategies include project-based learning, hands-on activities, and supervised learning, which are implemented through media such as applications, computer games, MOOCs, and smart devices. Although these strategies have shown practical effectiveness, they are generally not based on a theoretical framework that explains in depth the cognitive and affective mechanisms in CT development.

Furthermore, the thematic evolution analysis shows a shift in research focus from general technological aspects such as information technology and computer science (2007–2022) to specific applications in school students, programming, and higher education (2023–2024). In addition, there is increasing attention to the role of teachers and the relationship between CT and other abilities such as self-efficacy and creativity. These results indicate an urgent need to develop an AI-CT integration framework that is not only technical in nature but also considers the learning context, the role of educators, and student competencies as part of a complex digital education ecosystem. Thus, this study not only provides a literature mapping but also opens up space for further studies to build an AI-CT integrative framework that is based on educational theory, technological potential, and the needs of 21st-century skill development.

3. Research Questions and Objectives

As research on CT advances, it is important to map the status of the research domain in order to consolidate existing findings and improve our understanding of the application of AI in CT development. Although existing review studies have provided many useful insights, the increasing number of literatures in this field suggests the need for a more comprehensive and up-to-date review study to identify important research topics and themes and outline future trends and directions of research on the application of AI in CT development in education. Therefore, this study explores the trends and impacts of AI application in CT development published between 2007 and 2024 through a bibliometric analysis that can reveal some characteristics of the research. This study attempts to answer the following Research Questions (RQ).

RQ1: What is the general status of research trends on the application of AI in CT development in the annual distribution of publications and citations of research on the application of AI in CT development?

RQ2: How are the trends and impacts of AI application in the development of CT in the field of education developing from the research theme development path?

RQ3: What are the influential sources of journals, researchers, institutions, countries/regions, and papers in research on the application of AI in developing CT in education?

4. Method

Research trends are collective actions of a group of researchers, each of whom begins to pay great attention to a particular scientific topic (Chen *et al.*, 2023). This review study adopts a bibliometric analysis approach that allows identifying trends in studies of AI application in CT development. Bibliometric analysis uses mathematical and statistical techniques to quantitatively analyze the bibliographic features of a body of literature. It has been reported as "an effective and scientific way to discover and visualize patterns in the knowledge accumulated in a body of literature, uncover trends in a research field and analyze the underlying research structure, its evolution, and its dynamic aspects (Chen *et al.*, 2023). It is important to acknowledge, however, that bibliometric analysis offers a macro-level overview of the research landscape, rather than an in-depth examination of the content of individual studies (Gölgeci *et al.*, 2022). It emphasizes publication volume, citation counts, and network relationships, but does not evaluate the theoretical rigor, methodological quality, or pedagogical depth of the works analyzed. As a result, while this approach effectively identifies dominant trends and thematic clusters, it may overlook nuanced insights embedded in qualitative findings. This study emphasizes thematic analysis to see the trends and impacts of AI application in CT development in the field of Education.

4.1. *Article Selection Process and Timeframe Justification*

Determination of the search protocol according to Chen *et al.* (2023) can be done by determining several categories, namely search keywords, article access methods (open source, etc.), publication period, document type, and language used in the article. Scopus was chosen as the data source. Scopus is a quality database of published research that includes international journals. Scopus was created in 2004 by Elsevier and is a source of interdisciplinary reports. It is one of the largest "peer-reviewed" databases in the world, covering more than 24,000 active academic journal titles in various fields of high research interest, such as life sciences, social sciences, and health (Faruk *et al.*, 2021; Kamaruzzaman *et al.*, 2021).

In addition, Scopus covers more than 230,000 book titles and more than 10 million conference papers. Compared to other academic research databases, such as Google Scholar or Web of Science, Scopus has the lowest level of "inconsistency" in terms of content verification and quality (Ragazou *et al.*, 2022). Although Google Scholar and Web of Science provide accurate information, both often contain duplicate entries, even citations that appear more than twice (Ragazou *et al.*, 2022). This causes the total number of reports to cover the same items, resulting in less accurate data. In addition, Scopus offers the use of online tools for bibliometric analysis of publications, including calculating bibliometric indicators such as the h-index as well as providing statistical analysis tools, such as publication frequency charts over time (Ragazou *et al.*, 2022).

However, we recognize the potential for selection bias arising from the use of a single database, for example, limited access to local literature, non-English language publications, and emerging open access platforms that may not yet be indexed. Therefore, the findings of this study focus on presenting global trends based on reputable journals indexed by Scopus.

The selection of the 2007–2024 timeframe was based on an initial analysis of literature trends that showed that 2007 was the starting point for the emergence of early articles on AI integration in CT, while 2024 was used as a boundary because it was the last publication year available at the time of the search (November 8, 2024). This range allows for a longitudinal mapping of thematic evolution, including the identification of significant growth phases especially since 2019, which was marked by a surge in publications and a diversification of topics related to AI-CT integration.

Fig. 1 shows the selection process. The literature search yielded 238 documents using the keywords "Computational Thinking", "Artificial Intelligence", and "Education". These keywords were selected to ensure relevance to the intersection of CT and AI in the educational context. In the screening phase, we applied specific inclusion criteria to refine the dataset: (1) documents had to be final versions to avoid duplication with preprints (n = 236); (2) only peer-reviewed articles and conference papers were included to ensure academic quality and credibility (n = 196); and (3) only English-language publications were selected to ensure consistency in keyword and abstract analysis and due to the dominance of English in indexed academic databases. As a result, 191 full-text journal articles that met all criteria were included in the final dataset. These criteria were chosen to maintain the quality, comparability, and analytical relevance of the bibliometric results. Summary articles, editorials, and incomplete metadata entries were excluded to maintain the robustness of co-occurrence and citation analyses. The main characteristics of the selected documents are summarized in Table 1.

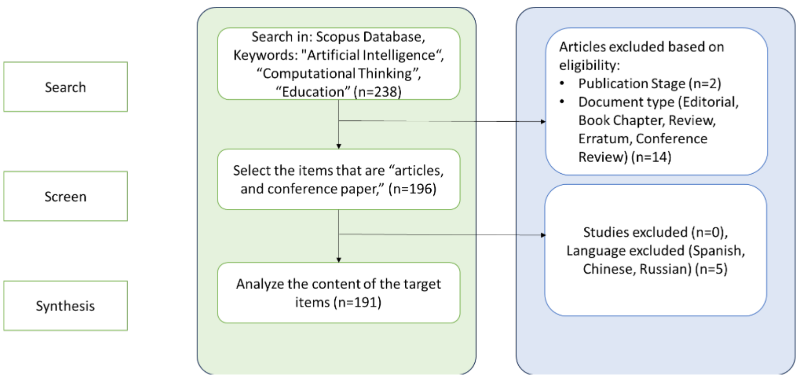

Fig. 1. Article selection process and methodological framework.

Table 1
Main information of search results

Description	Results
Main Information About data	
Timespan	2007:2024
Sources (Journals, Books, etc)	115
Documents	191,00
Annual Growth Rate %	25.1
Document Average Age	2.77
Average citations per doc	11.12
References	5816
Document Contents	
Keywords Plus (ID)	952
Author's Keywords (DE)	558
Authors	
Authors	590
Authors of single-authored docs	20
Authors Collaboration	
Single-authored docs	20,00
Co-Authors per Doc	3.64
International co-authorships %	19.37
Document Types	
article	76
conference paper	115

4.2. *Data Cleaning, Analysis, and Validation Procedures*

Data from the bibliometric search were extracted in Excel, Research Information Systems (.RIS) and Comma-Separated Values (.CSV) files, integrating information related to article title, publication date, author key details (name and affiliation), author keywords, abstract, and number of citations. To maintain data validity and cleanliness, the following steps were performed: document duplication free based on DOI and title-author combination; documents missing important metadata (e.g., empty keywords or abstracts) were keyword matching concatenation (e.g., "comp.thinking" concatenated to "computational thinking") was performed semi-manually to avoid distortion of the co-occurrence map; and Article verification was performed by reviewing titles and abstracts to ensure topic relevance.

We analyzed and visualized the data using the Biblioshiny package in RStudio and VOSviewer software. Both tools provide diagrams and maps such as thematic maps, country collaboration maps and network visualizations, which illustrate the research situation and dynamics of the research model. The use of Biblioshiny allows the exploration of bibliometric indicators such as h-index, publication frequency, as well as mapping of keywords and author collaborations. Meanwhile, VOSviewer is used to generate network visualizations such as co-citation maps, keyword clusters, and theme evolution. The combination of the two provides complementary perspectives: Biblioshiny excels in descriptive and thematic statistical analysis, while VOSviewer provides spatial visualization of the relationships between research entities. Co-occurrence maps are used to map frequently occurring keywords and assess the centrality of topics in the knowledge network. Co-citation analysis and cluster mapping are performed to identify important contributions from articles, institutions, and countries. Visual findings of annual publication and citation trends are reported in trend graphs, while thematic evolution analysis from 2007–2024 helps to reveal changes in research focus over the period.

To ensure the validity and reliability of the analysis conducted using VOSviewer and Biblioshiny, we followed the best practices of bibliometric research standards (Nandiyanto and Al Husaeni, 2022; Al Husaeni *et al.*, 2023; Al Husaeni & Nandiyanto, 2022; Kirby, 2023; Bukar *et al.*, 2023; Lim *et al.*, 2024). Both tools have been widely used and validated in the literature for their reliability in visualizing co-authorship, co-citation, and thematic networks.

In this study, various representations were selected to visualize data trends. As one of the main tools for data visualization in bibliometric analysis, co-occurrence knowledge mapping generated by Biblioshiny and VOSviewer packages provides a graphical representation of the relationships between knowledge areas, documents, or authors. Data from annual publications and citations in Scopus are presented in the form of trend graphs. Co-occurrence mapping is used to represent the development trend of CT research, keywords, and themes. Research shows that the most frequently appearing keywords reflect the popularity of a topic in a research field (Pei *et al.*, 2021). Therefore, keyword co-occurrence mapping is used to measure the frequency of keyword use in research and show its centrality in the co-occurrence knowledge map. We also conducted co-citation analysis and clustering mapping is used as the main representation to identify influential research citations from researchers, institutions, and countries or regions. Analyzing citation patterns between clusters can better identify important contributions in a particular topic or area (Park & Shea, 2020).

During the data analysis process, several challenges were encountered. The first challenge was inconsistency in keyword usage across articles, which required a semi-manual standardization process to unify variations to avoid fragmentation in co-occurrence mapping. Second, missing metadata in some records, particularly incomplete abstracts or keywords, led to the exclusion of these documents to maintain the quality of the analysis. Third, determining the threshold for inclusion in the network visualization (minimum keyword frequency) required careful calibration to ensure a balance between comprehensive coverage and meaningful clustering. These challenges were addressed through iterative validation, comparison of outputs across tools, and adherence to bibliometric analysis protocols suggested in previous literature.

5. Results

RQ1: *What is the general status of research trends on the application of AI in CT development in the annual distribution of publications and citations of research on the application of AI in CT development?*

5.1. *Annual Distribution*

In the current study, a total of 191 original articles published in the period 2007–2024 were analyzed. Fig. 2 presents the annual scientific production for research on the application of Artificial Intelligence (AI) to the development of Computational Thinking (CT) in the field of Education. Based on Fig. 2, if we look at the development of the number of publications in Scopus indexed journals, it is known that from 2007 to 2014 the development of research fluctuated with the number of documents consistently 1 or 0. However, from 2016 to November 3, 2024, there was an increase in the number of publications on the application of AI in the development of CT in Scopus. The sharp increase in research on the application of AI in the development of CT in Scopus occurred from 2019 to 2024 which can be linked to the increasing global attention to the integration of CT in education. During this period, many countries began to see CT as a fundamental skill that is important for students to master, especially in facing the challenges of the digital era. This effort is reflected in educational policies that include CT in the school curriculum, making it one of the 21st century skills that students must master (Aydeniz, 2018; Yeni *et al.*, 2024).

The Organisation for Economic Co-operation and Development (OECD) also recognized the importance of this skill by including aspects of computational thinking in the Programme for International Student Assessment (PISA) in 2021 (Stephens *et al.*, 2024). This assessment prompted many educational researchers and practitioners to study and explore the implementation of CT in formal education contexts, resulting in a surge of

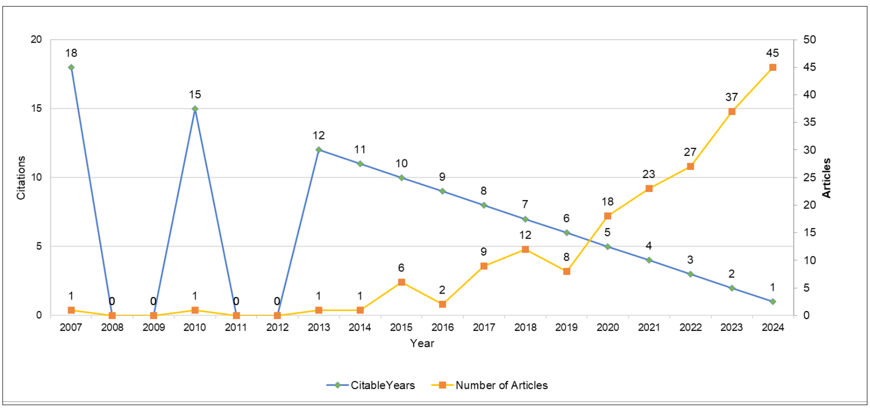

Fig. 2. Distribution of CT publications and citations over time.

publications in this field over the past few years. The influence of PISA and the increasing awareness of the importance of CT in global education created an impetus for more research, especially on the development of effective curricula, teaching strategies, and assessments in teaching CT.

In addition to the increasing attention to CT, the increasing number of studies on the application of AI in CT development can occur because since 2019, AI technology, especially machine learning, deep learning, and natural language processing (NLP), has developed rapidly (Kang *et al.*, 2020). Advances in hardware such as cloud computing and higher computing power have accelerated the development of AI, making it more accessible to companies, educational institutions, and researchers. AI has become one of the educational strategies during the digital transformation era (Cantú-Ortiz *et al.*, 2020). This is one of the factors in the high number of publications on the application of AI in CT development in Scopus in the period 2019 to 2024.

Meanwhile, if viewed from the trajectory of the number of citations of CT articles in the Scopus database, the highest citation peak occurred in 2007 with 18 citations, followed by 2010 (15 citations) and 2013 (12 citations). Interestingly, although the number of publications increased significantly after 2014, the number of citations tended to decrease. This phenomenon indicates that early articles in the topic of AI-based CT development have a high conceptual impact, because they become the main references and theoretical foundations for further research. The decline in citations in newer articles does not necessarily reflect a decline in quality, but rather indicates a shift in research direction from basic theory to specific applications and empirical studies in the context of pedagogy, learning technology, and other applied disciplines. Newer articles tend to carry practical contributions that are more limited theoretically but still important on a local or contextual scale. Thus, the citation pattern in this study not only describes the frequency of citations, but also reflects the transformation of scientific influence, from paradigmatic contributions in the early development of AI-CT to a wider diversity of applications and implementation contexts.

RQ2: *How are the trends and impacts of AI application in the development of CT in the field of education developing from the research theme development path?*

5.2. *Research Theme Development Path*

The frequency of keyword occurrences was determined to identify key topics and research trends in research on the application of AI in developing CT. A network visualization based on the co-occurrence of research keywords was then created, which is shown in Fig. 3. In Fig. 3, each circle represents a keyword and the size of each circle is proportional to the frequency of occurrence of the keyword, with larger circles representing higher frequencies and vice versa. Keywords with high frequencies represent popular research topics. We set the minimum frequency entered in the network visualization to be 5 times. As shown, the most frequently used or discussed keywords in research on the application of AI in developing CT skills are computational thinkings with 101 occurrences,

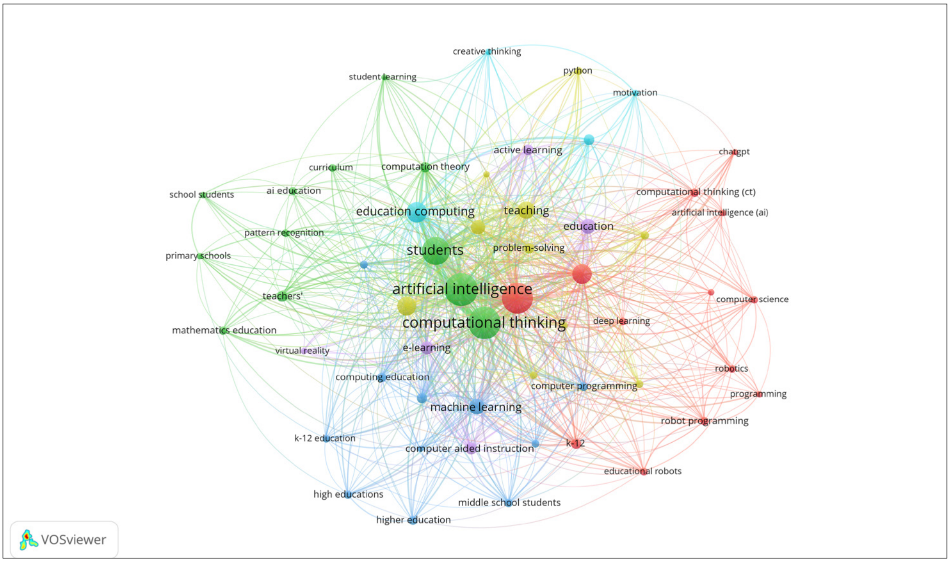

Fig. 3. Network visualization of keyword co-occurrence.

students with 80 occurrences, artificial intelligence with 75 occurrences, education computing with 43 occurrences, engineering education with 40 occurrences, curricula with 39 occurrences, teaching with 30 occurrences, and learning systems with 22 occurrences.

We conducted a thematic map analysis created using Biblioshiny software to display research clusters or themes based on keywords that frequently appear in related publications, and identify dominant themes and relationships between key concepts. Different colors indicate thematic clusters where each cluster represents a main theme or topic in the research. Fig. 4 shows the results of the Thematic Map Conceptual Structure by Keyword Plus analysis. This map helps identify the interrelationships between research topics and their level of development in related studies. The Thematic Map is divided into 12 clusters with cluster themes consisting of computational thinking, human computer interaction, machine learning, computer programming, pattern recognition, article, primary schools, educational innovations, paper analysis, language model, AI technologies, and programming profession. Table 2 shows the division of clusters on the Thematic Map, while Tables 3–6 shows several keywords in each group kuadran and the number of occurrences.

In the Thematic Map produced by Biblioshiny, each cluster is grouped into four main categories based on its relative position on the map, namely basic themes, emerging or declining themes, motor themes, and niche themes. These categories are determined by two axes on the map where the X-axis (Centrality) measures the level of connectedness of a theme to other themes in the study. The higher the centrality, the more important or common the theme is in the overall context. And the Y-axis (Density) measures the depth of development of the theme. The higher the density, the more mature or developed the theme is in the research study. Based on these two parameters, the themes on the thematic map are grouped as follows:

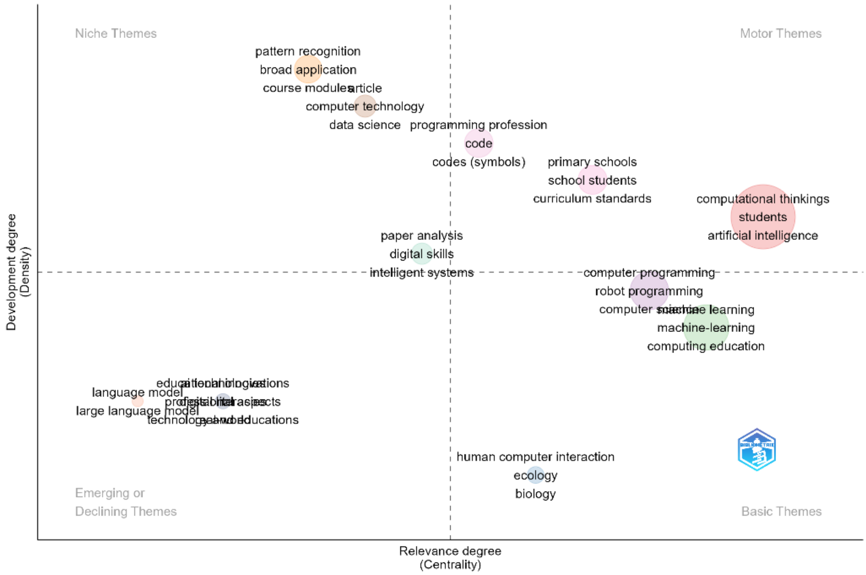

Fig. 4. Thematic map conceptual structure by keyword.

(i) **Basic Themes** (Lower Right Quadrant): This theme has high centrality but low density. Keywords in basic themes are basic or fundamental themes that are common and important for the field of research on the application of AI in developing CT capabilities in the field of Education, but are usually not developed in depth. Keywords in this Quadrant are keywords in the human computer interaction and machine learning clusters (see Table 3).

Themes in this quadrant have high centrality but low density, meaning that these topics are important and appear frequently in the literature but have not been conceptually developed in depth. Examples include machine learning and human-computer interaction. Although machine learning is one of the most widely used AI technologies in educational contexts (especially for classification and prediction), its theoretical and pedagogical studies on CT are still limited. This suggests that there is scope for further development regarding the integration of ML methodologies based on learning theory.

(ii) **Emerging or Declining Themes** (Lower Left Quadrant): This theme has low centrality and density. Themes in this quadrant can be considered as concepts that have just emerged and have not been developed much, or are actually experiencing a decline in interest. Keywords in this Quadrant are keywords in the language model and AI technologies clusters (see Table 4).

Topics in this quadrant have low centrality and density, indicating that these themes have received little attention in the literature or are being abandoned. Examples include AI technologies and language models. Despite their development in the fields of NLP and generative AI, the use of language models in CT development has not been widely studied. This opens up new research space to explore how LLMs (Large Language Models) such as ChatGPT can be used for logic training, programming, and problem-solving simulations.

(iii) **Motor Themes** (Upper Right Quadrant): This theme has high centrality and density. Keywords in this quadrant are themes that are closely related to the main topic, and research on this theme is growing rapidly and has high significance in the field. Keywords in this Quadrant are keywords in the computational thinkings, computer programming, primary schools, and programming profession clusters (see Table 5).

Topics in this quadrant have high centrality and density, meaning they are the main topics and are developing rapidly. These include computational thinking, primary schools, students, and computer programming. This shows that research on the development of CT, especially in elementary and secondary school students, is a mainstream that receives widespread attention, both in the context of curriculum and learning design. The studies here are generally empirical in nature, with the development of project-based learning models and evaluation of CT instruments.

(iv) **Niche Themes** (Upper Left Quadrant): These themes have high density but low centrality. Keywords in this quadrant are highly developed themes, but are less connected to the main theme or the overall discipline. They are usually very specific or unique. Keywords in this quadrant are keywords in cluster paper analysis, articles, and pattern recognition (see Table 6).

This quadrant is filled with themes with high density but low centrality, such as pattern recognition, paper analysis, and articles. Although these topics are studied intensively and may be very technical, their relevance to the main themes of CT and AI is still limited. Themes such as pattern recognition have the potential to be developed to support CT strategies, for example in code pattern recognition or algorithmic analysis in computing education.

Table 2 shows 12 main clusters in research on the application of AI for the development of CT in education. Each cluster describes a different thematic focus and depth of literature.

- **Cluster 1:** This cluster is the most central and developing, occupying a position as a motor theme with high centrality and density values. Keywords such as computational thinking, problem solving, curriculum, project-based learning, and K-12 education show that CT has become a main pillar in the transformation of 21st century education. This topic is widely studied in the context of curriculum development, active learning strategies, and cognitive assessment.
- **Cluster 2:** Although the keywords are few, this cluster is included in the basic themes category. This reflects the importance of human-computer interaction in supporting CT skills, especially on AI-based digital learning platforms. Keywords such as ecology and digital literacies also show cross-disciplinary influences.
- **Cluster 3:** This cluster is also in the basic themes, with keywords such as machine learning, image recognition, MOOC, and learning algorithms. Although often used as a supporting technology for CT, this study found that the topic of ML has not been explored in depth in a pedagogical context. This indicates the need to develop a conceptual model to link ML with CT-based learning strategies.

Table 2
Thematic map cluster division

Cluster	Cluster_Label	Total Keywords
1	Computational Thinkings	106
2	Human Computer Interaction	3
3	Machine Learning	35
4	Computer Programming	18
5	Pattern Recognition	9
6	Article	6
7	Primary Schools	7
8	Educational Innovations	3
9	Paper Analysis	5
10	Language Model	2
11	AI Technologies	3
12	Programming Profession	9

- **Cluster 4:** This cluster is strongly integrated with the CT cluster and is part of the motor themes. Keywords such as robotics, scratch, intelligent tutoring, and visual programming reflect the popular practice-based learning approach in teaching CT at various levels of education.
- **Cluster 5:** Included in the niche themes, this cluster emphasizes pattern recognition in the context of education and technology. Keywords such as course modules, broad application, and pedagogical approach highlight the analytical approach in developing CT skills, especially in analyzing data and designing algorithms.
- **Cluster 6:** This cluster contains general keywords such as data science, internet literacy, and computer technology. Placed in niche themes, this cluster tends to support major topics with theoretical background and basic technology.
- **Cluster 7:** As part of the motor themes, this cluster indicates an increasing focus of research on the integration of CT and AI in primary education. Keywords such as curriculum standards, teaching models, and student engagement indicate the importance of adaptive instructional design.
- **Cluster 8:** This cluster emerged as a new theme with an orientation towards AI-based teaching innovation. Placed in the emerging themes zone, this shows great potential but minimal exploration, such as the use of adaptive technology or intelligent systems in developing CT.
- **Cluster 9:** Categorized as a niche theme, this cluster reflects a methodological approach in assessing the effectiveness of CT teaching, including topics such as digital skills and intelligent systems.
- **Cluster 10:** This cluster is very relevant to the development of Large Language Models (LLM) such as ChatGPT. Included in emerging themes, keywords such as language models and large language models indicate the beginning of the involvement of NLP technology in supporting CT learning.

- **Cluster 11:** Although it contains important keywords such as digital literacies and technology in education, this cluster is still rarely used as the main focus and is classified as declining or underdeveloped themes.
- **Cluster 12:** Included in motor themes, this cluster includes topics such as code, encoding, and signal processing. This shows that CT is not only relevant in the context of basic education, but also at the advanced level and technology-based professions.

Table 3
Basic themes of research on the application of AI in developing CT capabilities in the field of Education

No	Number of Occurence	Words	Cluster Label
1	2	ecology	human computer interaction
2	3	human computer interaction	human computer interaction
3	26	machine learning	machine learning
4	8	computing education	machine learning
5	6	artificial intelligence learning	machine learning
6	5	application programs	machine learning
7	5	artificial intelligence course	machine learning
8	5	k-12	machine learning
9	4	learn+	machine learning
10	4	self-efficacy	machine learning
11	7	artificial intelligence education	machine learning
12	3	computer games	machine learning
13	3	higher education	machine learning
14	3	middle school	machine learning
15	3	personnel training	machine learning
16	3	primary and secondary schools	machine learning
17	3	project based learning	machine learning
18	3	teacher education	machine learning
19	2	assessment	machine learning
20	2	creatives	machine learning
21	2	cs education	machine learning
22	2	curricula design	machine learning
23	2	elementary schools	machine learning
24	2	hands-on activities	machine learning
25	2	image enhancement	machine learning
26	2	image recognition	machine learning
27	2	integral part	machine learning
28	2	learning algorithms	machine learning
29	2	machine learning techniques	machine learning
30	2	machine learning technology	machine learning
31	2	mooc	machine learning
32	2	on-machines	machine learning
33	2	smartphones	machine learning
34	2	supervised learning	machine learning

Table 4

Emerging or declining themes of research on the application of AI in developing CT capabilities in the field of Education

No	Number of Occurence	Words	Cluster Label
1	2	language model	language model
2	2	large language model	language model
3	2	AI technologies	AI technologies
4	2	digital literacies	AI technologies
5	2	technology and educations	AI technologies

Table 5

Motor themes of research on the application of AI in developing CT capabilities in the field of education

No	Occurrence Number	Words	Cluster Label	No	Occurrence Number	Words	Cluster Label
1	101	computational thinkings	computational thinkings	71	2	computer systems programming	computational thinkings
2	80	students	computational thinkings	72	2	contrastive learning	computational thinkings
3	75	artificial intelligence	computational thinkings	73	2	decision support systems	computational thinkings
4	43	education computing	computational thinkings	74	2	decision theory	computational thinkings
5	40	engineering education	computational thinkings	75	2	design and development	computational thinkings
6	39	curricula	computational thinkings	76	2	distributed computer systems	computational thinkings
7	30	teaching	computational thinkings	77	2	educational game	computational thinkings
8	22	learning systems	computational thinkings	78	2	educational resource	computational thinkings
9	16	computer aided instruction	computational thinkings	79	2	educational robotics	computational thinkings
10	16	e-learning	computational thinkings	80	2	educational tools	computational thinkings
11	16	education	computational thinkings	81	2	engagement	computational thinkings
12	13	active learning	computational thinkings	82	2	ethical technology	computational thinkings
13	12	teachers’	computational thinkings	83	2	foreign language	computational thinkings
14	11	computation theory	computational thinkings	84	2	high level languages	computational thinkings
15	10	computer sci-ence education	computational thinkings	85	2	internet of things	computational thinkings
16	9	problem-solving	computational thinkings	86	2	introductory programming	computational thinkings
17	8	‘current	computational thinkings	87	2	language education	computational thinkings

No	Occurrence Number	Words	Cluster Label
18	7	deep learning	computational thinkings
19	8	high educations	computational thinkings
20	8	middle school students	computational thinkings
21	7	educational robots	computational thinkings
22	7	mathematics education	computational thinkings
23	7	problem solving	computational thinkings
24	7	thinking skills	computational thinkings
25	6	game-based learning	computational thinkings
26	6	k-12 education	computational thinkings
27	5	higher school	computational thinkings
28	5	python	computational thinkings
29	5	student learning	computational thinkings
30	4	adversarial machine learning	computational thinkings
31	4	behavioral research	computational thinkings
32	4	creative thinking	computational thinkings
33	2	game design	computational thinkings
34	4	intelligent robots	computational thinkings
35	4	learning activity	computational thinkings
36	4	learning environments	computational thinkings
37	4	motivation	computational thinkings
38	4	scratch	computational thinkings
39	4	virtual reality	computational thinkings
40	4	young children	computational thinkings
41	3	computational creativities	computational thinkings
42	3	computer education	computational thinkings
88	2	large amounts	computational thinkings
89	2	ministry of education	computational thinkings
90	2	modeling environments	computational thinkings
91	2	problem based learning	computational thinkings
92	2	problem solving skills	computational thinkings
93	2	product design	computational thinkings
94	2	programming environment	computational thinkings
95	2	programming learning	computational thinkings
96	2	programming teaching	computational thinkings
97	2	stealth assessment	computational thinkings
98	2	surveys	computational thinkings
99	2	sustainable development	computational thinkings
100	2	teaching activities	computational thinkings
101	2	teaching practices	computational thinkings
102	2	teaching reforms	computational thinkings
103	2	theoretical framework	computational thinkings
104	2	undergraduate students	computational thinkings
105	2	virtual learning environments	computational thinkings
106	2	visual programming	computational thinkings
107	8	computer programming	computer programming
108	8	robot programming	computer programming
109	6	computer science	computer programming
110	6	robotics	computer programming
111	4	computers	computer programming
112	4	stem (science, technology, engineering and mathematics)	computer programming

No	Occurrence Number	Words	Cluster Label	No	Occurrence Number	Words	Cluster Label
43	3	computer software	computational thinkings	113	3	learning approach	computer programming
44	3	early childhood educations	computational thinkings	114	2	collaborative learning	computer programming
45	3	economic and social effects	computational thinkings	115	2	employment	computer programming
46	3	game-based learn-ing environments	computational thinkings	116	2	engineering research	computer programming
47	3	high school students	computational thinkings	117	2	experience report	computer programming
48	3	information and communication technologies	computational thinkings	118	2	innovation	computer programming
49	3	learning experiences	computational thinkings	119	2	intelligent tutoring	computer programming
50	3	mathematics teacher	computational thinkings	120	2	intelligent vehicle highway systems	computer programming
51	3	neural networks	computational thinkings	121	2	mathematical programming	computer programming
52	3	quality control	computational thinkings	122	2	robots	computer programming
53	3	school teachers	computational thinkings	123	2	students' engagements	computer programming
54	3	teacher preparation	computational thinkings	124	2	under-represented groups	computer programming
55	3	teaching and learning	computational thinkings	125	5	primary schools	primary schools
56	3	teaching contents	computational thinkings	126	5	school students	primary schools
57	3	teaching experience	computational thinkings	127	4	curriculum standards	primary schools
58	3	teaching methods	computational thinkings	128	4	teaching model	primary schools
59	2	abstract concept	computational thinkings	129	2	education curriculums	primary schools
60	2	academic achievements	computational thinkings	130	2	empirical studies	primary schools
61	2	ai course	computational thinkings	131	2	three dimensions	primary schools
62	2	application programming interfaces (api)	computational thinkings	132	4	programming profession	programming profession
63	2	artificial intelli-gence literacy	computational thinkings	133	3	code	programming profession
64	2	artificial intelli-gence research	computational thinkings	134	3	codes (symbols)	programming profession
65	2	augmented reality	computational thinkings	135	3	encodings	programming profession
66	2	case-studies	computational thinkings	136	2	chatgpt	programming profession
67	2	collaborative problem solving	computational thinkings	137	2	embedded systems	programming profession

No	Occurrence Number	Words	Cluster Label	No	Occurrence Number	Words	Cluster Label
68	2	computational methods	computational thinkings	138	2	gamification	programming profession
69	2	computer science and engineerings	computational thinkings	139	2	scaffolds	programming profession
70	2	computer science course	computational thinkings	140	2	signal encoding	programming profession

Table 6

Niche themes of research on the application of AI in developing CT capabilities in the field of education

No	Number of Occurrence	Words	Cluster Label
1	3	paper analysis	paper analysis
2	2	digital skills	paper analysis
3	2	intelligent systems	paper analysis
4	2	philosophical aspects	paper analysis
5	2	programming skills	paper analysis
6	2	article	article
7	2	computer technology	article
8	2	data science	article
9	2	human	article
10	2	information technology	article
11	2	internet literacy	article
12	5	pattern recognition	pattern recognition
13	2	broad application	pattern recognition
14	2	course modules	pattern recognition
15	2	disasters	pattern recognition
16	2	industry trends	pattern recognition
17	2	literature reviews	pattern recognition
18	2	natural disasters	pattern recognition
19	2	pedagogical approach	pattern recognition
20	2	social issues	pattern recognition

Based on the results of the Thematic Review analysis, keywords included in the computational thinking, computer programming, primary schools, and programming profession groups are keywords that are growing rapidly and have high significance in research on the application of AI in developing CT capabilities in the field of education. While AI technology such as machine learning is an AI technology that is often used, but is still included in the general basic theme. Machine learning is considered important for research on the application of AI in developing CT capabilities in the field of education, but is usually not developed in depth. Several previous research discussions that use Machine Learning technology in developing CT capabilities in the field of education are grouped as follows:

(i) **Field of application:** computing education, assessment, computer science education, curriculum design.
(ii) **Learning materials:** artificial intelligence, image enhancement, image recognition, learning algorithms, machine learning techniques, machine learning technology.
(iii) **Learning strategies/models:** project based learning, hands-on activities, supervised learning.
(iv) **Educational media:** application programs, computer games, Massive Online Open Courses (MOOC), smartphones.
(v) **Type of education:** artificial intelligence course, personnel training, teacher education.
(vi) **Education level:** K-12, higher education, middle school, primary and secondary schools, elementary schools.
(vii) **Connectedness with other abilities:** self-efficacy, creativity.

Fig. 5 shows the thematic evolution analysis used to analyze changes or developments in research themes on the application of AI in developing CT capabilities in education over time. With this analysis, we can see how key concepts and topics in the literature change, develop, or transform along with advances in research, technology, or changes in focus among academics. In this study, we divide two groups of research theme development ranges in the field of research on the application of AI in developing CT capabilities in education, namely the 2007–2022 and 2023–2024 ranges.

The results of the thematic evolution analysis show that Computational Thinking remains a major topic from 2007–2022 to 2023–2024, indicating that this topic has continued relevance and interest in related research. Several topics such as computer science, primary schools, and machine learning in the 2007–2022 period evolved into topics that focus more on school students, code, and machine learning in the 2023–2024 period. These results show a shift in attention from general technological aspects to more specific applications in school education and programming. In the 2023–2024 period, new topics such as higher educations emerged, indicating an increased focus on the application of CT and related technologies in the context of higher education. The topic of teachers remains from both periods, but it is seen that there is an

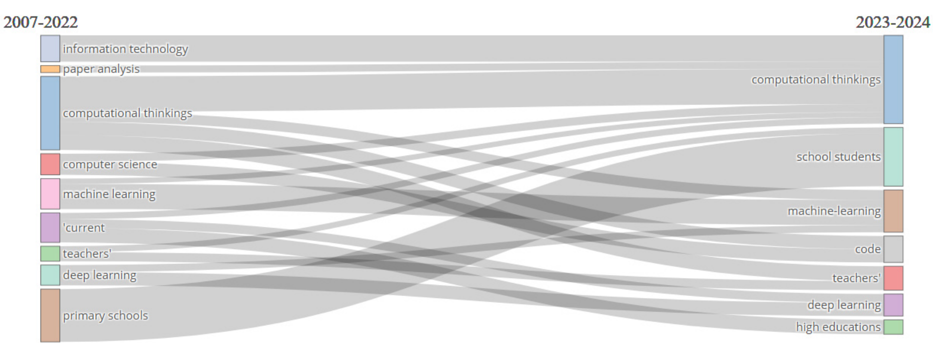

Fig. 5. Thematic evolution conceptual structure by keyword.

increased focus on the role of teachers in supporting CT-related education. Overall, the thematic evolution shown in Fig. 5 shows how research in the application of AI to CT development has transitioned from basic topics such as information technology and computer science to more specific applications for students, teachers, and various levels of education.

RQ3: *What are the influential sources of journals, researchers, institutions, countries/regions, and papers in research on the application of AI in developing CT in education?s*

5.3. *Sources' Local Impact Analysis*

Table 7 shows the top 10 sources' local impact on several journals and conferences that contribute to research related to Computational Thinking and Artificial Intelligence in education. The Computers and Education: Artificial Intelligence journal has the highest total citations (TC), which is 172, even though it only started in 2021 with only 4 publications. This data shows that the Computers and Education: Artificial Intelligence journal has a significant impact in publishing research in this field, with the highest m-index (1,000). In addition, the International Journal of Child-Computer Interaction also has a high TC (140) even though the number of publications is relatively small, indicating a high interest in the topic of child-computer interaction.

Lecture Notes in Computer Science (LNCS) and ACM International Conference Proceeding Series have high publication counts (NPs), 14 and 12 respectively, indicating the conferences' significant contribution to the dissemination of research related to computational thinking and AI in education. The highest h-index is 5 (LNCS), meaning at least

Table 7
10 Top Sources' Local Impact

No	Element	h_index	g_index	m_index	TC	NP	PY_start
1	Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)	5	9	0.500	87	14	2015
2	ACM International Conference Proceeding Series	4	8	0.800	64	12	2020
3	Computers And Education: Artificial Intelligence	4	4	1.000	172	4	2021
4	Frontiers In Psychology	3	3	0.750	45	3	2021
5	Ki – Kunstliche Intelligenz	3	3	0.750	24	3	2021
6	Annual Conference on Innovation and Technology in Computer Science Education, Iticse	2	2	0.400	5	2	2020
7	Education And Information Technologies	2	4	1.000	19	4	2023
8	IEEE Transactions on Learning Technologies	2	3	0.286	59	3	2018
9	International Journal of Child-Computer Interaction	2	2	0.400	140	2	2020
10	Lecture Notes in Networks And Systems	2	3	0.667	13	7	2022

5 publications from LNCS have 5 or more citations, indicating stability in contributing to the literature. The highest g-index is also held by LNCS (9), indicating a relatively good cumulative impact compared to other sources.

5.4. *Productive Authorship and Their Collaboration*

Table 8 shows the top 15 most relevant authors. TEDRE M is the author with the largest number of articles (6 articles) and has the highest fractionalized score (2.23). TEDRE M plays a significant role in the research of AI application for CT skill development in education. Meanwhile, HSU T-C and ROBLES G also have high contributions with 5 articles each and fractionalized scores of 1.78 and 1.25. The fractionalized scores shown in Table 8 indicate the relative contribution of each author to the articles they write. A higher fractionalized score indicates a greater contribution per article. TEDRE M and HSU T-C have quite high fractionalized scores, indicating significant contributions to research.

Some authors have the same number of articles but different fractionalized scores. For example, LEE J and LI X each have 4 articles, but their fractionalized scores are 1.25 and 0.98. This difference suggests that LEE J may have made a greater contribution to his articles than LI X. Authors with low fractionalized scores, such as SHELL DF (0.82) and BISWAS G (0.57), are likely to collaborate more on their articles, sharing contributions with other authors.

Fig. 6 shows a visualization of the collaboration network between authors of published articles on the application of AI in the development of CT education indexed by Scopus. Collaboration between authors is represented by nodes and edges. Each

Table 8
The top 15 most relevant authors

No.	Authors	Articles	Articles Fractionalized
1	Tedre M	6	2.23
2	Hsu T-C	5	1.78
3	Robles G	5	1.25
4	Lee J	4	1.25
5	Li X	4	0.98
6	Moreno-León J	4	1.00
7	Román-González M	4	1.00
8	Shell Df	4	0.82
9	Soh L-K	4	0.82
10	Valtonen T	4	0.89
11	Vartiainen H	4	0.89
12	Al Yakin A	3	0.75
13	Biswas G	3	0.57
14	Boyer Ke	3	0.64
15	Chen S-Y	3	0.62

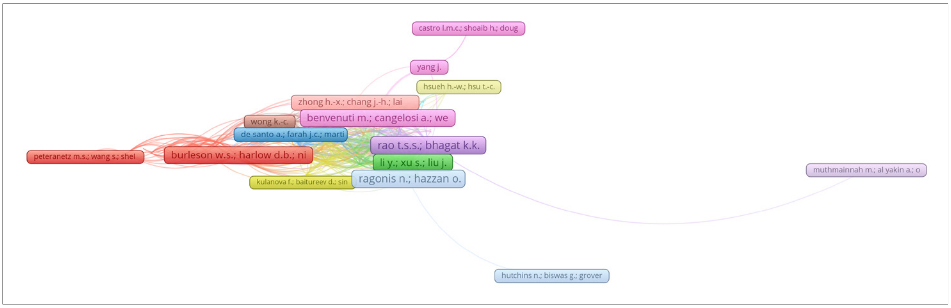

Fig. 6. Network visualization of author collaboration.

node represents an author, while the connecting lines indicate collaboration or joint involvement in research or publication. Fig. 6 provides an overview of the collaborative relationship between authors, where there are large collaborative groups, small groups, and several independent authors who contribute in their respective research fields.

There is one large group at the center of the network that includes many authors such as Burleson W.S., Harlow D.B., De Santo A., and Faraj J.C. Marti. They form a fairly dense collaborative network, suggesting that these authors frequently collaborate on multiple research projects or may be part of a large research team. This suggests strong interaction or collaboration among them. In addition to this large group, there are several authors who are on the periphery of the network and have few connections, such as Castro I.M.C., Shoaib H., and Doug. These authors appear to be involved in more limited collaborations or may be working independently of the main group. There are also several authors who are completely isolated with no connections to other authors, such as Muthmainnah M. and Al Yakin A.O., suggesting that they may be working alone or have very limited collaborations in this context.

5.5. *Contribution by Affiliates to Research on the Application of AI in the Development of CT in Education*

Fig. 7 displays the top 15 institutions contributing to research on the application of artificial intelligence (AI) to the development of computational thinking (CT) skills in education. Beijing Normal University leads with the most contributions, with 10 articles, demonstrating its strong commitment to this field. In second place, Itä-Suomen yliopisto and Universidad Rey Juan Carlos each contributed 7 articles, followed by Universidad Nacional de Educación a Distancia with 6 articles and National Taiwan Normal University with 5 articles. Several other institutions, such as Jeju National University, University of Kufa, University of Nebraska–Lincoln, National Cheng Kung University, Tecnológico de Monterrey, and NC State University, each contributed 4 articles. In addition, Vanderbilt University, Pontifícia Universidade Católica de São Paulo, INTEF, and Programamos.es each produced 3 articles.

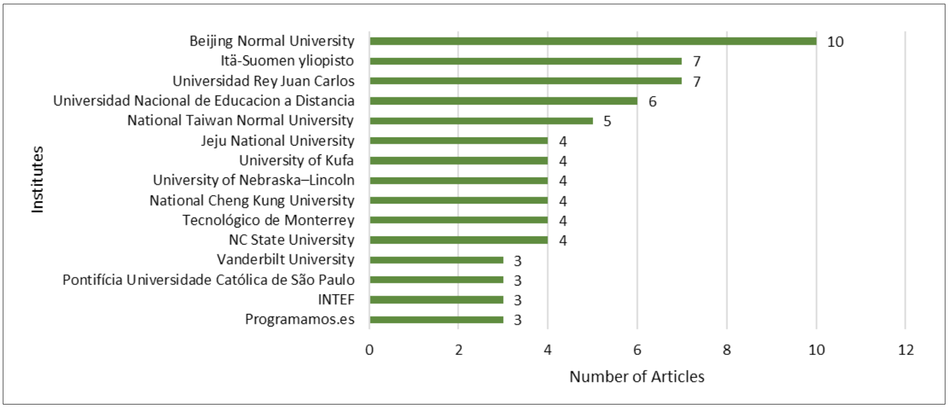

Fig. 7. Top 15 institutes that have contributed to research on the application of AI in developing CT in the field of education.

5.6. *Contributions by Countries/Regions to CT Research*

The data presented in Tables 9 and 10 provide in-depth insights into the country contributions to the writing of articles on the application of AI in the development of CT in education and international collaboration in this field. Table 9 shows the top 10 countries that contributed to the writing of articles on the application of AI for the development of CT skills in education. The United States ranked first with 181 articles that were cited 198 times, followed by China with 171 articles and a total of 220 citations, indicating the significant role of these two countries in the research field. Spain was in third place with 37 articles but only received 3 citations, while Finland with 28 articles received the highest citations, at 250 times, indicating a significant influence despite the smaller number of articles. South Korea was in fifth place with 27 articles and 12 total citations. Italy followed with 21 articles and 40 citations. Thailand, Brazil, Denmark, and Mexico contributed 16, 13, 13, and 12 articles respectively with varying citations, indicating their smaller but still significant contributions to global research in this area.

Meanwhile, Table 10 shows collaboration between countries in writing articles on the application of AI for developing CT skills in education. In addition, the United States also collaborated with countries such as Ireland, Turkey, and New Zealand twice each. Outside the United States, there are several other important collaborations, such as between Finland and Sweden, Italy and Germany, and New Zealand and Ireland, each of which has a collaboration frequency of 2 times. Spain also collaborated with Ireland and Mexico twice. There are also other collaborations with a lower frequency, namely once, between several countries such as Argentina with the Czech Republic and Serbia, and Austria with various countries, including South Africa and Brazil.

Although publication distribution is dominated by developed countries, collaboration patterns show significant geographical disparities in the AI-CT research landscape. Countries such as Thailand, Brazil, and Mexico, although beginning to actively contribute, tend to have low collaboration frequencies and are not yet integrated into broader global research networks. This suggests that there is great but untapped potential in enhancing cross-border knowledge exchange, especially in the Global South. Furthermore, the dominance of the United States and China reflects not only the large volume of publications but also stronger access to research resources, technological infrastructure, and strategic policy support. On the other hand, Finland's high influence with a relatively small number of publications indicates that the quality and focus of research rather than just quantity are key factors in determining academic impact. The study recommends the need for more collaborative and inclusive international research policies, including cross-border funding and partnership initiatives between institutions in developed and developing countries. This will strengthen the distribution of scientific contributions to the development of AI-based CT, and support the global agenda for inclusive and transformative education.

Table 9

Top 10 countries that contributed to writing articles on the application of AI in developing CT in the field of education

Country	Frequency	Total Citation
USA	181	198
China	171	220
Spain	37	3
Finland	28	250
South Korea	27	12
Italy	21	40
Thailand	16	2
Brazil	13	8
Denmark	13	7
Mexico	12	15

Table 10

Collaboration between countries in writing articles on the application of AI in developing CT in the field of education

No	From	To	Frequency
1	Usa	Portugal	4
2	Usa	Indonesia	3
3	USA	Canada	3
4	USA	China	3
5	Finland	Sweden	2
6	Italy	Germany	2
7	New Zealand	Ireland	2
8	Spain	Ireland	2
9	Spain	Mexico	2
10	USA	Ireland	2
11	USA	New Zealand	2
12	USA	Turkey	2
13	Argentina	Czech Republic	1
14	Argentina	Serbia	1
15	Austria	Argentina	1
16	Austria	Czech Republic	1
17	Austria	Serbia	1
18	Austria	South Africa	1
19	Brazil	Austria	1
20	Canada	Ireland	1

6. Discussion

As a contribution to the study of CT research trends, this study is critically compared with two previous relevant bibliometric studies, namely Chen and Nguyen (2024) and Triantafyllou *et al.* (2023). This comparison is done to show the contribution of novelty and strengthen the theoretical and methodological positions of this study. Chen and Nguyen (2024) conducted a bibliometric content analysis of 132 CT articles indexed in Scopus from 2008 to 2022. Their main focus was to identify the core content of CT literature by emphasizing the game-based learning (GBL) approach, integration in elementary education, and the dominance of quantitative methodology. They revealed that most studies used GBL to stimulate student participation and enhance cognitive aspects such as problem-solving and creativity. However, they did not explicitly map the involvement of AI in the structure or dynamics of CT and did not trace the thematic evolution of technological aspects longitudinally.

In contrast, this study broadens the scope by combining bibliometric performance analysis and science mapping through Biblioshiny and VOSviewer and extending the temporal coverage from 2007 to 2024. The main focus of this study is to analyze the integration of AI in the development of CT at various levels of education. The results of this study indicate that although AI is often used in educational contexts, its development is still classified as a basic theme that is not strongly tied to a solid pedagogical framework. Thematic analysis in this study also reveals the transformation of research direction from general topics (such as "information technology") to more specific topics, such as the role of teachers, basic education, and professional programming (see Fig. 5).

Another study by Triantafyllou *et al.* (2023) examines the role of gamification in CT through 94 articles and states that CT is often developed through interactive learning environments and challenge-based approaches. However, like the study by Chen & Nguyen (2024), their approach does not include the AI dimension and does not include citation evaluation, institutional collaboration, or co-occurrence visualization as part of the scientific structure mapping. Different from the two studies, this study presents new contributions by showing the growth rate of publications (CAGR 22.8%) related to AI-CT since 2019, mapping citation patterns as a reflection of the transition of conceptual to applied influence in the literature, using thematic evolution analysis to explain the shift in research focus, and presenting institutional and national collaborations as a map of global contributions in the field of AI-CT. With this more comprehensive approach, this study provides a stronger conceptual and visual foundation for understanding the dynamics of CT development in the AI era while opening up exploration space for deeper theoretical and pedagogical integration in the future.

While this study provides a stronger conceptual and visual foundation for understanding the dynamics of CT development in the AI era, the findings also reveal a number of real challenges in its implementation in the educational realm. One of the main challenges reflected in the results of the thematic analysis is that technologies such as machine learning, although frequently used, are still classified as basic themes that have not been widely integrated into a solid pedagogical framework. This indicates a gap between the use of AI technology and the theoretical understanding of how the technology supports the learning process. In addition, the emergence of new themes such as language models, teacher education, and AI technologies as emerging themes indicates that this field is still in the early stages of exploration, with limitations in terms of teacher readiness, curriculum, and learning strategies. On the other hand, the minimal involvement of institutions from developing countries, as seen in the analysis of international collaborations, also indicates challenges in access and equity of technology, which has the potential to widen the global digital divide. Therefore, a systemic and collaborative approach is needed that can address these methodological, practical, and policy challenges comprehensively so that the integration of AI in CT development can be effective and equitable.

The findings of this bibliometric and thematic analysis offer several implications for educational practitioners and researchers seeking to leverage AI to develop CT skills. We recommend several implications for education and researchers. The first recommendation for educators is that educators are encouraged to strategically integrate AI tools into active learning methodologies, including project-based learning, problem-solving tasks, and exploratory coding environments. This strategy is consistent with the core themes emerging from this study, particularly those related to computational thinking, computer programming, and elementary education, which form the basis of AI-CT research in the current literature. Second, contextual and ethical adoption of AI is critical. While AI-based technologies, such as machine learning and intelligent tutoring systems, offer promising avenues for personalized learning and automated feedback, their implementation must be sensitive to learner backgrounds, teacher readiness, and institutional infrastructure. Ethical considerations regarding data privacy, algorithmic transparency, and learner autonomy must be explicitly addressed in educational practices. Third, educators should engage in ongoing professional development to strengthen their AI literacy and pedagogical competence in facilitating CT skills. Structured training programs that bridge technological knowledge with instructional design theory are essential to ensure meaningful and responsible classroom implementation.

As for researchers, this study highlights several gaps and opportunities that deserve further investigation. There is a need for the development of a robust conceptual framework that synthesizes AI capabilities, especially in the domain of machine learning and large language models (LLMs), with established learning theories such as constructivism, metacognition, and social learning. In addition, longitudinal empirical studies are needed to assess the sustained impact of AI interventions on students' CT development across educational levels. Such studies should incorporate multidimensional assessment tools that evaluate not only cognitive outcomes but also affective and behavioral dimensions of CT. Emerging research themes identified in this study, such as AI technology, teacher education, and language models, are underexplored but highly promising. Future investigations should critically examine how these themes can be operationalized in educational settings to address real-world teaching and learning challenges. Finally, strengthening international and institutional collaborations is essential to building a more inclusive and globally representative research ecosystem. Particular emphasis should be placed on bridging the gap in research contributions between high-income and low- to middle-income countries by encouraging cross-regional partnerships, co-authorship networks, and capacity-building initiatives.

7. Conclusion

Using Biblioshiny RStudio and VOSvieweer package analysis tools, this review study provides a descriptive and bibliometric analysis of research trends and impacts of AI applications in developing CT capabilities. According to the research findings, the general status of research trends on AI applications in developing CT in the annual distribution of publications and research citations on AI applications in developing CT in education from 2007 to 2014 fluctuated with the number of documents consistently 1 or 0. The sharp increase in research on AI applications in developing CT in Scopus occurred from 2019 to 2024 which can be attributed to the increasing global attention to CT integration in education. Therefore, the rapid development trend observed in this study is expected to continue and mature.

A series of keyword-based co-occurrence mapping analyses visualize interesting topics and key themes in CT research. We use thematic map analysis to answer the trends and impacts of AI implementation in CT development in education. The results show that research topics on AI implementation in CT development are divided into 12 groups, namely computational thinking, human computer interaction, machine learning, computer programming, pattern recognition, articles, primary schools, educational innovations, paper analysis, language models, AI technologies, and programming profession. Thus, we get results where the impact of AI implementation in CT development occurs in several aspects of education, namely the field of application, learning materials, learning strategies/models, educational media, types of education, levels/levels of education, and the relationship between CT and other abilities/expertise.

Journal sources, researchers, institutions, countries/regions, and influential papers in research on the application of AI in the development of CT in education were analyzed. The results of this analysis show that Tedre, M. and Hsu T-C have a fairly high fractionalized score, indicating a significant contribution to the research. Beijing Normal University is the affiliate with the most contributions. Meanwhile, the country analysis shows that the United States ranks first with 181 articles that have been cited 198 times, followed by China with 171 articles and a total of 220 citations. Collaboration between countries has also occurred where the United States (USA) has quite extensive collaboration, with partnerships with Portugal 4 times, and collaborations with Indonesia, Canada, and China 3 times each.

A limitation of this study is the limited focus on articles published in Scopus-indexed journals, which may overlook significant contributions from other studies outside of the database. As a recommendation, future studies are suggested to expand the scope of the analysis by including publications from various sources and exploring underrepresented themes. We suggest that future studies could expand the scope by incorporating multi-database comparisons to enrich the comprehensiveness of the analysis. We also recommend that researchers focus on the integration of pedagogical strategies in CT education and explore underrepresented themes to support further development in the field of CT especially in the application of AI for developing CT capabilities in education.

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