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Mapping the Evolution of Computational Thinking in Education: A Bibliometrics Analysis of Scopus Database from 1987 to 2023

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Abstract. In today’s world, the ability to think computationally is essential. The skillset expected of a computer scientist is no longer solely based on the old stereotype but also a crucial skill for adapting to the future. This perspective presents a new educational challenge for society. Everyone must have a positive attitude toward understanding and using these skills daily. One thousand two hundred seven documents about computational thinking (CT) may be found while searching the Scopus database from 1987 to 2023. Data from Scopus were analyzed using VOSviewer software. This study educates academics by delving into the fundamentals of what is known about the CT of visual and quantitative research skills. This approach allows for a more in-depth look at the literature and a better understanding of the research gap in CT. This bibliometrics analysis demonstrates that (1) research on CT is common to all sciences and will develop in the future; (2) the majority of articles on CT are published in journals in the fields of education, engineering, science and technology, computing and the social sciences; (3) the United States is the most dominant country in CT publications with a variety of collaborations; (4) keywords that often appear are CT, engineering, education, and mathematics, and (5) research on CT has developed significantly since 2013. Our investigation reveals the beginnings and progression of the academic field of research into CT. Furthermore, it offers a road map indicating how this study area will expand in the coming years.

Keywords: computational thinking, Scopus, VOSviewer, bibliometrics analysis.

1. Introduction

Since there is no agreed-upon definition of CT in the literature (E. Lockwood *et al.*, 2016), the concept is fraught with debate. Because so many CT investigations and theoretical discussions occur in a programming setting, describing CT concepts and programming methods in the literature can be challenging (T.Y. Lee *et al.*, 2014). It may mislead readers into thinking that CT is the same as computer programming or, at the very least, that they need to be proficient in a programming language to practice. CT primarily aims to improve one's thinking ability and is currently accessible in fields other than computer science and computer engineering. The use of programming is not required for CT, and experts in the area do not recommend it as the setting for learning CT skills. Knowing the background of studies on programming and thinking abilities will help you understand why CT has selected this alternate way to enhance thinking skills. Whoever forgets the past is doomed to live in a perpetual present, as George Santayana once put it (Voogt *et al.*, 2015). Although CT, as we know it now, began in the 1950s, the concept has been around for much longer (Lodi and Martini, 2021). Ideas central to CT include abstraction, data representation, and the logical structure of data; these principles are shared by many other schools of thought, including scientific, engineering, systems, design, model-based, and more (Chan *et al.*, 2021). CT is not a brand new concept or set of ideas; terms like algorithms, procedural thinking, algorithmic thinking, and computational literacy have existed for some time (Braun and Huwer, 2022; Jacob and Warschauer, 2018).

It is essential to differentiate between computational science and other related fields, such as computer science and CT (Denning, 2019). It is because applying the computational science method to different scientific areas was the impetus for developing computational science (Piatti *et al.*, 2022). The result is that computational physics, bioinformatics, and digital humanities are now included among the subfields of every scientific subject specializing in computing (Denning, 2013). Computing, in particular, lends a hand to other scientific fields by assisting with the simulation and interpretation of natural information and numerical approaches (Sentance and Csizmadia, 2017). These subfields are kept separate from computer science because computer scientists typically lack the specialized training to work in those domains. Aside from that, calculations are utilized for a variety of purposes, including but not limited to the following: exploiting computing tools; using modeling and simulation to explore phenomena; putting hypotheses to the test; and making predictions, which are all tasks that are performed by computer scientists who study said tools (John Lemay *et al.*, 2021).

Using CT in the classroom can significantly improve students' ability to solve complex problems. However, research on incorporating CT into classrooms is still in its infancy. Preparing the next generation of educators to teach CT is crucial to successfully integrating it into the curriculum. Educators' professional development around CT was essential to successfully integrating it into the classroom, providing supporting evidence for this claim (Barr and Stephenson, 2011). Using CT in the classroom may not always lead to a mutually beneficial understanding between students and lecturers. The lack of a concrete plan for fostering its growth in its upcoming lessons is to blame. The professional audience must develop better educational skills to think computationally and quickly. To use this knowledge effectively, one must also be familiar with the curriculum, lesson plans, and strategies for implementing them (Bower and Falkner, 2015).

Since (Papert, 1988) initial presentation of CT, other researchers have debated its meaning, scope, and effectiveness in the classroom(Grover and Pea, 2013). According to (Wing, 2008), CT is more than just a programming talent computer scientists utilize. It is one of the standard life abilities that everyone requires. Therefore, the effective execution of message-processing agents necessitates operational thinking, which further describes it as a method of issue-solving (Grover and Pea, 2013). Here are the two ways the computer can aid with the solution: First, you need to think about what needs to be done to fix the issue, and then you may use your technical know-how to guide the computer to a solution. To solve problems with a computer, one must know mathematical formulas, be able to express the issue clearly, and employ rudimentary procedures or recipes. Also, before beginning to develop computer animations, designers must plot a tale and decide on a shooting style, all while doing duties with the help of computer software and hardware. CT is the mental preparation for using computers and machines in these two scenarios.

Computing entails thinking that explains how machines and software are run. The emphasis is not on computer hardware or trying to mimic computer thought processes (Wing, 2008) but on how people use computers to research and find solutions to issues. Moreover, CT is essential for finding solutions to problems and creating and recognizing new ones (Wing, 2008). It's evocative of earlier advancements in STEM and other fields (Cheung, 2013) in that it aids computers in problem-solving but also aids humans in comprehending the nature of the problems themselves and the possible solutions. Thus, humans can develop CT processes by controlling computers, but on the other hand, machines are not always needed for CT in some instances. Students not planning to go into computer science can no longer afford to ignore the importance of CT. These days, classroom educators are tasked with fostering the development of CT in their students. As (Heintz *et al.*, 2016) demonstrate, training students' CT has been used in computer classes and other courses across the globe. Differences in country education systems and cultural norms make it hard to replicate or copy strategies for developing CT. As a result, many nations have encouraged citizens to build CT and programming skills.

During programming, students learn about CT (Wing, 2006). Abstraction, debugging, remixing, and iteration are all computer science principles used in this process (Ioannidou *et al.*, 2011; Resnick *et al.*, 2009). Because it necessitates "thinking in numerous abstractions", this thinking might be considered fundamental for students. There is a close relationship between CT and 21st-century talents, such as creative problem-solving, critical thinking, and analytical reasoning (Ananiadou and Claro, 2009; Binkley *et al.*, 2012). Unsurprisingly, many educators place a premium on teaching kids how to code today (Resnick *et al.*, 2009). The recent resurgence of interest in setting-specific programming highlights the importance of thinking about how such initiatives might be made more directly relevant to the types of learning outcomes they aim to generate. Researchers have hypothesized several possible benefits, including improved analytical reasoning and mathematical and scientific proficiency (Kafai and Burke, 2013; Sengupta *et al.*, 2013). However, articles addressing CT through programming in context are scarce in the current literature (Grover and Pea, 2013). It is due to the increased frequency with which students taking CS courses in college must demonstrate their mastery of programming concepts on standardized tests (Brackmann *et al.*, 2017; Katai and Toth, 2010; Román-González, Moreno-León *et al.*, 2017; Román-González, Pérez-González, *et al.*, 2017). Consequently, this study aims to scour the literature for previously published empirical studies promoting student participation in higher education's curriculum-based programming.

Instead of being seen as something only computer scientists need to know, CT is now recognized as a core life skill (Li *et al.*, 2020). Everyone needs to take a more positive approach when grasping and using these abilities in typical situations. Whether problems are processed in people's minds or by computers, CT's powers and limitations depend on computational processing. As part of their early education, students should be taught the three R's (reading, writing, and arithmetic), CT, and the art of logical analysis (Wing, 2006, 2008). Simplifying, embedding, transposing, and simulating are the four operational skills of CT. It employs computer science fundamentals to formulate, analyze, and solve problems; it also serves to design and implement systems in a way that is accessible to humans. CT simultaneously enables a mindset comparable to that of computer scientists while confronting difficulties (Grover and Pea, 2013)

According to a more thorough definition, CT is a concept, not the act of writing code. It necessitates high degrees of abstract thought and analysis on the part of students. CT includes many ideas, including using computers in education. It is more valued to engage in reasoning than in mechanical activity. That's why learning how to think like a computer is crucial. They may be more flexible since they feel like humans rather than computers. CT is not an attempt to mimic the thought processes of computers but rather a means of problem-solving that acknowledges humans' superior intelligence and creativity (Wing, 2008). Methods from both mathematics and engineering are combined with strengthening mathematics' underpinnings: skills and abilities, problem-solving, behavior management, communication, and interpersonal relationship.

Several studies explore CT's educational benefits. CT is thought to help kids solve problems, analyze everyday concerns, explore, create, and invent (Denner *et al.*, 2011a), and grasp technology. Problem-solving, examining data patterns, and questioning evidence (Charlton and Luckin, 2012); collecting, analyzing, and representing data; decomposing problems; using algorithms and procedures; making simulations (Gretter and Yadav, 2016); using computer models to simulate scenarios (Exchange, 2015); dealing with open-ended problems and persisting in complex case studies (Armoni and Gal-Ezer, 2014). CT maps solution processes like iteration, selection, and sequencing onto computer capabilities since humans are articulating issues and constructing solutions for computers to execute (I. Lee and Malyn-Smith, 2020). CT entails decomposing a problem, identifying algorithms, writing instructions, and analyzing one's answer (Labusch *et al.*, 2019): abstractions, problem decomposition, and automation link CT to Computer Science. Jan Lepeltak emphasizes that CT involves how computers work and how we talk about and communicate with them (Voogt *et al.*, 2015).

The literature is recursively revealing a core set of notions and skills. Jeannette Wing's papers provide a clear CT description. CT defines the intellectual processes required to formulate a computer problem, including abstraction, algorithmic reasoning, automation, decomposition, debugging, and generalization. The definitions of CT core skills are shown in Table 1.

According to the International Society for Technology in Education (ISTE) and National Research Council (NRC), students can still show CT even if they aren't using technology to make something. By contrast, with programming, students build artifacts to demonstrate their computational reasoning (Kafai and Burke, 2013; Resnick *et al.*, 2009). As a result, the ISTE and NRC's broad concept of CT might not work well with code. Therefore, we employ Brennan and Resnick's Scratch framework in our overview of CT through programming (2012). Scratch is a widely adopted language for teaching computer science in elementary and secondary schools (Tangney *et al.*, 2010; Theodorou and Kordaki, 2010). There are three levels of CT concerning Scratch: computational concepts, computational actions, and computational views. The key points about these three factors are summarized in Table 2. Documentation of the data collection consisting of figures and tables that were collected and analyzed for this study can be seen on the open research platform provided by Zenodo (Rafiq *et al.*, 2023).

Because of their unity with familiarity with Mayer's proposed Logo programming language, these characteristics help analyze K12 students' approaches to programming. Knowledge of syntax, semantics, computer schematics, and strategy (computing practices) is included. Scratch has many of the same capabilities as modern student visual programming languages (e.g., Alice). These languages are simple for students to pick up since they give them immediate feedback on their code in the form of moving images (e.g., animations and games). As a result, this structure is suitable for contemplating CT inside computer programming.

Table 1

Core competencies and definitions for CT

CT Core Competencies	Definition
Abstraction	Abstraction reduces detail to simplify an artifact. Conception involves hiding the correct point to simplify the task without sacrificing anything significant. Selecting an appropriate system representation is crucial. Models simplify different tasks (Csizmadia *et al.*, 2015).
Algorithmic thinking	Algorithmic thinking uses defined steps to solve problems (Csizmadia *et al.*, 2015).
Automation	Automation saves time by instructing a computer to perform repetitive tasks faster than a human. Hence, computer programs are "automation of abstractions" (Denner *et al.*, 2011b).
Decomposition	Artifacts are decomposed into their pieces. Understanding, solving, developing, and evaluating each part is possible. It simplifies complex challenges, unique conditions, and huge system design (Csizmadia *et al.*, 2015).
Debugging	Debugging involves testing, tracing, and logical thinking to forecast and verify results (Csizmadia *et al.*, 2015).
Generalization	Exploiting patterns, similarities, and linkages is a generalization. Based on past solutions and experience, it solves new problems fast. Specific algorithms can tackle similar problems (Csizmadia *et al.*, 2015).

Table 2 summarizes some critical components of CT. Computing-based methods have been utilized in many fields over the past decade. Educators have experimented with various teaching methods to find the best ones. In Table 3, the authors of this study compiled a list of the different pedagogical approaches used in the past to teach students and enhance ICT skills. These include but are not limited to problem-based learning, collaborative learning, project-based learning, game-based learning, scaffolding, computational learning theory, aesthetic experience, concept-based learning, learning embodiment-based, human-computer interaction teaching, and universal learning design.

In this study, bibliometric research is conducted for a variety of reasons, including but not limited to identifying patterns of article and journal performance; identifying research constituencies; identifying patterns of collaboration; and determining the intellectual structure of a domain as revealed by the current body of literature (Verma and Gustafsson, 2020). The data that is the focus of a bibliometric analysis is typically extensive in quantity and objective (e.g., the number of citations and author's publications, the occurrence of keywords and topics). Still, their interpretation often depends on objective (e.g., performance analysis) and subjective evaluations (e.g., thematic analysis) established through informed techniques and procedures. Moreover, bibliometric analysis is helpful for rigorously comprehending vast volumes of unstructured data, which allows for the deciphering and mapping of the accumulated scientific knowledge and evolutionary nuances of a well-established area. Accordingly, a thorough bibliometric analysis can lay the groundwork for significant advances in an area. It enables and encourages researchers to (1) get a bird's-eye view of the study landscape, (2) spot gaps in our understanding, (3) find novel tools and approaches with which to probe previously unexplored areas, and (4) place the research's contribution in context.

3. Methodology

3.1. *Bibliometric Analysis*

VOSviewer version 1.6.17 was used to conduct bibliometric Analysis (Ariyani *et al.*, 2022; Masduki *et al.*, 2022; Muhammad *et al.*, 2022; Qin *et al.*, 2022; Suprapto *et al.*, 2021). The information collected was used to make charts and tables. Bibliometric indicators were determined to be most pertinent to this work and are discussed in this article. Together-occurring categories include (i) document type, (ii) author, (iii) institution, (iv) country, (v) referenced document, (vi) journal source, and (vii) authors' keywords (Christ-Ribeiro *et al.*, 2021; Rodríguez-Rojas *et al.*, 2021; Zyoud and Zyoud, 2021). The VOSviewer may generate a network of co-occurrence terms by reading exported Excel data and considering phrases from the index keyword. The simultaneous occurrence of events necessitates the identification of multidisciplinary techniques and the direction of future research (Christ-ribeiro *et al.*, 2021; Gall *et al.*, 2007; Guo *et al.*, 2019; Lulewicz-Sas, 2017; Nassaji, 2015; Zyoud and Zyoud, 2021). VOSviewer, Tableau Public, and Microsoft Excel were used to represent the data visually.

Since the early 20th century, bibliometric analysis has been used to examine the world's published literature (Sakata *et al.*, 2013; Zhang *et al.*, 2021; Zhou *et al.*, 2021). Information about books, writers, libraries, academic journals, and other sources can be compiled using bibliometrics, a branch of statistics (de Melo *et al.*, 2022). The proliferation of published works on any given topic necessitates the application of multiple quantitative criteria for evaluating the most critical advances in the field (Marvuglia *et al.*, 2020). Results from this Analysis can be trusted because they have been through a review process that can be repeated and is subject to public inspection. The dangers of conducting a subjective literature review are reduced when one uses objective judgments generated by computer programming (Bretas and Alon, 2021). Neither the passage of time nor the number of data samples may limit bibliometric study (Yu *et al.*, 2020). In a recent study, well-known pieces of bibliometric software such as VOS-viewer (Waltman *et al.*, 2010a), Bibliometrics (Aria and Cuccurullo, 2017), Hist-Cite (Bornmann and Marx, 2012; Garfield *et al.*, 2006; Lucio-Arias and Leydesdorff, 2008), CiteSpace (Chaomei Chen *et al.*, 2010; Chaomel Chen, 2006), CiteNetExplorer (van Eck and Waltman, 2014), SciMAT (Cobo *et al.*, 2012), and others have been utilized.

Bibliometric Analysis has several uses outside of academia. One of these is in the food science and technology industry (Christ-Ribeiro *et al.*, 2021; Musa *et al.*, 2021; Yeung *et al.*, 2018), engineering (Hincapie *et al.*, 2021; Huang and Xin, 2020), computer science (Zyoud and Zyoud, 2021), medical (Brimo Alsaman *et al.*, 2021; Santisteban-Espejo *et al.*, 2020), education (Goksu, 2021), economics (Donthu *et al.*, 2021; Saleem *et al.*, 2021), and social science (Palácios *et al.*, 2021). This study shows how research subjects, difficulties, and new developments have evolved (Flórez-Martínez *et al.*, 2022). Therefore, we require the data provided by this analysis to comprehend the current state of publication patterns and their prospective practicality.

3.2. *Data Mining*

We might perform a subject search in the Scopus database to obtain the scientific publications published between 1987 and 2023. Scopus was used as a bibliometric resource in our research because it is widely acknowledged as the most comprehensive citation database and collection of abstracts of scholarly literature. It occurred because Scopus is a far more comprehensive database than Web of Science or PubMed (Christ-Ribeiro *et al.*, 2021; Falagas *et al.*, 2008; Mongeon and Paul-Hus, 2016). Previous bibliometric studies made analytical use of data retrieved from Scopus. Bibliographic details, keyword combinations, and cited references were only some of the valuable information gleaned from Scopus. Fig. 1 shows the overall research methodology employed in this bibliometric analysis.

Data retrieval and analysis began on December 20, 2022. The search was conducted in a single day to avoid the introduction of bias caused by incremental changes in the database because of daily citation updates. As a result, we could find everything we needed in a single day (Ellegaard and Wallin, 2015; Musa *et al.*, 2021). Finding relevant articles in the literature required using the search term "computational think-

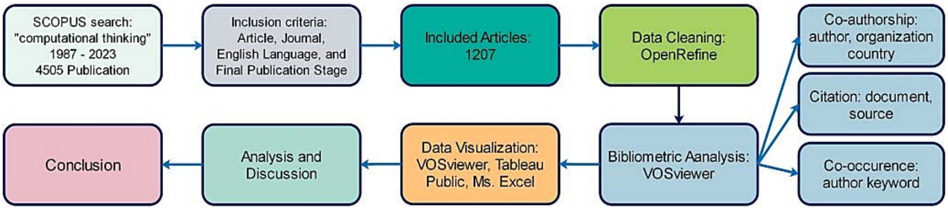


Fig. 1. Research methodology flowchart.

ing." According to the research process diagram, the database yielded 4.505 documents. Only documents that were entirely authored and published in English were considered. Specifically, 1,207 papers were located that discussed the topic of CT in some way. The information utilized in this analysis came solely from scholarly journal articles.

This bibliometric study excludes conference proceedings, review articles, book reviews, book chapters, and other publications not included in the Scopus database. There are several benefits to publishing in academic journals: (1) they are often subjected to a review by experts in the field (i.e., papers will be carefully evaluated for errors and may be rewritten several times); (2) It has a more extensive influence than the proceedings; (3) Well-researched, meticulously written papers; and (4) Constructive comments from reviewers.

3.3. *Data Cleanup*

Some data is duplicated in the primary dataset. First, duplicates were removed using Open Refine software. It's a free, open-source desktop program that can transform and clean data (Groves, 2016; Tillman, 2016). We classified nouns as singular or plural to transform them into the correct form. The terms "e-learning" and "E-learning" have been shortened to "E-Learning", for instance. It wasn't just words merged into a single terminology but also observations with the same meaning (Heikkinen and Marko, 2019). This cleaning procedure was subjected to multiple required manual checks and assessments. The information was sorted and scrubbed by hand using the VOSviewer's thesaurus.

3.4. *Findings*

A search on the Scopus database using keywords associated with CT between 1987 and 2023 yielded 1207 papers. In addition, this bibliometric study covers the same time frame as the results of a search on Scopus for the term "computational thinking" from 1987 to 2023. No journal articles were published between 1988–1993 and 1996–2007. Several important events must be considered during this time. As far as we can tell, no one has ever explained why no articles were produced during those times. According to

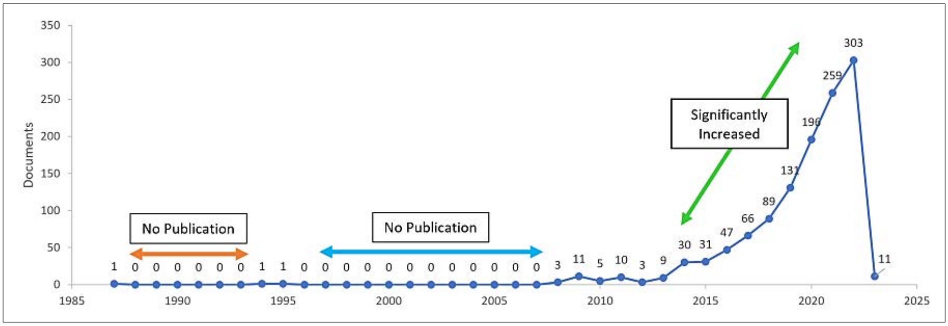


Fig. 2. Documents per year.

several scholarly sources, CT didn't appear in print until 2006. The number of articles published annually increased from 2008 to 2013, from an average of 3 to an average of 11 papers. Most reports were published between 2014 and 2022, as shown in Fig. 2, which shows that annual publication rates are rising, with a peak of 303 articles expected in 2022. We may attribute the fall to 2023 because few articles were written at the beginning of that year.

4. Result and Discussion

4.1. *Co-Authorship Analysis*

The interaction in a social setting between two or more scientists that promotes the sharing of meaning and the execution of tasks involving a mutually shared aim is characterized as author cooperation. The possibility of uncovering new knowledge, rising specialization within science, the complexity of the infrastructure necessary, and the necessity to combine varied expertise and abilities to handle complicated health problems urge authors to collaborate. The author's cooperation can also help widen the scope of a research study and stimulate innovation by providing access to new fields. The examination of co-authorship offers a picture of collaboration patterns between individuals and organizations (Fonseca *et al.*, 2016).

The author analysis data reveals 2792 authors who have written works on CT and made their work public. Fifty-two authors have five or more documents connected to their identities. These authors are associated with a total of 52 different documents. According to the number of documents shown in Fig. 3, there are a total of twenty authors who are among the most productive. The author with the most publications is Yadaw A, who has 12, followed by Hsu T.C. and Lee Y, who each have 11; Bers M.U. and Roman-Gonzalez M, who each have 10; Kong S.C., Kalogiannakis M., and Dagiene V., who each have 8, and Sun L., who is the last author on the list.

Brief references that identify a specific piece of literature are called citations (e.g., book, article, chapter, website). We can find these in article and book databases and

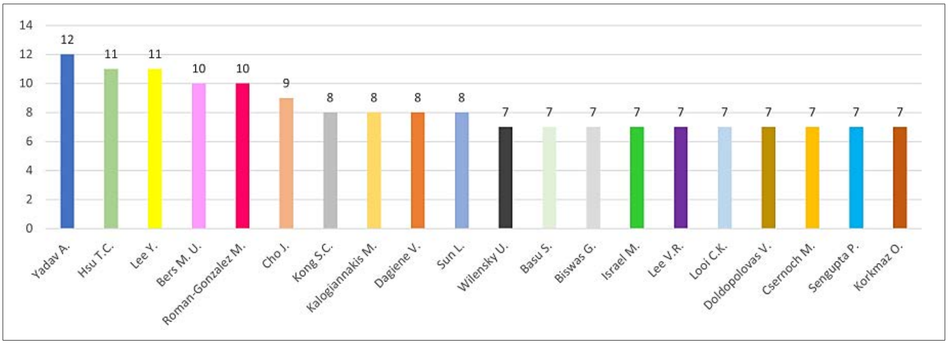


Fig. 3. Top author documents.

places like bibliographies and reference lists. The information required to identify and locate a publication is included in a citation comprised of standard elements. There are several good reasons to credit the resources used in research appropriately. There are four main reasons to properly cite your sources: (1) to demonstrate to the reader that you have conducted thorough research; (2) to demonstrate that you are a responsible scholar by giving credit to other researchers and acknowledging their ideas; (3) to prevent plagiarism by properly attributing the use of another author's words or ideas; and (4) to enable the reader to locate the sources you have used through the use of footnotes, a bibliography, or a reference list. As seen in Fig. 4, Yadav A (980) has been cited more times than anyone else. There were 934 works by Bers M.U., 800 works by Wilensky U., 772 results by Roman-Gonzales M., and 681 works by Weintrop D. Each of these articles has received numerous citations, indicating that researchers are still interested in the subject matter presented.

Citations are produced when one author acknowledges the work of another author who has previously published on a subject comparable to the one discussed in the current position. When we quote an earlier study, regardless of whether it was positive or negative, you demonstrate that you are familiar with it and that it has influenced the work that you are conducting at present. Citations are undeniably significant in the realms of both communication and scientific evaluation. It is because they constitute a

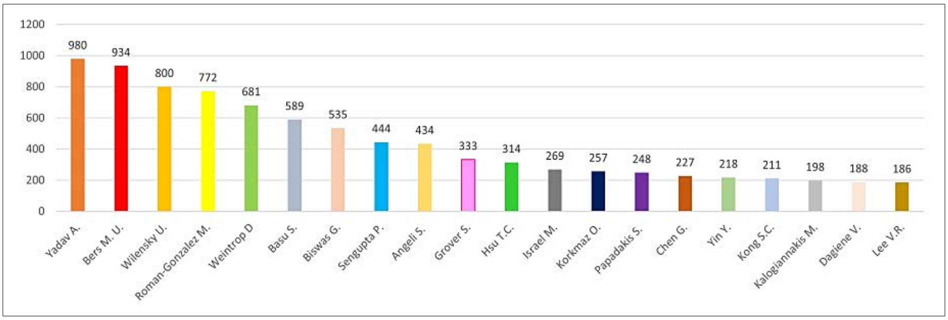


Fig. 4. Top 10 citations.

considerable fraction of most bibliometric indicators. To give one illustration, metrics like the Impact Factor, the H Index, and the Crown Indicator rely on citations to derive their values. In addition, Google Scholar and other academic search engines rank results according to the times that results have been mentioned (Rovira *et al.*, 2018). Citation is one of the essential metrics for measuring the influence of research. It enables a more comprehensive study of the work produced by authors, journals, and institutions. As a result of this, a citation is one of the most critical metrics. Most databases used for evaluating and researching science (such as Web of Science, Scopus, or Dimensions) construct their impact, repercussion, and similarity indicators from records of the primary descriptive elements of a publication (such as its title, authors, subject matter, etc.). Besides that, it comes from references to studies that have been indexed. It allows the databases to accurately measure the scientific community's reactions to new information. These data stores do not preserve the complete texts of the documents; instead, they save the information required to locate the records and generate the indicators (Repiso *et al.*, 2020).

The strength of the connections between writers, represented in Fig. 5, is also shown. As stated in the VOSviewer documentation, the power of each link is represented by a positive numeric value, with a more excellent value indicating a more robust connection. Total link strength, meanwhile, reveals how often two authors have been included in the same magazine. Fig. 5 shows that Garaizar P. and Guenaga M. have the highest total link strength, at 17, meaning they are connected to most other researchers through their work. It is followed by Eguiliz A. Jacka L., Yakov Herskovitz, and Yaakov Israel-Fishelon, each with 16. These results show that further opportunities to work with these writers on CT exist. According to these findings, the overall citation number and the total strength of links are not always proportionate to the vast number of papers. Figures 3, 4, and 5 reveal that although Garaizar P and Guenaga M have the highest total link strength, they do not have the most papers or citations.

Fig. 6 displays the densely packed bubbles of the leading institutions with the most documents on CT. This study successfully identified 2279 research institutions or universities engaged in the study of CT. There are 26 companies here that have released three or more albums. The sizes and colors of the data points represent different quantitative dimensions. U.S. educational institutions take up a third of the top 10 spots.

Regarding citations, the College of Education at Michigan State University in the United States and the Center for Learning, Teaching, and Technology at the University of Hong Kong in Hong Kong are tied first with 169 and 169, respectively. Next comes the University of Cyprus, which has four documents cited by 334 sources, making it the most-cited institution. Based on these numbers, there is much room for improvement in CT research in academic institutions.

The geographically dispersed document semantic network is depicted in Fig. 7. With 365 articles, 10546 citations, and a total link strength of 78, the United States dominates the field of CT publishing. Second place was taken by China, which contributed 80 documents, 783 citations, and 36 total link strengths. Next is Spain, with 79 papers, 1640 citations, and a total link strength of 26. The research on CT has flourished swiftly and played a significant role in universities worldwide. Countries like the United States,

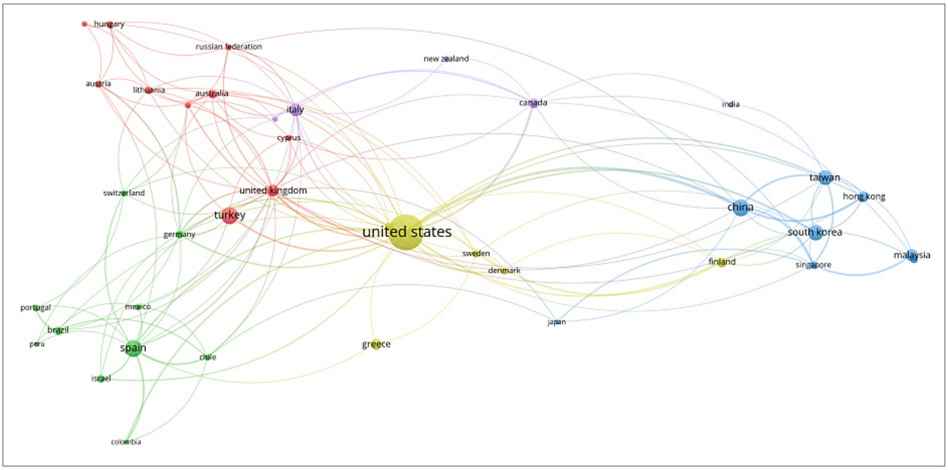


Fig. 7. Publication network between countries.

the United Kingdom, Turkey, Spain, and China produce a disproportionate share of the world's articles, as evidenced by the overall link strength figure between these countries. Technology also plays a significant part in generating research on CT. Therefore, technological expertise is an important consideration. For countries that don't traditionally produce publications in CT, this is a fantastic chance to join forces and build research networks.

In Fig. 8, we see a more in-depth visual representation of the country's significantly contributing to this field of study. Graphs of each country's output in CT, along with the number of documents produced by that country, its position within the area, and the total strength of its links, are presented in the first, second, and third bars, respectively.

Table 4 displays the top 10 CT publications. The top ten papers were published between 1987 and 2018. This information illustrates how this topic of study writing connected to CT is evolving. The problem raised by this study is mainly related to the concept of CT.

The article with the most citations (857) describe the critical role of CT in problem-solving. CT is a type of analytical thinking. It is usually based on mathematical thinking used for problem-solving. Furthermore, CT is also related to engineering thinking in a general way to design and evaluate broad and complex systems that operate with certain limitations in the real world. It is relevant to scientific thinking, widely used to understand computation, intelligence, human mindsets, and human behavior habits. CT will affect every individual activity in all fields. It poses a challenge for its role in the education sector, particularly in higher education. Harmony between science, technology, and society is needed in developing CT in education. Apart from that, the increasingly rapid technological advances and the demands of the digital era require individuals with the competence to think computationally well (Wing, 2008). In general, this article provides a fundamental foundation for applying CT.

A significant amount of research over the past three decades focused on questions about teaching and learning skills, concepts, and practices relevant to CT. Mathematics

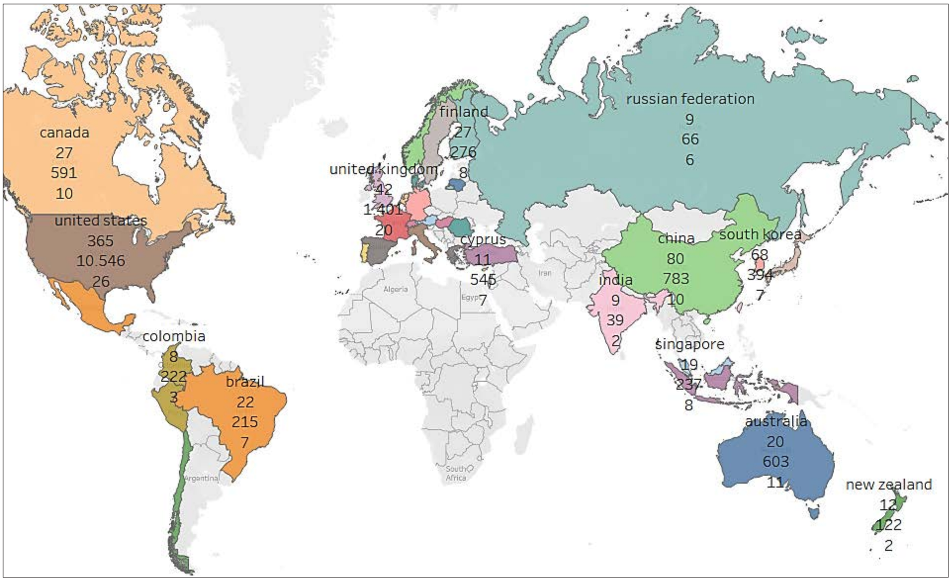
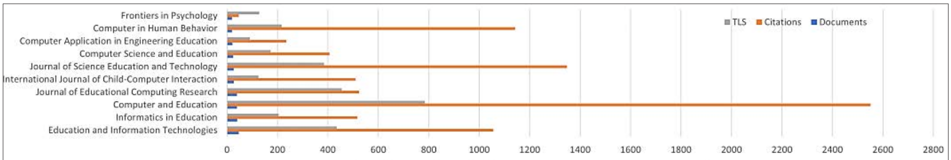


Fig. 8. Visualization of the top CT research countries.

and the natural sciences are two aspects of the world that are inextricably linked. This reality is mirrored in the rise of CT in education, from the basic to the tertiary level. The ability to think computationally is an essential component of scientific practice and should be taught to children at a young age. Given the difficulty of characterizing computational calculations, having this information is beneficial to have in the context of mathematics and the natural sciences. In addition, this article provides a theoretical framework and numerous strategies for approaching the problem-solving process within education and schooling. It's essential to ensure that data, modelling, simulation, problem-solving, and systems work together effectively. The core framework meets the requirements for the maturation of CT (Weintrop *et al.*, 2016). The fundamental explanation offered in this article presents several challenges and directions that can be followed to advance research on CT, which is one of the reasons this article receives a lot of traffic.

The journals with the most significant number of documents, citations, and total link strength from publications connected to CT are displayed in Fig. 9. The journal with the most important number of documents is Education and Information Technologies, which has 47. It is followed by Informatics in Education, Computers, and Education, and the Journal of Education Computing Research, all of which have the same number of documents (40). However, the journal with the highest number of citations overall is Computer and Education, which has 2551. It is followed by the Journal of Science Education and Technology, which has 1347 citations; Computer in Human Behavior, which has 1142 citations; and Education and Information Technology, which has 1056 citations. Based on these findings, the journals that publish the most documents do not necessarily also have the most citations.



	Education and Information Technologies	Informatics in Education	Computer and Education	Journal of Educational Computing Research	International Journal of Child-Computer Interaction	Journal of Science Education and Technology	Computer Science and Education	Computer Application in Engineering Education	Computer in Human Behavior	Frontiers in Psychology
TLS	435	205	784	455	125	385	173	91	217	128
Citations	1056	517	2551	524	510	1347	406	235	1142	47
Documents	47	41	40	40	28	27	25	22	20	20

Fig. 9. The top ten journals with the number of documents, citations, and total link strength.

In addition, Computers and Education possess the total link strength (TLS) that is greatest in the journal source, with 784 TLS. The Journal of Education Computing Research comes in a close second with 455 TLS, then Education and Information Technologies with 435 TLS, and finally, the Journal of Science Education and Technology with 385 TLS. This information demonstrates that having many documents and citations does not necessarily result in a high TLS.

4.2. *Co-Occurrence Analysis*

Index and author search terms are available to researchers in the Scopus database. Article authors often choose keywords for search engines that best characterize their work. The article's metadata can be improved with the author's addition of relevant keywords. As opposed to this, index terms in Scopus are selected for inclusion in the database using a predetermined set of criteria. This method considers the index and the text of the title, abstract, and authors' chosen keywords. VOSviewer provides three distinct methods for examining keywords: index-based, author-based, and a combination. As the author has the most intimate familiarity with the subject matter of this piece, the author keyword is used exclusively throughout. Keywords used in the index can cover more ground than those used in the author's bibliography (Xiao *et al.*, 2022).

Fig. 10 displays the author's keyword network used in the study of CT. A total of 2628 keywords were relevant to the author's analysis. A graph like this is revealed when only the keywords that have appeared at least once are considered. In a typeface, the size of a keyword indicates how frequently it is used. Because of its importance as a keyword for sorting papers in the Scopus database, "computational thinking" is often written in bold. The study of CT yields a set of keywords that may be visualized into five distinct clusters and then used to describe networks between the terms. Different lines of research on the same topic have been grouped. The study shows a pattern that sometimes arises that is more common among a subset of the population. Every new cluster conforms to this pattern. We've assigned each color to help distinguish between different keyword sets.

VOSviewer will default group network nodes into logical structures called "clusters." Groups of nodes that are very similar to one another form a cluster. In a network,

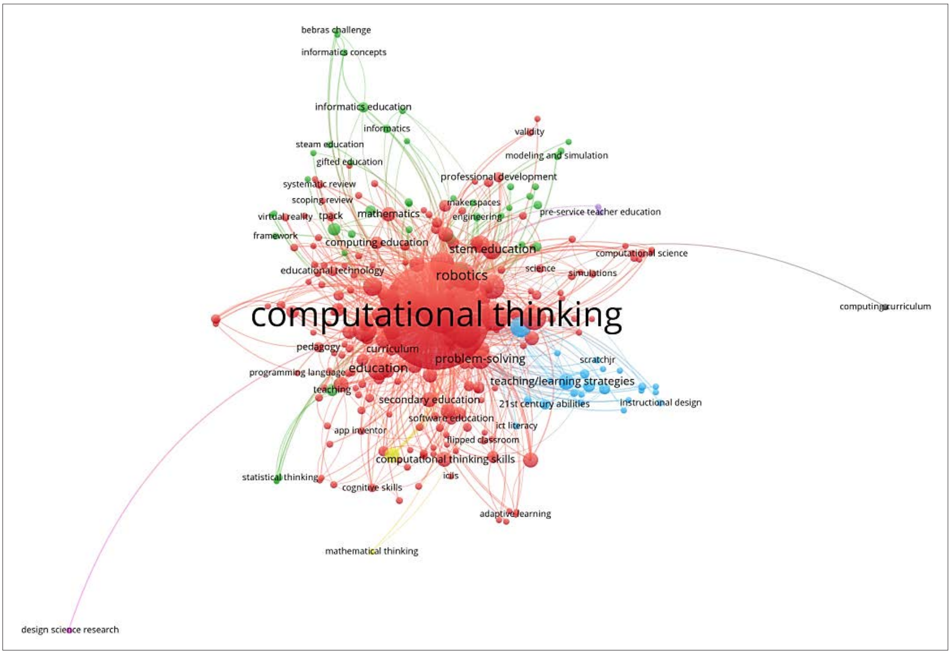


Fig. 10. Cluster visualization based on the topic of CT.

every node belongs to exactly one cluster. The resolution option controls the total number of clusters. Greater values for this parameter result in a more significant number of clusters. VOSviewer's bibliometric network visualization feature employs color to signify a node's membership in a .specific cluster (Waltman *et al.*, 2010b). An optimization algorithm is needed for the method. An intelligent local movement algorithm is used in VOSviewer for this purpose (Waltman and Van Eck, 2013).

According to Fig. 10, seven clusters of keywords were found by co-occurrence analysis with author keywords. These groups created network visualizations among terms derived from CT subjects. The resulting groups characterize different lines of inquiry grounded in CT. There are trends in CT, and new keywords that are more particular to each cluster are emerging.

There is a red cluster up front. The most used term is "computational thinking." Integration with "programming", "scratch", "educational robotics", "education", "problem-solving", "K-12 education", and "algorithm" has garnered attention. Since these concepts are most frequently mentioned in publications using terms from the red cluster, it's safe to assume that these works focus on the relationship between CT and some of these keywords. CT emphasizes teaching students how to think algorithmically, build computational solutions to issues, and code. It highlights the abilities children can acquire through programming and algorithmic practice, such as thinking abstractly, solving problems, seeing patterns, and reasoning logically (Angeli and Giannakos, 2020). Learning to code is a skill that must be fostered and nurtured. Tools like Scratch and App Inventor can make a big difference in helping students acquire this skill (Molina-Ayuso *et al.*, 2022; Pérez-Jorge and Martínez-Murciano, 2022). The use of educational robotics can shed light on where students are having trouble learning and where they are making progress in CT because of the robots' strong psychometric qualities (G. Chen *et al.*, 2017). By examining the terms that frequently appear in the abstracts of the red clusters, we can see that various research has merged CT into programming, educational robotics, education, problem-solving, K-12, and other domains. It shows that researchers are getting more serious about studying the educational implications of CT. However, the scope of the current investigation can only cover so much ground, demonstrating the need for additional research into CT across all disciplines. New research in this area, utilizing all available methods and tools, will undoubtedly advance the field considerably.

Typical domains where CT is used include "engineering", "informatics education", "modeling and simulation", "virtual reality", and "problem-solving", which make up the second green cluster. CT is a collection of abilities today's students need to effectively utilize and develop tools and comprehend the implications of their capabilities and limitations. Understanding the system, designing a solution, and coming up with innovative ideas are all processes that benefit from manipulating and generating computational artifacts in the context of problem-solving (Emara *et al.*, 2021) and engineering design (Lyon and J. Magana, 2020). There has been an increase in engineering specializations that rely on computational modeling, simulation, and software. (Lyon and J. Magana, 2020; Magana and Silva Coutinho, 2017). Alongside these developments, efforts have been made to incorporate CT with virtual reality technologies (Nguyen *et al.,* 2019; Nguyen and Dang, 2017).

Cluster 3 in blue is a group of dominant keywords in education. Keywords that often appear in this cluster include: "assessment", "teaching/learning strategies", "instructional design", "STEM education", and "teacher education". Researchers working in education have been increasingly interested in the concept of CT. Many researchers find it challenging to measure CT skills because there is an increasing demand for and interest in investigating how to assess the ability of CT skills in education. It has made it a challenge for researchers to measure them.(Shute *et al.*, 2017; Tang *et al.,* 2020). Using CT in the classroom is the same as any other educational practice. Improving students' CT skills requires tactics that aid their understanding when teaching and learning. One approach uses educational robots to supplement classroom instruction (Chevalier *et al.*, 2022) and employs virtual professional development techniques (Jocius *et al.*, 2022). ScratchJr (Chou, 2020), Scratch4SL and Second Life (Pellas and Peroutseas, 2017), SplashCode (Wangenheim *et al.*, 2019), and computer programming (Sun *et al.*, 2021) are some examples of instructional design in learning CT in STEM education. All these aspects are efforts to develop CT in education.

Cluster 4 in yellow shows how keywords associated with CT relate to those associated with mathematics. Scholars haven't spent much time exploring the intersection of these two terms. It is a promising sign that researchers can finally use to fill the void in this area. As the field of computing continues to advance at a rapid pace, governments around the world are placing greater emphasis on the importance of computer science education. That is to say that teachers at all educational levels have begun incorporating lessons in programming and CT into their IT classes. Research on CT often focuses on how students acquire and hone their CT abilities. Much research has neglected to examine how to foster students' CT best regarding mathematical thinking. Because of its centrality to educational research, the teaching field has traditionally focused on factors that have been shown to have a constructive impact on students' academic and personal development. Mathematical knowledge intervention research looks crucial for gauging students' academic progress with subpar intelligence. Unfortunately, studies bridging the computational and mathematical thinking gap are relatively scarce. Though it's critical to study how understanding mathematical thinking and students' pedagogical abilities concerning CT might improve student and teacher performance, this research has limitations (Liu *et al.*, 2019).

Only one interaction involving "computational thinking" and "pre-service teacher education" relates to the fifth cluster. This cluster suggests that the keywords pre-service teacher education and CT are not frequently used in the study linked to CT. It has not yet been possible to conduct research on a broad scale concerning the development of CT in primary education and higher education settings. According to one school of thought, CT abilities at a younger age resulting in better outcomes. As a result of teachers' significant role in ensuring that students are exposed to CT during the learning process, teachers need to prepare effectively. This introduction can be offered to all science subfields, beginning with the fundamentals and progressing to incorporating CT into educational practice (Butler and Leahy, 2021; Gabriele *et al.*, 2019; Umutlu, 2021). In this context, many gaps can still be employed in developing CT in pre-service teacher education. As a result, academics can explicitly join that area to create it if they choose to do so.

Only two words – "computational thinking" and "computing curriculum" – interact inside this black cluster. Based on research in this area, computers are barely touched upon in formal education settings. When dug more profound, the term "computer curriculum" reveals a wealth of nuanced topics for study by curriculum designers at all educational levels, from primary to graduate. One factor that determines whether students successfully learn CT is the curriculum they follow. A program's success in teaching CT depends on the individual teacher. The teacher's engagement concerns his pedagogical skills and his actual classroom practice. In addition, students' knowledge and CT skills might benefit from using technology in the classroom. There is an interplay between the instructors' knowledge, beliefs, habits, and culture when employing technology in the classroom. Educators have a significant obstacle when developing lessons for CT. Adopting technology into the curriculum is not straightforward. If changes occur by applying CT, instructors will encounter internal and extrinsic problems because of implementing such changes (Larke, 2019; Sentance and Csizmadia, 2017). The cluster of resources here addresses a significant knowledge vacuum in this area by providing studies and analyses on how to incorporate CT into educational programs best

CT and design science research are the two corresponding keywords that comprise the seventh cluster. Studying the paradigm that results from these two terms is crucial. Research in design science related to CT has roots primarily in engineering and artificial science, a way of problem-solving by producing novel objects designed with knowledge and innovation. CT and design science research aim to further human understanding.

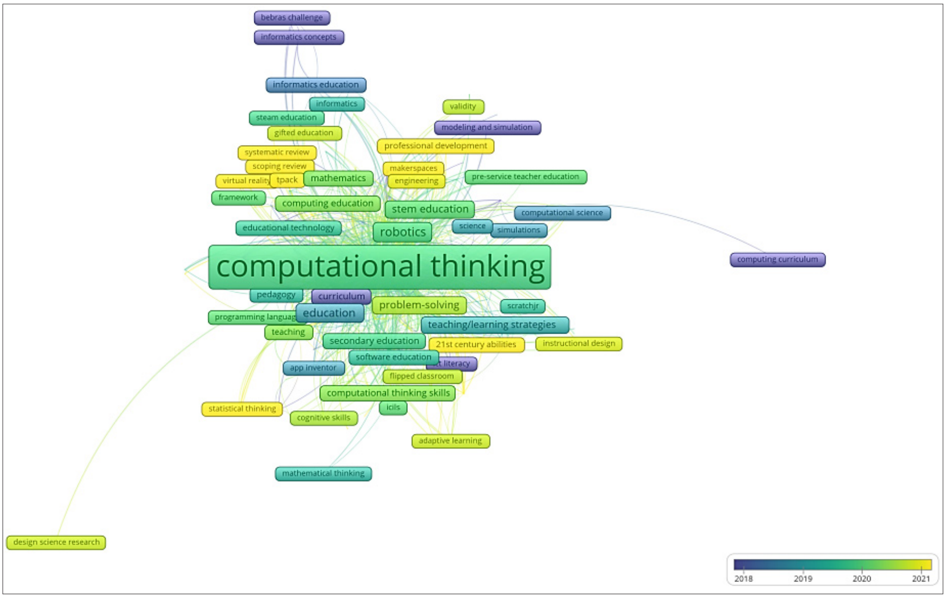


Fig. 11. Overlay visualization for authors' keywords in CT.

Research in design science examines issues that are pertinent to the real world. The need for research in this area is due to an alternative solution that needs to be empirically tested using technology. Needs analysis is frequently required for the early identification of needs when implementing design science research combined with CT. As a result, design science research evaluates the academic knowledge base to characterize how much design knowledge is available to solve challenges. However, there are also cases where development needs are based on research and data already collected. The plan is for students to use this framework to learn how to solve problems using data science theory and broaden their perspectives on data science issues (Song and Zhu, 2017). Based on the cluster analysis results, future studies in this area would likely advocate for greater incorporation of design science research into higher education technology curricula (Apiola and Sutinen, 2021). The low level of research around CT with design science research can also be identified through this cluster's analysis, allowing future studies to fill this gap.

4.3. *The Web of Science Database Provides Fundamental Analysis for the Comparison.*

This section will compare the fundamental analysis of the Web of Science (WoS) database using co-authorship and co-occurrence analysis. The results of these two primary analyses will demonstrate that each database utilizes a unique algorithm to present the data they contain.

In the WoS database, 17837 authors write on CT. There are 663 writers with multiple contributions. The WoS database reveals that five author chains have written the

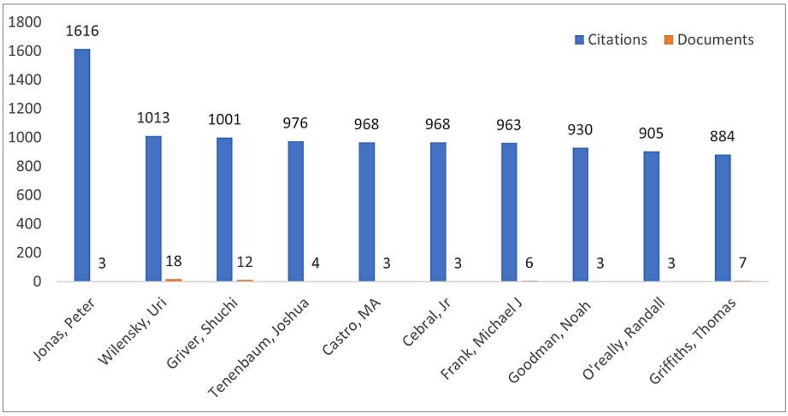


Fig. 13. The CT authors with the most citations in the WoS database.

most documents together (Fig. 12). Dagiene, V., has 22 papers. The writers with the most papers in the WoS dataset are Biswas, G., Wilensky, U., and Robles, G. Each of these authors has produced 18 unique documents, and Repenning, A. has produced 17 unique documents. Meanwhile, there are four authors with a combined total of 15 papers. These authors include Repenning, A., Barnes, T., Roman-Gonzales, M., and Magana, A.J.

The writers with the most citations are displayed in Fig. 13, which may be seen here. The number also considers the total number of papers in the authors' possession. According to this investigation, the number of citations does not appear to follow a linear relationship with the number of documents the authors own. Jonas, P. has a total of three papers that include a total of 1616 citations. The following in line is Wilensky, U., who has 1013 citations and 18 documents. In the meantime, Grover, S. has compiled 12 texts that have a total of 1001 references. The following person on the list is Tanenbaum., J. B., who has four documents and 976 citations. Both Castro, MA., and Cebral, Jr. have accumulated 968 citations. Finally, Michael Frank, Noah Goodman, Randall O'Reilly, and Thomas Griffiths each have 963, 930, and 905, 884 references to their names, respectively. Only Wilensky, Uri., included in Fig. 12's largest group of authors, was among the top 10 authors regarding the number of times other researchers cited their work.

In total, 4324 World of Science database organizations covers CT. Just 204 institutions are missing fewer than ten documents. In Fig. 14, we present a list of the organizations that have published the most numbers. The University of California, Los Angeles, is now in first place on this list with 98 documents created. After that comes Carnegie Mellon University with 98 documents, then on to Colorado University with 50 documents, and so on until we reach the end; notably, all ten organizations in this list with the most documents originate from the United States.

The Massachusetts Institute of Technology (MIT) is the institution that has been cited the most times (7143), as seen in Fig. 15. It makes MIT the organization that holds the record for the most significant number of citations. Next in line is Princeton Univer-

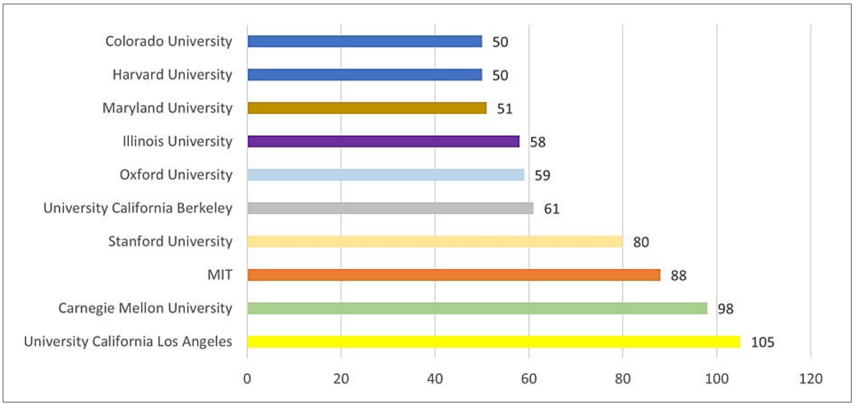


Fig. 14. The organization with the most documents about CT on the WoS database.

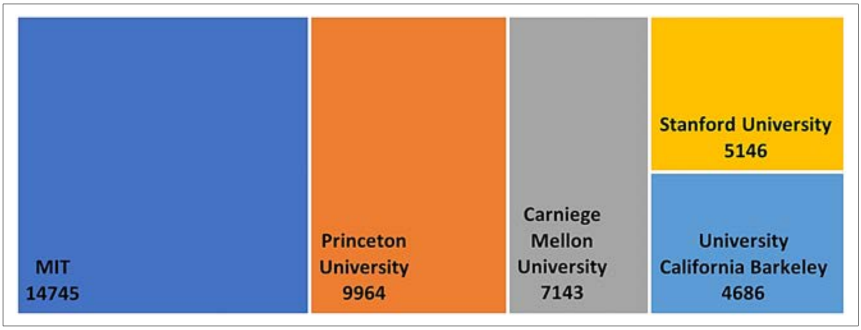


Fig. 15. The organization with the most citations in CT on the Web of Science.

sity, with 9964 citations, even though it only possesses 36 papers. It was next, followed by Carnegie Mellon University, which had 7143 citations. The University of California, Berkeley comes in last place with 4686 citations, falling behind Stanford University, which has 5146 citations.

In the WoS database, 107 countries have contributed to research on CT. However, only eight countries have produced at least 200 documents. The United States of America is the nation that has made the most significant contributions to the field of study on CT. Table 5 shows the number of documents created in the United States was 2369, 30.53% of the total documents created. The number of citations that were obtained was 81393 in total. Also, this was the highest number among the countries that contributed. In addition to these, China has 753 papers (6464 citations). Next is England, which has 481 documents (13440 citations). The following country on the list is Germany, which has 331 papers and 14023 citations. Even though there are fewer documents in German, the number of citations in German is more significant than in English.

The WoS database's co-occurrence analysis divides the data into three clusters from the VOSviewer's perspective (Fig. 16). The initial grouping is represented by green. The size of the bubbles that these phrases create shows how frequently they appear in this

Table 5

Countries with the most documents and citations in CT on the WoS database

Countries	Documents	Citations
USA	2369	81393
China	753	6464
England	481	13440
Germany	331	14023
Spain	263	6344
Italy	262	4160
Canada	242	4925
Japan	235	3946

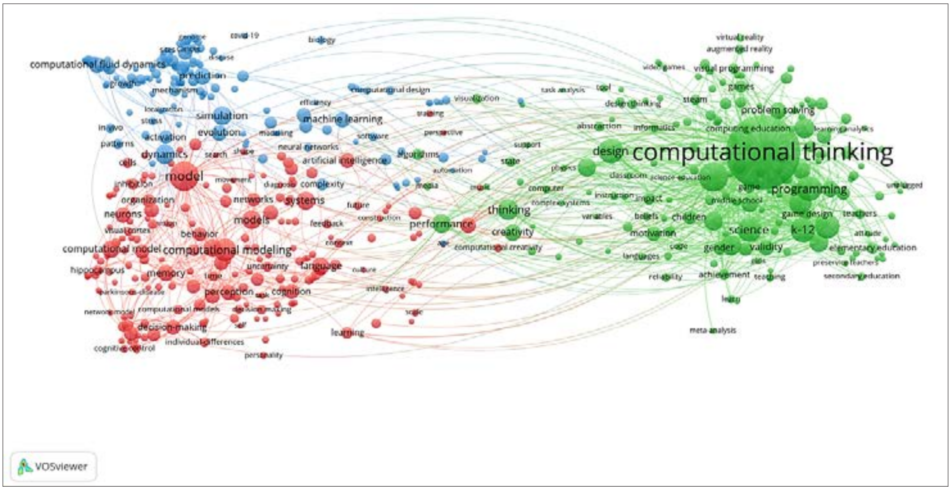


Fig. 16. Visualization of the co-occurrence analysis of CT on the WoS database.

cluster. The concept of CT seems more often than any other. Next are fields like physics, mathematics, computer science education, problem-solving technology, K-12 education, design, robots, coding, frameworks, students, and pedagogy. This group is exceptionally dedicated to the use of computers in academic settings. It is evidenced by the frequency with which terms from education, technologically oriented learning, computer science, and mathematics appear among the top searched terms.

Red was used for the second cluster. The word “model” will be the focus of this huddle. In addition, computational models, computer systems, artificial intelligence, decision-making, vision, cognition, computer networks, and language. If we keep closer attention, we’ll notice that the keywords frequently in this cluster suggest that a significant portion of the conversation focuses on applying CT.

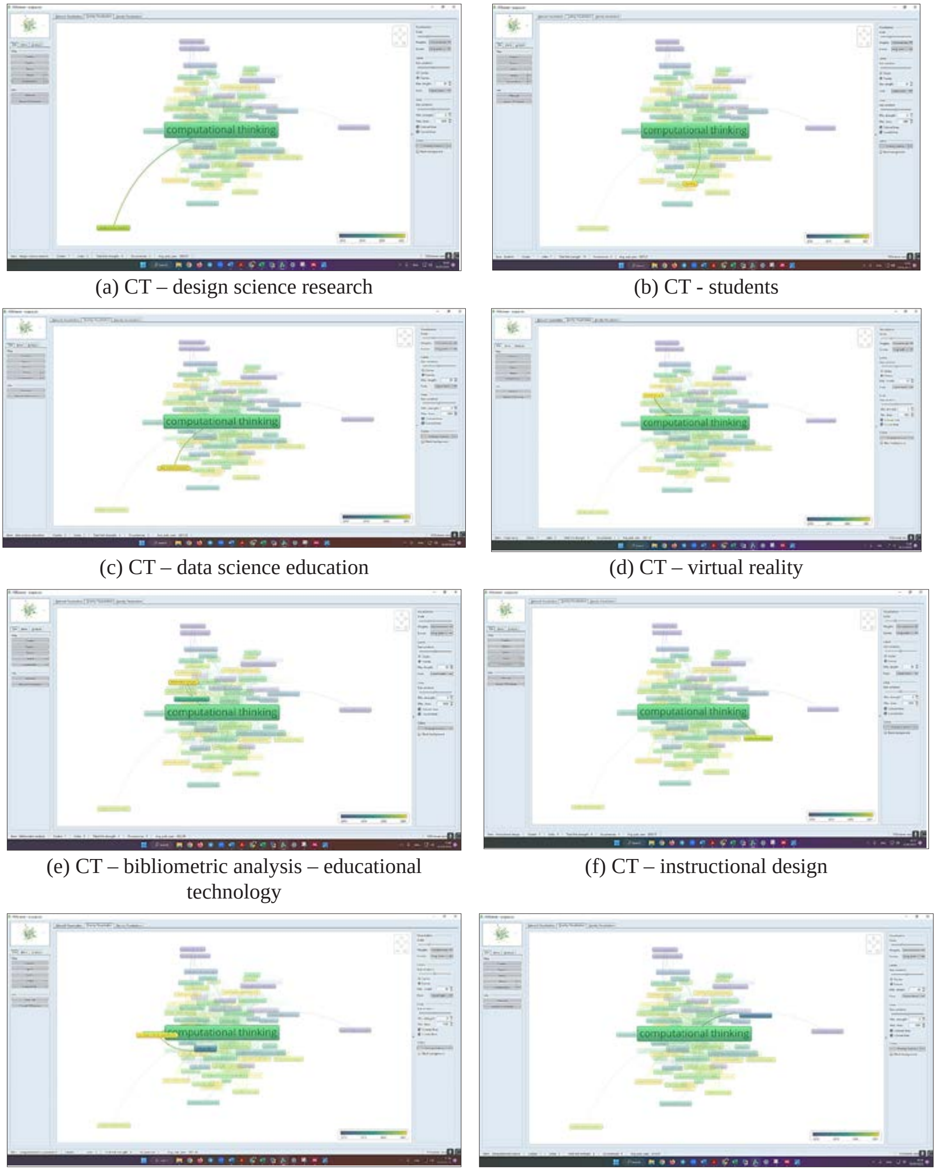
The next cluster is represented by blue. This group contains several instances when the most important keywords are repeated multiple times. This line is used more frequently than any other, as “dynamics” has the giant bubble of all the keywords. The words “simulation”, “evolution”, “algorithm”, “machine learning”, “optimization”, “prediction”, “system thinking”, and “computational fluid dynamics” are among the most common that appear in connection with this cluster.

Using the WoS database, a simple analysis was performed on CT, and the results revealed three critical differences between the Scopus and Web of Science databases. The first distinction between the databases is crucial since they both utilize citation counts to determine how frequently an article is referenced. The database size affects the total number of citations, with more extensive databases yielding more references (Osiński, 2018). There may be differences in citation patterns between document kinds, such as patents and journal articles, that impact the context in which publication norms are established (Cabeza *et al.*, 2020). Therefore, the range of documents included may also be significant. Second, when determining precise citation counts, another area where databases diverge is the precision with which internal matching of citation items is performed (Singh *et al.*, 2021; Stahlschmidt and Stephen, 2020).

On the other hand, incompleteness in the network was discovered. As for the third point, neither Scopus nor WoS is perfect. They have issues with missing references and incorrect connections. Inaccurate matching of quoted and quoted papers, missing references, and erroneous metadata in references are all issues plaguing WoS (Anker *et al.*, 2019). Even though both documents were indexed and had sufficient data to link, Scopus experienced problems with missing citation relationships between them.

5. Suggestions and Recommendations for Future Research

According to Fig. 11, there are a variety of recommendations for additional research on topics associated with the development of research on CT. According to the findings of the overlay visualization provided by VOSviewer, a few potential study patterns can be derived from the discovered themes. These innovative issues in this area of study have the potential to be investigated further. The upcoming research topics for this area are illustrated in Fig. 17. Many potential avenues for further study development are displayed in the visualization overlay because of the authors’ keyword, as depicted by the yellow node in Fig. 17. CT is linked to studies in data science in Fig. 17(a). The association between the two appears yellow, indicating that few CT themes have been explored in design science. Seven publications were found in the Scopus database between 2019 and 2023 when searching for “computational thinking” and “design science research”, indicating that further investigation is warranted. Fig. 17(a) suggests future design science research subjects as applicable frameworks for CT, software engineering, and STEM (science, technology, engineering, and mathematics) integration in higher education. Research conducted can be multidisciplinary if the goal is to discover how to prevent problems by creating effective remedies. Researchers hope their findings prove that data science research is the best method for teaching people how to handle critical situations. Moreover, design science research can be used to integrate the research approaches of many disciplines into technological endeavors. As a result,



(a) CT – design science research

(b) CT - students

(c) CT – data science education

(d) CT – virtual reality

(e) CT – bibliometric analysis – educational technology

(f) CT – instructional design

(g) CT – computational empowerment - education

(h) CT – computational science

Fig. 17. The future research potential topic in CT.

this has implications for many educational skills, such as innovative thought, practical discourse, sound reasoning, and fruitful teamwork.

The network words that include CT and students are displayed in Fig. 17(b). Searching for “computational thinking” and “students” returns 2913 results. However, we adapted our Scopus search to include both terms, CT, and vocational education, as the intended readers are students pursuing degrees in these fields. After searching Scopus, four papers were located. The possibilities for furthering the study of CT for vocational students are enormous, but the method has not yet been implemented in many facets of vocational education. Learning with living books (mobile learning, augmented reality, virtual reality, and mixed reality) within the framework of micro-learning methodologies is proposed to promote CT among vocational students, which could help advance the field of CT. The best way to determine a difference is to conduct the test with the experimental and control groups. More than that, we must create research tools that quantify these factors (e.g., lesson plans, assessment methods, etc.). The study's findings may indicate that students whose education centered on microlearning tactics utilizing live books were more likely to develop CT skills than their counterparts centered on more traditional learning approaches (Leela *et al.*, 2019).

Future research may use the keyword network depicted in Fig. 17(d). Interesting research directions include exploring the intersection of CT and virtual reality. The 78 papers covering 2008-2023 that may be found in Scopus are evidence of this. Scopus data also shows that only 16 publications are from peer-reviewed journals; the remainder is from conferences or other events. Therefore, there is much room for further development of this study area. The urgency with which the requirement for technological mastery must be met arises from the fact that modern technology is advancing at an unprecedented rate; this is directly related to the necessity of resolving tough and intricate challenges. The education sector must consider the current situation associated with integrating AI and IoT, which has become a popular new generation of technology. The purpose is to help pupils become better problem solvers so they may do better in school. Teaching kids to think computationally gives them the tools to analyze complex situations and develop workable solutions. It is recommended to use CT education applied in education that integrates virtual reality technology. The goal is to provide a more lifelike experience through VR. On the other hand, virtual reality (VR) can help students learn about a topic by allowing them to immerse themselves in a simulated environment and solve problems in a way that is like what they would encounter in the real world. Future research findings can reveal that students' enthusiasm to learn and their capacity to think computationally can be increased by utilizing virtual reality, in addition to the preset techniques focused on explaining the core of the problem and brainstorming potential problem-solving (Lai *et al.*, 2021).

Fig. 17(e) illustrates the possibilities for CT concerning bibliometric keywords and instructional technologies. Three articles in the Scopus search discussed the connections between the input terms (CT, bibliometric analysis, and educational technology). All three pieces appeared in the 2021–2022 Education and Information Technologies issue. Many scholars across many disciplines are now increasingly interested in CT. A bibliometric method is still handy in CT research since it allows researchers to track how the field has changed to benefit current and future scientific advancements. The following requirement is to know the outcomes of cross-national and cross-national research collaborations. Additionally, since there are still a lot of issues that can be studied, computational development in STEM is still necessary. In terms of educational technology, there is currently a great deal of interest in continuing to innovate and improve to ensure the sector's viability. It's a significant problem for researchers to address these needs in the period of the fourth industrial revolution, which calls for digitization in the sphere of education. These recommendations and ideas are generally based on current trends to offer guidance regarding the topic's relevance to research needs and directions for future research. With the use of bibliometric study and a CT method, it is intended that this concept would advance the field's research, inform future research, and advance the advancement of educational technology.

Fig. 17(f) shows a term network connecting "computational thinking" and "instructional design." Among the 41 documents returned by a search on Scopus for these two terms, 20 were journal articles, while the rest were either proceedings or reviews. It is clear from the search results that there is much room for growth around research dedicated to instructional design. Creating learning experiences that use instructional media is crucial in vocational education. To maximize the effectiveness of learning strategies, they should be combined with modern learning tools. Several challenges in different spheres of human existence can be overcome with technology in education. Since competence is a skill that can be honed through practice, developing strategies for confronting issues in the realm of technology presents an opportunity to be developed in education. It is advocated that instructional designers apply CT to their work to understand better and address the issues they face. Design-based research approaches, such as the ADDIE model, are commonly used in studies examining the creation of educational media. Media-based activities with an eye on assessing their effect on computational thinking abilities are recommended as part of a curriculum redesign.

A keyword network involving the terms "computational thinking", "computational empowerment", and "education" is shown in Fig. 17(g). We may do some severe digging by focusing on these three terms. There were seven results for these three keywords in Scopus: four proceedings and three journal articles. A strategy or model for advancing CT in education is the notion that needs to be carried out for future research. With the hope of fostering critical technology use in the classroom, computational empowerment can be utilized to extend CT. A current issue, however, is the inability to correctly identify the traits of advances in computer-based empowerment. The first step in achieving CT and computational enablement aims to get an understanding of and be able to communicate developments in computational enablement. Considering this analysis, some potential areas for improvement have been proposed. One is that gaining a sense of computing empowerment is simply becoming knowledgeable about computing concepts, computing practices, and technology's role in the educational system. As a result, the model may be used by educators and researchers to identify, define, and compare learning objectives in the context of empowering computers, ensuring that the goals of instruction are consistent and mutually reinforcing.

As seen in Fig. 17(h), computational science is a rapidly developing topic with much room for future study. Because "computational thinking" is a synonym for "computational science", it is impossible to split the two into distinct networks. There were 46 documents retrieved from Scopus, 16 of which were actual articles, and the rest were either proceedings or reviews. The need to learn CT is emphasized throughout the 16 papers, yet it is unclear where the scientific knowledge gap lies. There is still much room for growth in computational science, as scientists increasingly rely on computational modeling and data analysis to delve deeper into the natural world's mysteries and uncover solutions to long-standing scientific conundrums. The advancement and growth of research in the twenty-first century are inextricably linked to computational modeling, which has many applications in science and will continue to be crucial for science and engineering. Research along these lines seeks to equip the next generation of interdisciplinary scientists with the understanding, competence, and ethics to effectively address the myriad scientific, technical, and societal concerns facing the world today.

Some recommendations and suggestions may be utilized as starting points for more bibliometric investigation if one so chooses. Because of several restrictions imposed on the research, this bibliometric study does not go into detail regarding all the relevant topics and concerns.

6. Limitations

The process of data selection in a bibliometric study might provide several challenges. Not the least of these is how tricky estimating a field's ideal maturity and growth can be. Some limitations of this bibliometric approach can be seen in this setting. The primary restriction is that only papers included in the Scopus database have been used for this study. Peer-reviewed social sciences and education literature can be found in the Scopus database (Hallinger and Kovačević, 2019). However, it does not constitute a complete or exhaustive list of all relevant sources (Mongeon and Paul-Hus, 2016)**.** So, if more databases are used to compile additional publications, the analysis will probably produce different results. Second, this bibliometric study relies solely on scholarly journal articles as its data source. This review does not include articles published as conference papers, book chapters, reviews, editorials, notes, erratum, or correspondence. By doing so, we can refine the bibliometrics' utility and quality while decreasing the number of spurious results. In the future, investigations can use whichever forms of high-quality and filtered publications best suit the analysis's demands. Thirdly, we can't find everything related to CT by searching Scopus with only that term. Variations in monitoring data will allow for more nuanced conclusions in future research.

7. Conclusion

This research work uses a methodology known as bibliometric analysis to evaluate, analyze, and discuss academic journal articles on CT published between 1987 and 2023. Researchers from many countries praise CT and its benefits, increasing the number of studies on the topic. The increasing number of studies on this subject (Bower and Falkner, 2015; European Schoolnet, 2015; Falkner *et al.*, 2015; Heintz and Mannila, 2018; J. Lockwood and Mooney, 2018) indicates that it will be essential in helping academic achievement target. According to investigative findings, the types of classes that most often include CT activities focus on education. The ideas of CT have been applied to various fields of life, and various activities related to them have been incorporated into multiple areas of study in universities. CT is more than a tool for programmers; it is an essential life skill everyone should promote and value. As a result, CT is an area that requires additional research, as is the effect of CT on student achievement.

In addition, applications and methodologies for teaching CT are investigated. Most research has concentrated on the following four instructional strategies: problem-based learning, project-based learning, collaborative learning, and game-based education. Over the last ten years, several scholars have highlighted CT's benefits to students' educational experiences. This result suggests that future research should concentrate on developing and implementing various learning strategies to assist students in developing their subject knowledge and mastering complex skills such as critical thinking and problem-solving. Developing and implementing these learning strategies should be a primary focus of future research.

In sum, CT will face many problems in the future. Still, with further growth and adaptation, it will continue to be a powerful problem-solving technique that can assist in handling various issues in various sectors. CT will have to overcome many obstacles in the years ahead as technology advances. Among the many difficulties that must be overcome, a few stand out as particularly daunting: (1) keeping up with technology advances; (2) addressing ethical problems; (3) encouraging diversity and inclusion; (4) incorporating CT into other professions; and (5) managing complexity. The role of CT in education can be defined as a method of problem-solving that emphasizes the use of algorithms and logical reasoning to deconstruct and then solve even the most intractable of challenges.

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