Trends and Issues in STEM + C Research: A Bibliometric Perspective

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Keywords: STEM + C, Computational Thinking, Computing Education.

Abstract: The integration of computing education or computational thinking with STEM majors has gained substantial research interests. A number of research papers of the topic were published. This work is to provide a comprehensive overview of literature in the STEM + C field through both bibliometric and content analysis. We conducted a systematic search to identify articles and utilized machine-learning-based techniques to analyze these articles. Common bibliometric indicators were used for bibliometric analysis. Machine-learning-based text mining techniques such as LDA topic modelling and flow analysis were used for content analysis. Our analysis spotted STEM + C publication trends, popular topics and their dynamics over time. This work also pinpointed commonly used methodologies for integration study for both PK, K–12 and higher education. Meanwhile, several future research directions were identified. This work contributes to the literature by systematically examining the existing literature and bringing machine-learning-based data mining techniques to the analysis.

1 INTRODUCTION

STEM + C, defined as a field of "science, technology, engineering, mathematics (STEM) and computing", is also interpreted as an integration of computational thinking (CT) to STEM disciplines by National Science Foundation (NSF, 2020). The integration practice of CT into STEM disciplines has drawn increasing research interests over the years. Despite the discrepancies in the definition of and elements of CT among various research (NRC, 2010), STEM + C has remained an active research field in the past decade. However, to our best knowledge, no research has explored the existing literature on the topic using quantitative methods. Bibliometric analysis is used for the study of qualitative features and research performance, especially for large quantities of publications (Wallin, 2005). By conducting a bibliometric and content analysis on the field of STEM + C, this paper aims to provide valuable references on existing literature to researchers and potential topics for future work.

1.1 What Is STEM + C?

There is much discussion on what STEM, computing and CT are for. Although no common agreement has been achieved on their definition, we provide our perceptions and rationales before diving into the field. The goal here is not to exhaust various definitions of the terms, but to clarify the scope of our work. What the acronym STEM stands for is quite clear: Science, Technology, Engineering and Math, as are its alternative versions STEAM and STREAM, which include the Arts and Reading respectively. However, agreement has not yet been reached about what the four letters mean when strung together. Among many perspectives, adopted definitions assume STEM to be one or more of the four isolated subjects, or an integrated continuum of multidisciplinary elements (Bybee, 2010; Kelley & Knowles, 2016). Even within the integrated STEM field, the discussion on the relationships and conceptual frameworks for learning among science, technology, engineering and

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Du, H., Xing, W., Pei, B., Zeng, Y., Lu, J. and Zhang, Y.
Trends and Issues in STEM + C Research: A Bibliometric Perspective.
DOI: 10.5220/0010998800003182
In *Proceedings of the 14th International Conference on Computer Supported Education (CSEDU 2022) - Volume 1*, pages 69-80
ISBN: 978-989-758-562-3; ISSN: 2184-5026

mathematics remains unresolved (English, 2016; Kelley & Knowles, 2016).

The NSF's definition on STEM + C injects C with two components: computing education and CT education. This definition explicitly indicates that computing is a concept different from, but related to CT. Computing represents an integrated field of computer science, information science, computer engineering and information technology (Wing, 2008). According to a report that explores how computing is taught worldwide, computer science and information technology are categorized as disciplines of the field of computing (Jones, 2011). Similarly, computing education is considered to be a broad term that may include one or more of the following areas: computer science, technology literacy or fluency, and information technology (Krakovsky, 2010). Meanwhile, the term "computing" is often used interchangeably with "computation" and "computational" in the context of programming or calculations (Psycharis, 2018), as are "computing education" and "computer science education" (Garneli et al., 2015). The goal of this work is to investigate literature of the entire STEM + C field using bibliometric analysis methods. Hence, we will take computing education as a broad term which includes, but is not limited to, computing education.

Jeannette Wing (2006) argued that CT represents "a universally applicable attitude and skill set" that involves problem solving, system design and understanding human behaviour, and that CT will benefit everyone rather than solely computer scientists. Conceptualizing CT with a focus on problem solving has both advocates and critics (Barr & Stephenson, 2011; Bundy, 2007; Glass, 2006; The Royal Society, 2012). Despite the discrepancy on CT's definition, conceptual framework, and key elements, most literature does not question that CT is a skill related to computing or programming practice. Evidently, CT does not equal program writing. In particular, CT is generally considered to be a different skill from programming, while programming is commonly used to teach CT (Lye & Koh, 2014). As discussions on CT's definition and components continue, this work keeps an open mind on related publications and their adopted conceptual frameworks.

This work considers multiple perspectives on STEM and CT to be legitimate providing that they are in the context of the aforementioned core disciplines. Similarly, this work takes computing education in its broad form which includes computing education, information technology, information literacy and their variations.

1.2 Research on STEM + C

Reviews of literature on CT, computing education, and their integration with one or more isolated STEM subjects have been conducted. Grover & Pea (2013) went through various definitions of CT and illustrated how they were related to the idea of "computational literacy" or "procedural literacy" in past decades. They also examined research and educational practice in CT or computing education, however, STEM did not appear as a requirement to the integration practice. Many studies they mentioned aimed to prompt CT through computing education, rather than STEM. Garneli et al. (2015) examined 47 peer-reviewed articles on K–12 computer science education with a focus on educational contexts and efficient instructional tools and practices. Upadhyaya et al. (2020) collected over 500 publications on K–12 CT research in the USA and conducted a longitudinal analysis of publications from 2012 to 2018. Their focus was to provide a general description of the current status of computing education, including curriculum content, grade levels, and the way in which computing education was delivered. Similarly, several other studies investigated related publications focusing on either computing education (Robins et al., 2003), or CT from multiple perspectives like instructional tools and practice, conceptual frameworks, and assessments (Hsu et al., 2018; Kalelioglu et al., 2016; Tang et al., 2020; Zhang & Nouri, 2019).

Several review studies were conducted to explore the relationship between CT and mathematics and/or science. Weintrop et al. (2016) framed CT in a science and mathematics context by identifying a taxonomy of four categories. They reviewed discussions on CT's definition and its crucial connection to science and mathematics learning, as well as CT-promoting practices at K–12 schools. In addition to a practical taxonomy, their work provided a solid conceptual framework for future research. Barcelos et al. (2018) collected 42 publications that had an experimental design specifically aimed at developing CT skills through mathematics learning activities. They reported a systematic analysis on instructional tools and materials, experimental designs, assessments, and reported achievements. Hickmott et al. (2018) searched 6 databases and identified 393 peer-reviewed articles on CT in K–12 education, then classified results into five categories based on mathematical concepts like algebra or geometry. They found that most studies were from the domain of computer science and focused more on programming skills rather than mathematics concepts.

Existing works linking STEM to CT mainly focus on conceptual frameworks or pedagogical strategies, and most of them are empirical studies. Jona et al. (2014) suggested an alternative strategy to improve students' engagement and sustention in computer science by embedding CT activities within their ongoing STEM coursework. Similarly, Swaid (2015) proposed a comprehensive project to integrate CT into STEM by enforcing CT elements in STEM gate-keeping courses like the introductory level courses of STEM and computer science. Leonard et al. (2016) designed learning activities to integrate technology with CT utilizing robotics and game design. Psycharis (2018) outlined various research and practices for STEAM integration. Although the role of CT, computing education, and their integration was discussed, the goal was to support their proposed model: Computational STEAM Pedagogy. Their research was more qualitative than quantitative.

1.3 Research Goals

Bibliometric analysis uses statistical analysis to systematically extract measurable features from publications within a field (Agarwal et al., 2016). By utilizing various bibliometric indicators and different methodologies, bibliometric analysis can help assess the impact of research, measure the importance of publications, as well as decompose the evolution of a research topic, and identify potential research topics (Agarwal et al., 2016; Song et al., 2019). It has been shown as a reliable and useful tool to overview the existing literature of a research field (Campbell et al., 2010). However, bibliometric analysis has also been criticized for its exclusion of content (Hung, 2012). To address this issue, we extend this work by enabling data-based content analysis to provide a more comprehensive and systematic overview of STEM + C literature. Our work addresses the following research questions (RQ):

RQ 1. What are the current trends, popular topics and their dynamics in STEM + C research?

RQ 2. What is the role of CT or computing education in STEM + C research?

RQ 3. What potential research directions shall be addressed based on current literature?

2 DATA

For the purpose of investigating the whole STEM + C field of work, we take STEM, CT, and computing education in their broad terms and do not exclude articles based on discrepancies with one specific definition. The search terms are defined as a combination of x AND y AND z, as shown in Table 1. Both x and y are used to search article titles, representing key terms of STEM and C, respectively. Meanwhile, z is used to search within abstracts for educational articles where applicable. To search efficiently, "computer" was excluded from y: if "computer" was included in y, then it would form a combination "computer science" with "science" from x. Even with restrictions on abstracts, "computer science" would result in a dramatically large and unnecessary number of results. The term "computer science" or "CS" was excluded for this same reason.

Table 1: Search terms.

	Field	Key Terms
x	Title	STEM OR science OR technology OR engineering OR math OR biology OR chemistry OR physics
y	Title	computational thinking OR programming OR computing
z	Abstract	learn OR course

Figure 1 presents the data retrieval that consists of a two-round search. In the first round, we systematically searched three academic databases: Web of Science, IEEE Xplore, and ACM Digital Library. Publications were considered if they were: (1). Articles written in English, including journal articles and conference proceedings, excluding dissertations, books, or book chapters. (2). Included content and topics falling into the STEM + C field with a focus on integration practice, whether they were empirical studies or not. Based on search terms and restrictions, 2855 records were retrieved and manually filtered by checking the content of titles and abstracts. As a result, 56 records were kept after the first-round search.

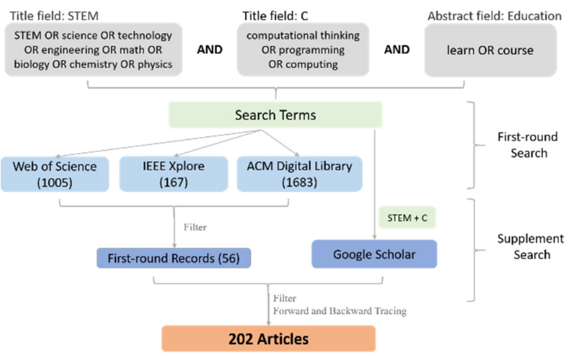


Figure 1: Data retrieval process.

Web of Science is a well-known database of high-quality academic work and widely used to search articles for bibliometric analysis. However, the journals it links to are selected by humans. Google Scholar is a scholarly search engine that connects to the entire Internet, covering more valuable records that cannot be found on Web of Science (Kiduk & Meho, 2006). However, due to the computational settings of the search engine, the search results can be different even one uses the same search term. In addition, search results from Google Scholar cannot be exported systematically for further processing. To maintain the systematic nature and consistency of the searching process, Google Scholar was only involved in the second-round search.

The goal of the second-round search, or supplement search, is to maximize the retrieval of related work which may have been neglected in the first-round search. First, in addition to search terms, we also used "STEM + C" in Google Scholar. Different from prior practice, both searching and filtering were conducted at the same time. Second, forward and backward tracing was conducted to supplement the search. We checked articles that cited the filtered results, as well as those cited by them. As a matter of fact, more records were identified at this stage. Our speculation is that those article titles do not necessarily meet the identified key terms combinations. Instead, more common terms were used like school, students, or education. However, if we used isolated search terms, including the ones mentioned, searched results may be too general to be an efficient search. As a result, 202 publications were finalized for this study.

3 METHODS

3.1 Bibliometric Indicators

Several popular bibliometric indicators were used in this work to measure the impact of collected articles. Publication and citation count are commonly used indicators to assess productivity and influence. Two thresholds of total citation count were used to measure the influence of an author: 100 and 300 (Merigó et al., 2015). Meanwhile, the h-index which measures the level of scientific achievement was also included. The *h*-index used in this work was collected from author's personal page on Google Scholar.

3.2 Sleeping Beauties in Science

Citations are commonly used to evaluate scholarly articles' impact and research performance. Citation dynamics and quoted papers describe the dissemination trajectories of research articles. Sleeping Beauties analysis is one way to examine the citation history of papers. Sleeping Beauties in science refer to articles that were not recognized until years later after publication (van Raan, 2004). Li (2014) proposed a parameter-free criterion to assess the imbalance of citation distribution and later was used to identify Sleeping Beauties in science. Let C be the total number of citations, and c_i ($i \in \{1, 2, \cdots, n\}$) be the number of citations received in the ith year. Gs is an adjustment of Gini coefficient and defined as:

$$Gs = 1 - \frac{2\times[n\times c_1+(n-1)\times c_2+\ldots+c_n]-C}{C\times n}, C > 0 \quad (1)$$

, where $Gs \in (-1, 1]$. When the article receives a total citation of 0, Gs is 1. Otherwise, the higher Gs is, the more citations one article receives in its later years.

3.3 Textual Data Pre-Processing

Data processing is necessary as it systematically and automatically helps trim and clean the textual data by eliminating redundant information. As a result, the textual data will be presented as more structured and relevant, and its meaningful structures can be captured. Several commonly used textual data processing techniques are involved in this work. Special characters and punctuation are removed. Commonly used words across fields that carry little information like "a", "the", and "of" are removed as well using a *stopwords* package. Tokenization divides a string into several substrings for future pre-processing. Lemmatization and stemming are commonly used techniques to reduce inflectional forms of terms. For example, "books", "book", "book's" and "books'" will be mapped to "book". The *lemmatizer* and *Porter stemmer* package are used in this process.

3.4 Keywords Flow Analysis

Using textual data mining techniques, word flow analysis is employed to present the keyword dynamics over time (Du et al., 2019). We define the keywords as terms used repeatedly in abstract. Term frequency of keywords over time are then calculated. The results are presented in a flow chart that provides a general overview of keyword dynamics over time.

The keywords flow will help identify popular research directions.

3.5 Latent Dirichlet Allocation (LDA)

Latent Dirichlet Allocation (LDA) is a widely used unsupervised machine learning algorithm for finding the relationship between documents and words in textual data (Blei et al., 2003). LDA is able to generalize a number of topics from given documents with each topic represented by a few words. The summarization capability makes LDA powerful and convenient for key feature extraction from large-size textual datasets. It has been broadly applied to various research scenarios, including social media content classification, bibliometric analysis, and scientific article recommendation (Blei et al., 2003; Iqbal et al., 2019). Coherence score, which measures how well a topic model fits the data set, is used to decide the number of topics. A higher coherence score means results of such a model represent the documents better than a lower one. We will also use abstracts of collected articles to train an LDA topic model. All analysis for this work is implemented in Python.

4 RESULTS

4.1 Trend & Prolific Analysis

We identified 202 articles with 512 distinctive authors of 187 institutions from 29 countries/regions worldwide. By March 2020, these 202 articles have 5590 total citations.

The annual publication and citation count are presented in Figure 2, where each data point stands for the number of publications or citations within a specific year. Beginning in 2008, there was an increasing trend for both the publication and citation count despite some fluctuation, indicating growing research interest towards the field. Since we only collected work that was available by February, 2020, it leads to a significant drop in year 2020 on both lines. In addition, the USA is the most prolific country with 156 publications, which includes more than 2/3 of the total publications.

In order to view the background distribution, authors' affiliated majors were categorized into four categories: Education, Computer Science, STEM and Other. The distribution is presented in Figure 3. Authors with an education background rank first, closely followed by those with a computer science background. Meanwhile, 8.8% of authors come from STEM majors. This indicates that more researchers in the field are from computer science or STEM majors rather than education.

4.2 Highly-cited Publications and Sleeping Beauties

We calculated the adjusted Gini coefficient (*Gs*) to measure the imbalance of citation history of identified highly-cited articles. Table 3 lists articles whose total citation count is one standard deviation higher the mean (M = 27.98, SD = 83.60) and their *Gs* values. Considering the highest *Gs* is less than 0.50, it is fair to say that most highly-cited publications of STEM + C receive immediate recognition.

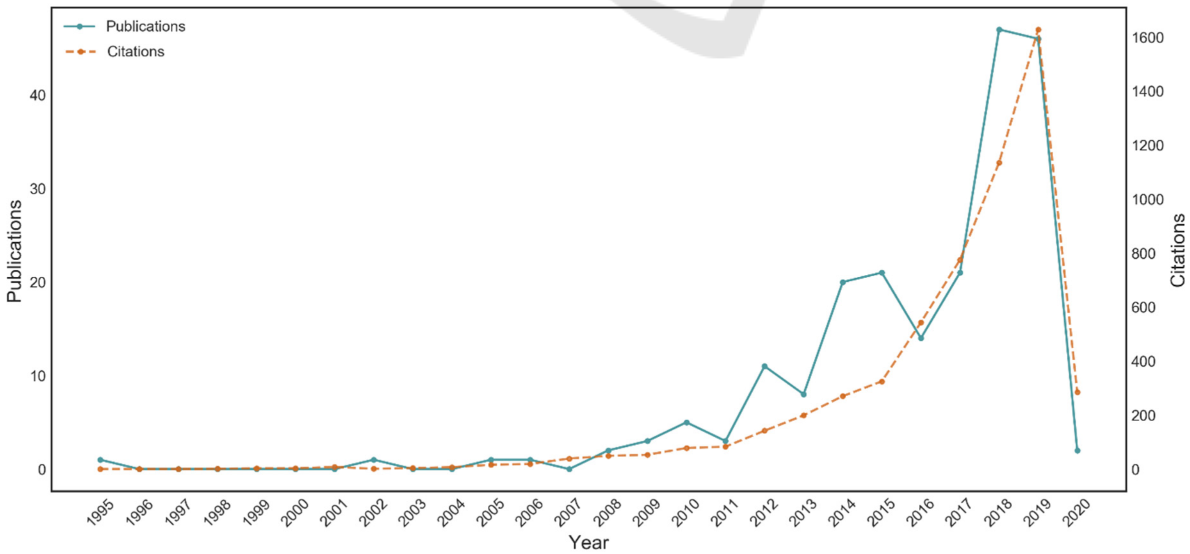


Figure 2: Annual publication and citation trend.

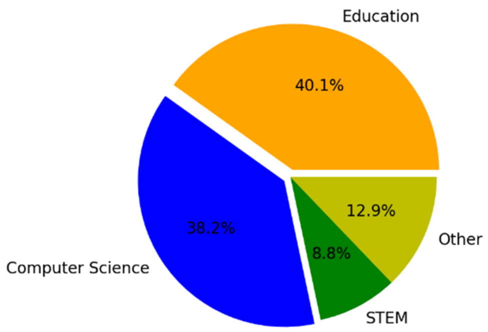


Figure 3: Author affiliated majors' distribution.

4.3 Keywords Flow Analysis

Figure 4 presents the identified keywords by term frequency and Figure 5 shows keywords flow over time. Terms of high frequency yet low information to our analysis like "education", "use", "school", "learn" and "integrate" were removed. The term "CT" was calculated under the term "computational thinking". "Computational thinking" attracts the most research interest over time. Computing-related terms like "programming", "modelling", "simulation", "concept", and "data" are also listed, indicating various aspects of CT or computing education were explored and discussed. Individual disciplines like science and math, as well as the acronym STEM, all received increasing attention over the years. However, research interest in engineering is rather limited in comparison with others. Meanwhile, "teachers" is mentioned far less than "students" in the field, indicating most research focuses on students.

Table 3: Highly-cited articles and their *Gs* value.

Articles	Citation
The learning effects of computer simulations in science education	673
Thinking like a wolf, a sheep, or a firefly: Learning biology through constructing and testing computational theories—an embodied modelling approach.	564
Defining computational thinking for mathematics and science classrooms	406
Computational thinking and tinkering: Exploration of an early childhood robotics curriculum	397
Development of system thinking skills in the context of earth system education	321
Integrating computational thinking with K–12 science education using agent-based computation: A theoretical framework	283
Computational thinking in K–9 education	253*
Visual programming languages integrated across the curriculum in elementary school: A two-year case study using "Scratch" in five schools	225
Computational thinking in compulsory education: Towards an agenda for research and practice	209*
A multidisciplinary approach towards computational thinking for science majors	166
Designing for deeper learning in a blended computer science course for middle school students	142*
Supporting all learners in school-wide computational thinking: A cross-case qualitative analysis	122

**Gs* >.40

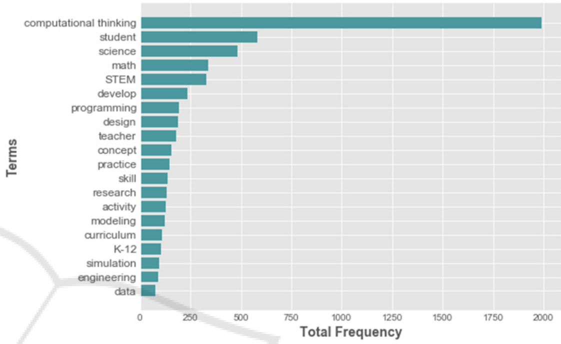


Figure 4: 20 Keywords identified by term frequency.

4.4 LDA Topic Modelling

We first evaluate the performance of our model by calculating the coherence score with topic numbers ranging from 1 to 15, setting the model parameter passes at 50 and *random_state* at 1. Suggested by c-oherence score, model has the highest interpretability when the topic number equals 4. Figure 6 shows the results of our trained LDA topic model and the topic distribution. The numbers in Figure 6(a) are the probability distribution over the topic words. The topic distribution result is displayed in Figure 6(b).

Some terms are common across topics with different probabilities, like "student", "ct", "comput", "scienc" and "school". This is common as topics are not mutually exclusive (DiMaggio, 2013). Several terms are unique to only one or two topics, like "mathemat", "program", "model", "teacher", "effect" and "transfer". Based on the topic words, we can summarize Topic 1 as mathematics/STEM research, Topic 2 as programming learning, Topic 3 as teacher and integration development, and Topic 4 as learning outcomes. As shown in Figure 6(b), more than half of the articles focused on a programming learning perspective of STEM + C research, around one third of articles discuss mathematics and STEM learning and research, while only a few studies address on teachers' perspectives and others.

5 CONCLUSION & DISCUSSION

5.1 What Are the Current Trends, Popular Topics and Their Dynamics in STEM + C Research?

The number of publications and citations in STEM + C consistently grow since 2007, and have increased rapidly for the last 5 years. The USA has contributed dramatically more publications and received more citations than any other country/region. Almost half of the authors are from CS or STEM majors, while around 40% are from education, indicating STEM + C has drawn interest from a wide range of majors. Sleep Beauty analysis suggests work of great importance has received immediate recognition.

LDA topic modelling was used to identify topics: mathematics/STEM research, programming learning, teacher and integration development, and learning outcomes. Most articles in the field focus on the first two topics, while the other two are less discussed. In particular, more than half of the studies focus on the programming learning, indicating that the most popular way to conduct STEM + C research is to integrate programming practice into STEM learning. Prompting integration of CT through mathematics or STEM learning has also gained popularity. More than one third of the collected articles are assigned with the topic of mathematics/STEM research. The percentage explicitly suggests the importance of mathematics in the field.

While the LDA topic modelling sees data on the document level, a term level analysis, keywords flow, is conducted to provide a dynamic and comprehensive view. The term "computational thinking" (including "CT") is the single most frequent keyword and its frequency is about 3 times that of the second term, "student". The frequency of "student" is about 3 times that of "teacher", indicating that many studies focus on students' learning perspectives. Researchers seem to prefer "science" and "math" over "engineering" or "technology". In particular, both "science" and "math" are more frequently mentioned than "STEM". "Engineering" ranks 19th

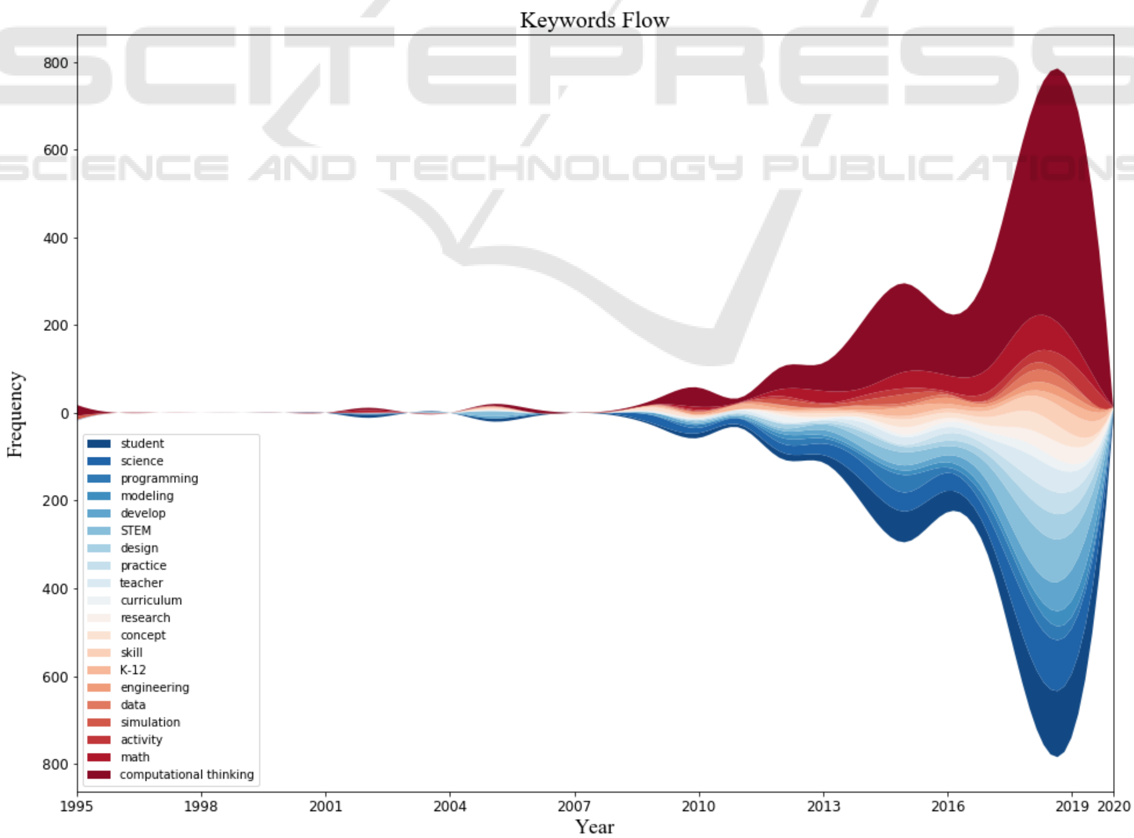
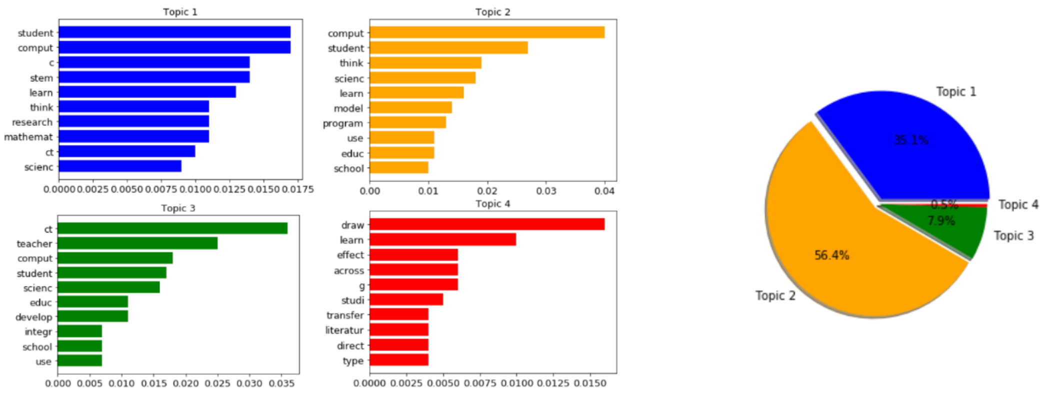


Figure 5: A general keywords flow of all keywords over time: 1995 – 2020.



a. Topic results

b. Topic distribution

Figure 6: LDA results (a) and the topic distribution (b).

mentioned than "STEM". "Engineering" ranks 19th and "technology" is not listed at all. This indicates that attention is not equally distributed within STEM disciplines. Meanwhile, several terms are explicitly computing education related: "programming", "modeling", "simulation" and "data". These can be viewed as popular computing education components in STEM + C research. Among these four, scholars favour "programming" the most. "Data" seems to have received some attention only in the past 5 years.

5.2 What is the Role of CT or Computing Education in STEM + C Research?

CT has been commonly accepted as an effective strategy to benefit and advance STEM learning in the research community (Assaraf & Orion, 2005; Hambrusch et al., 2009; Jona et al., 2014; Perković et al., 2010; Swaid, 2015; Weintrop et al., 2016). It is intuitive to develop CT through programming. Meanwhile, programming is the most commonly used way to teach CT (Lye & Koh, 2014). An alternative way to integrate CT is through computation concepts, modelling and simulations, especially for young children (Assaraf & Orion, 2005; Bers et al., 2014; Sáez-López et al., 2016; Sengupta et al., 2013; Wilensky & Reisman, 2006). To summarize, programming practice, computation concepts, modelling and simulation, and data manipulation are commonly involved in STEM + C research.

One shared interest in STEM + C research is the development of a CT framework that can be widely applied across disciplines in K–12 or higher education (Hambrusch et al., 2009; Jona et al., 2014; Perković et al., 2010; Sengupta et al., 2013; Swaid, 2015; Weintrop et al., 2016). Several goals are extensively addressed by these works, one is to advance STEM learning with help of CT and prepare the next generation to be modern citizens (Hambrusch et al., 2009; Jona et al., 2014; Perković et al., 2010; Sengupta et al., 2013; Weintrop et al., 2016). Meanwhile, embedding CT with current K-12 STEM courses is considered as an alternative solution to K-12 schools' inability to offer computer science or programming classes (Jona et al., 2014; Weintrop et al., 2016). Works focusing on framework development can be roughly classified into 2 categories: K–12 or college level education.

College-level practices of STEM + C framework development often take the form of developing a new course with joint efforts across disciplines. These courses are designed for early years of college education, and mostly involve programming. Several studies on this provided detailed course descriptions. Meanwhile, data manipulations, programming concepts, and simulations are widely adopted by several frameworks to help students learn scientific inquiry, STEM gate-keeping courses, and general courses like Liberal Studies (e.g., Hambrusch et al., 2009; Perković et al., 2010; Swaid, 2015).

K–12 STEM + C framework development mostly attempt to embed CT in current STEM courses. However, programming is not always involved. This strategy potentially saves schools from the financial concerns of hiring new teachers and supporting new courses (Jona et al., 2014; Weintrop et al., 2016). Meanwhile, all students are required to take STEM courses in school, the integration will expose a much wider range of population than a specific course does (Jona et al., 2014; Weintrop et al., 2016). In particular, Perković et al. (2010) proposed an agent-based learning environment for science learning and modeling. In addition to proposed framework, they also specified the computational architecture underlying the learning environment. Their work also conducted an empirical study using the developed tools. All these provide valuable reference to future development. Weintrop et al. (2016) focused on embedding CT in STEM courses for traditional classrooms. Through examining literature, practice, and interviewing teachers, STEM experts and computer scientists, they define CT through a taxonomy. They examined developed skills and generalized four categories: data, modelling and simulation, computational problem solving, and systems thinking. The taxonomy provides significant reference to future research and course development.

Although calls to computing education have received substantial advocates in the past years, the lack of qualified teachers, budgets, and standards barricades its popularization in K–12 education (Israel et al., 2015; Wang et al., 2016). Addressing CT provides a feasible solution to many situations. First, embedding CT within students' current STEM workload guarantees students' exposure while assuring the teacher's comfort with learning materials (Jona et al., 2014). Such practice requires less budget, expertise and effort than developing and supporting a new computer science course. Second, learning programming is not easy, especially for young children. Learning CT lowers the threshold significantly. Although the youngest group of learners are kindergarten children (Bers et al., 2014), most of the work targets students in 5th grade or higher. Block-based programming is preferred when programming is involved. Third, CT addresses adaptability to STEM courses, which takes form in programming, data manipulation, modelling and simulation, or systems thinking (e.g., Assaraf, 2005; Wilensky & Reisman, 2006).

5.3 What Potential Research Directions Shall Be Addressed based on Current Literature?

There are several potential research topics in addition to what has been identified as popular in the past. First, from a disciplinary perspective, more efforts can be made to explore engineering and technology. Some college-level learning activities are designed to utilize CT to solve engineering problems (Hambrusch et al., 2009; Perković et al., 2010; Swaid, 2015). However, this engineering context is much less addressed in K–12 education. Second, there is a potential lack of research on teachers' professional development or training. The work of Israel (2015) is one of the few works that focuses on teacher's professional development. This qualitative study reveals K–12 teachers' concerns and needs to teach CT in K–5 classrooms. Third, community college seems absent from the current research scope. It remains unclear how the college-level STEM + C courses can be adopted by community colleges. Fourth, "data" did not receive much research attention until the past five years. Related activities like data literacy, data science, data manipulation worth more investigation.

5.4 Conclusion

Bibliometric analysis is useful to investigate and explore existing literature in the field of STEM + C. Based on 202 identified publications collected from Web of Science, IEEE Xplore, ACM Digital Library and Google Scholar, this work presents a comprehensive overview of the field by showing publication trends, identifying prolific countries/regions, institutions and authors, visualizing collaborations among countries/regions, institutions and authors, generalizing content-based topics, recognizing research keywords, popular research fields and understudied research perspectives.

There are a few interesting findings. The number of publications and citations in STEM + C have consistently grown since 2007, and have increased rapidly for the last 5 years. STEM + C as an interdisciplinary field has drawn interest from a wide range of majors. We anticipate there will be more publications in the future. Meanwhile, mathematics has the highest frequency among the four STEM subjects, making it the most popular STEM subject for existing STEM + C research practice. When it comes to computing education, the terms like "programming", "modelling", "simulation" and "data" have rather high frequency. Among these four aspects, scholars favour "programming" the most, while "data" seems to start to receive attention in the past 5 years only.

5.5 Limitation

Bibliometric analysis, by its nature, focuses on numbers instead of content. Although we have conducted both term-level and document-level content analysis through a data mining method to address the issue, this work did not fully review all identified articles. Meanwhile, this work only searched three databases and one search engine: Web of Science, IEEE Xplore, ACM Digital Library, and Google Scholar. Search terms were identified based on our understanding of the field as well as search efficiency. It will be helpful if future work can identify more efficient search terms or mechanisms within the field and explore more databases. Meanwhile, our work did not fully examine other expressions that are argued similar to CT, like computational literacy or systems thinking, leading to unidentified related articles.

ACKNOWLEDGEMENTS

This work is supported by the National Science Foundation (NSF) of the United States under grant number 1901704. Any opinions, findings, and conclusions or recommendations expressed in this paper, however, are those of the authors and do not necessarily reflect the views of the NSF.

REFERENCES

Agarwal, A., Durairajanayagam, D., Tatagari, S., Esteves, S. C., Harlev, A., Henkel, R., Roychoudhury, S., Homa, S., Puchalt, N. G., Ramasamy, R., Majzoub, A., Dao Ly, K., Tvrda, E., Assidi, M., Kesari, K., Sharma, R., Banihani, S., Ko, E., Abu-Elmagd, M., … Bashiri, A. (2016). Bibliometrics: Tracking research impact by selecting the appropriate metrics. In *Asian Journal of Andrology* (Vol. 18, Issue 2). https://doi.org/10.4103/1008-682X.171582

Assaraf, O. B. Z., & Orion, N. (2005). Development of system thinking skills in the context of earth system education. *Journal of Research in Science Teaching*, *42*(5). https://doi.org/10.1002/tea.20061

Barcelos, T. S., Munoz, R., Villarroel, R., Merino, E., & Silveira, I. F. (2018). Mathematics learning through computational thinking activities: A systematic literature review. In *Journal of Universal Computer Science* (Vol. 24, Issue 7).

Barr, V., & Stephenson, C. (2011). Bringing computational thinking to K-12: What is involved and what is the role of the computer science education community? *ACM Inroads*, *2*(1). https://doi.org/10.1145/1929887.1929905

Bers, M. U., Flannery, L., Kazakoff, E. R., & Sullivan, A. (2014). Computational thinking and tinkering: Exploration of an early childhood robotics curriculum. *Computers and Education*, *72*. https://doi.org/10.1016/j.compedu.2013.10.020

Blei, D. M., Ng, A. Y., & Jordan, M. I. (2003). Latent Dirichlet allocation. *Journal of Machine Learning Research*, *3*(4–5). https://doi.org/10.1016/b978-0-12-411519-4.00006-9

Bundy, A. (2007). Computational Thinking is Pervasive. *Journal of Scientific and Practical Computing*, *1*(2).

Bybee, R. (2010). Advancing STEM Education: A 2020 Vision. *Technology and Engineering Teacher*, *70*(1).

Campbell, D., Picard-Aitken, M., Côté, G., Caruso, J., Valentim, R., Edmonds, S., Williams, G. T., Macaluso, B., Robitaille, J. P., Bastien, N., Laframboise, M. C., Lebeau, L. M., Mirabel, P., Larivière, V., & Archambault, É. (2010). Bibliometrics as a performance measurement tool for research evaluation: The case of research funded by the national cancer institute of Canada. *American Journal of Evaluation*, *31*(1). https://doi.org/10.1177/1098214009354774

Carmichael, C. C. (2017). *A state-by-state policy analysis of stem education for K–12 public schools.* Seton Hall University.

DiMaggio, P., Nag, M., & Blei, D. (2013). Exploiting affinities between topic modeling and the sociological perspective on culture: Application to newspaper coverage of US government arts funding. *Poetics*, 41(6), 570-606.

Du, H., Nguyen, L., Yang, Z., Abu-Gellban, H., Zhou, X., Xing, W., Cao, G., & Jin, F. (2019). Twitter vs News: Concern analysis of the 2018 California wildfire event. *Proceedings - International Computer Software and Applications Conference*, *2*. https://doi.org/10.1109/COMPSAC.2019.10208

English, L. D. (2016). STEM education K-12: perspectives on integration. In *International Journal of STEM Education* (Vol. 3, Issue 1). https://doi.org/10.1186/s40594-016-0036-1

Garneli, V., Giannakos, M. N., & Chorianopoulos, K. (2015). Computing education in K-12 schools: A review of the literature. *IEEE Global Engineering Education Conference, EDUCON*, *2015-April*. https://doi.org/10.1109/EDUCON.2015.7096023

Glass, R. L. (2006). Call it problem solving, not computational thinking [8]. In *Communications of the ACM* (Vol. 49, Issue 9).

Grover, S., & Pea, R. (2013). Computational Thinking in K-12: A Review of the State of the Field. In *Educational Researcher* (Vol. 42, Issue 1). https://doi.org/10.3102/0013189X12463051

Grover, S., Pea, R., & Cooper, S. (2015). Designing for deeper learning in a blended computer science course for middle school students. *Computer Science Education*, *25*(2). https://doi.org/10.1080/08993408.2015.1033142

Hambrusch, S., Hoffmann, C., Korb, J. T., Haugan, M., & Hosking, A. L. (2009). A multidisciplinary approach towards computational thinking for science majors. *SIGCSE Bulletin Inroads*, *41*(1). https://doi.org/10.1145/1539024.1508931

Hickmott, D., Prieto-Rodriguez, E., & Holmes, K. (2018). A Scoping Review of Studies on Computational Thinking in K–12 Mathematics Classrooms. *Digital Experiences in Mathematics Education*, *4*(1). https://doi.org/10.1007/s40751-017-0038-8

Hsu, T. C., Chang, S. C., & Hung, Y. T. (2018). How to learn and how to teach computational thinking: Suggestions based on a review of the literature. *Computers and Education*, *126*. https://doi.org/10.1016/j.compedu.2018.07.004

Hung, J. L. (2012). Trends of e-learning research from 2000 to 2008: Use of text mining and bibliometrics. *British Journal of Educational Technology*, *43*(1). https://doi.org/10.1111/j.1467-8535.2010.01144.x

Iqbal, W., Qadir, J., Tyson, G., Mian, A. N., Hassan, S. ul, & Crowcroft, J. (2019). A bibliometric analysis of publications in computer networking research. *Scientometrics*, *119*(2). https://doi.org/10.1007/s11192-019-03086-z

Israel, M., Pearson, J. N., Tapia, T., Wherfel, Q. M., & Reese, G. (2015). Supporting all learners in school-wide computational thinking: A cross-case qualitative analysis. *Computers and Education*, *82*. https://doi.org/10.1016/j.compedu.2014.11.022

Jona, K., Wilensky, U., Trouille, L., Horn, M., Orton, K., Weintrop, D., & Beheshti, E. (2014). Embedding Computational Thinking in Science, Technology, Engineering, and Math (CT-STEM). *Future Directions in Computer Science Education Summit Meeting*, *2002*.

Jones, S. P., Bell, T., Cutts, Q., Iyer, S., Schulte, C., Vahrenhold, J., & Han, B. (2011). Computing at school. *International comparisons. Retrieved May,7, 2013*.

Kalelioglu, F., Gulbahar, Y., & Kukul, V. (2016). A Framework for Computational Thinking Based on a Systematic Research Review. *Baltic Journal of Modern Computing*, *4*(3).

Kelley, T. R., & Knowles, J. G. (2016). A conceptual framework for integrated STEM education. In *International Journal of STEM Education* (Vol. 3, Issue 1). https://doi.org/10.1186/s40594-016-0046-z

Krakovsky, M. (2010). CSEdWeek expands its reach. *Communications of the ACM*, *53*(12). https://doi.org/10.1145/1859204.1859213

Leonard, J., Buss, A., Gamboa, R., Mitchell, M., Fashola, O. S., Hubert, T., & Almughyirah, S. (2016). Using Robotics and Game Design to Enhance Children's Self-Efficacy. *STEM Attitudes*, *Compu*(Journal of Science Education and Technology).

Li, J. (2014). Citation curves of "all-elements-sleeping-beauties": "flash in the pan" first and then "delayed recognition." *Scientometrics*, *100*(2). https://doi.org/10.1007/s11192-013-1217-z

Li, J., & Ye, F. Y. (2016). Distinguishing sleeping beauties in science. *Scientometrics*, *108*(2). https://doi.org/10.1007/s11192-016-1977-3

Lye, S. Y., & Koh, J. H. L. (2014). Review on teaching and learning of computational thinking through programming: What is next for K-12? In *Computers in Human Behavior* (Vol. 41). https://doi.org/10.1016/j.chb.2014.09.012

Merigó, J. M., Mas-Tur, A., Roig-Tierno, N., & Ribeiro-Soriano, D. (2015). A bibliometric overview of the Journal of Business Research between 1973 and 2014. *Journal of Business Research*, *68*(12). https://doi.org/10.1016/j.jbusres.2015.04.006

NRC. (2010). Report of a Workshop on The Scope and Nature of Computational Thinking. In *Report of a Workshop on The Scope and Nature of Computational Thinking*. https://doi.org/10.17226/12840

NSF. (2020). *STEM + C call for proposals*. https://www.nsf.gov/funding/pgm_summ.jsp?pims_id=505006. ([Online; accessed 15-June-2020])

Perković, L., Settle, A., Hwang, S., & Jones, J. (2010). A framework for computational thinking across the curriculum. *ITiCSE'10 - Proceedings of the 2010 ACM SIGCSE Annual Conference on Innovation and Technology in Computer Science Education*. https://doi.org/10.1145/1822090.1822126

Psycharis, S. (2018). Steam in Education: A Literature Review on the Role of Computational Thinking, Engineering Epistemology and Computational Science. Computational Steam Pedagogy (Csp). *S. Psycharis Scientific Culture*, *4*(2).

Robins, A., Rountree, J., & Rountree, N. (2003). Learning and teaching programming: A review and discussion. *International Journal of Phytoremediation*, *21*(1). https://doi.org/10.1076/csed.13.2.137.14200

Sáez-López, J. M., Román-González, M., & Vázquez-Cano, E. (2016). Visual programming languages integrated across the curriculum in elementary school: A two year case study using "scratch" in five schools. *Computers and Education*, *97*. https://doi.org/10.1016/j.compedu.2016.03.003

Sengupta, P., Dickes, A., & Farris, A. (2018). Toward a phenomenology of computational thinking in STEM education. In *Computational Thinking in the STEM Disciplines: Foundations and Research Highlights*. https://doi.org/10.1007/978-3-319-93566-9_4

Sengupta, P., Kinnebrew, J. S., Basu, S., Biswas, G., & Clark, D. (2013). Integrating computational thinking with K-12 science education using agent-based computation: A theoretical framework. *Education and Information Technologies*, *18*(2). https://doi.org/10.1007/s10639-012-9240-x

Swaid, S. I. (2015). Bringing Computational Thinking to STEM Education. *Procedia Manufacturing*, *3*. https://doi.org/10.1016/j.promfg.2015.07.761

Tang, X., Yin, Y., Lin, Q., Hadad, R., & Zhai, X. (2020). Assessing computational thinking: A systematic review of empirical studies. *Computers and Education*, *148*. https://doi.org/10.1016/j.compedu.2019.103798

The Royal Society. (2012). Shut down or restart? The way forward for computing in UK schools. *Technology*, *January*.

Tenenberg, J., & McCartney, R. (2014). *Computing education in (k-12) schools from across-national perspective*. ACM New York, NY, USA.

Upadhyaya, B., McGill, M. M., & Decker, A. (2020). A longitudinal analysis of K–12 computing education research in the united states: Implications and recommendations for change. In *Proceedings of the 51st ACM technical symposium on computer science education (pp. 605–611).*

van Raan, A. F. J. (2004). Sleeping Beauties in science. *Scientometrics*, *59*(3). https://doi.org/10.1023/B:SCIE.0000018543.82441.f1

Wallin, J. A. (2005). Bibliometric methods: Pitfalls and possibilities. In *Basic and Clinical Pharmacology and*

Toxicology (Vol. 97, Issue 5). https://doi.org/10.1111/j.1742-7843.2005.pto_139.x
Wang, J., Hong, H., Ravitz, J., & Hejazi Moghadam, S. (2016, February). Landscape of K-12 computer science education in the US: Perceptions, access, and barriers. In *Proceedings of the 47th ACM Technical Symposium on Computing Science Education* (pp. 645-650).
Weintrop, D., Beheshti, E., Horn, M., Orton, K., Jona, K., Trouille, L., & Wilensky, U. (2016). Defining Computational Thinking for Mathematics and Science Classrooms. *Journal of Science Education and Technology*, *25*(1). https://doi.org/10.1007/s10956-015-9581-5
Wilensky, U., & Reisman, K. (2006). Thinking like a wolf, a sheep, or a firefly: Learning biology through constructing and testing computational theories - An embodied modeling approach. In *Cognition and Instruction* (Vol. 24, Issue 2). https://doi.org/10.1207/s1532690xci2402_1
Wing, J. M. (2006). Computational thinking. *Communications of the ACM, 49*(3),33–35.
Wing, J. M. (2008). Computational thinking and thinking about computing. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, *366*(1881). https://doi.org/10.1098/rsta.2008.0118
Zhang, L. C., & Nouri, J. (2019). A systematic review of learning computational thinking through Scratch in K-9. *Computers and Education*, *141*. https://doi.org/10.1016/j.compedu.2019.1