

Computational Thinking and Learning Strategy in Technical Education: A Bibliometric Analysis of Global Trends, Knowledge Structure, and Future Research Directions

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Abstract—This study analyzes global research on computational thinking (CT) and learning strategies in technical education using 3,899 Scopus-indexed documents published from 2008 to 2026 and mapped with Bibliometrix, BiblioShiny, and VOSviewer. The results show that the growth of publications since 2019 is fast, led by China, Indonesia, and the United States, and the dominant subject areas are Social Science, Computer Science, and Engineering. Keyword mapping revealed two major thematic clusters and eight recurring pedagogical approaches: inquiry-based learning, problem-based learning, creative pedagogy, flipped learning, gamification, online literacy integration, collaborative learning, and CT skill-oriented approaches. Nevertheless, CT research in Technical and Vocational Education and Training (TVET) is still fragmented, with gaps in contextual learning models, teacher readiness, assessment, and integration with practice-based approaches such as the Teaching Factory. The findings suggest that there is a need for more curriculum integration, teacher development, and industry-relevant learning to support students' digital literacy skills, employability, and readiness for technical work.

Keywords—bibliometric analysis, computational thinking, learning strategy, technical education, TVET.

I. INTRODUCTION

Nowadays, global competition is about the value of 21st-century skills in the workplace. One such skill is computational thinking (CT), which means the ability to apply algorithmic techniques to solve complex tasks by decomposing a problem into smaller, more manageable processes and constructing logical, systematic, and analytical reasoning steps. Thus, the Indonesian government has an intention to strengthen digital education, as seen in laws on coding and computational thinking learning in the national curriculum, including within technical and vocational secondary education (SMK). However, some studies reveal the fact that Indonesian students' computational thinking skills are at a low level. The presence of this problem can be explained by two primary causes: (i) students are not familiar with CT being used in real-world or

applied workplace learning situations; and (ii) teachers have had limited exposure to CT or have been using it minimally while teaching.

The results of PISA 2022 show that Indonesian students are still experiencing difficulties in their performance in the subjects of mathematics, reading, and science. Even if PISA does not directly measure computational thinking, these results add to broader concerns about analytical reasoning and problem-solving skills relevant to CT development. CT is a systematic way of problem solving with two levels: identification, analysis, and implementation of solutions (including seeing alternative possibilities and acting accordingly; taking effective strategic steps) versus generalization/transferability (transferring mapping strategies to different situations). Thus, CT is beyond the use of technology and includes systematic problem solving, analytical reasoning, and structured decision making. Its incorporation into contemporary education may also overlap with wider competencies regarding responsible and ethical technology use (Kamha & Chookhampaeng, 2023; Lee et al., 2024).

CT was highlighted by Wing (2006), resulting in increasing attention to STEM Education. Few CT investigations have been done in relation to fields of technical education (engineering, business and office administration, agriculture, health services, or other applied vocational specializations). Instead, most CT studies focus on science or technology or STEM education in general classroom settings. CT skills are very important in technical education, as they allow students to systematically solve technical and workplace problems, interpret production- or service-related data, and apply logical procedures directly to real industrial situations. Recent bibliometric mapping indicates that research on CT in Indonesian technical and vocational education is fragmented and underexplored despite the increasing growth of publication activity (Samual et al., 2025). Most previous research has addressed CT in general education and STEM education, with less developed systematic application of CT in technical and vocational

education contexts. However, recent research emphasizes an increasing interest in digital transformation, Industry 4.0 readiness, and emerging technologies in technical and vocational education (Anwar & Minghat, 2024; Rahmiyanti, 2024; Yang et al., 2026).

Studies in CT have also pointed out that incorporating CT in technical and vocational learning helps to (1) improve cognitive load management and problem-solving skills among vocational/engineering education students (Rahmawati & Sari, 2025) and (2) show that CT and design-thinking integration in TVET often stay within isolated pilot projects lacking strategic institutional anchoring, highlighting the need for continued professional development. Therefore, teachers can meaningfully integrate CT into workplace-based curricula (Jusoh et al., 2026); (3) show that authentic, applied CT interventions in vocational training (e.g., a case study of the relation between CT, STEM and agricultural education and training in a Greek vocational institute) demonstrate how CT and STEM can be linked with applied problem-solving in technical and vocational agricultural education (Chondrogiannis et al., 2021), and; (4) support students' ability to understand the impact of digital technology on industry, contributing to their development as adaptive, work-ready graduates through a CT integration framework linking CT practices to the engineering design process in the VET context (Hermans et al., 2024). Overall, this research's findings provide evidence that the integration of CT in the field has great potential in enhancing quality learning, particularly in areas like workplace readiness, e-literacy, and higher-order technical thinking. Nevertheless, several issues still need to be resolved, such as the absence of a contextual learning model that is specific to SMK lessons at the secondary school level, the lack of understanding among instructors regarding the concept of CT, and limited access to educational technology that meets the industry norms.

These findings lead to the necessity for further investigation as to how CT-based technical and vocational learning models can be developed in a way that relates more closely to the cognitive characteristics of students and the sociocultural and industrial environment in Indonesia. This type of investigation is expected to support the development of adaptive and reflective technical students capable of responding to the socio-industrial demands of the 21st-century workforce. However, research on the relationship between technical education and CT is still scattered and has not been comprehensively reviewed. The conceptual dimension of CT in technical and vocational contexts (e.g., data-informed technical practices, industrial process simulation, or modeling real workplace problems) has not been deeply investigated; instead, existing work focuses more on technology adoption and learning motivation factors. Therefore, this bibliometric study aims to map trends, approaches, and evidence concerning the development of CT in SMK instruction. This research also seeks to identify the gaps in the literature, successful pedagogical approaches, and future inquiry prospects that help in the incorporation of CT into technical education to foster better students' socio-technical/computational skills.

CT competencies in technical education have been studied worldwide (Chondrogiannis et al., 2021; Hermans et al., 2024). However, questions need to be answered about whether Indonesian pedagogy has influenced the conceptions of CT, especially regarding teaching and learning patterns and technology use in instruction. This is because there has been no thorough mapping of the various conceptualizations of CT, and the various teaching methods, technology integration, and assessment instrumentation of CT, which can be broadly used in Indonesian technical and vocational institutions. Weintrop et al. (2016) and Yadav et al. (2021) suggest that CT knowledge should be developed systematically, starting from the CT activity design, instruction and evaluation, and finishing with the technology used to convey the idea of CT. These goals are formulated in two research questions (RQs):

- (i) RQ1. What are the global research trends in computational thinking and learning strategies in technical education?
- (ii) RQ2. Which pedagogical approaches are currently used to support computational thinking in technical education?

II. METHODOLOGY

A. Research Design

This study used bibliometric analysis to map global research trends in computational thinking, technical education, and learning strategies. Bibliometric analysis allows for the quantitative investigation of publication patterns, collaboration networks, research impact, and theme development over time (Aria & Cuccurullo, 2017; Donthu et al., 2021). Bibliometrics provides a way for researchers to analyze the trends of publications, collaborating authors, and shifts of research focus over time. This technique offers a quantitative analysis of the scientific literature. It examines publication trends, collaboration networks, and research impact, for example (Aria & Cuccurullo, 2017).

The expansion of computational thinking in schools and the distribution of papers in the Scopus database by affiliation, research theme, and scientific journal are addressed. Data were analyzed with Scopus and VOSviewer software using RStudio to display literature mapping. It is the intention that such an analysis will enable a holistic impression to be made of the dynamics and orientation of current research trends to underpin both future research developments and academic policy. Data selection was performed according to PRISMA protocols (Moher et al., 2009; Page et al., 2021), while the bibliometric workflow followed the five stages illustrated in Figure 1.

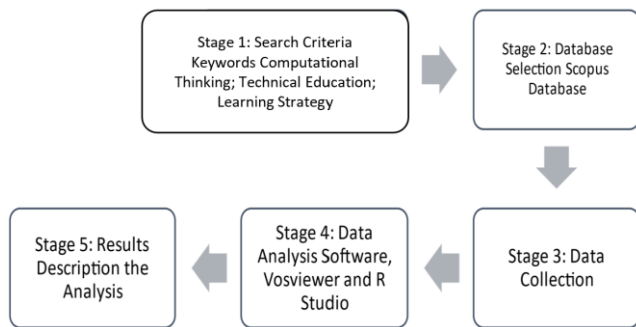


Fig. 1. Stages of bibliometric analysis of computational thinking.

B. Data Collection

Data were collected from the Scopus database using search terms related to computational thinking, technical education, and learning strategies (Donthu et al., 2021). The retrieved records were then prepared for bibliometric analysis, including publication trends, co-authorship patterns, thematic development, and science mapping. This approach is used to analyse the scientific literature (that is, research impact, collaboration networks, and publishing patterns) quantitatively (Aria & Cuccurullo, 2017).

This is a quantitative-descriptive study that analyzes the evolution of Computational Thinking in schools and shows the distribution of publications by affiliation, research

themes, and scientific journals inferred from the Scopus database. Three software tools (Bibliometrix R, BiblioShiny, and VOSviewer) were used for data analysis in RStudio to represent literature mapping. This way, it is intended to provide an integrated overview of the dynamics and trends in research being conducted today that will be useful for prospective development and academic policy. Data selection was performed according to PRISMA protocols (Moher et al., 2009; Page et al., 2021), following five stages of scientific mapping: data collection, analysis, visualisation, and interpretation of results (Figure 2).

C. Data Analysis

The analytical phase : Data were extracted from SCOPUS into CSV (comma-separated values) files. Analysis and visualization were conducted using Microsoft Excel and VOSviewer. Data were prepared and presented in tables, charts, and frequency/percentage distributions using Microsoft Excel. A visual map of a network relationship between authors, institutions, countries, and interrelated keywords and research topics was generated by VOSviewer. The combination of the two pieces of software helped to obtain a comprehensive view of the structure of knowledge, trends of publications, and scientific collaborations in the research field of Computational Thinking in education.

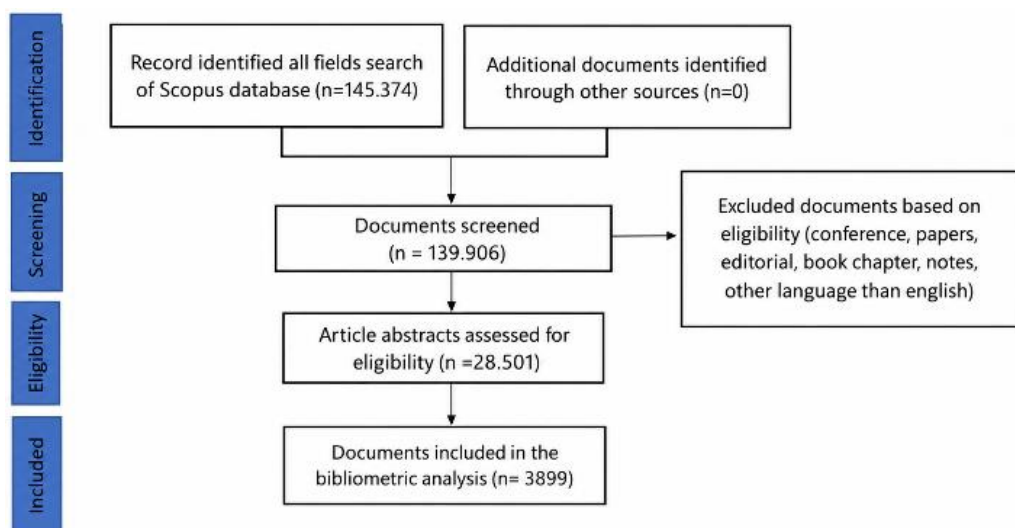


Fig. 2. PRISMA Procedure.

III. RESULTS AND DISCUSSION

A. Global Trends in Computational Thinking and Learning Strategy of Technical Education Research

Results of the search for 3,899 documents on computational thinking and a summary of the trends of documents per year. Figure 3 illustrates a relatively low and stable distribution of publications in the period 2008-2014 with approximately 10-45 documents per year. Following

some fluctuations between 2015 and 2018, the number of publications started to increase gradually from 2019. This growth became more pronounced in 2021 (about 200 documents) and 2022 (about 310 documents). There was a big jump in 2023 (about 410 documents), and this trend continued in 2024 (about 750 documents) and peaked in 2025 with about 1,000 documents. At the time of data retrieval, approximately 680 documents were recorded in 2026, but as 2026 is an incomplete year of publication, this value should not be taken as an indication of a sustained decline. The results of Figure 3 show that the number of

publications has increased significantly, especially from 2021 to 2025, suggesting that computational thinking and technical education are receiving more attention from scholars.

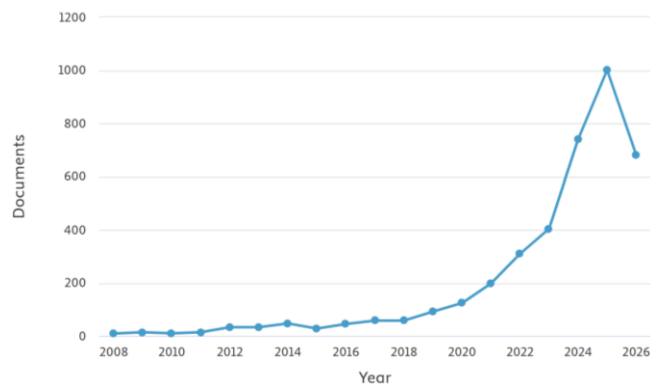


Fig. 3. Documents by Year.

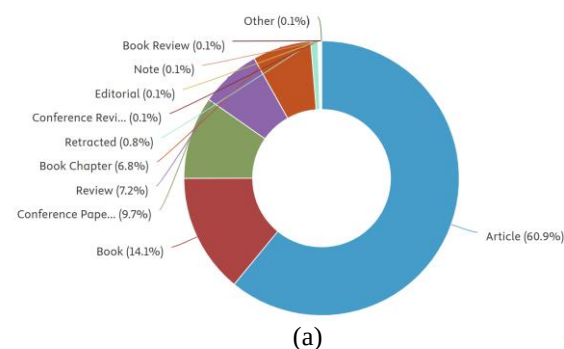
1. Documents by Type and Subject Area

Figure 4(a) shows that Article dominates with the largest percentage at 60.9%, followed by Book at 14.1%, Conference Paper at 9.7%, Review at 7.2%, Book Chapter at 6.8%, Retracted at 0.8%, and then Conference Review, Editorial, Note, Book Review, and Other, each accounting for 0.1%. Figure 4(b) shows that Social Sciences occupies the largest subject area at 31.5%, followed by Computer Science at 19.2%, Engineering at 8.0%, Psychology at 7.4%, Business, Management and Accounting at 7.1%, Arts and Humanities at 4.1%, Mathematics at 3.4%, Economics, Econometrics and Finance at 3.3%, Decision Sciences at 2.0%, Environmental Science at 1.9%, and Other at 12.0%.

2. Documents per Year by Source

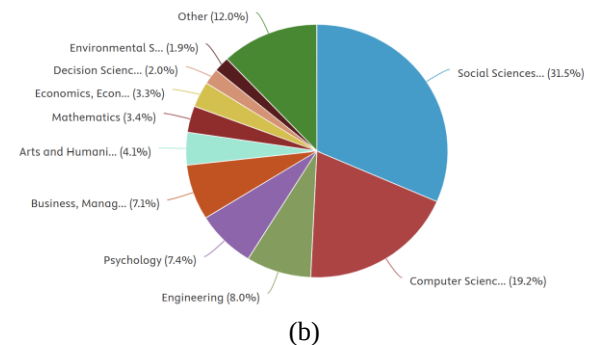
The documents were published in various sources. The following are the five most productive journals publishing in the analyzed fields (Figure 5). The distribution of documents based on the five most productive sources reveals a pattern of gradual growth followed by a sharp but short-lived peak, rather than sustained dominance by any single journal.

Documents by type



(a)

Documents by subject area



(b)

Fig. 4. Documents by type (a) and subject Area (b).

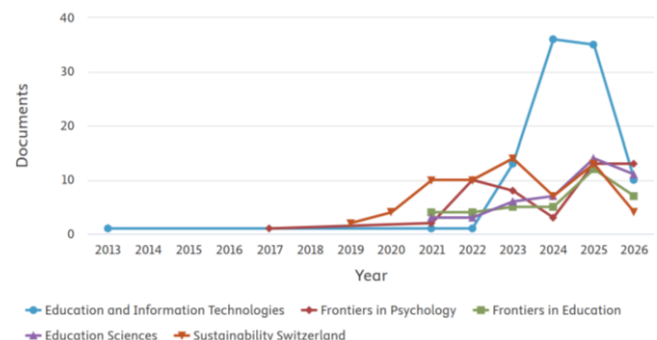


Fig. 5. Documents per year by source.

The output of Education and Information Technologies was low but stable, with about one document per year from 2013 to 2022. It then rose sharply to become the leading source with 36 documents in 2024 and 35 documents in 2025, then fell sharply to about 10 documents in 2026. Frontiers in Psychology was launched in 2019 and reached a first peak in 2022 with 14 documents, fell to 6 documents in 2024, increased again with a peak of 15 documents in 2025, and then dropped sharply to around 3 documents in 2026. The Sustainability Switzerland indicator was launched in 2020 and then showed a fluctuating development, with a peak of 13 documents in 2023 and almost 14 in 2025, and then dropped to about 5 documents in 2026. Education Sciences was founded in 2021 and steadily grew to 13 documents in 2025, before dropping to about 9 documents in 2026. Similarly, Frontiers in Education, which was also published in 2021, stayed at a relatively low level throughout, then increased slightly to around 13 documents in 2024, and then decreased steadily to around 3 documents in 2026. All five sources suggest a substantial increase in output in 2024-2025, largely due to the extraordinary rise of Education and Information Technologies. All sources suggest lower recorded output in 2026. The 2026 data represent an incomplete publication year, so this pattern should be interpreted with caution. So far, no journal has won a permanent hegemony in the field. The rapid increase in publications in 2024-2025 might be a temporary phenomenon, rather than a sign of a stable, core outlet for research on computational thinking and learning strategy in technical education.

3. Documents by Authors

Analysis of the author category shows the most productive authors (Figure 6). The distribution of documents by author shows that publications on computational thinking and learning strategy in technical education are led by a small group of highly productive researchers, with Wu, T.T. standing out as the most prolific contributor with approximately 34 documents, well ahead of the rest. Huang, Y.M. follows with around 26 documents, and Hwang, G.J. ranks third with about 23 documents. Beyond these leading contributors, Nandiyanto, A.B.D. and Lee, H.Y. show moderately high productivity with approximately 18 and 17 documents, respectively. The remaining authors (Hidayat, H., Lin, C.J., Tsai, C.W., and Wang, W.S.) each contributed around 11 documents, forming a cluster of researchers with comparatively similar, lower levels of output.

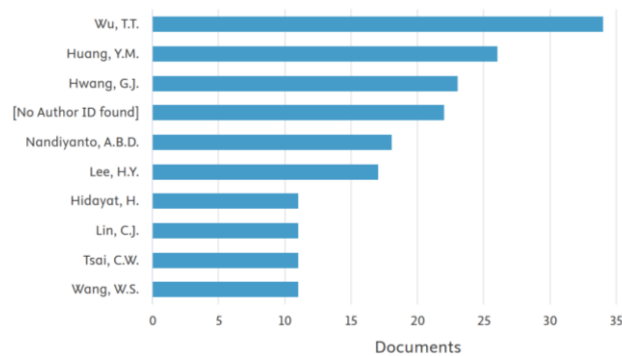


Fig. 6 Documents by Authors (Top 15 most productive authors).

This pattern indicates that research in this field is still concentrated among a limited number of key authors, particularly Wu, T.T., Huang, Y.M., and Hwang, G.J., who appear to play a central role in shaping the discourse. The relatively steep drop-off after the top three authors, combined with the notable share of unidentified authorship, suggests that the research community around computational thinking and learning strategy in technical education remains relatively small and not yet broadly distributed across a wide range of active scholars.

4. Documents by Country

This study was also based on the 10 countries with the most publications and citations for the entire 2008–2026 publication period. This analysis contributes to the research landscape, with China being the leading country in both categories (Figure 7).

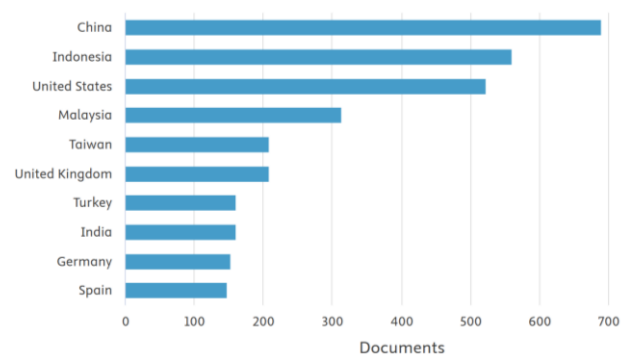


Fig. 7. Documents by Country (Top 10 most Productive Countries).

The distribution of documents by country or territory shows that research on computational thinking and learning strategy in technical education is led predominantly by China with approximately 690 documents, followed by Indonesia (around 560) and the United States (around 530), which together form the primary hub of scholarly activity in this field; Malaysia trails as the next most active contributor with about 310 documents, while Taiwan and the United Kingdom show fairly similar output at roughly 210 documents each, and the remaining countries (Turkey, India, Germany, and Spain) cluster at a more modest level, each contributing between approximately 150 and 165 documents, indicating that scholarly contributions are geographically concentrated in a few dominant countries while a wider group of nations maintains a more modest but still meaningful level of engagement, reflecting the field's growing yet unevenly distributed global interest.

5. Documents by Citation Number

Table 1 shows the ten most cited documents identified in the dataset, and highlights the large variation in both citation counts and field-weighted citation impact. The most cited document is Tzeng and Huang (2011) with 2123 citations, followed by Haleem et al. (2022) with 1954 citations and Uttal et al. (2013) with 1593 citations. But the highest FWCI of 92.4 is reported by Haleem et al. (2022), followed by Sawyer and Henriksen (2023) with 88.28, indicating a very high citation impact in their respective fields. The most cited documents address a variety of topics including digital technologies in education, spatial skills, creativity, STEM participation, game-based learning, and assessment of computational thinking. Among the ten documents, the one most directly related to computational thinking measurement is that of Román-González et al. (2017) with 727 citations and an FWCI of 14.80. The intellectual base of the field is interdisciplinary, drawing on research in education, technology, cognition, creativity, and STEM.

TABLE I
TOP TEN MOST CITED DOCUMENTS.

Rank	Authors and Year	Documents Title	CT	FWCI
1	(Tzeng, Gwo-Hshiung; Huang, Jih-Jeng, 2011)	Multiple attribute decision making: Methods and applications	2123	8.51
2	(Haleem, Abid., et al, 2022)	Understanding the role of digital technologies in education: A review	1954	92.4
3	(Uttal, David H., et al., 2013)	The malleability of spatial skills: A meta-analysis of training studies	1593	29.76
4	(Sawyer, R. Keith, Henriksen, Danah, 2023)	Explaining creativity: The science of human innovation	1435	88.28

5	(Cheryan, Sapna, 2017)	Why are some STEM fields more gender balanced than others?	1124	28.50
6	(Laurillard, Diana, 2012)	Teaching as a design science: Building pedagogical patterns for learning and technology	996	23.76
7	(Honey, Margaret A., Pearson, Greg., Schweingruber, Heidi., 2014)	STEM integration in K-12 education: status, prospects, and an agenda for research	979	28.01
8	(Qian, Meihua., Clark, Karen R., 2016)	Game-based Learning and 21st-century skills: A review of recent research	905	19.07
9	(Reber, Arthur S., 2018)	Implicit Learning and Tacit Knowledge: An Essay on the Cognitive Unconscious	836	15.12
10	(Román-González, Marcos, Pérez-González, Juan-Carlos, Jiménez-Fernández, Carmen 2017)	Which cognitive abilities underlie computational thinking? Criterion validity of the Computational Thinking Test	727	14.80

Note. CT = total citations; FWCI = field-weighted citation impact.

6. Mapping the Evolution of Computational Thinking in Technical Education

Most of the CT research originated in the United States and China, followed by the United Kingdom and Germany (see “Documents by Country or Territory” chart) (See Figs. 8(a) and (b)). The bibliometric data show that these countries are major contributors to the field; however, the present analysis does not directly establish the institutional or curricular factors responsible for their publication dominance. Within the technical education research community, CT is employed to promote digital literacy, workforce readiness, data-driven technical decision-making, and critical thinking skills. As far as linking CT to workplace problem-solving and data-driven learning is concerned, the leaders are the US and China, followed closely by the UK. In the meantime, Indonesia also shows substantial publication activity in the dataset. Further research is needed to determine how national curriculum reforms, including Kurikulum Merdeka, may have contributed to this trend. This demonstrates that CT as a 21st-century skill in technical education is moving in the right direction.

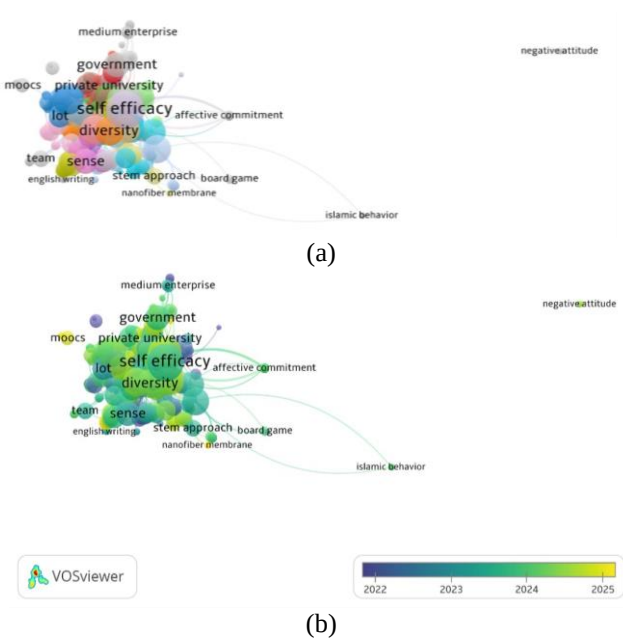


Fig. 8. Trends of research on CT in technical education: (a) distribution; and (b) scale number.

In this VOSviewer image, the relationships among research keywords (2008–2026) germane to CT in technical education are visually depicted. The colors represent the temporal sequence of occurrence of themes: yellow corresponds to newer topics (2025), and blue represents the earliest year (2022). Prominent and closely connected keywords visible in the network (self-efficacy, diversity, and STEM approach) suggest that CT research in technical education has a strong concern with promoting diversity and collaborative learning through STEM-based approaches, and with enhancing students’ self-efficacy in computational thinking.

Furthermore, the importance of both being related to the public sector and different types of educational institutions favours CT literacy in education policies and digital citizenship. Affective Commitment, Team Sense, and Diversity: The constructs of affective commitment, team sense (group identity), and diversity indicate that CT in technical education stresses not only technological competences but also the social and emotional dimensions, including cooperation, empathy, and multicultural awareness. The themes of ‘Islamic behavior’ and ‘ethical attitude’ suggest a local adaptation of CT implementation, characteristic of a Muslim society, touching on social values and ethics, along with how research is extending the cultural or religious dimensions. Taken as a whole, this map reflects that the state of technical education research on computational thinking is evolving in a context-rich and humanistic direction – one underpinned by diversity, social values, self-efficacy development, and integrating technology into citizenship education. CT is being considered an essential tool to develop moral, educated, and informed digital citizens in 21st-century society.

7. Pedagogical Strategies Used in CT-Based Technical Education

A search of documents on computational thinking, technical education, and pedagogy resulted in 250 documents and an overview of document trends in the form of visual mapping from VOSviewer (see Figure 9). The VOSviewer visualization of thinking skills, intervention, and technical education reveals the potential links between CT research terms. This depicts the dissemination of CT research on enhancing higher-order cognitive thinking abilities via numerous instructional strategies. Below are just some examples of clusters, which cover a variety of study topics: developing creativity and critical thinking, integrating CT into technical education and digital learning, and education policy and employability skills. CT in technical education promotes the development of critical thinking skills, online literacy, and problem-solving skills needed to diagnose and solve real-world problems and technical issues. CT studies are not only sensitive to character education, but they are also especially sensitive to technology and provide the means for digital ethics and to face the workforce challenges of the twenty-first century.

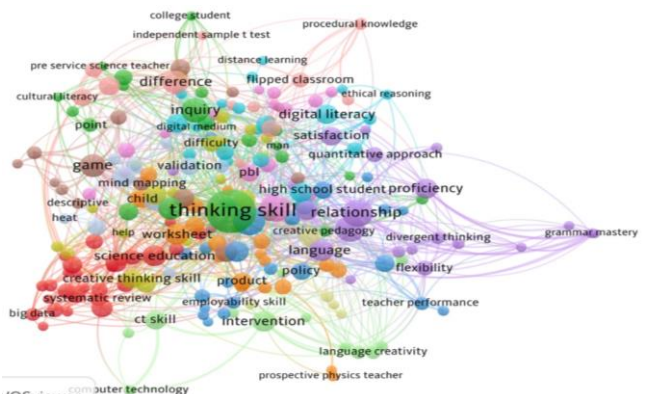


Fig. 9. Trends of Research about Pedagogical Strategies in CT-based Technical Education Learning.

The keywords that stand out in the pedagogical-strategy map are "thinking skills", "intervention" and "creative thinking skills", reflecting the emphasis on higher-order thinking through CT-oriented learning strategies. This means that research in technical education is about developing students' ability to analyze, reflect on, and solve real technical and workplace problems. CT can be developed by means of technology-supported activities in which students are involved in algorithmic reasoning, digital problem solving and structured interpretation of

information. Previous research has also examined the development of computational thinking through digital learning environments and explicit CT-oriented instructional models (Adsawatithsakul & Cojorn, 2026; Reskianissa et al., 2022).

Keywords such as "inquiry", PBL (problem-based learning), creative pedagogy, flipped classroom, and game show that the research was based on project, cooperative, and activity teaching. These tactics assist CT by:

- a. Inquiry learning: Use of digital and scientific processes to explore questions or inferences made and recognize patterns in technical and workplace processes.
- b. Problem-based learning (PBL): Uses CT to solve real-world technical and industrial problems, e.g., inefficient production practices or sustainable resource use.
- c. Creative Pedagogy: Explores technical and workplace phenomena by bringing together creativity and computational logic.
- d. Gamification and online literacy: Using games or virtual environments to foster ethical decision-making and understanding of production and workplace systems.
- e. Inverted classroom. Students study technical or production data out of class, promoting independent learning and critical thinking.

Table II summarizes these strategies, expanding the keyword-map findings into eight recurring pedagogical approaches together with their associated keywords, learning objectives, and illustrative examples of implementation in technical education. It turns out that effective teaching strategies for promoting computational thinking in technical education, according to the keyword map, revolve around three lines of work: (i) seeking and exploring data (inquiry, PBL); (ii) learning together creatively (creative pedagogy, game-based learning); and (iii) technology/literacy integration. They also help learners better understand the technical and industrial dimensions of the digital era while learning to "think algorithmically".

B. Discussion

Results of the bibliometric analysis indicate that CT has become an increasingly visible topic in contemporary education. This pattern is consistent with growing use of bibliometric approaches to map emerging themes in engineering, vocational, and technology-related education (Rahmiyanti, 2024; Susilawati, 2024), with studies growing exponentially from 2018 to 2025.

TABLE II
PEDAGOGICAL STRATEGY AND LEARNING OBJECTIVES FOR TECHNICAL EDUCATION.

No.	Pedagogical Strategy	Related Keywords (from map)	Learning Objectives	Examples of Implementation in Technical Education
1	Inquiry-Based Learning	inquiry, validation, difference	Train students to discover technical patterns and understand cause-and-effect relationships through data exploration and analysis.	Students investigate machine or process fault patterns using sensor/production data, then build models of their causes and effects.
2	Problem-Based Learning	PBL, relationship,	Students research workplace and	Student teams investigate causes of

	(PBL)	intervention	production patterns using process data, then build models of their causes and impacts.	production downtime or defect rates using shop-floor data and propose evidence-based fixes.
3	Creative Pedagogy	creative pedagogy, language, creativity, employability skill	Encourage creativity and innovative thinking in understanding technical and workplace phenomena.	Students design a digital product prototype or promotional infographic, applying creativity and computational logic.
4	Flipped Classroom	flipped classroom, distance learning, satisfaction	Empower students to learn independently through digital resources before class or workshop sessions.	Students study circuit diagrams or equipment manuals online at home; in the workshop, they apply the concepts to hands-on troubleshooting.
5	Game-Based Learning / Gamification	game, mind mapping, science education	Increase learning engagement through game-based simulations.	Students use a virtual factory-floor simulation to practice production planning and decision-making under resource constraints.
6	Digital Literacy Integration	digital literacy, quantitative approach, ethical reasoning	Develop digital literacy skills, ethics, and appropriate use of technology in a workplace context.	Students analyze workplace data dashboards to identify quality issues and discuss ethics in industrial IoT and automated decision-making.
7	Collaborative Learning	team, relationship, language	Train collaborative and communication skills for solving complex technical problems.	Cross-disciplinary group project: students design a digital solution to a real industry problem using shared production data.
8	CT Skill-Oriented Approach	CT skill, thinking skill, creative thinking skill	Cultivate computational thinking patterns such as decomposition, pattern recognition, and abstraction.	Students analyze factors causing production defects using an algorithmic troubleshooting flowchart.

Currently, there is a major shift in the perception of CT, not only as a computer science technical skill, but as a cross-disciplinary competency necessary for creativity, problem solving, and critical thinking across various disciplines including technical education. Several main issues will be examined to answer the study questions and to assess the degree of progress in CT research in technical education today and in the coming years.

1. Global Patterns and the Emergence of Computational Thinking

Following an initial focus on STEM and technology education, CT development has extended into the social sciences, business, and applied technical fields that make up much of technical education, as demonstrated in a bibliometric review of 3,899 papers. This expansion is a basic reconceptualization of CT not only as a technical programming skill but as a cognitive-style construct applicable to multiple domains and transcending disciplinary boundaries (Wing, 2006, 2017). The 3 categories in the CT literature are Social Sciences (31.5%), Computer Science (19.2%), and Engineering (8.0%), which suggest the inherently interdisciplinary nature of technical education, which cuts across technical, business, and workplace-communication competencies. This finding supports Grover and Pea’s (2018) assertion that CT is “a competency whose time has come”—not simply a computer science skill, but an important literacy necessary for workforce readiness in the twenty-first century. A companion bibliometric study of CT within the Teaching Factory model in Asian TVET also reveals “technical education” and “computational thinking” as the two most central, closely co-occurring themes in this literature (Handito et al., 2026).

It presents three different stages in the development of CT research. The first period (2000–2010) was foundational and was characterized by few publications, and CT remained largely a computer science topic. Wing (2006) framed computational thinking as a fundamental competence

beyond computer scientists, which helped expand the interest in integrating CT across educational contexts. This perspective opened up new frontiers for curriculum integration of CT. The second period (2011–2017) was characterized by steady growth of CT as it became integrated into K–12 educational contexts, especially in the STEM fields. Around this time, educators began to consider how to teach CT to younger students, often using visual programming environments such as Scratch (Resnick et al., 2009). The third phase (2018–2025) experienced rapid growth, with an annual publication output of approximately 1,000 documents in 2025. This growth also reflects the evolution of CT as a transdisciplinary concept that has been adopted in various educational domains, including vocational and technical education, where it supports systematic diagnosis of technical problems, interpretation of workplace data, and modeling of industrial processes (Voogt et al., 2015; Weintrop et al., 2016; Wang et al., 2022).

2. Theory and Application of Computational Thinking in Technical Education

The technology dimension of computational thinking fits naturally with workplace practice in vocational and technical education (the domain underpinning this review). This result suggests that scholars and education professionals increasingly recognize the potential of CT to improve students’ understanding of technical systems and production processes. CT provides a basis for comprehending workflow patterns and cause-and-effect relationships in machinery or production systems, modeling industrial or business processes, and practicing data-driven technical decision-making (Hermans et al., 2024; Chondrogiannis et al., 2021). Here we extend the concept of CT, which involves higher-order cognitive skills (generalizing and transferring) as well as problem-solving processes (identification, analysis, and solution finding).

On the second point, students apply algorithmic thinking to comprehend industrial and workplace processes, including the steps necessary to operate machines or offer

services and predict patterns in production or workflow systems (Bråten & Arnesen, 2020). Third, modeling and simulation: students model technical, mechanical, agricultural, or business systems (Chondrogiannis et al., 2021; Shute et al., 2017) to test hypotheses, examine the effects of process changes, and understand the systemic interconnections within industry. Fourth, students deconstruct complex technical or workplace problems (e.g., production bottlenecks, quality-control failures, supply-chain problems) into smaller, manageable units so they can follow root causes and take a systematic approach to problem-solving (Tang et al., 2020).

The broad application of CT in vocational and technical fields is in good harmony with the current learning environments which are centered on workforce readiness, Industry 4.0 competencies and the integration of new technologies in engineering and technical curricula (Anwar & Minghat, 2024; Nandiyanto et al., 2026). TVET strategy reviews have advocated for competency-based, applied learning, where students learn how to diagnose problems, gather technical information, and communicate solutions to real workplace scenarios (Rajamanickam et al., 2024). The practices are similar to the core CT processes of decomposition, pattern recognition, and abstraction (Angeli et al., 2016). Voogt et al. (2015) report that the Partnership for 21st Century Learning (P21) defines CT as providing practical strategies and resources

3. Teaching Methods and Models of Application

The network of terms reveals some pedagogical approaches that are often associated with CT in technical education, such as flipped classroom, inquiry learning, PBL (problem-based learning), creative pedagogy, and gamification. These tactics are based on student participation, problem-solving in real-world situations, cooperation, and digital resources. However, their effectiveness in CT development in technical and vocational settings differs based on the quality of implementation and context.

One approach often talked about for integrating CT into technical education is inquiry-based learning. As Pedaste et al. (2015) have noted, inquiry-based learning is a process in which students hypothesize, collect and evaluate data, develop justifications, and formalize their conclusions. This process fits well with computational practices such as pattern recognition, data collection and analysis, and systematic problem solving. Inquiry-based activities allow students to employ digital resources to investigate technical faults, data-visualization tools to analyze patterns in production data, or simulation tools to understand industrial processes. As reported by Kong and Chookhampaenga (2024), the use of an inquiry- and problem-oriented teaching model with higher technical and vocational college students significantly improves students' capacity to generate researchable technical questions, evaluate evidence, and make data-supported claims regarding workplace problems.

PBL moves CT into authentic technical problems, where students apply computational methods to problems in real workplaces. Hmelo-Silver (2004) described PBL as learning

focused on open-ended challenges that require students to self-direct their inquiry and collaborate in the construction of knowledge. For technical education, PBL can involve real technical and workplace problems that require students to use systematic reasoning, data analysis, and iterative problem solving. A useful framework for understanding how teachers may integrate technology, pedagogy, and disciplinary content within such learning is the TPACK (Technological Pedagogical Content Knowledge) model (Mishra & Koehler, 2006). Likewise, data visualization is both a technical issue (how to use data-visualization tools) and a matter of pedagogical know-how (scaffolding student inquiry) and content knowledge (understanding the principles and practices of a given vocational trade).

Game-based learning and gamification represent another promising avenue for CT innovation in technical education. Dichev and Dicheva (2017) differentiate between game-based learning, which employs games as the principal method of teaching, and gamification, which transfers game elements into a non-game setting. The iterative problem-solving and higher-level strategic decision-making processes that are common to both methods can foster the development of CT when students engage with rule-based systems. In vocational content, students can use computational thinking in virtual factory-floor simulations, IT troubleshooting games, and robotics-based programming activities. Durak et al. (2019) reported positive associations between robotics-based programming activities, computational thinking, programming self-efficacy, and problem-solving. While the study is not specifically situated in technical and vocational education, the findings illustrate the potential relevance of robotics-based learning for technical education contexts.

There are also potential opportunities for CT infusion into the flipped classroom. Flipped classrooms reverse traditional lecture and homework arrangements, with content viewed by students outside class and "homework" becoming an in-class activity. Flipped methods in technical education might have students review technical concepts (such as circuit diagrams or machine operation manuals) at home, then perform hands-on computational tasks, such as simulation or troubleshooting, in the workshop or laboratory. Since learners can explore computational concepts independently and then focus classroom time on applied CT tasks addressing real technical problems, this approach allows for more personalized, hands-on instruction.

4. Obstacles and Prospects

However, there are still several hurdles in the way of promoting the growth of CT research in technical education. The first one is teacher readiness and professional development. Industry 4.0 requires TVET teachers to move beyond traditional instructional practice and to be skillful in technology-supported technical learning (Shahroni et al., 2022). Embedding 21st-century skills competences in technical and vocational education is a big problem (Mutohhari et al., 2021). These larger implementation challenges underscore the need for targeted teacher

preparation and pedagogical support in the CT context. Jusoh et al. (2026) say that the combination of CT and design thinking in TVET frequently results in stand-alone pilot projects that are not embedded within the institutional strategy. Good professional development should also include pedagogical techniques to implement CT in addition to technical abilities and a strong understanding of how CT promotes technical and vocational learning goals (Yadav et al., 2021).

The second challenge is resource fairness, especially in developing countries such as Indonesia. Indeed, the countries dominating CT research and publication output (China, the United States, and increasingly Indonesia itself) are leading the field (see “Documents by Country” above), but implementation in resource-limited technical and vocational contexts may be limited by digital infrastructure, institutional readiness, and availability of appropriate technology-supported learning resources (Jamil et al., 2023). The government’s vision of integrating CT through curriculum revision is encouraging, but fair implementation will require continued investment in infrastructure, materials development, and teacher support.

Thirdly, evaluation is still a huge problem. Technical education requires instruments that are able to measure not only the performance of procedures but also the cognitive and problem-solving skills that support technical learning (Fiandini et al., 2024). Tang et al. (2020) report that the assessment of CT needs to be multi-dimensional, including students’ computational ability, conceptual understanding, problem-solving strategies, and the degree to which they can transfer CT skills across a broad spectrum of technical situations. Designing reliable, valid, and effective CT assessments for technical education remains an ongoing challenge.

Fourth, the linguistic and cultural aspects of the implementation of CT should be considered, especially since technical terms and disciplinary language must be expressed clearly to support students’ interpretation of technical concepts (Nandiyanto & Yulistiani, 2024). Most CT material is generated from national contexts such as the USA, China, and other high-output countries, all of which are the most prolific producers of publications. But the CT implementation may need to be adapted to different vocational and cultural contexts (respecting regional industries, local trade traditions and community values) (Bråten & Arnesen, 2020). The literature on culturally responsive CT instruction in technical education is very limited, including work that connects CT to local industries, traditional craft and trade knowledge, and culturally and regionally relevant examples.

These gaps will have to be filled by future studies, along with a number of new directions. First, longitudinal studies that investigate the development of CT over time in technical education would offer insight into long-term effects and developmental trajectories. Second, further comparative inquiry across cultural and national contexts (e.g., Indonesia, Malaysia, and China) might clarify whether effective CT implementations can be transferred and which situational elements influence their success. Third, the research on the

connection of CT with other important competencies (computer literacy, employability, entrepreneurial skills) will enhance the understanding of how CT works in a full engineering curriculum. Fourthly, and especially for the Indonesian context, future work should investigate how CT can be systematically integrated with the Teaching Factory model that supports the Revitalization SMK reform. A companion bibliometric study found that although “technical education” and “computational thinking” are the two most central themes in this literature, the Teaching Factory model remains empirically disconnected from CT research clusters (Handito et al., 2026), a concrete gap this field is well positioned to address. Third, design-based research approaches might generate valuable knowledge for teachers and curriculum developers through the development and evaluation of innovative CT pedagogies, specifically adapted to SMK settings.

This review shows that CT has been transformed from a computer-science specialist skill into a foundational capability for vocational and technical education. CT offers valuable tools for understanding complex technical and industrial processes, for strengthening workplace problem-solving, and for preparing students to engage in an increasingly data-driven and automated workforce, as the growing scientific evidence in this field indicates. But to realize this potential, ongoing attention is needed to teacher preparation, resource development, assessment, and culturally and industry-relevant teaching. Infusing CT into technical education is one such strategy that can help develop graduates who are technically competent, adaptive, and ready to meet the challenges of a rapidly changing labor market.

CONCLUSION

CT has evolved from a specialized technical skill into a broader competency relevant to vocational and technical education. Bibliometric findings show strong research growth across Social Sciences, Computer Science, and Engineering, confirming the interdisciplinary nature of CT. Typical pedagogical approaches include inquiry-based learning, problem-based learning, creative pedagogy, gamification, and flipped learning, all of which focus on active participation, real-world problem-solving, and digital technology. However, challenges remain in assessment, teacher readiness, resource availability, cultural and industrial relevance, and integration with practice-based models such as Teaching Factory. Future research should be longitudinal, cross-contextual, design-based, and for vocational and technical education.

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