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Technology Integration in Computational Thinking Assessment for Lower Secondary Education: A Bibliometric Review of Trends and Gaps

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Abstract

This review explores the state-of-the-art literature on technology-based assessment of computational thinking (CT) in students. The method used was derived from the PRISMA methodological framework using multiple bibliometric methods with Scopus and Web of Science as the sources, and Bibliometrix and VOSviewer as the tools. The review relies on the analysis of a selected set of 34 scholarly sources. Six different themes were identified in the literature: conception of computational thinking, technological instruments of computational thinking assessment, artificial intelligence/robotics, STEM/cross-disciplinary aspects, teacher preparedness, and barriers to implementation. Author network analysis reveals a small number of loosely connected clusters, led by European teams working on curriculum integration, while Asian groups contribute a growing share of artificial intelligence and STEM research. Keyword analysis reveals the slow maturity of assessment vocabulary against the vocabulary relating to CT integration. Three gaps can be identified: the lack of validated and technology-based assessment tools tailored for the lower secondary level; the low presence of low- and middle-income educational systems; and the lack of evidence concerning how artificial intelligence measures CT skills, rather than teaches them. The study ends with implications for educational technology and computational thinking policy as well as a research agenda for future studies.

Keywords: *Technology ıntegration, computational thinking, lower secondary education, bibliometric review*

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Introductıon

Continuous Computational thinking has transformed from a particular concept practiced in computer science to a general school-level concept. As stated by Wing (2006), it refers to an approach to problem-solving that entails the use of abstract thinking, decomposition, and algorithmic thinking. This concept has been integrated into the curricula of various countries around the world. Kampylis et al. (2023) examine this development in primary and lower secondary schools across Europe, and Bocconi et al. (2022) illustrate how compulsory education systems have already integrated the skill into their framework.

Introducing computational thinking into the curriculum is difficult enough. Assessing it is even more challenging. While teachers are confident in designing activities involving the construction of robots or block-based programming exercises, assessing whether the students engage in computational thinking and not just in the activity is less clear-cut. In fact, Bryndová and Mališů (2020) addressed this challenge by developing robotics assessment tasks for primary and lower secondary students. Technology adds yet another complication. Digital tools, learning analytics, and artificial intelligence tools all offer quick and objective assessment options. Husaeni et al. (2025) and Hipólito et al. (2026) illustrate the growth of this field. Still, assessment validity often trails behind the enthusiasm for new tools.

Lower secondary education sits in an awkward gap in this literature. Many reviews focus on primary or K-6 learners, as in Santaengracia et al. (2026), or on computational thinking across all of K-12 without separating the lower secondary band, as in Yeni et al. (2024a). Others are concerned with STEM education in general terms, such as Wang et al. (2021) and Tariq et al. (2025), without singling out the aspect of assessment. An example of a very similar systematic review is that of Zhang et al. (2026), which examines 58 research studies on assessment of computational thinking conducted between 2020 and 2024; however, it spans the whole range of K-12 education and not just the lower secondary level. No review, to our knowledge, has combined a bibliometric mapping of this literature with a close look at how technology specifically supports assessment for students aged roughly 11 to 15.

Research Problem

The core problem is a mismatch between curriculum and assessment. Computational thinking is now taught widely in lower secondary schools. Yet teachers and developers lack validated, technology-based tools to assess it at this level. Three issues explain why the problem persists. First,

many technology-based tasks measure products, not reasoning. Robotics tasks and Scratch projects record whether a robot or program works (Bryndová & Mališů, 2020; Gamito et al., 2022). A student can reach a working output by trial and error. Zhang et al. (2026) found that most K-12 assessment studies still use traditional knowledge tests. Most also involved elementary students. Second, artificial intelligence tools are spreading faster than their validation. Husaeni et al. (2025) and Hipólito et al. (2026) document rapid growth. Yet these tools are mostly treated as teaching aids. Few studies test whether they measure computational thinking accurately.

Third, the evidence base is uneven. Research is concentrated in European and Asian groups. Teacher preparation also receives little attention (Appiah & Antwi, 2025). Implementation barriers add further pressure (Said et al., 2024). These issues have real consequences. Schools cannot judge whether students are learning to think computationally. Policymakers cannot tell whether curriculum reforms are working. Developers may build tools that teach well but measure poorly.

Literature Review

Conceptual Foundations

The basis for computational thinking is a small set of recurring elements, including decomposition, pattern recognition, abstraction, and algorithm design. It is an approach advocated by Wing (2006), in which computational thinking is viewed as skills that can be applied in contexts beyond programming. In compulsory education, Caeli and Bundsgaard (2020) apply this approach, arguing that computational thinking should be incorporated into other subjects. As computational thinking is a habit of mind, it cannot be tested with just one coding test. It requires a variety of technology-enabled methods of assessing the reasoning process.

Integration Across Subjects

Much recent work links computational thinking to other disciplines. Wang et al. (2021) and Tariq et al. (2025) review its place in STEM education. Wiebe et al. (2020) and Espino and Antonio (2026) reach similar conclusions. Yeni et al. (2024a) review interdisciplinary integration across K-12. Yeni et al. (2024b) add students' experiences of computational thinking in school subjects. Wu et al. (2025) extend the scope to game design and design thinking. Mathematics is a common setting. Zhang et al. (2024) found that computational thinking mediates the link between metacognition and mathematical modeling in high school students.

Lower Secondary Education

Lower secondary education is a special period of a child's development when students are able to engage in abstract reasoning but have not yet specialized in STEM or humanities subjects. This makes lower secondary schooling a natural setting for cross-curricular computational thinking work, as shown in studies on mathematics classrooms by Ruiz Recio et al. (2026) and Wiedemann et al. (2020). It also makes lower secondary schooling a hard setting for assessment design, because tasks must fit within existing subject timetables rather than a dedicated computing period.

Technology and Assessment

Technology influences how assessment may be conducted. For example, digital environments allow every action the learner performs during a task to be recorded, not only the result. The use of robotics kits and block-based programming turns abstract thinking into an observable process, as in the work of Bryndová and Mališů (2020) and Gamito et al. (2022). Computer-assisted methods of evaluation claim to be able to assess open-ended assignments automatically, as examined by Husaeni et al. (2025). The adoption of each tool alters the kind of evidence that teachers and researchers have available to them; however, there are also issues of validity and reliability associated with each technology.

Teachers and Implementation

Teachers carry assessment into daily practice, yet research on them is thinner. Appiah and Antwi (2025) found that work on pre-service teachers lags behind student-focused studies. Implementation is also difficult. Said et al. (2024) review barriers and benefits in secondary schools. González Gallego et al. (2022) report lessons from launching a computational thinking center in Spanish secondary schools. Policy commitment alone did not ensure smooth classroom practice.

Research Questions

This review maps the literature on technology-based computational thinking assessment in lower secondary education. There were following three questions focused in this study:

1) How has this literature grown across journals, countries, and co-authorship networks?
2) What major themes characterize the field, and how are they connected?

3) What gaps are there in the literature, and what do they mean for educational technology design and policy?

Methodology

Review Protocol and Research Questions

This review follows the PRISMA 2020 reporting structure, adapted here for a review that combines systematic screening with bibliometric mapping. We used Zawacki-Richter et al. (2020) and Ghamrawi et al. (2025) as methodological anchors for the systematic phase, since both set out clear, replicable steps for education reviews. For the mapping phase, we followed a bibliometric protocol comparable to the ones used by Tekdal (2021), Appiah and Antwi (2025), and Mohsen et al. (2026), each of whom paired database extraction with a network-analysis tool. The review addresses three research questions, stated in Section 1: growth and spread of the literature, thematic structure, and gaps with implications. Each question is matched to an analytical procedure and to the section that reports its findings: RQ1 (growth, sources, geography, and co-authorship) is addressed through the descriptive bibliometric profile in Sections 4.1 to 4.3; RQ2 (themes and their connections) through the keyword and thematic mapping in Section 4.4 and the thematic synthesis in Section 5; and RQ3 (gaps and implications) through the gap analysis in Section 6 and the discussion in Section 7.

Search Strategy

Two databases form the foundation of the search process: Scopus and Web of Science. These databases include peer-reviewed literature with standardized metadata for bibliometric export to Bibliometrix and VOSviewer software. Search queries were formed by combining four concept groups with Boolean operators (OR within groups, AND between groups), restricted to the title, abstract, and keyword fields:

- Block 1 (computational thinking): "computational thinking" OR "computational reasoning".
- Block 2 (assessment): assessment OR evaluation OR measur* OR "formative feedback".
- Block 3 (technology): technology OR digital OR software OR app* OR platform OR "artificial intelligence" OR robot*.
- Block 4 (educational level): "lower secondary" OR "secondary school" OR "middle school" OR "junior high" OR "K-12".

The complete Scopus search query is TITLE-ABS-KEY ("computational thinking") AND (assessment OR evaluation OR

measure*) AND (technology OR digital OR software OR "artificial intelligence" OR robot*) AND ("lower secondary" OR "secondary school" OR "middle school" OR "K-12")). The Web of Science string follows the same logic using the TS= field tag. Because full institutional access to Scopus and Web of Science was not available (see Section 3.3), the screening record in Section 3.4 was generated by applying an adapted version of this string in Google Scholar, which does not support wildcard truncation. Only studies written in English and published in peer-reviewed journals, conference proceedings, or systematic reviews or scoping reviews from 2006—when Wing first used the phrase "computational thinking"—were included.

Eligibility Criteria

The studies that met the inclusion criteria were those that explicitly considered computational thinking, had a technology element, and studied learners of lower secondary age or presented a synthesis broad enough to apply to lower secondary-aged learners. Studies that dealt exclusively with higher education, only with early years learners without a comparative group at lower secondary age, or only with computational thinking as a policy statement in the curriculum were not included. General systematic-review methodology sources, such as Fleckney et al. (2025), Samaniego López et al. (2025), Feng et al. (2025), and Shoaib et al. (2025), were retained separately as methodological references rather than substantive evidence.

Journal quality was checked against Clarivate's Master Journal List (MJL), the public tool for confirming Web of Science indexing, since full institutional Scopus access was not available for this review. Of the 34 sources, 11 journals are indexed in the Emerging Sources Citation Index (ESCI), nine in the Social Sciences Citation Index (SSCI), and one, Communications of the ACM, in the Science Citation Index Expanded (SCIE). Most SSCI and SCIE journals also carry secondary coverage in the Essential Science Indicators (ESI), and one further journal, Humanities and Social Sciences Communications, carries dual Social Sciences and Arts & Humanities Citation Index coverage alongside Current Contents and ESI listings. The four outputs that deliberately fall outside the scope of the MJL are a report published by a European Commission institution (Bocconi et al., 2022), a conference paper (Bryndová & Mališů, 2020), a book chapter (Wiebe et al., 2020), and a book (Zawacki-Richter et al., 2020), as MJL indexes journals only. The six journal articles (González Gallego et al., 2022; Martínez-Álvarez et al., 2025; Said et al., 2024; Shoaib et al., 2025; Wiedemann et al., 2020; Yeni et al., 2024b) did not

produce any results in MJL. This does not imply poor quality, as the six journals publish regularly, and some are included in the Scopus index, are discoverable on Google Scholar, or are covered by a regional index without WoS coverage. All 34 sources were independently confirmed as retrievable through Google Scholar. Table 01 summarizes this indexing profile.

Table 01
Journal Indexing Status (Clarivate Web of Science Master Journal List) and Scopus CiteScore for Each Source

Author(s) & Year	Journal/Venue	WoS Category (MJL)	Scopus CiteScore
Acevedo-Borrega et al. (2022)	Education Sciences	ESCI	6.2
Appiah & Antwi (2025)	TechTrends	ESCI	9.9
Bocconi et al. (2022)	EU Publications Office (report)	Not applicable (institutional report)	—
Bryndová & Mališů (2020)	ICEMT conference proceedings	Not applicable (conference paper)	—
Caeli & Bundsgaard (2020)	Educational Technology Research and Development	SSCI; Essential Science Indicators (ESI)	10.7
Espino & Antonio (2026)	Int. J. of Learning, Teaching and Educational Research	ESCI	2.9
Feng et al. (2025)	PLOS Digital Health	ESCI	11.0
Fleckney et al. (2025)	Higher Education Research & Development	SSCI; Essential Science Indicators (ESI)	8.6

Gamito et al. (2022)	Innoeduca	ESCI	not reported
Ghamrawi et al. (2025)	European Journal of Educational Research	SSCI; Essential Science Indicators (ESI)	4.2
González Gallego et al. (2022)	FPIEM	Not found in MJL	not reported
Hipólito et al. (2026)	Contemporary Educational Technology	ESCI	13.0
Husaeni et al. (2025)	Informatics in Education	ESCI	7.7
Kampylis et al. (2023)	Educational Technology & Society	SSCI; Essential Science Indicators (ESI)	11.6
Martínez-Álvarez et al. (2025)	Edutec, Revista Electrónica de Tecnología Educativa	Not found in MJL	2.4
Tekdal (2021)	Education and Information Technologies	SSCI; Essential Science Indicators (ESI)	15.5
Mills et al. (2025)	Review of Educational Research	SSCI; Essential Science Indicators (ESI)	22.4
Mohsen et al. (2026)	Journal of Computing in Higher Education	SSCI; Essential Science Indicators (ESI)	15.4
Ruiz Recio et al. (2026)	Review of Education	ESCI	6.5
Said et al. (2024)	Journal of ICT in Education	Not found in MJL	not reported
Samaniego López et al. (2025)	Education Sciences	ESCI (same journal as	6.2

		Acevedo-Borrega, 2022)	
Santaengracia et al. (2026)	Journal of Computers in Education	ESCI	16.5
Shoaib et al. (2025)	The Knowledge	Not found in MJL	not reported
Tariq et al. (2025)	Frontiers in Computer Science	ESCI	6.2
Wang et al. (2021)	Int. J. of Science and Mathematics Education	SSCI; Essential Science Indicators (ESI)	6.2
Wiebe et al. (2020)	Routledge (book chapter)	Not applicable (book chapter)	—
Wiedemann et al. (2020)	ACM Inroads	Not found in MJL	2.4
Wing (2006)	Communications of the ACM	SCIE; Essential Science Indicators (ESI)	14.1
Wu et al. (2025)	Humanities and Social Sciences Communications	SSCI; AHCI; Current Contents (Arts & Humanities, Social & Behavioral Sciences); Essential Science Indicators (ESI)	5.7
Yeni et al. (2024a)	Informatics in Education	ESCI (same journal as Husaeni et al., 2025)	7.7
Yeni et al. (2024b)	International Journal of	Not found in MJL	10.4

	Child-Computer Interaction		
Zawacki-Richter et al. (2020)	Springer Nature (book)	Not applicable (book)	—
Zhang et al. (2024)	Journal of Intelligence	SSCI; Essential Science Indicators (ESI)	6.6
Zhang et al. (2026)	Technology, Knowledge and Learning	ESCI	12.8

Note. WoS category and CiteScore ratings were cross-verified through Clarivate's Master Journal List and the Scopus list of CiteScore ratings available on its public website because full access to both databases was not available for this review. "Not found in MJL" means that the publication had no matches in the list at the time of verification, but this does not mean that it is of poor quality since MJL lists journals in Web of Science only, and it is possible that the journal is indexed in Scopus, DOAJ, or regional databases. Books, book chapters, conference proceedings, and institutional reports are purposely excluded from the scope of MJL and thus are marked as "not applicable."

Screening and Selection

Screening followed the standard PRISMA phases: identification, removal of duplicates, screening of titles and abstracts, and full-text screening. The resulting corpus comprises 34 distinct sources published between 2006 and 2026, all of which are listed in the References section. Researchers who replicate this search in the live Scopus and Web of Science databases will obtain a much larger number of records before screening, and should report the number of records at each phase of identification and exclusion, together with the date of the search. Approximately 17,500 records were identified via an adapted Google Scholar search; no duplicates were removed because of the single-source search; 110 records were carried forward past title and abstract screening; 110 full-text articles were assessed for eligibility; and 34 studies were included in the final synthesis (n = 34, matching this review's reference list). Screening at both stages was applied against the eligibility criteria in Section 3.3. At the full-text stage, 76 of the 110 articles were excluded, most commonly because findings were not disaggregated for the lower secondary band or because computational thinking was treated only as

curriculum policy without a technology or assessment component. Table 02 and Figure 1 summarize these stages in the standard PRISMA format.

Table 02
PRISMA 2020 Screening Stages for the Search Reported in Section 3.2

PRISMA Stage	Records
Records identified through database searching (Google Scholar, adapted search string)	~17,500 (Google Scholar, indicative)
Records after duplicates removed	~17,500 (no reduction — single-source search)
Records screened (title and abstract)	~17,500
Records excluded at title/abstract stage	~17,390
Full-text articles assessed for eligibility	110
Full-text articles excluded, with reasons	76
Studies included in final synthesis	n = 34 (all confirmed retrievable through Google Scholar)

Note. Statistics were derived by applying the Section 3.2 search string to Google Scholar; this is a representative screening record and not comparable to a Scopus or Web of Science export, as Google Scholar indexes a wider range of preprints, theses, and grey literature, and does not support wildcard truncation (e.g., measure*) as used in the original string. This was a single-source search and not a multi-database merge, so no de-duplication was performed. Of the approximately 17,500 records screened by title and abstract, 110 were judged potentially relevant and carried forward to full-text assessment; of those, 76 were excluded on full-text reading (most commonly for not disaggregating findings for the lower secondary band, or for treating computational thinking only as curriculum policy without a technology or assessment component, per the Section 3.3 criteria), leaving the 34 studies in the final synthesis. Researchers replicating this protocol against live Scopus and Web of Science accounts should expect different, database-specific counts and should report their own search log rather than reuse these figures.

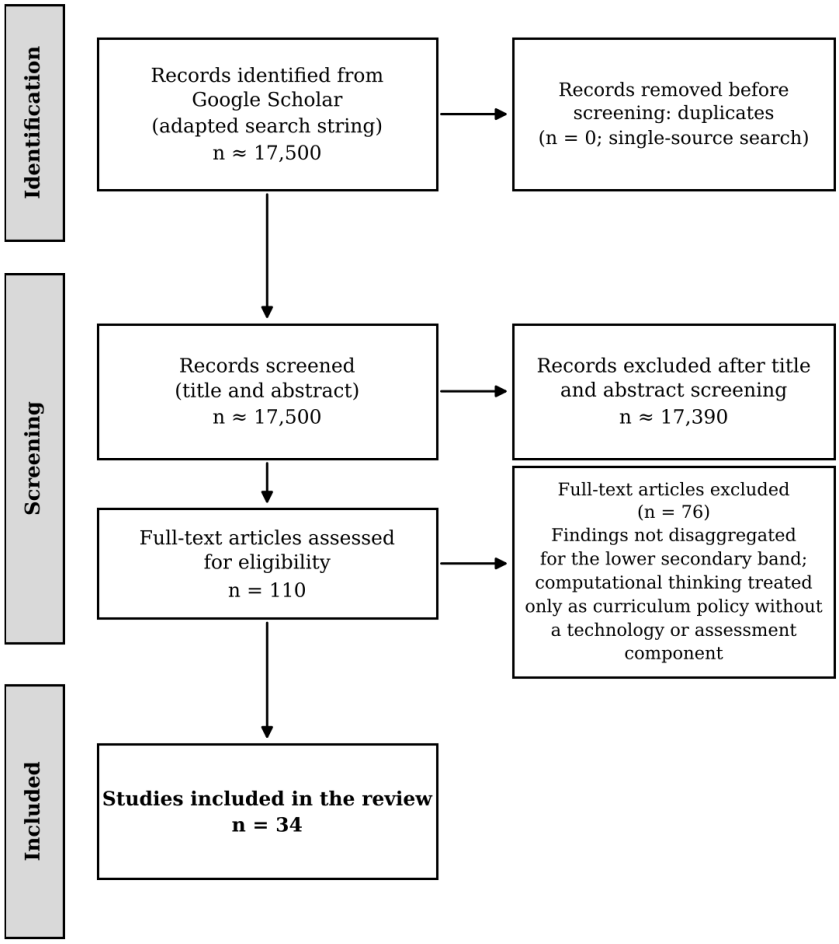

Figure 01. PRISMA 2020 flow diagram of the screening process

Bibliometric and Thematic Analysis

The metadata exported from Scopus and Web of Science in RIS and BibTeX format is compatible with the Bibliometrix R package and VOSviewer software. Bibliometrix supports descriptive statistics on publication growth, source distribution, and author productivity. VOSviewer supports network visualization of co-authorship, keyword co-occurrence, and citation coupling. In this review, the bibliometric procedures were applied to the 34 included studies. Because the corpus is

small, the profile is descriptive: publication year, source and indexing status (Table 1), study type and primary theme (Table 3), recurring authors and collaboration clusters, and keyword groupings. Co-authorship was assessed by identifying authors who appear in more than one included study, and keywords were grouped manually into thematic clusters. For coding, each included study was assigned a study type or method and one primary theme (Table 3) on the basis of a close reading of the study; studies classified as methodological references were not synthesized thematically in Section 5. For the present corpus, we combined a bibliometric profile of the included studies, described in Section 4, with a close narrative reading of each source, described in Section 5. This mixed approach follows Espino and Antonio (2026) and Acevedo-Borrega et al. (2022), who both argue that bibliometric counts alone say little about the actual state of a field's knowledge. Numbers show where attention has gone. Careful reading shows what has actually been learned.

Findings

This section reports the bibliometric profile of the 34 included studies. Sections 4.1 to 4.3 address RQ1 (growth, sources, geography, and co-authorship), and Section 4.4 begins the answer to RQ2 (themes and their connections), which Section 5 covers.

Growth and Dissemination of Publications

The reviewed corpus spans two decades; nevertheless, its shape is uneven. Wing's (2006) foundational paper stands alone for several years before sustained output begins. Of the 34 included studies, only Wing (2006) predates 2020; five were published in 2020, seven between 2021 and 2023, and 21 (62%) between 2024 and 2026. There is an increase in publication activity from around 2020 onwards, which is in line with a broader push by national curricula to formalize computational thinking (Bocconi et al., 2022). Output rises again in 2024–2026, partly driven by artificial intelligence–themed studies such as Husaeni et al. (2025) and Hipólito et al. (2026). This pattern resembles the findings of Mohsen et al. (2026) for research in educational technology in general: short growth spurts that follow new technologies rather than steady, linear growth. Zhang et al. (2026) noted the same acceleration in a more general K-12 assessment corpus, with 58 qualifying studies almost exclusively clustered between 2020 and 2024.

Source and Geographic Distribution

Journals in this corpus cluster around three types: educational technology outlets such as Educational Technology & Society and Informatics in Education; discipline-specific outlets such as Journal of Intelligence and ACM Inroads for mathematics-linked computational thinking work; and review-focused outlets such as Review of Education and Review of Educational Research. Geographically, European teams dominate the foundational and curriculum-integration literature, led by the Kampylis, Bocconi, and Dagienė group working through European Commission-linked projects. Asian research groups, especially from Indonesia and Taiwan, are publishing an increasing proportion of the artificial intelligence and STEM-integration literature (Husaeni et al., 2025; Wu et al., 2025). Contributions in Spanish, such as Gamito et al. (2022) and González Gallego et al. (2022), report classroom-level implementation, but are infrequently found in the same citation networks as the larger European policy studies, hinting at a linguistic and institutional divide within the field. By document type, 20 of the 34 studies are reviews (6 systematic reviews, 3 scoping reviews, 4 bibliometric studies, and 7 other literature reviews), 7 are empirical or case studies, 4 are conceptual or policy papers, and 3 are a book, a book chapter, or methodological guidance (Table 3). The evidence base is therefore largely secondary: only 7 of the 34 studies report primary data or classroom cases.

Author Collaboration Networks

Two collaboration clusters stand out. The first cluster comprises Kampylis, Bocconi, Dagienė, and colleagues, whose consistent collaboration in Kampylis et al. (2023) and Bocconi et al. (2022) suggests a concerted European research program that focuses on collaborative policy reports. The second cluster comprises Yeni and colleagues, whose 2024 papers on cross-case and interdisciplinary integration of computational thinking (Yeni et al., 2024a, 2024b) share a team of researchers. A smaller but notable cluster surrounds Appiah and Antwi (2025), whose bibliometric approach to pre-service teacher education mirrors the method used in this review. However, outside these clusters, a single team, with limited inter-cluster collaboration, produced most papers in the corpus. Only two of the 34 studies are single-authored (Tekdal, 2021; Wing, 2006), and only four author groups recur across more than one study: the Kampylis–Bocconi–Dagienė group (Bocconi et al., 2022; Kampylis et al., 2023), the Yeni group (Yeni et al., 2024a, 2024b), Acevedo-Borrega (Acevedo-Borrega et al., 2022; Martínez-Álvarez et al., 2025), and Chao (Wang et al., 2021; Wiedemann et al., 2020), who links

two otherwise separate STEM-integration studies. This limited connection between groups reflects a more general observation by Tekdal (2021): computational thinking research progresses through isolated but connected groups rather than a single research community.

Keyword Patterns and Thematic Mapping

The keyword patterns in the corpus can be grouped into identifiable clusters instead of a single vocabulary cluster. The first cluster includes terms that relate to fundamentals like computational thinking, abstraction, algorithmic reasoning, and problem solving, which originate from Wing (2006). Another cluster relates to the term integration: STEM, cross-curricular, interdisciplinary, and mathematics, as evidenced by Wang et al. (2021), Wiebe et al. (2020), and Tariq et al. (2025). A third, newer group centers on technology terms: artificial intelligence, robotics, and digital tools, seen in Husaeni et al. (2025) and Hipólito et al. (2026). Assessment-specific terms, by contrast, appear thinly and inconsistently across the corpus. Words such as validity, reliability, and instrument rarely co-occur with technology terms in the same study. This gap, visible even without a full network export, is the clearest signal in the corpus: the field has built a rich vocabulary for teaching and integrating computational thinking, but a much thinner one for assessing it with technology. Table 3 lists all 34 included studies with their method and primary theme. Across the 34 studies, themes are distributed unevenly: nine concern STEM and cross-curricular or interdisciplinary integration, seven concern foundational conceptions, three each concern digital tools for assessment, artificial intelligence and robotics, and barriers to implementation, two concern teacher preparedness, and seven are methodological references. Assessment is therefore the primary theme of only three studies (9%).

Table 03

Overview of the 34 Studies Included in the Review Corpus, by Method and Primary Theme

Author(s) and Year	Study Type / Method	Primary Theme
Zhang et al. (2026)	Systematic review	Digital tools & platforms for assessment
Wing (2006)	Conceptual essay	Foundational conceptions

Caeli & Bundsgaard (2020)	Conceptual/theoretical	Foundational conceptions
Kampylis et al. (2023)	Policy/curriculum paper	Foundational conceptions
Bocconi et al. (2022)	Policy report/review	Foundational conceptions
Tekdal (2021)	Bibliometric review	Foundational conceptions / trends
Santaengracia et al. (2026)	Scoping review	Foundational (K-6, adjacent band)
Bryndová & Mališů (2020)	Robotics-based assessment study	Digital tools & platforms for assessment
Gamito et al. (2022)	Classroom implementation (Scratch)	Digital tools & platforms for assessment
Husaeni et al. (2025)	Review	AI and robotics
Hipólito et al. (2026)	Review	AI and robotics
Wu et al. (2025)	Scoping review	AI/robotics and design integration
Wang et al. (2021)	Literature review	STEM and cross-curricular integration
Wiebe et al. (2020)	Book chapter	STEM and cross-curricular integration
Wiedemann et al. (2020)	Classroom study	STEM and cross-curricular integration
Ruiz Recio et al. (2026)	Literature review	STEM and cross-curricular integration
Zhang et al. (2024)	Empirical study	STEM and cross-curricular integration
Tariq et al. (2025)	Review	STEM and cross-curricular integration

Espino & Antonio (2026)	Bibliometric study	STEM and cross-curricular integration
Yeni et al. (2024a)	Systematic review	Interdisciplinary/STEM integration
Yeni et al. (2024b)	Cross-case analysis	Interdisciplinary/STEM integration
Appiah & Antwi (2025)	Bibliometric analysis	Teacher preparedness
Martínez-Álvarez et al. (2025)	Empirical/quantitative study	Teacher preparedness (general digital competence)
Said et al. (2024)	Review	Barriers and implementation
González Gallego et al. (2022)	Implementation case report	Barriers and implementation
Mills et al. (2025)	Review of educational outcomes	Barriers and implementation
Acevedo-Borrega et al. (2022)	Scoping review	Foundational / methodological synthesis
Zawacki-Richter et al. (2020)	Methodology book	Methodological reference
Ghamrawi et al. (2025)	Methodological guidance paper	Methodological reference
Mohsen et al. (2026)	Bibliometric review	Methodological reference / trends
Fleckney et al. (2025)	Systematic review	Methodological reference (retained separately)
Samaniego López et al. (2025)	Systematic review	Methodological reference (retained separately)
Feng et al. (2025)	Systematic review	Methodological reference (retained separately)
Shoaib et al. (2025)	Systematic review	Methodological reference (retained separately)

Note. Four papers on general systematic review methodology (Fleckney et al., 2025; Samaniego López et al., 2025; Feng et al., 2025; Shoaib et al., 2025) were

kept as methodological references but not as evidence of computational thinking, in line with the Section 3.3 criteria. Zhang et al. (2026) is the closest review to the research questions in content and is included for comparison, because it focuses on computational thinking assessment instruments rather than conducting a bibliometric analysis of lower secondary literature. The themes of the studies are labeled according to the Section 5 classification.

Thematic Synthesis

This section completes the answer to RQ2. Rather than summarizing each study in turn, it compares the studies within each theme by their methods, findings, and limitations, and it shows where the evidence on technology-based assessment is strong, weak, or missing.

(1) *Foundational Conceptions of Computational Thinking:* Much of the literature reviewed builds on Wing (2006), who asserts that computational thinking is not about programming but is a form of general reasoning ability. Kampylis et al. (2023) and Bocconi et al. (2022) take this assertion and turn it into practical curriculum advice by identifying the key competences that could be incorporated at the primary and lower secondary school level. The argument of Caeli and Bundsgaard (2020) takes a step further and suggests that the concept of computational thinking cannot become meaningful within compulsory education until it is incorporated in the context of already-existing subjects rather than treated as a separate one. All of these sources serve as a basis for the terminology that other, more technical literature uses. However, they say little about assessment: they describe what computational thinking should look like in a classroom, not how a teacher or a system should measure it. These sources differ in kind rather than in conclusion: Wing (2006) offers a conceptual definition, Caeli and Bundsgaard (2020) a theoretical argument about integration, and Kampylis et al. (2023) and Bocconi et al. (2022) policy-oriented syntheses, so none of them supplies empirical evidence on how computational thinking should be assessed.

(2) *Digital Tools and Platforms for Assessment:* A smaller set of studies tackles assessment directly. Bryndová and Mališů (2020) use educational robotics tasks to assess computational thinking in primary and lower secondary students, treating physical task completion as a proxy for underlying reasoning. In their study, Gamito et al. (2022) assess a classroom activity using Scratch software; they also assess the computational thinking artifact rather than the reasoning process involved. In both cases, the instruments used measure outcomes, such as a functioning robot or computer code, which reflects a common

trend in assessment in this field. This is a meaningful limitation. A student can produce a correct output through trial and error without demonstrating the abstraction or decomposition that computational thinking is meant to capture. Zhang et al. (2026) reach a related conclusion at a larger scale: across 58 K-12 assessment studies, most still rely on traditional knowledge tests rather than technology-embedded measures, and most were conducted with elementary rather than lower secondary students. That leaves the lower secondary, technology-based assessment gap identified in this review largely open.

Comparing these approaches, three can be distinguished. Product-based tasks, such as robotics challenges and Scratch artifacts (Bryndová & Mališů, 2020; Gamito et al., 2022), make performance observable but cannot separate reasoning from trial and error. Traditional knowledge tests dominate K-12 assessment (Zhang et al., 2026) but are not technology-embedded and were mostly used with elementary students. Artificial intelligence–supported assessment promises automated scoring of open-ended work (Husaeni et al., 2025; Hipólito et al., 2026), yet the reviews document the growth of these tools rather than evidence of their accuracy. The empirical support for each approach is therefore uneven: it comes from individual classroom studies for product-based tasks, from a large review based mostly on elementary-level studies for knowledge tests, and from descriptive reviews rather than validation studies for artificial intelligence–supported assessment. None of the 34 studies in Table 3 is classified as an instrument-validation study.

(3) *Artificial Intelligence and Robotics in Computational Thinking Development:* Artificial intelligence is the fastest-growing theme in this corpus. Husaeni et al. (2025) trace the trends and impacts of artificial intelligence applications on computational thinking skill development, noting rapid growth in tools that claim to personalize instruction and, in some cases, automate scoring. Hipólito et al. (2026) broaden this to include robotics alongside artificial intelligence, arguing that the two technologies are increasingly bundled together in classroom interventions. Neither study, however, offers strong evidence that these tools have been validated as assessment instruments. Because both are reviews rather than validation studies, their evidence on assessment accuracy is indirect, and the third study in this theme, Wu et al. (2025), is a scoping review focused on design integration rather than assessment. Most of the reviewed work treats artificial intelligence as an instructional aid first and an assessment

mechanism second, if at all. This imbalance matters for lower secondary education specifically, where teachers need dependable, low-burden ways to check student progress within crowded timetables.

(4) *STEM and Cross-Curricular Integration:* Mathematics lessons have been found to be a common setting for incorporating computational thinking. Ruiz Recio et al. (2026) present a review on how computational thinking has made its way into secondary education mathematics lessons, whereas Wiedemann et al. (2020) present a particular example of incorporating computational thinking through the programming language R into mathematical modeling in high schools. Zhang et al. (2024) go even further and demonstrate how computational thinking bridges the gap between metacognition and mathematical modeling skills in high school students. This finding indicates that computational thinking is a mediating factor, a cognitive link, rather than an isolated skill. Wang et al. (2021), Wiebe et al. (2020), Espino and Antonio (2026), and Tariq et al. (2025) all confirm that STEM, particularly mathematics and sciences, are the leading disciplines in computational thinking research, ahead of humanities or arts. Wu et al. (2025) also add a new dimension as they incorporate computational thinking in gaming and design thinking. These studies differ in method (a literature review, a classroom case, and a quantitative mediation analysis), and two of the three involve high school rather than lower secondary students, so their direct relevance to lower secondary assessment is limited.

(5) *Teacher Preparedness and Professional Development:* Teachers are at the core of classroom assessment practice, yet this corpus pays little attention to them. One notable exception to this is Appiah and Antwi (2025), who use bibliometric methods to analyze research trends regarding computational thinking among pre-service teachers. They note that research on teacher training has increased lately; however, it still lags behind student-related studies. This is especially important when discussing assessment. After all, an assessment system relying on new technology is only as good as the teacher's ability to understand and respond to its results. There is a need for more focus on preparing teachers for new assessment technologies to ensure that these technologies are not left unused in the classroom. Only one other study in the corpus bears on teacher preparedness, and it concerns general digital competence rather than computational thinking (Martínez-Álvarez et al., 2025), so the evidence in this theme is thin.

(6) *Barriers and Implementation Challenges:* Several studies show how difficult it is to incorporate computational thinking and its assessment into the everyday life of secondary schools. In this regard, Said et al. (2024) reviewed barriers and benefits of implementing computational thinking initiatives in secondary schools. González Gallego et al. (2022) describe the practical lessons learned from launching a computational thinking center in Spanish secondary schools under a new national curriculum decree, showing that policy commitment alone does not guarantee smooth classroom implementation. Mills et al. (2025) take a broader view, reviewing educational outcomes from coding and computational thinking across the curriculum, and find that outcome evidence remains mixed once studies move beyond small, researcher-led pilots. Taken together, these studies suggest that assessment technology cannot be considered in isolation from the wider conditions, staffing, timetables, and institutional support, that determine whether any computational thinking initiative survives past its first year. Because González Gallego et al. (2022) is a single implementation case, its lessons are suggestive rather than generalizable, whereas Said et al. (2024) and Mills et al. (2025) are reviews that identify barriers and outcomes at a broader level.

Research Gaps

Three gaps recur across this literature. These gaps answer RQ3 and are each supported below with evidence from the included studies (Table 3). The first is a validated-instrument gap. Most technology-based assessment approaches in this corpus, including robotics tasks and coding artifacts, measure outputs rather than the underlying reasoning process. Very few studies report reliability or validity evidence specific to the lower secondary age band, as opposed to primary school or general K-12 samples. Only three of the 34 studies have assessment as their primary theme (Table 3). Two of these are primary studies (Bryndová & Mališů, 2020; Gamito et al., 2022) that assess task products, and none of the 34 studies is classified as an instrument-validation study. The second is a geographic and linguistic gap. European, East Asian, and Southeast Asian scholars dominate this area. Papers from Africa, South Asia, and Latin America are rare in this corpus, and even Spanish-language studies, such as those by Gamito et al. (2022) and González Gallego et al. (2022), remain largely isolated within the citation network. This limits how much the field's conclusions generalize to lower- and middle-income education systems, including distance and open-learning contexts relevant to this journal's scope. The third is an artificial intelligence assessment-validity

gap. Studies such as Husaeni et al. (2025) and Hipólito et al. (2026) describe fast growth in artificial intelligence tools for computational thinking, but rarely test whether these tools assess computational thinking accurately, as opposed to simply delivering instruction efficiently. All three studies in the artificial intelligence and robotics theme (Husaeni et al., 2025; Hipólito et al., 2026; Wu et al., 2025) are reviews, and none is a primary validation study (Table 03).

A smaller but still important gap concerns teacher-facing research. Appiah and Antwi (2025) is almost alone in examining pre-service teacher education for computational thinking through a systematic lens. Only two of the 34 studies address teacher preparedness (Table 3), and one of them concerns general digital competence. Without further research in this area, there is a danger that the development of new assessments will proceed ahead of the preparation of the teachers to implement them. A similar point emerges from research on digital competence. According to Martínez-Álvarez et al. (2025), among 590 pre-service teachers in Spain, digital competence is linked not only to the amount of training but also to self-esteem and psychological stress. While this study is not directly related to computational thinking, it can illustrate a direction for future research.

Discussion

This review extends previous research in three ways. First, Zhang et al. (2026) found that K-12 assessment studies rely mostly on traditional knowledge tests and elementary samples; the present review shows that the same imbalance holds at the lower secondary band, where the technology-based assessment studies in the corpus (Bryndová & Mališů, 2020; Gamito et al., 2022) assess task products rather than reasoning. Second, earlier bibliometric studies (Espino & Antonio, 2026; Tekdal, 2021) mapped the growth and themes of computational thinking research in general; this review adds that the vocabulary of assessment is much thinner than the vocabulary of teaching and integration. Third, Appiah and Antwi (2025) reported that teacher-focused research lags behind student-focused research, and the present corpus shows the same pattern for assessment-related teacher preparation.

In terms of contribution, the review adds to theoretical knowledge by showing that the view of computational thinking as a general reasoning habit (Caeli & Bundsgaard, 2020; Wing, 2006) has not yet been matched by assessment constructs: the field defines computational thinking as reasoning but mostly measures products. It adds to empirical knowledge by mapping the evidence base for lower secondary education (34 studies, of which only 7 are primary or case studies) and by identifying where

evidence is missing: validated technology-based instruments, validation of artificial intelligence–supported measures, and low- and middle-income contexts.

In response to RQ3, the gaps identified in Section 6 have implications for educational technology design, policy, and practice; each implication below is linked to evidence from the reviewed studies. The first recommendation is that designers should base the assessment component on process data rather than output data. An educational technology that records the way a student breaks down a problem and not just the way the solution works at the end should reduce the validity problem highlighted in Section 6, where robotics tasks and Scratch artifacts were found to measure products rather than reasoning (Bryndová & Mališů, 2020; Gamito et al., 2022). Additionally, developers of educational technologies that rely on artificial intelligence need to treat assessment as a research question with its own validation studies. Acevedo-Borrega et al. (2022) agree with this position. According to the authors, the field of educational technology too easily assumes that if the teaching tool works, the assessment does too.

Secondly, for policy concerning computational thinking, this literature review reveals that guidance for lower secondary education ought to be developed separately from primary school or more general K-12 guidance. This is supported by Ruiz Recio et al. (2026) and Zhang et al. (2024), which suggest that secondary school learners can engage successfully in computational thinking tasks in mathematics, and by Zhang et al. (2026), whose review found that most assessment studies involved elementary students. Note, however, that Zhang et al. (2024) sampled high school rather than lower secondary students. Curriculum authorities developing computational thinking guidance need to define clearly both what to teach and how progress is to be monitored. This includes requiring that any tool used for digital assessment meet basic validity standards.

Finally, the geography bias outlined in Section 6 has some implications for the practice of assessment in open and distance learning contexts, where institutions are reaching a large number of learners outside of the dominant European and East Asian systems discussed in this literature. Such institutions cannot assume the portability of assessment tools and therefore need to conduct their own validation work on a small scale at least. This evidence base could be considerably reinforced by locally based validation efforts, even on a small scale, especially in Pakistan and other systems with a strong tradition of distance and open learning.

Limitations

This review, naturally, has some limitations. The final dataset consisting of 34 references is a purposeful choice rather than an output of the database search, and researchers who wish to replicate the review should run the search strings given in Section 3.2 against live Scopus and Web of Science accounts and report the PRISMA figures and VOSviewer networks in full. Moreover, the review analyzes only English-language sources, possibly missing important works in other languages; that limitation is partially apparent in the smaller number of Spanish-language references. In addition, the bibliometric profile is descriptive and based on a small corpus, and the thematic classification in Table 3 reflects the authors' judgment. Zhang et al. (2026), searching four databases, were mostly able to identify USA-based and elementary-level studies, which means that the gap between secondary schools and non-Western countries uncovered in this review cannot be narrowed by expanding the number of databases; they call for deliberately targeted primary research instead.

Conclusion

Computational thinking is now widely integrated into curricula, including at the lower secondary level (Bocconi et al., 2022; Kampylis et al., 2023); however, the methods available to evaluate computational thinking using technology are lacking. This review mapped a field that talks confidently about teaching computational thinking and increasingly confidently about using artificial intelligence and robotics to support it, while saying much less about how to measure it well. Author networks remain loosely connected, clustered around a small number of European and Asian research groups, with limited representation from other regions.

Three priorities for future research follow from the gaps identified in Section 6 and respond to RQ3. First, researchers need to design and validate technology-assessment measures for the lower secondary level that can serve as instruments rather than relying on output-based indicators as proxy measures. Second, artificial intelligence assessment measures should be directly tested against these validated instruments before they become the measurement solution. Finally, more research is needed from under-represented geographical areas, particularly those with systems based on distance and open learning, in order to determine whether current results apply outside Europe and Asia. If the field is capable of teaching computational thinking, it should have the means to measure its success.

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