



Artificial intelligence literacy in social research: A bibliometric analysis of conceptual evolution and emerging trends

Eluard Alexander Mendoza-Zenozain ^{1*}

 0000-0002-1051-9207

Franklin Cordova-Buiza ²

 0000-0002-7623-7472

¹ Faculty of Engineering, Universidad Privada del Norte, Lima, PERU

² Department of Research and Innovation, Universidad Privada del Norte, Lima, PERU

* Corresponding author: eluard.mendoza@upn.edu.pe

Citation: Mendoza-Zenozain, E. A., & Cordova-Buiza, F. (2026). Artificial intelligence literacy in social research: A bibliometric analysis of conceptual evolution and emerging trends. *Contemporary Educational Technology*, 18(4), Article ep698. <https://doi.org/10.30935/cedtech/19597>

ARTICLE INFO

Received: 28 May 2026

Accepted: 11 Sep 2026

ABSTRACT

In contemporary digital society, artificial intelligence literacy (AI literacy) has become a key competence that enables citizens to understand and actively participate in increasingly automated environments. However, despite the rapid growth of scientific output, partly driven by tools such as ChatGPT, the literature reveals substantial conceptual fragmentation that hinders an integrated understanding of its educational and ethical dimensions. In this context, this study aimed to analyze the intellectual evolution and conceptual structure of research on AI literacy, based on Scopus-indexed literature. A bibliometric methodology was applied to a corpus of 2,645 documents using scientific mapping techniques to identify publication patterns, collaboration networks, and dominant thematic streams. The results reveal an accelerated expansion of the field and a shift from early approaches focused primarily on educational contexts such as K-12 education and computational thinking toward more complex frameworks that incorporate algorithmic ethics, psychological acceptance of technology, critical thinking, and academic integrity challenges associated with generative AI (GenAI). Overall, this study contributes to the educational technology literature by providing a longitudinal bibliometric interpretation of the evolution of AI literacy and by identifying emerging research agendas related to GenAI, ethical reasoning, and critical digital competencies in contemporary education.

Keywords: AI literacy, artificial intelligence, generative AI, educational technology, bibliometric analysis, higher education

INTRODUCTION

From the perspective of the social sciences and humanities, artificial intelligence (AI) goes beyond purely instrumental technological innovation, as it constitutes a social and cultural process that reshapes civic participation, power, and individual autonomy (Cordova-Buiza et al., 2026; Crawford, 2021; Floridi et al., 2020). Interaction with intelligent systems involves more than functional use; it encompasses ethical, cognitive, and critical dimensions in contexts where algorithms mediate access to information, social visibility, and decision-making (Beer, 2017; Swart, 2021).

In contemporary digital environments, the need to understand these mechanisms has given rise to AI literacy, a set of competencies for interpreting, critically evaluating, and engaging with algorithmic systems in an informed manner (Biagini, 2025; Tadimalla & Maher, 2025). Accordingly, AI literacy is a social practice that combines technical skills with attention to privacy, human agency, and equity in increasingly automated environments (Kalantzis & Cope, 2025; Traga Philippakos & Rocconi, 2025). The expansion of generative AI

(GenAI) and automated decision-making has shifted the focus toward algorithmic understanding, ethical evaluation, and critical thinking (Chiu, 2024; Walter, 2024).

Previous studies have examined complementary aspects of AI literacy, including conceptualization and assessment (Almatrafi et al., 2024), learning methods and effects (Pinski & Benlian, 2024), definitions and approaches to teaching and learning across 17 reviews (Zhang et al., 2025), and the bibliometric evolution of the field through 2021 (Tenório et al., 2023). Despite these contributions, fragmentation persists across definitions, disciplines, contexts, and assessment approaches (Biagini, 2025; Pinski & Benlian, 2024; Rodriguez-Fernandez et al., 2026). However, the joint evolution of the field's conceptual structure and collaboration patterns during the expansion of GenAI remains insufficiently understood.

To address this gap, this study analyzes the conceptual evolution, trends, and gaps in AI literacy research from 2015 to 2025 through co-authorship, bibliographic coupling, and keyword co-occurrence analyses of 2,645 Scopus-indexed documents. It asks: How has AI literacy evolved conceptually in social research during 2015-2025, and what are the main trends and thematic gaps emerging from global scientific output? The study thus extends previous reviews and bibliometric mappings by integrating the field's longitudinal conceptual, intellectual, and collaborative development rather than merely updating publication trends.

LITERATURE REVIEW

Conceptual Development and Fragmentation of Artificial Intelligence Literacy

Over the past decade, and especially since 2015, academic literature has experienced sustained growth in the analysis of competencies related to AI, progressively situating this debate at the intersection of education, digital citizenship, and sociotechnical transformation (Černý, 2024; Mahadewi et al., 2025; Olortegui-Alcalde et al., 2025). A substantial portion of this research has been conducted within formal educational contexts, not merely as a pedagogical objective, but as one of the primary social spaces in which the implications of AI for employability, civic participation, and the formation of critical subjects in digital environments are observed and problematized (Almatrafi et al., 2024; Pinski & Benlian, 2024; Zhang et al., 2025). From this perspective, a range of empirical studies has examined AI literacy across different educational levels and social sectors, identifying key dimensions such as conceptual understanding of AI, ethical awareness, technological self-efficacy, and the capacity for critical interaction with intelligent systems (Dai et al., 2020; Kong et al., 2023; Laupichler et al., 2022; Wang et al., 2023).

Nevertheless, this growth in scientific output has been accompanied by notable thematic and conceptual dispersion, complicating the consolidation of a coherent theoretical framework capable of systematically explaining the field's evolution. The literature reveals persistent conceptual fragmentation: while some studies focus on algorithmic literacy, others prioritize data literacy or AI-related competencies, reflecting epistemological and disciplinary tensions within contemporary social research (Ng et al., 2021b; Pangrazio et al., 2020). Viewed together, these studies suggest that this fragmentation is associated with disciplinary separation, the absence of a dominant theoretical anchor, and differences in target populations and assessment approaches. Consequently, the constructs and instruments used in the field are not always directly comparable across educational levels and sociocultural contexts (Almatrafi et al., 2024; Ng et al., 2021b; Pangrazio et al., 2020; Pinski & Benlian, 2024).

Critical Comparison of Existing Reviews

Although previous studies have contributed through reviews and conceptual discussions on AI literacy (Ng et al., 2021a), their scopes and analytical purposes differ. Almatrafi et al. (2024) systematically reviewed 47 articles published between 2019 and 2023 and synthesized six constructs: recognize, know and understand, use and apply, evaluate, create, and navigate ethically. Their framework provides detailed conceptual and assessment guidance, but its inclusion criteria were restricted to studies explicitly framed as AI literacy. Pinski and Benlian (2024), drawing on 68 papers, developed a user-oriented framework organized around learning methods, AI literacy components, and effects. Their findings also indicate that research efforts remain partly disconnected across disciplines and user groups.

More recent reviews have broadened this perspective. Biagini (2025) analyzed 87 studies and emphasized that AI literacy extends beyond technical proficiency to encompass ethical considerations, societal implications, and practical applications in educational and workplace contexts. Zhang et al. (2025), through an umbrella review of 17 reviews, identified emerging agreement on definitions and approaches to teaching and learning AI literacy, while also reporting unresolved needs in interdisciplinary pedagogy, ethics, AI policy, and standardized assessment across educational levels and cultures. Taken together, these reviews provide substantial conceptual, pedagogical, and assessment-related depth; however, their primary emphasis lies in conceptual and educational synthesis rather than in the longitudinal mapping of the field's intellectual structure and patterns of scientific collaboration.

Bibliometric Precedents and Remaining Research Gap

A direct bibliometric precedent is provided by Tenório et al. (2023), who analyzed 244 English-language publications produced between 1989 and 2021 and examined publication evolution, research contributors, collaboration patterns, publication venues, and keyword trends. Their study establishes an important historical baseline, but its temporal coverage ends before the widespread adoption of GenAI after 2022. More recently, Yang et al. (2025) conducted a bibliometric analysis of 335 articles on AI literacy education published between 2014 and 2024, using CiteSpace to analyze publication trends, developmental trajectories, keyword relationships, and thematic priorities. Although this study provides an updated account of AI literacy education, its scope remains centered on educational research. In contrast, the present study adopts a broader social research perspective and jointly examines co-authorship, bibliographic coupling, and keyword co-occurrence.

Taken together, these precedents show that the remaining gap is not the absence of reviews or bibliometric mappings, but the limited integration of recent conceptual change with the intellectual and collaborative organization of AI literacy research across broader social contexts. This distinction clarifies that the present study's contribution extends beyond updating publication trends to 2025 by integrating the conceptual evolution, intellectual structure, and patterns of scientific collaboration in AI literacy research during the expansion of GenAI.

Given the conceptual fragmentation documented above, it is essential to adopt approaches that clarify the field's intellectual and structural evolution (Mhlana & Dzingirai, 2024; Öztürk et al., 2024). In this study, bibliometric analysis is therefore employed not only as a descriptive tool but also as an interpretive framework for connecting conceptual, intellectual, and collaborative patterns (Donthu et al., 2021).

Research Objectives

Consistent with the general objective and research question stated in the Introduction, the study is structured around the following specific research objectives (ROs), in accordance with established applications of bibliometric analysis (Thaha et al., 2025; Verma et al., 2025):

- RO1:** To identify key scientific outputs by recognizing leading authors, journals, and documents.
- RO2:** To analyze the thematic structure to detect dominant clusters and emerging lines of research.
- RO3:** To examine collaboration networks and thematic gaps through co-authorship and keyword co-occurrence analyses.

METHODS

This study adopts a descriptive and longitudinal bibliometric design to systematically analyze the intellectual architecture, temporal evolution, and thematic trends of the scientific literature on AI literacy. Bibliometrics is employed as a methodological strategy due to its capacity to process large volumes of bibliographic metadata, allowing the study to overcome the subjectivity inherent in narrative reviews and to provide an objective visualization of the knowledge structure in emerging scientific fields (Donthu et al., 2021; Leydesdorff, 2007; Moed, 2005). Likewise, through scientific mapping techniques, this approach facilitates the identification of academic collaboration patterns, research fronts, and the field's conceptual configurations (Börner et al., 2010; Chen, 2006).

The period of analysis spans from 2015 to 2025, selected to capture the transition of AI literacy from a specialized technical competence to a critical civic skill, driven by the expansion of intelligent systems and the recent consolidation of GenAI in the social sphere. The final corpus includes 2,645 documents, ensuring a sufficiently robust empirical basis for examining the conceptual maturation of the field.

Data retrieval was conducted using the Scopus database (Elsevier). The selection of Scopus was based on its rigorous content-selection procedures, curated bibliographic and citation metadata, and broad multidisciplinary coverage, including publications from the Social Sciences and Humanities (Baas et al., 2020; Mongeon & Paul-Hus, 2016). The exclusive use of Scopus also ensured a consistent metadata structure across the corpus and avoided potential inconsistencies that could arise from combining databases with different indexing and citation practices. Data extraction was carried out in January 2026 by exporting the records in CSV format, including full metadata (affiliations, cited references, keywords, and abstracts), to ensure comprehensive processing.

To ensure methodological rigor and thematic relevance, a structured search strategy was developed and applied to the title, abstract, and keyword fields within the Scopus database, following procedures commonly adopted in bibliometric research (Donthu et al., 2021). The search equation incorporated Boolean operators and conceptual variations associated with AI literacy: TITLE-ABS-KEY ("AI literacy" OR "artificial intelligence literacy" OR "algorithmic literacy" OR "competencies in artificial intelligence").

The search focused on expressions that explicitly identify AI literacy as the principal construct. Broader terms such as "AI competencies," "AI competence," "AI skills," "AI capability," and "AI awareness" were not included as standalone expressions because they may also refer to technical abilities, organizational capabilities, or general attitudes toward AI without specifically addressing literacy. This decision favored thematic precision but may have excluded relevant studies that used only those alternative terms. Consequently, the corpus should be interpreted as a focused rather than exhaustive representation of AI literacy research. Only peer-reviewed documents published between 2015 and 2025 were considered. Editorial notes, errata, and records with incomplete metadata were excluded during the refinement stage. This procedure enabled the identification of a coherent documentary corpus that integrates educational, technological, and sociocultural perspectives associated with AI competencies.

To improve the consistency and reliability of the dataset, duplicate records and incomplete metadata entries were manually reviewed and excluded when necessary. A normalization process was then applied to disambiguate author names and institutional affiliations and to unify conceptually equivalent keywords through a controlled thesaurus (Ioannidis et al., 2020). The thesaurus was also used to standardize institutional labels by removing redundant geographical information and harmonizing naming variants, while preserving distinct affiliation units such as faculties, departments, schools, and research centers as separate entities. This procedure reduced artificial fragmentation and enhanced the interpretability and reliability of the thematic and institutional networks generated through VOSviewer.

Data processing was structured through three complementary bibliometric techniques. First, a co-authorship analysis was conducted to examine the dynamics of scientific collaboration and the social structure of the research community, identifying networks of academic interaction and cores of scientific output (Cobo et al., 2011; Moral-Muñoz et al., 2020; Zupic & Čater, 2015). Second, bibliographic coupling was used to identify the intellectual streams and journals that theoretically structure the field, based on the similarity of shared references among the analyzed documents (Boyack & Klavans, 2010; Chen, 2017). Finally, a keyword co-occurrence analysis was conducted to map the domain's conceptual structure, enabling the identification of central themes, emerging areas, and evolving research fronts (Aria & Cuccurullo, 2017; Donthu et al., 2021).

Network visualization and bibliometric mapping were performed using VOSviewer version 1.6.20, a widely used software for science mapping studies because of its ability to identify conceptual structures and collaboration patterns through distance-based visualizations (van Eck & Waltman, 2010). The analysis was conducted using co-occurrence, co-authorship, and bibliographic coupling techniques based on full-counting procedures. Minimum occurrence thresholds were established for keywords, authors, and organizations to improve network interpretability and reduce peripheral noise.

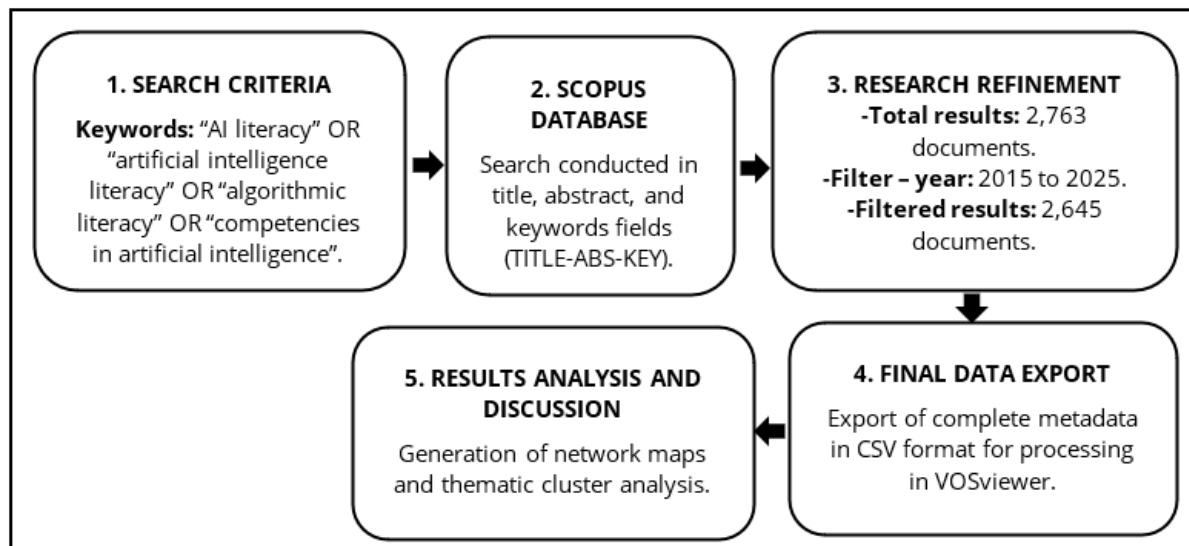


Figure 1. Bibliometric workflow and data processing stages (the authors' own elaboration)

For the keyword co-occurrence analysis, a minimum threshold of 10 occurrences produced a final network of 121 interconnected keywords. VOSviewer directly generated eight clusters from this network and determined the keyword membership in each cluster. The authors subsequently interpreted and labeled the eight research streams by examining the dominant keywords, occurrence frequencies, total link strength, and representative highly cited documents associated with each cluster. Therefore, the eight-stream structure was retained because it corresponded to the final clustering solution generated by VOSviewer rather than to a predetermined typology. The overall workflow for data retrieval, refinement, normalization, and visualization is summarized in [Figure 1](#).

Although Scopus provides extensive international coverage and high indexing standards, the exclusive use of a single database may limit the inclusion of regional publications and emerging literature indexed alternative repositories. Because bibliographic databases differ in their coverage of fields, publishing countries, and languages, excluding Web of Science and regional indexes may reduce the visibility of non-English publications and research produced in the Global South (Mongeon & Paul-Hus, 2016). Consequently, the geographical concentration observed in Hong Kong and the United States should be interpreted as a pattern within the Scopus-indexed scientific landscape rather than as a complete measure of the worldwide distribution of AI literacy research.

Ethics Statement

Ethics approval was not required for this bibliometric analysis because it used publicly available, anonymized publication data from Scopus. No human participants, personal data, or sensitive information were involved in this research.

RESULTS

Temporal evolution of scientific production. [Figure 2](#) presents the evolution of the scientific literature on AI literacy in social research, based on a bibliometric analysis of 2,645 Scopus-indexed documents covering the 2015-2025 period.

Although this study adopts the integrative term "artificial intelligence literacy", the literature reveals a progressive evolution in terminology. In the early years, notions such as algorithmic literacy or advanced digital competencies predominated, gradually converging toward a more specific conceptualization centered on competencies directly related to AI. This shift reflects a transition from general digital skills toward a more contextualized understanding of AI within social and educational domains.

The analysis reveals a non-linear growth structured in three phases. Between 2016 and 2020, scientific output was limited and stable, with fewer than 20 documents published annually, indicating that AI literacy

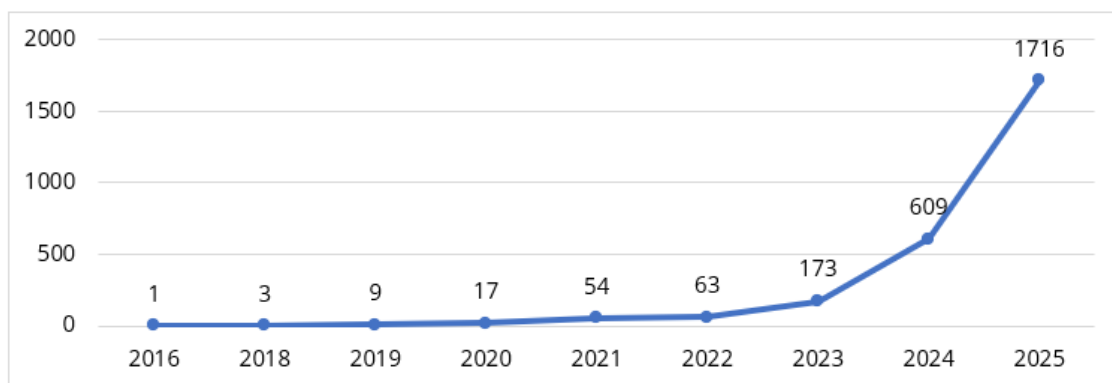


Figure 2. Evolution of scientific output on AI literacy (2015-2025) (the authors' own elaboration using data from Scopus)

was an emerging topic largely confined to technical and specialized educational contexts. Between 2021 and 2022, a transitional phase is evident, marked by a sustained increase to 63 documents in 2022, coinciding with the intensification of public debates on algorithmic ethics and the responsible use of AI.

The period from 2023 to 2025 marks a phase of accelerated expansion, culminating in 2025 with 1,716 published documents. This accelerated growth coincided with the expansion of GenAI and the widespread adoption of tools such as ChatGPT, which intensified academic interest in the field. Consequently, AI literacy has consolidated as an educational and civic priority, shifting the focus from predominantly technical approaches to the analysis of the ethical, social, and educational implications of interaction with algorithmic systems.

Overall, this evolution highlights a rapid intensification of academic interest in AI literacy, particularly in the last years of the analyzed period. The marked growth in scientific output suggests that the topic has moved beyond a peripheral position to become a central axis within social research, reflecting its increasing relevance in contemporary educational, technological, and societal debates.

The keyword co-occurrence analysis enabled the identification of dominant concepts and key thematic relationships associated with the conceptualization of AI literacy in social research (Figure 3). The network was constructed using VOSviewer software, integrating author-provided keywords, thereby revealing the intellectual structure and conceptual configuration of the field (Alharthi et al., 2023; Donthu et al., 2021).

The keywords were filtered by applying a minimum threshold of 10 occurrences to exclude isolated or low-frequency terms, resulting in a map of 121 interconnected nodes. The resulting network is organized into multiple clusters based on occurrence frequency and total link strength, reflecting the degree of conceptual proximity among the analyzed themes.

The results show a high concentration of terms associated with educational and technological domains, with AI literacy, AI, GenAI, and higher education standing out as structural nodes of the field. In particular, AI literacy emerges as the node with the highest number of occurrences (928) and the greatest total link strength, acting as an articulating axis between technical innovations (such as machine learning) and pedagogical application contexts.

Likewise, a strong association is observed between AI literacy and concepts such as ethical AI, trust, and critical thinking, highlighting the central role of ethical and reflective mechanisms in the study of digital competencies. Complementarily, terms such as teacher education and professional development display high connectivity, confirming their role as key variables in the effective adoption of these technologies in classroom settings.

Finally, the analysis identifies emerging thematic lines represented by keywords such as ChatGPT, prompt engineering, GenAI, and responsible AI, which, although exhibiting lower historical frequency, have high average publication-year values. These results suggest the progressive consolidation of new research agendas oriented toward integrating GenAI and prompt engineering into recent educational and social processes.

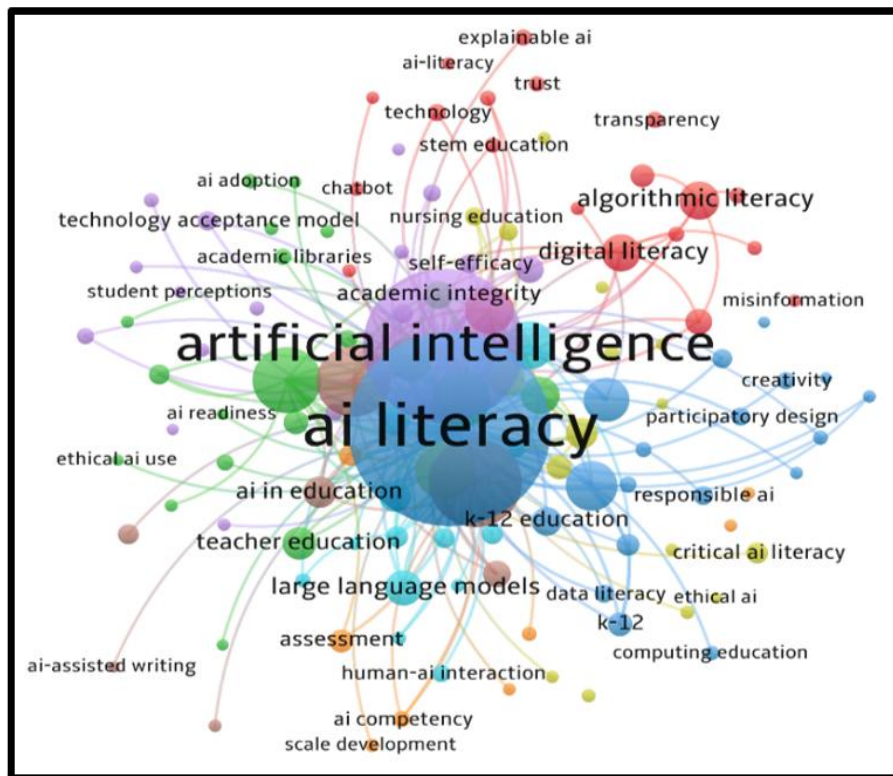


Figure 3. Keyword network analysis (the authors' own elaboration using data from Scopus and VOSviewer)

Under the threshold and full-counting settings described in the Methods section, VOSviewer generated an eight-cluster solution. The number of clusters was not predetermined by the authors; the eight-cluster structure was retained because it corresponded to the final solution generated by the software. The clusters were subsequently interpreted and labeled by the authors according to their dominant keywords, occurrence frequencies, total link strength, and representative documents:

- (1) algorithmic and digital literacy
- (2) ethics and adoption in higher education,
- (3) K-12 education and computational thinking,
- (4) critical thinking and the humanities,
- (5) psychological factors and acceptance,
- (6) language models and educational technology,
- (7) competency assessment and metrics, and
- (8) GenAI and academic writing.

The complete eight-stream synthesis is presented and further examined in the discussion.

To identify the intellectual structure of the field, co-authorship and citation patterns were analyzed using VOSviewer, thereby distinguishing between highly productive authors and those with greater academic impact. **Figure 4** illustrates the collaboration networks, while **Table 1** presents the main contributors according to scientific productivity and citation influence.

The analysis reveals two differentiated dynamics in the consolidation of the field. In terms of productivity, Kong, Siu Cheung and Ng, Tsz Kit Davy lead scientific output with 23 documents each, reflecting sustained contributions to the development of AI literacy. However, when citation impact is considered, a dissociation between publication volume and citation counts becomes evident. Although Ng maintains leadership across both metrics (3,100 citations), Leung, Jac Ka Lok, stands out for high citation influence (2,117 citations) despite a more limited publication output.

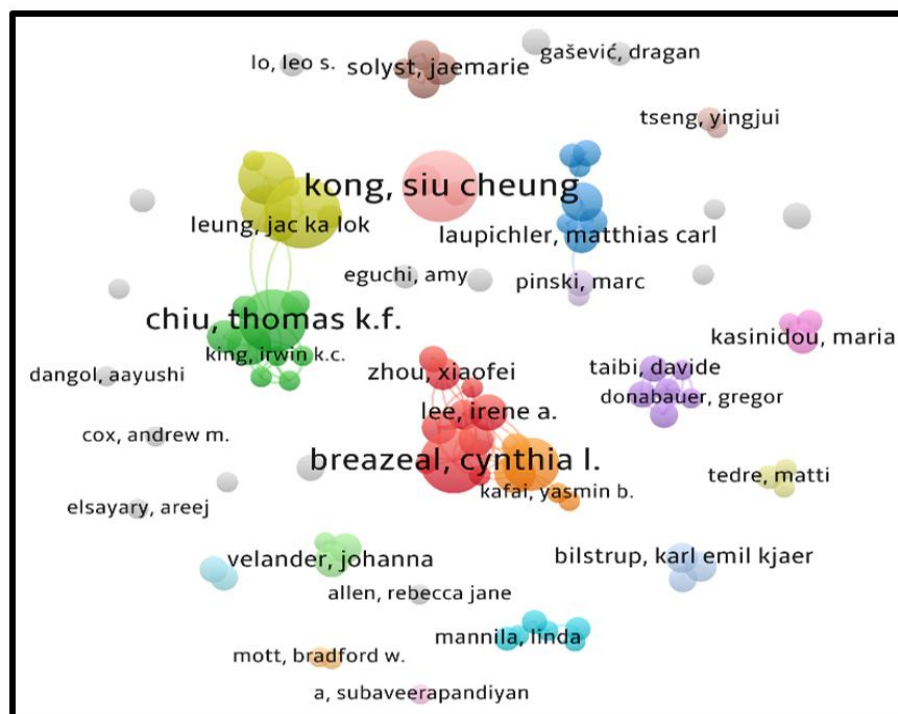


Figure 4. Co-authorship network of the most relevant researchers in AI literacy (the authors' own elaboration using data from Scopus and VOSviewer)

Table 1. Main contributors according to scientific productivity and citation impact

Rank	Author by number of documents	Documents	Author by citations	Citations
1	Kong, Siu Cheung	23	Ng, Tsz Kit Davy	3,100
2	Ng, Tsz Kit Davy	23	Chu, Samuel Kai Wah	2,882
3	Breazeal, Cynthia L.	20	Leung, Jac Ka Lok	2,117
4	Chiu, Thomas K. F.	20	Long, Duri	1,857
5	Long, Duri	16	Chan, Cecilia Ka Yuk	1,848
6	Su, Jiahong	16	Magerko, Brian S.	1,836
7	Chu, Samuel Kai Wah	14	Su, Jiahong	1,468
8	Chai, Ching Sing	12	Chiu, Thomas K.F.	1,278
9	Magerko, Brian S.	11	Breazeal, Cynthia L.	810
10	Schleiss, Johannes	11	Laupichler, Matthias Carl	791

This pattern suggests that the theoretical architecture of AI literacy is supported by a relatively small set of highly influential works rather than by the quantitative accumulation of publications. Taken together, the authors represented across both rankings constitute a prominent intellectual core in the field's development.

Figure 5 presents the geographical distribution of scientific output on AI literacy based on a country-level co-authorship analysis. The network was constructed by considering 52 countries that surpassed the threshold for sustained productivity (≥ 15 documents), thereby allowing examination of scientific collaboration patterns and the transnational configuration of the field (Waltman, 2016).

The ranking of the main actors (**Table 2**) reveals a clearly dominant position for the United States, which leads in both production volume (682 documents) and scientific impact (10,040 citations), evidencing its influence in shaping research agendas on AI-related competencies. In second place, China emerges as a major contributor with 335 documents, demonstrating its substantial participation in AI literacy research.

The most significant finding concerns Hong Kong, which, despite ranking fifth in production volume (164 documents), is the second most influential country in terms of citations (9,226). This pattern indicates exceptional impact efficiency, with an average citation rate notably higher than that of European countries with larger publication volumes, such as Germany and the United Kingdom. The network also reflects the participation of countries such as Australia, Turkey, and Spain, indicating that AI literacy research spans diverse educational and scientific contexts. Nevertheless, within the analyzed Scopus corpus, highly visible

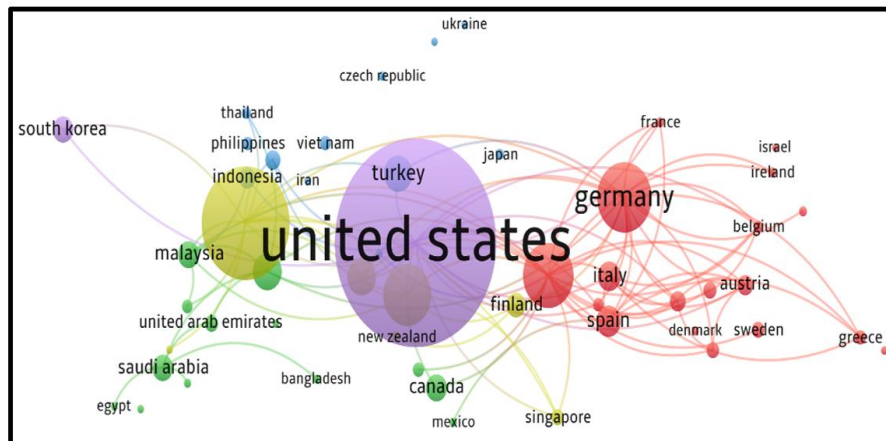


Figure 5. Scientific collaboration network analysis among countries (the authors' own elaboration using data from Scopus and VOSviewer)

Table 2. Prominent countries ranked by documents and citations

Rank	Country by number of documents	Documents	Country by citations	Citations
1	United States	682	United States	10,040
2	China	335	Hong Kong	9,226
3	Germany	190	China	3,501
4	United Kingdom	175	Germany	3,156
5	Hong Kong	164	United Kingdom	1,860
6	India	92	Australia	1,595
7	Australia	91	Canada	1,257
8	Turkey	89	Singapore	979
9	Spain	75	Sweden	938
10	Italy	70	Switzerland	938

and citation-intensive scientific production remains concentrated in North America and East Asia. This pattern is broadly consistent with previous bibliometric evidence identifying the United States and China among the leading contributors to AI literacy research (Tenório et al., 2023).

Although India appears among the ten most productive countries, differences in accumulated citations persist, highlighting the importance of incorporating broader sociocultural perspectives from the Global South into discussions of AI literacy, digital inequality, and algorithmic ethics. Because Scopus coverage varies across countries and languages, the comparatively lower visibility of Global South research may partly reflect both database coverage and differences in indexed scientific output (Mongeon & Paul-Hus, 2016). Accordingly, the observed geopolitical asymmetry should be understood as a pattern of publication and citation visibility within the Scopus-indexed literature.

Figure 6 presents the source citation network constructed from the references of the analyzed corpus, using VOSviewer and data extracted from Scopus, to visualize the intellectual relationships among the main publications and to delineate the editorial cores that structure the field of AI literacy (Aria & Cuccurullo, 2017; Zupic & Čater, 2015). The top 10 sources were ranked according to productivity (number of documents) and academic impact (accumulated citations).

As shown in **Table 3**, *Computers and Education: Artificial Intelligence* occupies a hegemonic position, leading both in publication volume (68 documents) and citation impact (5,350 citations), consolidating its role as the primary outlet for empirical research on AI literacy in educational contexts. It is followed by journals focused on educational technology, such as *Education and Information Technologies* and *Computers and Education Open*. Notably, the *International Journal of Educational Technology in Higher Education* stands out for its impact efficiency, ranking as the second most cited source (2,024 citations) despite a relatively modest number of publications. In parallel, high productivity is observed in technical conference proceedings such as *Lecture Notes in Computer Science* and *Communications in Computer and Information Science*, although with lower citation impact. This suggests that part of the scholarly debate unfolds within fast-dissemination circuits characteristic of the computer sciences. Overall, the network reveals a specialized and relatively

[illegible]

Note. D: Documents & C: Citations

Table 4. Documents with the greatest structural influence in AI literacy

Study (document)	Type	Citations
Long and Magerko (2020)	Conceptual	1,535
Chan and Hu (2023)	Empirical	1,192
Ng et al. (2021b)	Conceptual review	1,090
Wang et al. (2023)	Instrument (scale development)	430

Note. The documents were selected to represent complementary analytical contributions and do not constitute an exhaustive ranking of the most cited publications. Citation counts were reported by Scopus in January 2026

Table 5. Institutional leadership and distribution of scientific output

Rank	Organization/university	Country	Documents
1	The Education University of Hong Kong	Hong Kong	61
2	The University of Hong Kong	Hong Kong	51
3	Chinese University of Hong Kong	Hong Kong	43
4	Carnegie Mellon University	United States	34
5	Massachusetts Institute of Technology	United States	26
6	University of Florida	United States	23
7	Beijing Normal University	China	22
8	University of Oulu	Finland	21
9	Nanyang Technological University	Singapore	18
10	Northwestern University	United States	18

Note. Data obtained through the Scopus affiliation analysis tool

“Students’ voices on generative AI”, which, with 1,192 citations, marks the emergence of a research agenda focused on students’ perceptions of generative technologies such as ChatGPT.

Likewise, the structural influence of conceptual reviews such as Ng et al. (2021b), “Conceptualizing AI literacy”, is evident. With 1,090 citations, this work has provided the theoretical frameworks necessary to integrate AI literacy competencies into educational curricula. The presence of recent high-impact empirical studies, such as Wang et al. (2023), “Measuring user competence in using AI: validity and reliability of an AI literacy scale” (430 citations), indicates that the field has rapidly moved from abstract theoretical definitions toward the empirical validation of assessment instruments.

This pattern of citation concentration confirms that AI literacy is a field undergoing accelerated consolidation, in which a limited number of contributions define the dominant interpretative frameworks guiding global empirical research (Table 4).

Based on data extracted from Scopus and through an analysis of scientific productivity by institutional affiliation, the leading academic organizations in the production of knowledge on AI literacy were identified. The results presented in Table 5 enable examination of the field’s institutional structure and reveal a marked concentration of research within highly specialized academic nodes.

The analysis shows an undisputed leadership of institutions based in Hong Kong, which occupy the top three positions in the global ranking. The Education University of Hong Kong leads in productivity with 61 documents, followed by The University of Hong Kong (51) and The Chinese University of Hong Kong (43). This finding suggests that Hong Kong has consolidated itself as a central hub for AI literacy research, reflecting a high level of institutional concentration in universities specializing in education and technology.

At a second level of influence are elite technological institutions from the United States, such as Carnegie Mellon University (34 documents) and Massachusetts Institute of Technology (26 documents). The presence of these organizations confirms that the field’s development is not merely pedagogical but is also directly informed by centers of innovation in engineering and computer science. In addition, European representation is evident through the University of Oulu (Finland), indicating a cross-cutting interest in AI and digital literacy within Nordic educational systems. The observed institutional concentration reinforces the idea that AI literacy is developing along two main axes: a pedagogical-curricular axis, led by Asian universities with a strong focus on education, and a technological-experimental axis, driven by North American technical institutes.

To examine the relational dimension of the field, an organizational-level bibliographic coupling analysis was conducted using VOSviewer. The purpose of this technique was to identify academic communities sharing theoretical frameworks, common references, and convergent lines of research in the study of AI literacy. This approach enables visualization of the intellectual architecture of the field through bibliographic links among

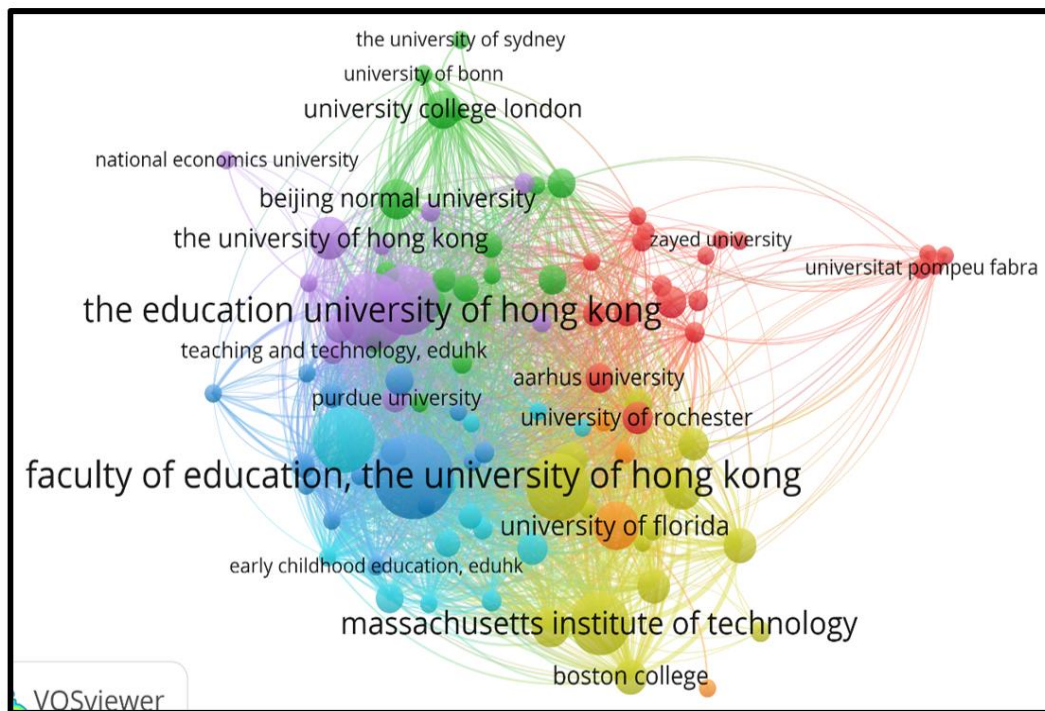


Figure 7. Bibliographic coupling network among organizations (Node size represents the number of documents, link thickness indicates bibliographic-coupling strength, colors identify the clusters generated by VOSviewer, and shorter distances represent greater bibliographic relatedness) (the authors' own elaboration using data from Scopus and VOSviewer)

documents affiliated with different institutions, moving beyond a strictly volumetric analysis of scientific output (van Eck & Waltman, 2014).

The resulting network (**Figure 7**) shows that the faculty of education at The University of Hong Kong presents the highest total link strength (2,165), together with 32 documents and 3,511 accumulated citations. This indicates that this affiliation unit has the strongest aggregate bibliographic-coupling relationships within the analyzed network. The Education University of Hong Kong and The Chinese University of Hong Kong also occupy prominent positions in the Hong Kong-centered portion of the map; however, the colors indicate that these affiliations and their constituent units are distributed across different VOSviewer clusters.

A second prominent grouping comprises North American technology-oriented institutions. The Massachusetts Institute of Technology and Carnegie Mellon University, with total link strengths of 1,271 and 955, respectively, are assigned to the same VOSviewer cluster. Their proximity and shared cluster membership suggest similarity in the reference bases used by their publications, rather than necessarily demonstrating direct institutional collaboration.

Table 5 and **Figure 7** therefore provide complementary but distinct institutional perspectives. **Table 5** reports scientific productivity aggregated by university, whereas **Figure 7** represents the affiliation labels recorded in Scopus, including parent universities and some faculties, departments, schools, and research units. Consequently, the document counts and positions shown in **Figure 7** should not be equated directly with the parent-institution totals reported in **Table 5**. Taken together, the results reveal two prominent poles of scientific production and bibliographic relatedness within the Scopus-indexed corpus (Hong Kong and the United States) while European institutions such as the University of Oulu and University College London occupy less central positions but retain bibliographic links with other institutional groups.

DISCUSSION

Based on a comprehensive bibliometric analysis, eight differentiated research streams were identified from the keyword co-occurrence structure generated by VOSviewer. These clusters represent patterns of

thematic proximity and should not be interpreted as evidence of complete theoretical agreement within each stream.

For each cluster, representative authors were selected from among the most highly cited studies, together with their analytical purposes, main findings, and research orientations. This procedure follows established approaches in scientific mapping and co-occurrence analysis to identify research streams and formulate prospective research agendas (Boyack et al., 2005; Cobo et al., 2011). On this basis, guiding questions and thematic proposals were formulated to synthesize the consolidated foundations of the field and to make visible its theoretical tensions, empirical gaps, and emerging lines of inquiry. [Table 6](#) summarizes the individual clusters, whereas the following discussion examines their relationships and theoretical implications.

The eight clusters are discussed through five connected analytical groupings: clusters 1, 2, and 4; cluster 6 and cluster 8; cluster 5 and cluster 7; and cluster 3. This organization includes all eight clusters and avoids repeating the descriptive information already presented in [Table 6](#).

The first grouping centers on cluster 1 (algorithmic and digital literacy) and considers its conceptual links with critical-thinking concepts. Studies within this stream seek to redefine literacy not merely as the ability to code, but as the competence to navigate and understand algorithmic curation in everyday life (Long et al., 2021). Research such as Swart (2021) demonstrates that young users develop “intuitive tactics” for interacting with algorithms, although they often lack the technical vocabulary to articulate these processes. The proximity of algorithmic literacy to critical-thinking concepts in the co-occurrence network links these everyday tactics to the transition from operational skills to critical engagement with algorithmic systems. From this perspective, AI literacy is understood as a situated, social practice essential for critical digital citizenship.

The second grouping connects cluster 2 (ethics and adoption in higher education) with cluster 4 (critical thinking and the humanities). The literature highlights that integrating AI into classrooms is not primarily a technical challenge, but a pedagogical and ethical one. Walter (2024) argues that prompt engineering must be taught alongside critical thinking to avoid cognitive dependency. Ng et al. (2023) identify competency gaps among educators and emphasize the need for renewed frameworks that incorporate ethical and critical use of AI. Similarly, Schleiss et al. (2023) highlight the importance of adapting AI literacy instruction to different disciplines. Together, these studies show that teacher competence, ethical reasoning, and critical thinking are interdependent components of responsible educational adoption.

The third grouping integrates cluster 6 (language models and educational technology) and cluster 8 (GenAI and academic writing). Studies by Chan and Hu (2023) and Rasul et al. (2023) examine students’ perceptions of tools such as ChatGPT. Their findings reveal a tension between the personalization and efficiency provided by GenAI and concerns regarding privacy, accuracy, academic integrity, and human agency. The relationship between these clusters indicates that the educational use of GenAI cannot be separated from the redesign of assessment and the protection of autonomous learning and writing.

The fourth grouping connects cluster 5 (psychological factors and acceptance) with cluster 7 (competency assessment and metrics). Wang et al. (2023) developed a validated scale covering awareness, use, evaluation, and ethics. This empirical contribution complements the conceptual dimensions proposed by Ng et al. (2021b) and links the definition of AI literacy with its measurement. This line of research also shows how self-efficacy, anxiety, and trust may influence attitudes toward intelligent systems. AI literacy should therefore be understood as a spectrum of competencies rather than as a binary condition.

The fifth grouping corresponds to cluster 3 (K-12 education and computational thinking). Kandlhofer et al. (2016) demonstrate that abstract AI concepts can be introduced through playful and modular approaches. This stream emphasizes incorporating AI literacy into school curricula to democratize access to technological knowledge and encourage early STEM aspirations. It also seeks to prevent AI understanding from becoming the privilege of experts alone (Lee et al., 2021). Its relationship with the higher-education clusters suggests a need for curricular continuity from early computational understanding to critical and ethical AI use.

These relationships help explain the conceptual fragmentation of the field. AI literacy has developed across education, computer science, psychology, communication, and the humanities, each using different populations, instruments, and theoretical assumptions. Some approaches emphasize operational competence, whereas others prioritize ethics, citizenship, or sociotechnical critique. Therefore, the

Table 6. Cluster analysis, content analysis, and future research questions

Cluster	Representative author (top 20)	Purpose	Key findings	Future research questions
1. Algorithmic and digital literacy	Swart (2021)	To explore how young people understand, feel about, and engage with algorithmic news curation on social media from a user-centered perspective.	Algorithmic literacy is situational and context-dependent; users develop intuitive “tactics” to navigate algorithms but lack the technical vocabulary to articulate how they function.	How do users’ intuitive tactics evolve in response to increasingly opaque and rapidly changing algorithms?
2. Ethics and adoption in higher education	Ng et al. (2023)	To explore the opportunities and challenges of AI systems in teaching and to propose a digital competence framework for teachers adapted to the AI era.	Teachers lack both technical and pedagogical competencies to integrate AI; existing digital frameworks (e.g., DigCompEdu) require updating to include ethical and critical AI use.	Which teacher professional development strategies are most effective in reducing AI competency gaps in the short term?
3. K-12 education and computational thinking	Kandlhofer et al. (2016)	To develop and evaluate an educational concept to foster AI and computer science literacy from kindergarten (K-12) to university level.	Core AI concepts (search, graphs, classification) can be effectively taught from an early age when pedagogically adapted through playful and modular approaches.	How does early exposure to AI concepts influence long-term STEM career choices among school students?
4. Critical thinking and the humanities	Walter (2024)	To examine the transformative impact of AI in the classroom, emphasizing the need for AI literacy, prompt engineering, and critical thinking.	AI integration requires a paradigm shift toward personalized learning; critical thinking is essential to evaluate AI hallucinations and avoid cognitive dependency.	How can prompt engineering be integrated into humanities curricula to foster logical and critical argumentation?
5. Psychological factors and acceptance	Wang et al. (2023)	To develop and validate a quantitative scale to measure user competence in the use of AI literacy.	A four-construct AI literacy model (awareness, use, evaluation, ethics) was validated; perceived competence correlates positively with attitudes toward robots and daily AI use.	How do AI literacy levels measured by this scale vary across different demographic and cultural groups?
6. Language models and educational technology	Rasul et al. (2023)	To examine the benefits and challenges of using ChatGPT in higher education under constructivist learning theory.	ChatGPT supports adaptive learning and personalized feedback but poses significant risks to academic integrity and traditional assessment practices.	How should university assessments be redesigned to measure higher-order competencies in AI-saturated learning environments?
7. Competency assessment and metrics	Ng et al. (2021b)	To conceptualize “AI literacy” and propose a consolidated theoretical framework for its definition, teaching, and evaluation.	Four key dimensions are defined: know/understand, use/apply, evaluate/create, and ethics; a theoretical foundation is established for standardized assessment tools.	What evaluation criteria are needed to objectively measure the ethical and creative dimensions of AI literacy?
8. GenAI and academic writing	Chan and Hu (2023)	To investigate university students’ perceptions, familiarity, and willingness to interact with generative AI technologies such as ChatGPT.	Students show a positive and pragmatic attitude toward GenAI as a learning assistant, while expressing concerns about accuracy, privacy, and technological dependency.	How does prolonged use of generative AI assistants affect the development of students’ cognitive and autonomous writing skills?

Note. Representative authors were selected from the most influential documents in each cluster, based on citation impact and thematic centrality and when an author has multiple publications in the same year, they are listed alphabetically in accordance with APA guidelines

fragmentation reflects disciplinary silos, the absence of a dominant theoretical anchor, and unresolved epistemological tensions rather than simple terminological variation.

Overall, the identified streams reveal the field's progressive evolution, moving from an initial phase focused on technical definitions and computational thinking to a current stage increasingly shaped by ethical,

critical, and social concerns associated with GenAI. This evolution represents an increasing integration of technical, pedagogical, psychological, and ethical perspectives rather than the replacement of one approach by another. The findings indicate that AI literacy has expanded beyond a purely technological domain and is now understood as a transversal competence necessary for interpreting interactions between individuals and intelligent systems.

Unlike previous reviews focused primarily on definitions, competencies, teaching, and assessment (Almatrafi et al., 2024; Zhang et al., 2025), this study integrates temporal evolution with thematic, collaborative, geographical, and institutional structures. Its contribution therefore extends beyond updating publication trends by explaining how different research streams interact in the consolidation of AI literacy.

From an educational perspective, these findings suggest that AI literacy should shift from isolated technological training initiatives to a transversal curricular component integrated across higher education programs. Universities may need to strengthen competencies related to critical evaluation of algorithmic systems, ethical reasoning, prompt design, and responsible interaction with GenAI tools. Likewise, teacher training programs should incorporate pedagogical strategies that enable educators to critically mediate the use of AI rather than simply adopting technological tools at an operational level.

The practical implications also extend to public institutions, professional organizations, libraries, and workplaces. These organizations may develop guidelines and training programs on algorithmic transparency, privacy, misinformation, bias, and responsible decision-making. Educational policy should similarly establish progressive competency standards while allowing their adaptation to different professional and sociocultural contexts.

The concentration of publications and citations in Hong Kong, the United States, and China suggests that a limited number of institutional environments influence the field's research agendas. Consequently, educational frameworks developed in highly digitized settings should be validated before being transferred to contexts with different infrastructures, languages, or social inequalities. Expanding regional research networks would help incorporate perspectives currently underrepresented in the indexed literature.

These findings must be interpreted in light of the limitations of bibliometric analysis. Citation counts may favor older, highly visible publications, whereas keyword co-occurrence identifies thematic relationships but does not demonstrate theoretical agreement. In addition, Scopus coverage may reduce the visibility of non-English and regionally indexed research, particularly from the Global South (Mongeon & Paul-Hus, 2016). The identified clusters and geographical patterns therefore represent the structure of the analyzed corpus rather than a complete measurement of worldwide AI literacy research.

Based on the cluster analysis and the information synthesized in [Table 6](#), several priority research lines are identified to expand the understanding of AI literacy beyond its technical dimension. Following Donthu et al. (2021), these directions are linked directly to the gaps identified in the corresponding clusters.

First, the evidence highlights the need to advance toward greater theoretical unification of the field. Although operational definitions of AI literacy exist (Ng et al., 2021a, 2021b), research remains fragmented. In relation to cluster 1 and cluster 7, future studies should test whether common conceptual dimensions and assessment criteria operate consistently across educational and cultural contexts. Such models should articulate technical knowledge, cognitive skills, and civic autonomy in the face of algorithmic systems (Swart, 2021).

Second, the rapid expansion of GenAI introduces new challenges for academic integrity. Based on cluster 6 and cluster 8, comparative studies should examine how unaided, disclosed AI-supported, and intensive AI-assisted writing affect creativity, argumentation, source verification, and autonomous learning. These findings could support pedagogical uses of AI without compromising students' intellectual agency (Chan & Hu, 2023; Rasul et al., 2023).

Cluster 5 and cluster 7 reveal a specific need for longitudinal and cross-cultural research on the psychological effects of AI use. Future studies should determine whether measured AI literacy predicts technological anxiety, calibrated trust, emotional well-being, and demonstrated performance across different demographic groups (Wang et al., 2023).

Cluster 2 and cluster 3 highlight the relationship between teacher preparation and curricular equity. Future studies should compare professional-development strategies and determine whether early AI education improves students' recognition of algorithmic bias, privacy risks, and automated decision-making. These questions are particularly relevant in vulnerable communities with unequal access to technological education (Kandlhofer et al., 2016; Ng et al., 2023; Su et al., 2023).

Finally, the literature underscores the importance of promoting critical AI literacy. Instrumental mastery of technology does not guarantee an understanding of its ethical and social implications (Walter, 2024). Research related to cluster 1 and cluster 4 should evaluate specific strategies such as comparing human and AI-generated outputs, identifying algorithmic bias, and verifying automated information. These outcomes would provide observable evidence of critical AI literacy beyond self-reported confidence.

Taken together, these research directions point toward moving beyond a narrow conception of AI literacy centered on technical training and toward understanding AI literacy as a socially situated phenomenon with profound normative, epistemic, and cultural implications. From this perspective, AI literacy emerges as a fundamental civic competence for interpreting, questioning, and negotiating the role of algorithmic systems in everyday life, reinforcing the need for interdisciplinary approaches rooted in the social sciences and humanities.

CONCLUSIONS

The objective of this study was to analyze, from a bibliometric perspective, the intellectual evolution and conceptual architecture of research on AI literacy using Scopus-indexed literature. The results indicate that AI literacy has gained increasing prominence in global academic debates over the past decade. Initially associated mainly with technical and computational perspectives, AI literacy has evolved into a broader interdisciplinary field encompassing ethical, pedagogical, and social dimensions. In this regard, themes such as critical thinking, algorithmic ethics, and interaction with GenAI systems emerge as recurring elements in discussions concerning the relationship between individuals and automated environments.

From an academic standpoint, this study contributes to the organization and synthesis of a body of literature developed within the context of rapid technological transformation. Scientific mapping enabled the identification of collaboration patterns and thematic concentrations that reflect the field's evolution from an initially fragmented stage toward a progressively more articulated configuration, characterized by international research networks and increasing interaction among fields such as education, psychology, and the social sciences, with a particularly strong presence in Asia and North America.

The cluster analysis identified eight major thematic streams, ranging from computational thinking in school education to debates surrounding GenAI and large language models. Taken together, these results suggest a gradual shift from approaches focused on the instrumental use of technology toward more critical and integrative perspectives that consider factors such as psychological acceptance of AI, academic integrity, and the analysis of algorithmic bias. This shift highlights an expanded understanding of AI literacy, which is no longer confined to developing operational skills but increasingly encompasses the ability to comprehend, interpret, and critically question the functioning and implications of intelligent systems.

Nevertheless, the study presents certain limitations inherent in its methodological design. The exclusive use of the Scopus database, while ensuring high standards of source quality, may exclude relevant literature published in other languages or in regional repositories. In addition, the dynamic nature of the field implies that citation patterns reflect accumulated scientific impact but may not fully capture the most recent debates disseminated through conferences or other rapidly evolving publication formats.

Overall, the findings indicate that AI literacy has evolved into a rapidly expanding interdisciplinary field that increasingly connects education, ethics, digital culture, and social transformation. The study demonstrates that contemporary debates on AI literacy extend beyond technical competencies and are progressively oriented toward the development of critical and reflective capacities required to navigate algorithmically mediated societies. In this regard, the present research contributes by offering an integrated longitudinal perspective that organizes the field's conceptual evolution and identifies emerging educational challenges associated with GenAI.

Author contributions: **EAM-Z:** conceptualization, investigation, software, visualization, writing – original draft; **FC-B:** investigation, methodology, supervision, validation, writing – reviewing & editing. Both authors approved the final version of the article.

Funding: The authors received no financial support for the research and/or authorship of this article.

Ethics declaration: This study did not require approval from an ethics committee because it was a bibliometric investigation based exclusively on the analysis of scientific publications indexed in the Scopus database between 2015 and 2025. It did not involve human participants, clinical procedures, surveys, interviews, or the collection of personal or sensitive data. All analyzed information corresponded to publicly accessible scientific documents related to AI literacy, educational technology, and social research. Furthermore, it adhered to principles of academic integrity, transparency, and responsible scientific use through the proper citation, analysis, and interpretation of the bibliographic sources included in the dataset.

AI statement: ChatGPT (OpenAI) was used to improve the wording of the manuscript. The authors reviewed all changes and took full responsibility for the final text.

Declaration of interest: The authors declared no competing interest.

Data availability: Data generated or analyzed during this study are available from the authors on request.

REFERENCES

- Alharthi, R. H. E., Salleh, N. Z., Abdullah, M., Ali, A., Faisal, F., & Mohd Nor, R. (2023). Research trends, developments, and future perspectives in brand attitude: A bibliometric analysis utilizing the Scopus database (1944-2021). *Heliyon*, 9(1), Article e12765. <https://doi.org/10.1016/j.heliyon.2022.e12765>
- Almatrafi, O., Johri, A., & Lee, H. (2024). A systematic review of AI literacy conceptualization, constructs, and implementation and assessment efforts (2019-2023). *Computers & Education Open*, 6(1), Article 100173. <https://doi.org/10.1016/j.caeo.2024.100173>
- Aria, M., & Cuccurullo, C. (2017). *bibliometrix*: An R-tool for comprehensive science mapping analysis. *Journal of Informetrics*, 11(4), 959-975. <https://doi.org/10.1016/j.joi.2017.08.007>
- Baas, J., Schotten, M., Plume, A., Côté, G., & Karimi, R. (2020). Scopus as a curated, high-quality bibliometric data source for academic research in quantitative science studies. *Quantitative Science Studies*, 1(1), 377-386. https://doi.org/10.1162/qss_a_00019
- Beer, D. (2017). The social power of algorithms. *Information, Communication & Society*, 20(1), 1-13. <https://doi.org/10.1080/1369118X.2016.1216147>
- Biagini, G. (2025). Towards an AI-literate future: A systematic literature review exploring education, ethics, and applications. *International Journal of Artificial Intelligence in Education*, 35, 2616-2666. <https://doi.org/10.1007/s40593-025-00466-w>
- Börner, K., Chen, C., & Boyack, K. W. (2010). Visualizing knowledge domains. *Annual Review of Information Science and Technology*, 37(1), 179-255. <https://doi.org/10.1002/aris.1440370106>
- Bornmann, L., & Daniel, H.-D. (2008). What do citation counts measure? A review of studies on citing behavior. *Journal of Documentation*, 64(1), 45-80. <https://doi.org/10.1108/00220410810844150>
- Boyack, K. W., & Klavans, R. (2010). Co-citation analysis, bibliographic coupling, and direct citation: Which citation approach represents the research front most accurately? *Journal of the American Society for Information Science and Technology*, 61(12), 2389-2404. <https://doi.org/10.1002/asi.21419>
- Boyack, K. W., Klavans, R., & Börner, K. (2005). Mapping the backbone of science. *Scientometrics*, 64(3), 351-374. <https://doi.org/10.1007/s11192-005-0255-6>
- Černý, M. (2024). University students' conceptualisation of AI literacy: Theory and empirical evidence. *Social Sciences*, 13(3), Article 129. <https://doi.org/10.3390/socsci13030129>
- Chan, C. K. Y., & Hu, W. (2023). Students' voices on generative AI: Perceptions, benefits, and challenges in higher education. *International Journal of Educational Technology in Higher Education*, 20(1), Article 43. <https://doi.org/10.1186/s41239-023-00411-8>
- Chen, C. (2006). CiteSpace II: Detecting and visualizing emerging trends and transient patterns in scientific literature. *Journal of the American Society for Information Science and Technology*, 57(3), 359-377. <https://doi.org/10.1002/asi.20317>
- Chen, C. (2017). Science mapping: A systematic review of the literature. *Journal of Data and Information Science*, 2(2), 1-40. <https://doi.org/10.1515/jdis-2017-0006>

- Chiu, T. K. F. (2024). Future research recommendations for transforming higher education with generative AI. *Computers and Education: Artificial Intelligence*, 6, Article 100197. <https://doi.org/10.1016/j.caeai.2023.100197>
- Cobo, M. J., López-Herrera, A. G., Herrera-Viedma, E., & Herrera, F. (2011). Science mapping software tools: Review, analysis, and cooperative study. *Journal of the American Society for Information Science and Technology*, 62(7), 1382-1402. <https://doi.org/10.1002/asi.21525>
- Cordova-Buiza, F., Jimenez-Del-Carpio, P. S., Conde-Galindo, H. J., & Rosas-Falconi, D. (2026). Contribution of the digitisation of cultural tourism to the resilience of local communities in the face of global crises: An integrative review. In *Proceedings of the International Conference on Tourism Research* (pp. 99-106). <https://doi.org/10.34190/ictr.9.1.4476>
- Crawford, K. (2021). *Atlas of AI: Power, politics, and the planetary costs of artificial intelligence*. Yale University Press. <https://doi.org/10.12987/9780300252392>
- Dai, Y., Chai, C.-S., Lin, P.-Y., Jong, M. S.-Y., Guo, Y., & Qin, J. (2020). Promoting students' well-being by developing their readiness for the artificial intelligence age. *Sustainability*, 12(16), Article 6597. <https://doi.org/10.3390/su12166597>
- Donthu, N., Kumar, S., Mukherjee, D., Pandey, N., & Lim, W. M. (2021). How to conduct a bibliometric analysis: An overview and guidelines. *Journal of Business Research*, 133, 285-296. <https://doi.org/10.1016/j.jbusres.2021.04.070>
- Floridi, L., Cows, J., King, T. C., & Taddeo, M. (2020). How to design AI for social good: Seven essential factors. *Science and Engineering Ethics*, 26(3), 1771-1796. <https://doi.org/10.1007/s11948-020-00213-5>
- Ioannidis, J. P. A., Boyack, K. W., & Baas, J. (2020). Updated science-wide author databases of standardized citation indicators. *PLOS Biology*, 18(10), Article e3000918. <https://doi.org/10.1371/journal.pbio.3000918>
- Kalantzis, M., & Cope, B. (2025). Literacy in the time of artificial intelligence. *Reading Research Quarterly*, 60, Article e591. <https://doi.org/10.1002/rrq.591>
- Kandlhofer, M., Steinbauer-Wagner, G., Hirschmugl-Gaisch, S., & Huber, P. (2016). Artificial intelligence and computer science in education: From kindergarten to university. In *Proceedings of the Frontiers in Education Conference* (pp. 1-9). IEEE. <https://doi.org/10.1109/FIE.2016.7757570>
- Kong, S.-C., Cheung, W. M.-Y., & Zhang, G. (2023). Evaluating an artificial intelligence literacy programme for developing university students' conceptual understanding, literacy, empowerment and ethical awareness. *Educational Technology and Society*, 26(1), 16-30. [https://doi.org/10.30191/ETS.202301_26\(1\).0002](https://doi.org/10.30191/ETS.202301_26(1).0002)
- Laupichler, M. C., Aster, A., Schirch, J., & Raupach, T. (2022). Artificial intelligence literacy in higher and adult education: A scoping literature review. *Computers and Education: Artificial Intelligence*, 3, Article 100101. <https://doi.org/10.1016/j.caeai.2022.100101>
- Lee, I., Ali, S., Zhang, H., DiPaola, D., & Breazeal, C. (2021). Developing middle school students' AI literacy. In *Proceedings of the 52nd ACM Technical Symposium on Computer Science Education* (pp. 191-197). ACM. <https://doi.org/10.1145/3408877.3432513>
- Leydesdorff, L. (2007). Mapping interdisciplinarity at the interfaces between the science citation index and the social science citation index. *Scientometrics*, 71(3), 391-405. <https://doi.org/10.1007/s11192-007-1694-z>
- Long, D., & Magerko, B. (2020). What is AI literacy? Competencies and design considerations. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems* (pp. 1-16). <https://doi.org/10.1145/3313831.3376727>
- Long, D., Blunt, T., & Magerko, B. S. (2021). Co-designing AI literacy exhibits for informal learning spaces. *Proceedings of the ACM on Human-Computer Interaction*, 5(CSCW2), Article 293. <https://doi.org/10.1145/3476034>
- Mahadewi, M. P., Aysya, A. A. A., Sofiyani, Z., & Fahmi, F. (2025). The importance of literacy on artificial intelligence for higher education students: A systematic literature review. *International Journal of Advances in Data and Information Systems*, 6(1), 1-14. <https://doi.org/10.59395/ijadis.v6i1.1350>
- Mhlanga, D., & Dzingirai, M. (2024). Bibliometric study on organizational resilience: Trends and future research agenda. *International Journal of Corporate Social Responsibility*, 9, Article 9. <https://doi.org/10.1186/s40991-024-00098-8>
- Moed, H. F. (2005). *Citation analysis in research evaluation*. Springer. <https://doi.org/10.1007/1-4020-3714-7>

- Mongeon, P., & Paul-Hus, A. (2016). The journal coverage of Web of Science and Scopus: A comparative analysis. *Scientometrics*, 106(1), 213-228. <https://doi.org/10.1007/s11192-015-1765-5>
- Moral-Muñoz, J. A., Herrera-Viedma, E., Santisteban-Espejo, A., & Cobo, M. J. (2020). Software tools for conducting bibliometric analysis in science: An up-to-date review. *El Profesional de la Información*, 29(1), Article e290103. <https://doi.org/10.3145/epi.2020.ene.03>
- Ng, D. T. K., Leung, J. K. L., Chu, S. K. W., & Qiao, M. S. (2021a). AI literacy: Definition, teaching, evaluation and ethical issues. *Proceedings of the Association for Information Science and Technology*, 58(1), 504-509. <https://doi.org/10.1002/pr2.487>
- Ng, D. T. K., Leung, J. K. L., Chu, S. K. W., & Qiao, M. S. (2021b). Conceptualizing AI literacy: An exploratory review. *Computers and Education: Artificial Intelligence*, 2, Article 100041. <https://doi.org/10.1016/j.caeai.2021.100041>
- Ng, D. T. K., Leung, J. K. L., Su, J., Ng, R. C. W., & Chu, S. K. W. (2023). Teachers' AI digital competencies and twenty-first century skills in the post-pandemic world. *Educational Technology Research and Development*, 71(1), 137-161. <https://doi.org/10.1007/s11423-023-10203-6>
- Olortegui-Alcalde, L. M., & Cordova-Buiza, F. (2025). Digital innovation and performance of student startups in Peru: A PLS-SEM evaluation. *Problems and Perspectives in Management*, 23(4), 407-420. [https://doi.org/10.21511/ppm.23\(4\).2025.30](https://doi.org/10.21511/ppm.23(4).2025.30)
- Öztürk, O., Kocaman, R., & Kanbach, D. K. (2024). How to design bibliometric research: An overview and a framework proposal. *Review of Managerial Science*, 18, 3333-3361. <https://doi.org/10.1007/s11846-024-00738-0>
- Pangrazio, L., Godhe, A.-L., & Ledesma, A. G. L. (2020). What is digital literacy? A comparative review of publications across three language contexts. *E-Learning and Digital Media*, 17(6), 442-459. <https://doi.org/10.1177/2042753020946291>
- Pinski, M., & Benlian, A. (2024). AI literacy for users – A comprehensive review and future research directions of learning methods, components, and effects. *Computers in Human Behavior: Artificial Humans*, 2(1), Article 100062. <https://doi.org/10.1016/j.chbah.2024.100062>
- Rasul, T., Nair, S., Kalendra, D., Robin, M., Santini, F. O., Ladeira, W. J., Sun, M., Day, I., Rather, R. A., & Heathcote, L. (2023). The role of ChatGPT in higher education: Benefits, challenges, and future research directions. *Journal of Applied Learning and Teaching*, 6(1), 41-56. <https://doi.org/10.37074/jalt.2023.6.1.29>
- Rodriguez-Fernandez, I. C., Jurado-Vera, S. Y., Ramos-Cavero, M. J., & Cordova-Buiza, F. (2026). Digital transformation and operational efficiency in fast-moving consumer goods companies: A systematic review of Industry 4.0 applications. *International Journal of Sustainable Development and Planning*, 21(1), 51-60. <https://doi.org/10.18280/ijstdp.210105>
- Schleiss, J., Laupichler, M. C., Raupach, T., & Stober, S. (2023). AI course design planning framework: Developing domain-specific AI education courses. *Education Sciences*, 13(9), Article 954. <https://doi.org/10.3390/educsci13090954>
- Su, J., Ng, D. T. K., & Chu, S. K. W. (2023). Artificial intelligence (AI) literacy in early childhood education: The challenges and opportunities. *Computers and Education: Artificial Intelligence*, 4, Article 100124. <https://doi.org/10.1016/j.caeai.2023.100124>
- Sugimoto, C. R., & Larivière, V. (2018). *Measuring research: What everyone needs to know*. Oxford University Press. <https://doi.org/10.1093/wentk/9780190640118.001.0001>
- Swart, J. (2021). Experiencing algorithms: How young people understand, feel about, and engage with algorithmic news selection on social media. *Social Media + Society*, 7(2). <https://doi.org/10.1177/20563051211008828>
- Tadimalla, S. Y., & Maher, M. L. (2025). AI literacy as a core component of AI education. *AI Magazine*, 46, Article e70007. <https://doi.org/10.1002/aaai.70007>
- Tenório, K., Olari, V., Chikobava, M., & Romeike, R. (2023). Artificial intelligence literacy research field: A bibliometric analysis from 1989 to 2021. In *Proceedings of the 54th ACM Technical Symposium on Computer Science Education* (pp. 1083-1089). ACM. <https://doi.org/10.1145/3545945.3569874>
- Thaha, A. R., Riau, D. P., Antoro, A. F. S., & Aziz, F. (2025). Digital economy and SME research landscape: A bibliometric analysis of emerging themes and trends. *Journal of Scientometric Research*, 14(1), 272-282. <https://doi.org/10.5530/jscires.20251711>

- Traga Philippakos, Z. A., & Rocconi, L. (2025). AI literacy: Elementary and secondary teachers' use of AI tools, reported confidence, and professional development needs. *Education Sciences*, 15(9), Article 1186. <https://doi.org/10.3390/educsci15091186>
- van Eck, N. J., & Waltman, L. (2010). Software survey: VOSviewer, a computer program for bibliometric mapping. *Scientometrics*, 84(2), 523-538. <https://doi.org/10.1007/s11192-009-0146-3>
- van Eck, N. J., & Waltman, L. (2014). Visualizing bibliometric networks. In Y. Ding, R. Rousseau, & D. Wolfram (Eds.), *Measuring scholarly impact: Methods and practice* (pp. 285-320). Springer. https://doi.org/10.1007/978-3-319-10377-8_13
- Verma, R., Kumar, A., Mashroofa, M. M., & Gupta, N. (2025). A comprehensive bibliometric analysis of research trends in sustainable inclusive economic growth within the SDG 8 framework from 2015 to 2025 using Biblioshiny and VOSviewer. *Discover Sustainability*, 6, Article 1221. <https://doi.org/10.1007/s43621-025-02124-6>
- Walter, Y. (2024). Embracing the future of artificial intelligence in the classroom: The relevance of AI literacy, prompt engineering, and critical thinking in modern education. *International Journal of Educational Technology in Higher Education*, 21, Article 15. <https://doi.org/10.1186/s41239-024-00448-3>
- Waltman, L. (2016). A review of the literature on citation impact indicators. *Journal of Informetrics*, 10(2), 365-391. <https://doi.org/10.1016/j.joi.2016.02.007>
- Wang, B., Rau, P.-L. P., & Yuan, T. (2023). Measuring user competence in using artificial intelligence: Validity and reliability of artificial intelligence literacy scale. *Behaviour & Information Technology*, 42(9), 1324-1337. <https://doi.org/10.1080/0144929X.2022.2072768>
- Yang, Y., Zhang, Y., Sun, D., He, W., & Wei, Y. (2025). Navigating the landscape of AI literacy education: Insights from a decade of research (2014-2024). *Humanities and Social Sciences Communications*, 12, Article 374. <https://doi.org/10.1057/s41599-025-04583-8>
- Zhang, S., Prasad, P. G., & Schroeder, N. L. (2025). Learning about AI: A systematic review of reviews on AI literacy. *Journal of Educational Computing Research*, 63(5), 1292-1322. <https://doi.org/10.1177/07356331251342081>
- Zupic, I., & Čater, T. (2015). Bibliometric methods in management and organization: A review. *Organizational Research Methods*, 18(3), 429-472. <https://doi.org/10.1177/1094428114562629>

