Scientometrics (2022) 127:5139–5158
https://doi.org/10.1007/s11192-022-04477-5

Evolutionary stages and multidisciplinary nature of artificial intelligence research

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Received: 19 August 2021 / Accepted: 29 July 2022 / Published online: 16 August 2022

Abstract

This paper analyzed the growth and multidisciplinary nature of Artificial Intelligence research during the last 60 years. Web of Science coverage since 1960 was considered, and a descriptive research was performed. A top-down approach using Web of Science subject categories as a proxy to measure multidisciplinarity was developed. Bibliometric indicators based on the core of subject categories involving articles and citing articles related to this area were applied. The data analysis within a historical and epistemological perspective allowed to identify three main evolutionary stages: an emergence period (1960–1979), based on foundational literature from 1950s; a re-emergence and consolidation period (1980–2009), involving a "paradigmatic" phase of development and first industrial approach; and a period of re-configuration of the discipline as a technoscience (2010–2019), where an explosion of solutions for productive systems, wide collaboration networks and multidisciplinary research projects were observed. The multidisciplinary dynamics of the field was analyzed using a Thematic Dispersion Index. This indicator clearly described the transition from the consolidation stage to the re-configuration of the field, finding application in a wide diversity of scientific and technological domains. The results demonstrated that epistemic changes and qualitative leaps in Artificial Intelligence research have been associated to variations in multidisciplinarity patterns.

Keywords Artificial intelligence · Scientific production · Multidisciplinarity · Bibliometric indicators · Thematic dispersion index

Introduction

The speed, scope and impact with which emerging technologies are transforming industrial systems have caused the irruption in our time of a new stage of development for humanity. The phenomenon, called by economists the fourth industrial revolution or revolution 4.0, is already part of the reality of many nations worldwide (Schwab, 2017). Its essence lies in automating industrial processes through cyber-physical systems capable of cooperating and

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making decentralized decisions. This has allowed Artificial Intelligence (AI) to become an area of knowledge (or set of areas) that generates a lot of research and innovation.

The extensive application of AI in everyday scenarios, and the combination of physical and tangible machinery with digital processes through advanced technologies (cloud computing, internet of things, big data analysis, machine learning, deep neural networks, etc.), has sparked the increasing interest of Science of Science practitioners. They are particularly interested in the characteristic of AI research, its main actors and interactions, and the different research areas involved in scientific production. In this paper, we combine bibliometric methods with historical and epistemological approaches to understand how the multidisciplinary nature of research can play a determining role in the development of the discipline.

Background

AI has been a recurrent topic in scientometric studies and has been identified as the most productive subfield of computer science (Fiala & Tutoky, 2017). Many papers have used AI datasets to introduce new bibliometric indicators and methods (Rokach & Mitra, 2013; Serenko, 2010; Zhang et al., 2019). Applications of AI have been recently studied in biology (Chiarello et al., 2019), medicine (Chen et al., 2020; Tran et al., 2019; West et al., 2019), engineering (Darko et al., 2020), higher education (Hinojo-Lucena et al., 2019), environmental sciences (Zhao et al., 2020), industries and businesses (Munim et al., 2020; Shi & Li, 2019), political sciences (Savaget et al., 2019) and telecommunications (Abbas et al., 2019). Dimensions of AI literature within the Computer Sciences domain have been frequently analyzed, including country-based approaches (Devyatkin et al., 2017; Fiala & Willett, 2015; Gao et al., 2019; Gupta & Dhawan, 2018). Research fronts inside AI literature have received special attention, particularly Machine Learning and Deep Learning (Alejo-Machado et al., 2015; Bhattacharya, 2019; Kulakli & Osmanaj, 2020; Tolcheev, 2019).

Quite important bibliometric papers characterized AI research. Van den Besselaar and Leydesdorff (1996) conducted a relevant study during the nineties, using journal-to-journal citation measures to analyze the dynamics and characteristics of this field. When asked if AI were in a “paradigmatic” or “pre-paradigmatic” phase of development, in the Kuhnian sense, they offered a bibliometric answer. Focused on the scientific output and the patterns of their cross-references, their results suggested that AI emerged as a discipline in the late eighties. During this period, the field became more centered and accepted in a specific community of researchers, stabilizing the field delineation after 1988, and entering a “paradigmatic” phase with a coherent set of journals specialized in expert systems research and applied artificial intelligence (Van den Besselaar & Leydesdorff, 1996).

The idea that AI plays a crucial role in knowledge economies was taken into account by Tseng and Ting (2013). They studied patents granted by the United States patent and trademark office (USPTO) from 1976 to 2010. They introduced quantitative and qualitative patent-based measures to analyze the technology flow of AI in the top ten specialized countries, dividing the field into four subfields: problem reasoning and solving, machine learning, network structures, and knowledge processing systems.

Niu and colleagues (2016) analyzed scientific outputs, subject categories, main journals, author productivity, geographic distribution, international collaboration, hot issues and research trends in the AI domain during the period 1990–2014. This study introduced GIS-based spatial analysis, combining R&D investment and academic output and finding a high correlation between both elements. The authors developed keyword-based subject analysis, classifying the most frequent keywords into two groups: (a) method and models and (b) applications. This approach allowed them to identify trends during the period, as well as established (artificial neural networks, genetic algorithm, fuzzy logic, support vector machine, machine learning, swarm intelligence, particle swarm optimization, distributed artificial intelligence, computational intelligence and ontology) and emergent topics (artificial bee colony, ant colony optimization, artificial immune system, artificial endocrine system, rough set). These methods and models would be useful to improve the precision of any search strategy for AI documents in bibliographic databases. Likewise, the identification of established applications (expert systems, optimization, classification, design, prediction, multi-agent systems, simulation, diagnosis, decision support systems, pattern recognition, knowledge-based systems, case-based reasoning, knowledge representation, management, identification, decision making, fault diagnosis, recognition and data mining), as well as emergent ones, such as mobile robot or reinforcement learning, allow the authors confirm the cross-thematic nature of AI, taking into account the use of its algorithms to solve practical applications in different fields (Niu et al., 2016).

Some authors have analyzed the field using an AI specialized journal as the data source (Baier-Fuentes et al., 2018; Shukla et al., 2019; Yu et al., 2019; Zhang et al., 2017). While Van den Besselaar and Leydesdorff used the journal *Artificial Intelligence*, Zhang and colleagues (2017) selected the journal *Knowledge-based System*. A Latent Dirichlet Allocation model was used to identify six main research areas for 25 years: expert systems, machine learning, data mining, decision making, optimization, and fuzzy (Zhang et al., 2017). They applied a learning-based process to detect the topic changes of the journal in sequential time slices, identifying during the last time slice (2011–2016) that artificial intelligence and decision making grew rapidly, especially in two directions: (1) fuzzy logic and computational intelligence, and (2) information uncertainty-oriented studies (probabilistic and prediction models). Social networks and ontologies were also detected as emergent interests of the journal authors' community.

Liu and colleagues (2018) defined the set of AI articles using nine specialized journals and twelve conferences. They observed the rising growth of the field during the period 2000–2015, as a consequence of the emerging technological shifts (e.g., machine learning techniques, etc.), the growing number of authors involved, and the increasing average of authors per paper. They also explored the inner structure in terms of topics' evolution over time, and exposed the most influential papers, researchers and institutions. On the other hand, Zhang and colleagues (2019) applied altmetric indices and word cloud analysis in AI sets of literature published in 62 journals and 25 conferences covered by Scopus during 2011–2017. They confirmed the increasing growth of literature.

Moreover, Bobadilla et al. (2019) introduced data mining, natural language processing and machine learning techniques to select topics, provide topic rankings, detect research areas, generate research area rankings, and compare the qualities versus quantities of the topics and research areas in the AI context. They analyzed eight specialized journals, showing a strong decline in AI classical research and a strong increase in machine learning methods. Optimization-based learning was the most promising area; and research trends considered evolutionary algorithms, learning algorithms, and learning systems as hot topics. The same strategy, but more comprehensive, was developed by Qian et al. (2020), who analyzed 65 887 records from 35 AI journals to study the hierarchical structural evolution of the field, using the behavior of 7901 keywords to assess its disciplinary development during the period 2009–2018. Despite all these antecedents, the multidisciplinary dynamics of AI has not been sufficiently studied based on a bibliometric approach.

The multidisciplinary approach

Measuring multidisciplinarity is always a challenge for scientometrics practitioners. If classical approach is focused on these kinds of research as a social environment where motives and interactions of researchers define the multidisciplinary context, the bibliometric perspective takes another route. Considering publications as the final container of scientific results, bibliometricians are focused on measures that show the integration of knowledge in a single paper or a body of research (Wagner et al, 2011). They basically use two methods: a Bottom-up approach based on grouping sets of articles according to a criterion (bibliographical coupling or co-citation networks), and a Top-down approach dependent on existing classifications (Moschini et al, 2020). They usually are looking for communication vessels between authors, institutions, canonical cited authors, cited or citing journals, cited or citing documents, and usually illustrate the diversity of research areas represented by these items using maps (Chen, 2017; Klavans & Boyack, 2011; Porter & Rafols, 2009).

Some authors have used social network measures for visual representations, using the centrality degree or betweenness to identify elements that define the confluence of disciplines or research topics (Chen, 2004; Lewis, 2020; Leydesdorff, 2007; Thomas & Zaytseva, 2016). Similarly, some studies analyze author-journal bipartite networks (Carusi & Bianchi, 2020) and interactive overlays in journal maps (Leydesdorff et al., 2015). Other authors have adopted indicators from diverse thematic domains, as biodiversity measures (from ecology) or concentration measures (from economics) (Bache et al., 2013; Garner et al., 2018). Leinster-Cobbold diversity index (LCDiv) (Leinster & Cobbold, 2012; Mugabushaka, Kiriakou & Papazoglou, 2016), Integration Scores (Porter et al., 2007, 2008), Rao-Stirling diversity (Rafols & Meyer, 2010; Rao, 1982; Stirling, 2007), Diffusion Scores (Carley & Porter, 2012; Garner, Porter & Newman, 2014) Cross-research domain knowledge interchange (Porter et al., 2013) and Herfindahl–Hirschman index (Moschini et al, 2020) are some of these indicators. But anyway, as previously noted by Schubert et al. (1989), a crucial point of the bibliometric approach is the field/subfield classification of papers.

Classification schemes have been frequently used in bibliometric practices. Initially created for information retrieval purposes, it uses in evaluative bibliometrics procedures have been evolved since the beginning of the twenty-first century (Glanzel & Schubert, 2003). Observing the citation differences of scientific fields, many authors considered a classification scheme as a proxy for the normalization of citation scores (Moed et al., 1995; Ruiz-Castillo & Waltman, 2014; Waltman & van Eck, 2012; Waltman et al., 2011). This methodological approach of evaluative bibliometrics has been used to compare researchers, research groups, institutions, journals, and even countries. However, this method is not exempt of criticism, based on the idea that the indexation process (the assignment of a journal to a subject category or a subject area, especially through a machine-based process) is heuristic and subjective (Pudovkin & Garfield, 2002), and some journals (especially those involving interdisciplinary topics) are not sufficiently disciplinarily oriented to be used for the normalization (Klavans & Boyack, 2011; Leydesdorff & Bornmann, 2016).

Web of Science list of subject categories (WCs) is the most used scheme in bibliometric studies, regularly used as a baseline taxonomy for science (Leydesdorff & Rafols, 2009; Leydesdorff et al., 2013). Leydesdorff and Bornmann (2016) question its analytical clarity for normalization in research assessments, based on empirical evidence and remarking on the negative effect of the indexation process. But other authors assume that the assignation of journals to multiple subject categories can be considered to analyze the interdisciplinarity and complexity of journal structures (Bordons et al., 2004; Katz & Hicks, 1995; Morillo et al., 2001; Moya-Anegón et al., 2004).

Consequently, this bibliometric study analyzes the multidisciplinary nature of AI research, with the aim to explore the dynamics and characteristics of this knowledge domain. Conceptually, our approach used a broad definition of multidisciplinarity, considering all research practices involving disciplines interaction (Alvargonzález, 2011; Moschini et al, 2020). However, the study is focused mainly on the variety (number of different disciplines in a set) of a representative core of documents. We consider documents (disciplines) and citing documents (influenced disciplines) in a new method to measure multidisciplinarity, demonstrating how elements from different disciplines are present in the scientific output of entities and in their spheres of influence. A top-down approach that uses WCs as a proxy to measure multidisciplinarity is developed, and a set of WCs-based bibliometric indicators is used to define the different stages within the field.

Materials and methods

Data source and search strategy

Web of Science (WoS, v5.35 launched by Clarivate Analytics) was used as a data source. Search strategies were performed in the Core Collection databases subscribed by the National Autonomous University of Mexico (which includes Science Citation Index Expanded, Social Sciences Citation Index, Arts & Humanities Citation Index, Emerging Sources Citation Index, as well as the two WoS Conference Proceedings Citation Indexes, and the two WoS Book Citation Indexes). The research approach was focused on WCs, also considered by previous studies (Leydesdorff & Rafols, 2009; Leydesdorff et al., 2013).

The definition of an AI dataset has always been a challenge for previous bibliometric methodologies. Some papers define AI papers as papers published in AI journals (Liu et al., 2018). This approach is very useful to retrieve research on AI methods and models, but lost applied research published in interdisciplinary journals or journals from other specialties. A similar phenomenon occurs when the subject category *Computer Science, Artificial Intelligence* is used as a dataset (Fiala & Tutoky, 2017).

The identification of the term “Artificial Intelligence” in the paper’s title, abstract and keywords (Niu et al., 2016), or only in the paper’s titles (Lei & Liu, 2019) solve this limitation. Taking into account the main objective of this study, we chose the first of these search strategies, without time limits. This approach offers the possibility to analyze the literature dispersion in WCs, which is essential to calculate our battery of indicators. Nevertheless, this restrictive strategy also has limitations. During the last years, the impressive growth of AI and the emergence of new research areas have implied that the term is not always used as metadata. Therefore, for a more exhaustive domain characterization, we suggest for future studies a combination of related terms that could offer more pertinent datasets (e.g. artificial intelligence, machine learning, deep learning, natural language analysis, intelligent planning, intelligent neural networks, etc.), increasing coverage.

Procedure and indicators

Literature on AI during the period 1960–2019 was retrieved. Evolution since 1960 was graphically represented and analyzed. A descriptive study was conducted over the past 60 years, using 5-year periods to measure the scientific production and citations. The search strategy was performed for each period, comprehensively studied using standard bibliometric measures: number of articles, sources of publications, countries involved, WCs, citing WCs, the authors mean by article, and H-index. A new set of indicators were developed to analyze the multidisciplinary nature of AI literature.

Considering the power law nature of bibliometric distributions (Ivancheva, 2001), we experimentally used 80% as the threshold (based on Pareto's principle) to calculate the thematic concentration in publications (TCp) and citations (TCc) (Arencibia-Jorge et al., 2021) during each analyzed period. TCp or Thematic concentration of production is the minimum number of WCs involving, at least, 80% of published documents. Thus, the indicator counts the number of WCs which characterize the majority of all AI scientific production.

A practical method of calculating this indicator is the following: (1) deploy the search strategy in WoS; (2) define the publications set to analyze; (3) find all the WCs corresponding to the selected publications set; (4) arrange it by frequency, in descending order; (5) and count the number of WCs, from the highest frequency down, necessary to reach 80% of the total number of articles. Our approach conceived that one document could be included in several WCs. Therefore, full counting was considered in frequency arrangements.

Similarly, to estimate the multidisciplinary impact of the considered production, we used the function *"citation inform"* of WoS. First, the total amount of documents citing the selected publications set is automatically calculated. Then, following the previous principle and procedure, we estimate the number of WCs involved in most part of the total citation set through the TCc or Thematic concentration of citations, which is the minimum number of WCs involving at least 80% of the total citing documents.

Both indicators, modeled in Fig. 1, analyze two different dimensions of multidisciplinarity. Here, we combined them to produce a more comprehensive multidisciplinarity estimation for AI scientific production. The new indicator, called Thematic Dispersion Index (TDI), is obtained by calculating the square root of the TCp and TCc product (Arencibia-Jorge et al., 2021). This is a positive index bounded from above by the

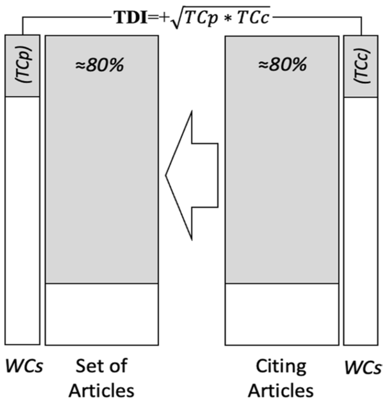


Fig. 1 Model representation of the TCp, TCc and TDI indicators

highest number of WCs (254). Small values of TDI correspond to a high level of specialization or disciplinary concentration and it grows bidirectionally, taking into account both the degree of multidisciplinarity of the set of published documents, and the multidisciplinarity of the research fronts influenced by these documents (Fig. 1).

TCc and TDI were calculated considering the whole period after publication. The limitation of the source (the function *"citation inform"* in WoS is available for datasets with less than 10,000 registers) meant that for the last 5-year period, only the range of citations between 2015 and 2017 was considered. A review of the literature was developed to contrast results exposed in Figs. 2, 3 and 4 with historical and epistemological approaches.

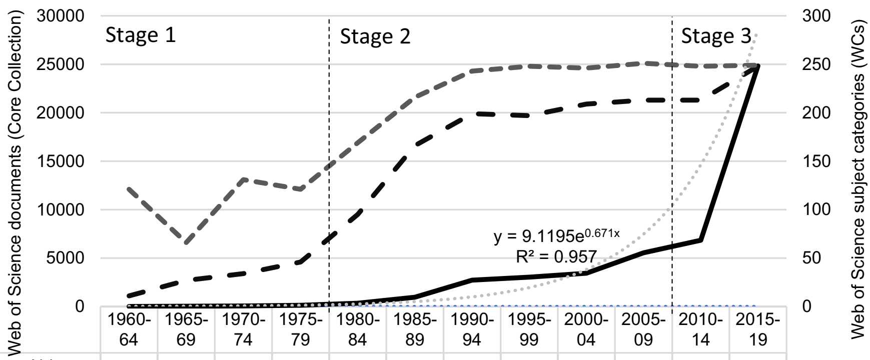
Results

General data

The data considered in this study are described in Table 1.

AI literature covered by WoS has undergone an exponential growth during the last 60 years (Fig. 2). In fact, more than 95% of the total output (44,891 of 46,422 documents) were published during the last 30 years. Conference proceedings represented 56.8% of sources (10,561 of 18,607), and 41.3% of papers were presented in these conferences (19,184 of 46,422 documents). This high proportion of conference proceedings is distinctive characteristic of literature on Computer Science (Bar-Ilan, 2010).

During each 5-year period, a growing trend was observed in the total of documents generated by researchers, and the total of sources they chose to publish (Table 1). The average number of authors per article increased from 1.11 to 3.75 during the whole period. The number of countries identified in authors' affiliations evolved from two in the 1960s to 153 countries in the period 2015–2019. The H-index only decreased in the last decade (2010–2019), which is related to the time factor (the citation window is smaller than the remaining years of the analyzed period).



	1960-64	1965-69	1970-74	1975-79	1980-84	1985-89	1990-94	1995-99	2000-04	2005-09	2010-14	2015-19
Ndoc	9	30	60	124	341	967	2726	3035	3434	5550	6835	24828
WCs	11	27	34	46	95	166	199	197	209	213	213	248
Cit WCs	121	66	131	121	169	216	243	248	246	251	248	249

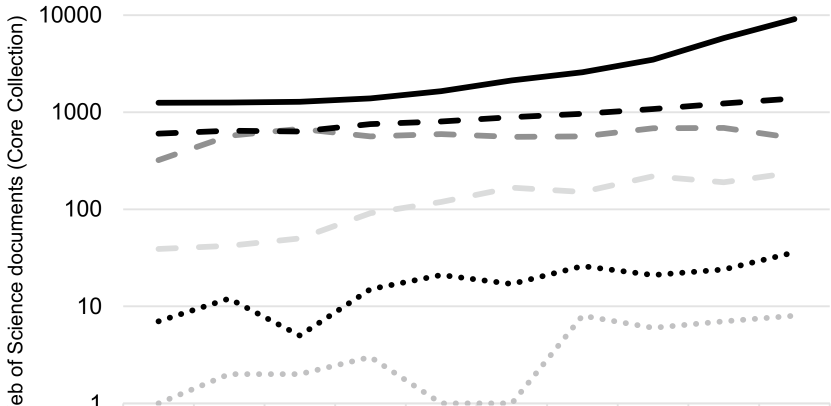
Fig. 2 Total output, WCs and citing WCs involved in AI literature during the period 1960–2019

Figure 2 also shows the evolution of WCs covering the articles published and the citing articles involved in AI literature. An increasing trend was observed from 1960 to 1979, when the covered WCs evolved from 11 to 46. During this period, despite a drop observed in the stage 1965–1969, citing papers were covered by approximately 121–131 WCs. From 1980 to 1994, WCs and citing WCs values showed a more accelerated growth. And then, from 1994 to 2014, the coverage showed a stable behavior, involving 199–213 WCs, and 243–248 citing WCs. During the last *lustrum*, the values of WCs (248) and Citing WCs (249) represented 98% of all subject categories of WoS classification scheme. These values expressed activity and impact in almost all fields of knowledge.

Three phases of development

The scientific output volume plotted in Fig. 2 (represented over decades in Fig. 3) revealed three main evolutionary stages of AI research. These stages were determined by the annual productivity (average of published papers by year) of each decade involved, considering also historical and epistemological factors:

(1) Emergence (1960–1979), based on foundational literature generated during the 1950s: Four (1960s) to 18 (1970s) papers per year as an average.
(2) Re-emergence and consolidation as a scientific discipline (1980–2009), involving a first industrial introduction: 131 (1980s), 576 (1990s) and 899 (2000s) papers per year.
(3) Re-configuration (2010–2019) of the discipline as a technoscience, where an explosion of solutions for productive systems is observed: 2994 papers per year.



	0	1	2	3	4	5	6	7	8	9
1960-1969	1	2	2	3	1	1	8	6	7	8
1970-1979	7	12	5	15	21	17	26	21	24	36
1980-1989	39	42	50	91	119	167	151	219	190	240
1990-1999	321	571	674	564	596	557	564	683	689	542
2000-2009	602	644	634	754	802	890	964	1078	1231	1387
2010-2019	1252	1257	1280	1388	1648	2130	2587	3486	5806	9109

Fig. 3 Scientific production on Artificial Intelligence during the period 1960–2019. Evolution by decades (logarithmic scale). Stages were represented by type of the lines

Table 1 Evolution of articles, sources, countries involved, authors mean by article, H index and thematic concentration of AI literature (1960–2019)

Years	Articles	Sources	Countries	Authors per article (mean)	H-index	TCp	TCc	TDI
1960–64	9	8	n/d	1.11	5	7	23	12.69
1965–69	30	27	2	1.67	7	15	10	12.25
1970–74	60	47	10	2.02	18	15	19	16.88
1975–79	124	70	13	1.61	21	14	20	16.73
1980–84	341	193	24	1.45	22	28	34	30.85
1985–89	967	535	35	1.72	30	43	35	38.79
1990–94	2,726	1,227	64	2.15	75	36	47	41.13
1995–99	3,035	1,463	76	2.36	99	28	38	32.62
2000–04	3,434	1,892	88	2.68	110	18	37	25.81
2005–09	5,550	3,236	93	2.81	113	17	37	25.08
2010–14	6,835	4,123	109	3.14	104	20	34	26.08
2015–19	24,828	10,785	153	3.75	106	38	37	37.50

Source: The authors, based on Web of Science, Core Collection data. Recovered: March 20, 2021

A further description of the distinctive characteristics of these phases of development is presented in the Discussion section.

The evolution of multidisciplinarity

The evolution of the multidisciplinary nature of AI research was analyzed using the TDI (Fig. 4). During the Emergence Stage (1960–1979), TDI measures showed the lower values, averaging 12 during the first decade, and 17 during the second one (Fig. 4).

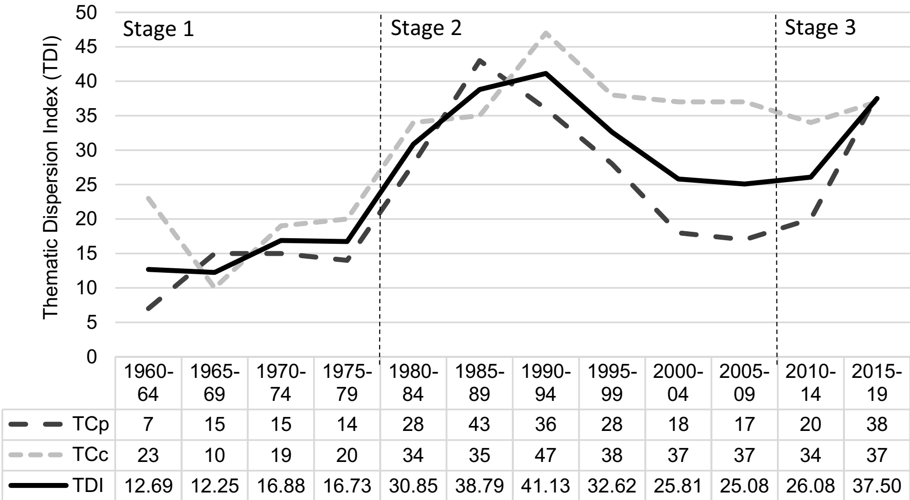


Fig. 4 TCp, TCc and TDI observed in AI literature during the period 1960–2019

The re-emergence and consolidation of the field involved 30 years (1980–2009). The multidisciplinary scope of AI research was clear from 1980 to 1994. TDI increased from 31 to 41. From then on, TDI decreased until 2009, when 80% of articles were published in (or cited from) journals belonging to 25 WCs. This can be considered the most specialized period of the field during the last 40 years.

However, a new increasing trend was observed during the last ten years, reaching a peak in 2015–2019 for TDI value (37.5). This is evidence of an explosion of research involving multiple knowledge domains, which could be related to the emergence of innovative shifts and changes in the nature of the field.

Discussion

In this section, some historical and epistemological aspects have been considered to analyze the main evolutionary stages of AI research. An evaluation of the utility of the proposed indicators for the analysis of multidisciplinary contexts was also discussed.

Emergence (1960–1979)

During the emergence period, AI research had a continuous but slow increase. Average annual productivity during each decade barely advanced from 4 to 18 papers per year, which is well observable on a logarithmic scale (Fig. 3), but not very significant in a disciplinary context.

Many of the AI expectations revealed during the "Dartmouth Summer Research Project on Artificial Intelligence" (a conference led by John McCarthy in 1956, considered by many authors the birth of AI as we know it today) were unable to materialize. Neither games such as chess or checkers had managed to outperform humans, nor had the automatic translation of texts into different languages reached significant developments, much less the general replacement of human jobs occurred. This provoked the cut of funding from the Advanced Research Projects Agency (ARPA) for AI researchers during the early 1970s, which is commonly called the "first AI winter" (Kaplan & Haenlein, 2019; Kaul et al., 2020). The period closed with a slight trend towards the growth of scientific literature, but no variations in TDI values.

From an epistemological approach, the emergence of AI (1960–1979) was supported by the reciprocal confluence of various areas of knowledge, mentioned by Wang (2019), and which are also present today, such as: computer science, engineering, linguistic, biology, psychology, mathematics, statistics, logic, philosophy and business (Wang, 2019). In fact, this stage is characterized by the heterogeneity of visions and methods, the lack of well-defined disciplinary boundaries (Van den Besselaar & Leydesdorff, 1996), and the insertion of research results in journals from related communities.

Re-emergence and consolidation (1980–2009)

During the second stage, it is clear the gradual consolidation of the field and its impact on an increasing number of knowledge domains. A take-off was observed, reaching a first significant peak (more than a hundred of published articles) in 1984. The development of "expert systems" was a dominant topic during the early 1980s. The research focused on solving domain-specific problems, more than emulating the general problem-solving functionalities of the human brain, which had an important repercussion on industry. WCs covered by TDI in 1980–1984 mainly involved journals specialized on *Medicine, General and Internal*, a field into which many of the AI solutions have been directed since the late 1970s.

Japan and United States began a fast race to dominate AI research. Japan's Ministry of International Trade and Industry launched the ambitious Fifth Generation Computer Systems (FGCS) project, with the aim develop a robust platform for AI development (Myers & Yamakoshi, 2020); and the United States government immediately launched the Strategic Computing Initiative (SCI). Governments and companies from both countries invested billions of dollars a year in expert systems. A promissory market of LISP Machines (computers based on AI LISP programming language) also emerged, led by companies like Symbolics, Lisp Machines Inc., Lucid Inc., Texas Instruments and Xerox. However, the "expert systems" and the industry of LISP machines were very expensive and easily relegated after 1987 by simpler and cheaper alternatives. This provoked a "second AI winter", characterized by a drastic reduction of research funds, lack of support from the government and private sector, hundreds of research projects closed, and the collapse of the LISP Machines industry (Gonsalves, 2019; Kaplan & Haenlein, 2019; Kaul et al., 2020).

Despite this critical moment, from 1985 to 1991 the growing trend continued, and a second significant peak was reached in 1992 (more than 600 articles). Scientific production was stable for the rest of the 1990s, but the jump in the average annual productivity was quite evident: 131 (80 s), 576 (90 s) and 899 (2000s) published papers by year. The "paradigmatic" phase identified by Van den Besselaar and Leydesdorff (1996) since the late eighties, is also well described by the TDI (Fig. 4), which exposed the concentration of AI specialized journals through a decreasing number of categories included in WCs core. Note that WCs core decreased from 1994 to 2009, despite the increasing number of WCs and citing WCs covering AI literature.

At this stage, AI built its own theoretical-methodological corpus. This is reflected in an increase in the depth of science (Kuhn, 1971), a greater specialization, the establishment of disciplinary limits and the development of a specific scientific community. In this way, the community is being configured and distinguished through the actions and elements that constitute reflections of its work objectives and its own role in society, such as: knowledge organization, community structure, cooperation patterns, language (concepts and meanings) and forms of communication, information systems and needs, and instruments (Hjørland, 2002; Hjørland & Albrechtsen, 1995). From a Kuhnian notion (Kuhn, 1971), the specific scientific community of AI during this period was focused on the functions of research, education and dissemination of knowledge, using certain channels and types of sources in its scientific production. In particular, the role of common language, communication, values and shared visions becomes important. All this ensures the integrity, singularity and unity of the community (Vega-Almeida, 2010). In fact, WCs covered by TDI during the periods 1995–1999, 2000–2004, and 2005–2009 mainly involved journals of Computer Sciences and Engineering.

The great coincidence of the second stage with the second winter of the AI (1988–2010), leads one to wonder if the disciplinary concentration described by the TDI indicator is actually due to the consolidation of the field or to the abandonment by some researchers. However, despite the lack of general interest during this period, collaboration among pioneers in the field of AI continued (Hendler, 2008; Kaul et al., 2020), which is confirmed by Figs. 2 and 3, showing that scientific production never decreased. In fact, a revolution in artificial neural network research was probably brewing from this stage.

Re-configuration (2010–2019)

The stability of scientific production was broken again during the last stage. A third peak was reached in 2007 (more than 1000 articles), when a new growing period started. The explosion of literature during the last decade is quite evident on a logarithmic scale (Fig. 3), which is also revealed by the leap in the average annual productivity by decade: 2994 published papers per year (three times higher than the previous decade). The last stage reached an unprecedented behavior during the period 2017–2019, when it was published 40% of the whole AI literature.

In the last stage (2010–2019), the AI re-emergence as a technoscience based on a re-configuration of the discipline and an explosion of solutions for productive systems was evidenced. Especially, the new re-emergence is established on the basic framework of a transversal discipline (Villalba Gómez, 2016) and revisited from an ethical approach (Bostrom and Yudkowsky, 2014). Therefore, the transformation that occurred in this period is metamorphic. AI brings together revolutionary and evolutionary, conservative and regenerative traits to create a metasystem. This metasystem must solve the new problems in that spiral of progress supported in the science-technology-production relationship identifiable in technoscience (Morin & Delgado, 2017). Consequently, we are in the presence of "the erasure of the boundaries dividing science and technology arises from the fact that in the modern world science and technology have developed a symbiotic relationship with one another" (Channell, 2017).

Indeed, AI is progressing so quickly and has become a technological driver of the fourth industrial revolution. This revolution is the result of the growing harmonization and integration of many different disciplines and discoveries. In this context, AI is constantly transforming people's lives. In fact, AI has made impressive advances, driven by exponential increases in computing power and by the availability of vast amounts of data, from software used to discover new drugs to algorithms that predict our cultural interests (Schwab, 2017). Contemporary industrial applications of AI involved smart assistants (like Siri and Alexa), disease mapping and prediction tools, manufacturing and drone robots, personalized healthcare treatment recommendations, conversational bots for marketing and customer services, robo-advisors for stock trading, spam filters on email, social media monitoring tools for dangerous content or false news, song or TV show recommendations from Spotify or Netflix, and a considerably diverse number of innovative technological solutions.

Specifically, Qian et al. (2020) defined the period as a "flourishing" stage. In particular, Liu and colleagues (2018) demonstrated in a recent article, at the beginning of the 21st Century, that the inner structure of AI is not monolithic and contains dozens of topics (machine learning, natural language processing, expert systems, neural networks, data mining, robotics, automation) which are individual and have their own intellectual challenges, methodologies and culture. Wang (2019) shared their conclusion when affirming that the current field of AI is actually a mixture of multiple research fields, each with its own goal, methods, and applicable situations; and this is also considered by Baker and Smith (2019), who explained that AI is an umbrella term used to describe a wide range of technologies and methods. However, Wang admitted that they are all called "AI" mainly for historical, rather than theoretical, reasons (Wang, 2019).

Additionally, Serna et al. (2017) state that AI today has become a multidisciplinary branch of study in science in general, which requires the support of other areas of knowledge, such as: Philosophy, Psychology, Linguistics, Science Computation, Biology, Neuroscience, Mathematics, Physics, Chemistry, Cybernetics, Electronics and Communications. In a positive sense, Qian et al. (2020) expressed that the content and composition of knowledge within the discipline are evolving and fluctuating. All these elements are the consequence of the development of related technologies.

According to these considerations, Liu and colleagues (2018) described AI during this period as a more collaborative field, extremely diverse due to the continuous development of techniques and tools, more open-minded, more widely sharing, and with research projects of greater scope. This is the basis for why in the last stage, after a deep specialization period, the AI looks again for journals on various topics, by converting these areas of knowledge into its own applied research objects in connection with productive activity. A production and citation activity from more than 90% of all WCs, and a TDI involving 20%, express without a doubt the multidisciplinary nature of AI research nowadays.

Final considerations and implications

The relationship between scientific production and disciplinary progress has been a subject extensively addressed (Bornmann & Mutz, 2015). The composition of research groups and their behavior patterns are expressed in scientific communication, and the quantitative approach infers, from the growth of the published literature, the development of scientific ideas and associations (Kuhn, 1971; Price, 1963; Tabah, 1999). However, the evolution of science -and AI research is one of the best examples- is conditioned by endogenous (intellectual) and exogenous (political, economic, technological) factors, whose complementarity is crucial for an exhaustive analysis of the transformations that occur in a knowledge domain (Hjorland, 1995, 2002).

In this paper, the bibliometric study of a sample of AI documents obtained from WoS was combined with the historical and epistemological analysis. This exercise was essential not only to identify critical transitions in the disciplinary development, but also to characterize the evolutionary stages. Particularly, it was necessary to avoid that an a priori quantitative-based delimitation of stages could constitute a distortion of the evolutionary process.

Our research also allowed us to focus on the differentiating elements that evidenced a rupture and a thematic reconstruction of AI research at each stage of its disciplinary progress. In fact, the variety or confluence of disciplines was a characteristic element of the studied domain clearly identified by the indicators proposed in this paper, which can be included in the large list of bibliometric measures developed to analyze multidisciplinarity. The TDI presented here has been useful to compare different knowledge domains in previous studies. At macro level, it was applied to analyze research on solar flares (SF) and ethnomethodology (ETM), and even the study of several pandemics (Arencibia-Jorge et al., 2020; Arencibia-Jorge et al., 2021).

Particularly, the comparison of research on AI, SF and ETM during the last five decades allowed us to consider TDI as a scientometric marker for historical and epistemological analysis (Arencibia-Jorge et al., 2021). Dataset of the three knowledge domains showed an increasing number of papers and WCs involved. However, TDI calculated for 5-year periods revealed different trends. Research on solar flares showed the classic disciplinary behavior, with less than five WCs involved in 80% of papers and citing papers during the whole period, and the predominance of physicists and astrophysicists' approaches. On the other hand, research on ethnomethodology exposed a gradual transition from a very specialized topic of Sociology to a transversal methodology used by linguists, psychologists, physicians, and professionals in the field of management, communication, business, computer science, and even Library and Information Science (Arencibia-Jorge et al., 2021).

The evidence provided by these reports predicts low and invariable TDI values for research with high thematic specialization and low levels of application, and increasing TDI values for research that, no matter its specialization, experiences significant advances in the level of application beyond its discipline. In contrast, the observed AI research evolution, the irregular behavior of the TDI curve, and especially the coincidence between its peaks and falls with the different stages in the history of the discipline, demonstrated not only the non-scale dependent nature of the indicator, but also the importance of the multidisciplinarity variable in social studies of science and technology (Alvargonzález, 2011). Nevertheless, it is important to remark that the multidisciplinary scope expressed by TDI does not distinguish the integration of topics involved in WCs cores (Rafols & Meyer, 2010). It is just a quantitative reflection of the main bodies of knowledge distributed in these cores.

Despite this limitation, our approach offered clues to understand the dynamics of AI research, in its historical and epistemological context. Probably, the disruptive effect of "AI winters", characterized by the considerable decrease in funding and incentives for research, has contributed to enhance the peculiarity of this dynamics. However, what is clear to us is that the characteristics of the reconfiguration of AI research (2010–2019) reveal a new revolutionary stage in which we are currently involved, where the application of previously generated knowledge has the greatest impact on society. And this is congruent with the last phase of the four-stage model proposed by Schneider (2009) to describe the evolution of a scientific discipline.

The huge leap of TDI during this last stage can be considered an expression not only of multidisciplinarity, but also of transdisciplinary research to deal with the complexity of real-world problems (Baum, 2020). Moreover, the new advances in machine learning, deep learning, neural networks, text mining, data science, or data visualization merely reaffirm AI as one of the key pillars of technological development for the next decade. More importantly, despite some concerns derived from excess of expectations that have always haunted the discipline (Hendler, 2008), a "third AI winter" was not observed during the last stage, and nor is it forecast in the short term.

Conclusions

The analyzed sample of AI literature (covered by the WoS from1960 to 2019) exhibits an exponential growth. Three well-delimited stages were identified and described using bibliometric, historical, and epistemological approaches. The dynamics of AI research evolved during the whole period from an initial emergence of the discipline to a "paradigmatic" phase of development; and then, to a re-configuration of the discipline as a technoscience. This re-configuration involved an explosion of technological solutions for productive systems, where wide collaboration networks and multidisciplinarity characterized the research projects. The dynamics of the Thematic Dispersion Index showed how multidisciplinarity can be used as a proxy to understand the knowledge organization and critical transitions of a scientific domain. Our results demonstrated that epistemic changes and qualitative leaps in AI research have been associated to variations in multidisciplinary patterns.

Acknowledgements This research was supported by the program "Scientometrics, Complexity, and Science of Science", at the Complexity Science Center of the National Autonomous University of Mexico (UNAM). We would like to thank Dr. Javier García-García for reviewing an earlier version of this article.

Authors contributions All authors have substantial contributions to the conception of the work. Initial drafting of the work was done by RAJ; the remaining authors did critical revisions and completed the manuscript. All authors agreed to be accountable for all aspects of the work. All authors read and approved the final draft of the manuscript and are aware that this paper is submitting to this journal.

Funding Not applicable.

Data availability Data available at https://figshare.com/articles/dataset/Multidisciplinarity_of_Artificial_Intelligence_Research_dataset/15411231

Code availability Not applicable.

Declarations

Conflict of interest The authors have no conflict of interest to declare that are relevant to the content of this article.

References

Abbas, N. N., Ahmed, T., Shah, S. H. U., Omar, M., & Park, H. W. (2019). Investigating the applications of artificial intelligence in cyber security. *Scientometrics, 121*(2), 1189–1211. https://doi.org/10.1007/s11192-019-03222-9

Alejo-Machado, O. J., Fernández-Luna, J. M., & Huete, J. F. (2015). Bibliometric study of the scientific research on "Learning to Rank" between 2000 and 2013. *Scientometrics, 102*(2), 1669–1686. https://doi.org/10.1007/s11192-014-1467-4

Alvargonzález, D. (2011). Multidisciplinarity, interdisciplinarity, transdisciplinarity, and the sciences. *International Studies in the Philosophy of Science, 25*(4), 387–403. https://doi.org/10.1080/02698595.2011.623366

Arencibia-Jorge, R., García-García, L., Galban-Rodriguez, E., & Carrillo-Calvet, H. (2020). The multidisciplinary nature of COVID-19 research. *Iberoamerican Journal of Science Measurement and Communication, 1*(1), 003. https://doi.org/10.47909/ijsmc.13

Arencibia-Jorge, R., Vega-Almeida, R. L., & Carrillo-Calvet, H. (2021). A new thematic dispersion index to assess multidisciplinarity at different levels of aggregations. In W. Glanzel, S. Heeffer, P. S. Chi & R. Rousseau (Eds.), *Proceedings of the 18th International Conference of Scientometrics and Informetrics ISSI'2021* (pp. 1439–1440). Leuven, Belgium: International Society of Scientometrics and Informetrics.

Bache, K., Newman, D., & Smyth, P. (2013, August). Text-based measures of document diversity. In *Proceedings of the 19th ACM SIGKDD international conference on Knowledge discovery and data mining* (pp. 23–31).

Baier-Fuentes, H., Cascón-Katchadourian, J., Sánchez, Á. M., Herrera-Viedma, E., & Merigó, J. (2018). A bibliometric overview of the international journal of interactive multimedia and artificial intelligence. *International Journal of Interactive Multimedia and Artificial Intelligence, 5*(3), 9–16. https://doi.org/10.9781/ijimai.2018.12.003

Baker, T., & Smith, L. (2019). Educ-AI-tion rebooted? Exploring the future of artificial intelligence in schools and colleges. Retrieved from Nesta Foundation website: Retrieved from https://media.nesta.org.uk/documents/Future_of_AI_and_education_v5_WEB.pdf [October 21, 2020]

Bar-Ilan, J. (2010). Web of Science with the conference proceedings citation indexes: The case of computer science. *Scientometrics, 83*(3), 809–824. https://doi.org/10.1007/s11192-009-0145-4

Baum, S. D. (2020). Artificial interdisciplinarity: Artificial intelligence for research on complex societal problems. *Philosophy & Technology*. https://doi.org/10.1007/s13347-020-00416-5

Bhattacharya, S. (2019). Some salient aspects of machine learning research: A bibliometric analysis. *Journal of Scientometric Res, 8*(2s), s85–s92. https://doi.org/10.5530/jscires.8.2.26

Bobadilla, J., Gutiérrez, A., Patricio, M. Á., & Bojorque, R. X. (2019). Analysis of scientific production based on trending research topics. An Artificial Intelligence case study. *Revista Española De Documentación Científica, 42*(1), 1–16. https://doi.org/10.3989/redc.2019.1.1583

Bordons, M., Morillo, F., & Gómez, I. (2004). Analysis of cross-disciplinary research through bibliometric tools. In H. F. Moed, W. Glanzel, & U. Schmoch (Eds.), *Handbook of quantitative science and technology research* (pp. 437–456). Kluwer.

Bornmann, L., & Mutz, R. (2015). Growth rates of modern science: A bibliometric analysis based on the number of publications and cited references. *Journal of the Association for Information Science and Technology, 66*(11), 2215–2222. https://doi.org/10.1002/asi.23329

Bostrom, N., & Yudkowsky, E. (2014). The ethics of artificial intelligence. In K. Frankish & M. Ramsey (Eds.), *The Cambridge handbook of artificial intelligence*. Cambrigde University Press.

Carley, S., & Porter, A. L. (2012). A forward diversity index. *Scientometrics, 90*(2), 407–427. https://doi.org/10.1007/s11192-011-0528-1

Carusi, C., & Bianchi, G. (2020). A look at interdisciplinarity using bipartite scholar/journal networks. *Scientometrics, 122*(2), 867–894. https://doi.org/10.1007/s11192-019-03309-3

Channell, D. F. (2017). *A history of technoscience: Erasing the boundaries between science and technology*. Routledge.

Chen, C. (2004). Searching for intellectual turning points: Progressive knowledge domain visualization. *Proceedings of the National Academy of Sciences of the United States of America, 101*(suppl.), 5303–5310. https://doi.org/10.1073/pnas.0307513100

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

Chen, X., Chen, J., Cheng, G., & Gong, T. (2020). Topics and trends in artificial intelligence assisted human brain research. *PLoS ONE, 15*(4), e0231192. https://doi.org/10.1371/journal.pone.0231192

Chiarello, F., Steiner, M. T. A., Oliveira, E. B. D., Arce, J. E., & Ferreira, J. C. (2019). Artificial neural networks applied in forest biometrics and modeling: State of the art (January/2007 to July/2018). *Cerne, 25*(2), 140–155. https://doi.org/10.1590/01047760201925022626

Darko, A., Chan, A. P., Adabre, M. A., Edwards, D. J., Hosseini, M. R., & Ameyaw, E. E. (2020). Artificial intelligence in the AEC industry: Scientometric analysis and visualization of research activities. *Automation in Construction, 112*, 103081. https://doi.org/10.1016/j.autcon.2020.103081

de Price, D. J. S. (1963). *Little science, big science*. Columbia University Press.

Devyatkin, D. A., Suvorov, R. E., & Tikhomirov, I. A. (2017). A method for the identification of competence centers based on the example of the artificial intelligence domain. *Scientific and Technical Information Processing, 44*(4), 253–260. https://doi.org/10.3103/S0147688217040086

Fiala, D., & Tutoky, G. (2017). Computer science papers in Web of Science: A bibliometric analysis. *Publications, 5*(4), 23. https://doi.org/10.3390/publications5040023

Fiala, D., & Willett, P. (2015). Computer science in Eastern Europe 1989–2014: A bibliometric study. *Aslib Journal of Information Management, 67*(5), 526–541. https://doi.org/10.1108/AJIM-02-2015-0027

Gao, J., Huang, X., & Zhang, L. (2019). Comparative analysis between international research hotspots and national-level policy keywords on artificial intelligence in China from 2009 to 2018. *Sustainability, 11*(23), 6574. https://doi.org/10.3390/su11236574

Garner, J., Porter, A. L., Leidolf, A., & Baker, M. (2018). Measuring and visualizing research collaboration and productivity. *Journal of Data and Information Science, 3*(1), 54–81. https://doi.org/10.2478/jdis-2018-0004

Garner, J., Porter, A. L., & Newman, N. C. (2014). Distance and velocity measures: Using citations to determine breadth and speed of research impact. *Scientometrics, 100*(3), 687–703. https://doi.org/10.1007/s11192-014-1316-5

Glanzel, W., & Schubert, A. (2003). A new classification scheme of science fields and subfields designed for scientometric evaluation purposes. *Scientometrics, 56*(3), 357–367. https://doi.org/10.1023/a:1022378804087

Gonsalves, T. (2019). The summers and winters of artificial intelligence. In M. Khosrow-Pour (Ed.), *Advanced methodologies and technologies in artificial intelligence, computer simulation, and human-computer interaction* (pp. 168–179). IGI Global.

Gupta, B. M., & Dhawan, S. M. (2018). Artificial intelligence research in India: A scientometric assessment of publications output during 2007–16. *DESIDOC Journal of Library & Information Technology*. https://doi.org/10.14429/djlit.38.6.12309

Hendler, J. (2008). Avoiding another AI winter. *IEEE Intelligent Systems, 23*(2), 2–4.

Hinojo-Lucena, F. J., Aznar-Díaz, I., Cáceres-Reche, M. P., & Romero-Rodríguez, J. M. (2019). Artificial intelligence in higher education: A bibliometric study on its impact in the scientific literature. *Education Sciences, 9*(1), 51. https://doi.org/10.3390/educsci9010051

Hjørland, B. (2002). Epistemology and the socio-cognitive perspective in information science. *Journal of the American Society for Information Science and Technology, 53*(4), 257–270. https://doi.org/10.1002/asi.10042

Hjørland, B., & Albrechtsen, H. (1995). Toward a new horizon in information-science—domain-analysis. *Journal of the American Society for Information Science, 46*(6), 400–425. https://doi.org/10.1002/(SICI)1097-4571(199507)46:6%3c400::AID-ASI2%3e3.0.CO;2-Y

Ivancheva, L. E. (2001). The non-Gaussian nature of bibliometric and scientometric distributions: A new approach to interpretation. *Journal of the American Society for Information Science and Technology, 52*(13), 1100–1105. https://doi.org/10.1002/asi.1176

Kaplan, A., & Haenlein, M. (2019). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. *Business Horizons, 62*(1), 15–25. https://doi.org/10.1016/j.bushor.2018.08.004

Katz, J.S., & Hicks, D. (1995, June). The classification of interdisciplinary journals: A new approach. Paper presented at the *Proceedings of the Fifth International Conference of the International Society for Scientometrics and Informetrics*, River Forest, IL, (pp. 105–115).

Kaul, V., Enslin, S., & Gross, S. A. (2020). History of artificial intelligence in medicine. *Gastrointestinal Endoscopy, 92*(4), 807–812. https://doi.org/10.1016/j.gie.2020.06.040

Klavans, R., & Boyack, K. W. (2011). Using global mapping to create more accurate document-level maps of research fields. *Journal of the American Society for Information Science and Technology, 62*(1), 1–18. https://doi.org/10.1002/asi.21444

Kuhn, T. S. (1971). *La estructura de las revoluciones científicas*. Fondo de Cultura Económica.

Kulakli, A., & Osmanaj, V. (2020). Global research on big data in relation with artificial intelligence (A bibliometric study: 2008–2019). *International Journal of Online and Biomedical Engineering, 16*(02), 31–46.

Lei, Y., & Liu, Z. (2019). The development of artificial intelligence: A bibliometric analysis, 2007–2016. *Journal of Physics: Conference Series, 1168*(2), 022027.

Leinster, T., & Cobbold, C. A. (2012). Measuring diversity: The importance of species similarity. *Ecology, 93*(3), 477–489. https://doi.org/10.1890/10-2402.1

Lewis, J. (2020). How transdisciplinary is design? An analysis using citation networks. *Design Issues, 36*(1), 30–44. https://doi.org/10.1162/desi_a_00573

Leydesdorff, L. (2007). Betweenness centrality as an indicator of the interdisciplinarity of scientific journals. *Journal of the American Society for Information Science and Technology, 58*(9), 1303–1319. https://doi.org/10.1002/asi.20614

Leydesdorff, L., & Bornmann, L. (2016). The operationalization of fields as WoS subject categories (WCs) in evaluative bibliometrics: The cases of library and information science and science & technology studies. *Journal of the American Society for Information Science and Technology, 67*(3), 707–714. https://doi.org/10.1002/asi.23408

Leydesdorff, L., Carley, S., & Rafols, I. (2013). Global maps of science based on the new Web-of-Science Categories. *Scientometrics, 94*(2), 589–593. https://doi.org/10.1007/s11192-012-0784-8

Leydesdorff, L., de Moya-Anegón, F., & Guerrero-Bote, V. P. (2015). Journal maps, interactive overlays, and the measurement of interdisciplinarity on the basis of scopus data (1996–2012). *Journal of the Association for Information Science and Technology, 66*(5), 1001–1016. https://doi.org/10.1002/asi.23243

Leydesdorff, L., & Rafols, I. (2009). A global map of science based on the ISI subject categories. *Journal of the American Society for Information Science and Technology, 60*(2), 348–362. https://doi.org/10.1002/asi.20967

Liu, J., Kong, X., Xia, F., Bai, X., Wang, L., Qing, Q., & Lee, I. (2018). Artificial intelligence in the 21st century. *IEEE Access, 6*, 34403–34421. https://doi.org/10.1109/ACCESS.2018.2819688

Moed, H. F., De Bruin, R. E., & Van Leeuwen, T. N. (1995). New bibliometric tools for the assessment of national research performance: Database description, overview of indicators and first applications. *Scientometrics, 33*(3), 381–422. https://doi.org/10.1007/bf02017338

Morillo, F., Bordons, M., & Gómez, I. (2001). An approach to interdisciplinarity through bibliometric indicators. *Scientometrics, 51*(1), 203–222. https://doi.org/10.1023/a:1010529114941

Morin, E., & Delgado Díaz, C. (2017). *Reinventar la educación. Abrir caminos a la metamorfosis de la humanidad*. Editorial UH.

Moschini, U., Fenialdi, E., Daraio, C., Ruocco, G., & Molinari, E. (2020). A comparison of three multidisciplinarity indices based on the diversity of Scopus subject areas of authors' documents, their bibliography and their citing papers. *Scientometrics, 125*(2), 1145–1158. https://doi.org/10.1007/s11192-020-03481-x

Moya-Anegón, F., Vargas-Quesada, B., Herrero-Solana, V., Chinchilla-Rodriguez, Z., Corera-Alvarez, E., & Muñoz-Fernandez, F. (2004). A new technique for building maps of large scientific domains based on the cocitation of classes and categories. *Scientometrics, 61*(1), 129–145. https://doi.org/10.1023/B:SCIE.0000037368.31217.34

Mugabushaka, A. M., Kyriakou, A., & Papazoglou, T. (2016). Bibliometric indicators of interdisciplinarity: The potential of the Leinster-Cobbold diversity indices to study disciplinary diversity. *Scientometrics, 107*(2), 593–607. https://doi.org/10.1007/s11192-016-1865-x

Munim, Z. H., Dushenko, M., Jimenez, V. J., Shakil, M. H., & Imset, M. (2020). Big data and artificial intelligence in the maritime industry: A bibliometric review and future research directions. *Maritime Policy & Management, 47*(5), 577–597. https://doi.org/10.1080/03088839.2020.1788731

Myers, J. P., Jr., & Yamakoshi, K. (2020). The Japanese fifth generation computing project: A brief overview. *Journal of Computing Sciences in Colleges, 36*(2), 53–60. https://doi.org/10.5555/3447065.3447072

Niu, J., Tang, W., Xu, F., Zhou, X., & Song, Y. (2016). Global research on artificial intelligence from 1990–2014: Spatially-explicit bibliometric analysis. *ISPRS International Journal of Geo-Information, 5*(5), 66. https://doi.org/10.3390/ijgi5050066

Porter, A.L., Schoeneck, D.J., Solomon, G., Lakhani, H., & Dietz, J. (2013). Measuring and mapping interdisciplinarity: Research & evaluation on education in science & engineering ("REESE") and STEM. In *American Education Research Association Annual Meeting*, April 27–May 1, San Francisco.

Porter, A. L., Cohen, A. S., Roessner, J. D., & Perreault, M. (2007). Measuring researcher interdisciplinarity. *Scientometrics, 72*(1), 117–147. https://doi.org/10.1007/s11192-007-1700-5

Porter, A., & Rafols, I. (2009). Is science becoming more interdisciplinary? Measuring and mapping six research fields over time. *Scientometrics, 81*(3), 719–745. https://doi.org/10.1007/s11192-008-2197-2

Porter, A. L., Roessner, D. J., & Heberger, A. E. (2008). How interdisciplinary is a given body of research? *Research Evaluation, 17*(4), 273–282. https://doi.org/10.3152/095820208X364553

Pudovkin, A. I., & Garfield, E. (2002). Algorithmic procedure for finding semantically related journals. *Journal of the American Society for Information Science and Technology, 53*(13), 1113–1119. https://doi.org/10.1002/asi.10153

Qian, Y., Liu, Y., & Sheng, Q. Z. (2020). Understanding hierarchical structural evolution in a scientific discipline: A case study of artificial intelligence. *Journal of Informetrics, 14*(3), 101047. https://doi.org/10.1016/j.joi.2020.101047

Rafols, I., & Meyer, M. (2010). Diversity and network coherence as indicators of interdisciplinarity: Case studies in bionanoscience. *Scientometrics, 82*(2), 263–287. https://doi.org/10.1007/s11192-009-0041-y

Rao, C. R. (1982). Diversity and dissimilarity coefficients: A unified approach. *Theoretical Population Biology, 21*(1), 24–43. https://doi.org/10.1016/0040-5809(82)90004-1

Rokach, L., & Mitra, P. (2013). Parsimonious citer-based measures: The artificial intelligence domain as a case study. *Journal of the American Society for Information Science and Technology, 64*(9), 1951–1959. https://doi.org/10.1002/asi.22887

Ruiz-Castillo, J., & Waltman, L. (2014). Field-normalized citation impact indicators using algorithmically constructed classification systems of science. *Journal of Informetrics, 9*(1), 102–117. https://doi.org/10.1016/j.joi.2014.11.010

Savaget, P., Chiarini, T., & Evans, S. (2019). Empowering political participation through artificial intelligence. *Science and Public Policy, 46*(3), 369–380. https://doi.org/10.1093/scipol/scy064

Schubert, A., Glanzel, W., & Braun, T. (1989). Scientometric datafiles. A comprehensive set of indicators on 2,649 journals and 96 countries in all major science fields and subfields 1981–1985. *Scientometrics, 16*(1), 3–478. https://doi.org/10.1007/bf02093234

Schwab, K. (2017). *The fourth industrial revolution*. Crown Bussiness.

Serenko, A. (2010). The development of an AI journal ranking based on the revealed preference approach. *Journal of Informetrics, 4*(4), 447–459. https://doi.org/10.1016/j.joi.2010.04.001

Serna A., Acevedo E., & Serna E. (2017). Principios de la Inteligencia Artificial en las Ciencias Computacionales. In Serna E. (Ed.). *Desarrollo e Innovación en Ingeniería.* 2da ed. Antioquia: Editorial Instituto Antioqueño de Investigación.

Shi, Y., & Li, X. (2019). A bibliometric study on intelligent techniques of bankruptcy prediction for corporate firms. *Heliyon, 5*(12), e02997. https://doi.org/10.1016/j.heliyon.2019.e02997

Shneider, A. M. (2009). Four stages of a scientific discipline; four types of scientist. *Trends in Biochemical Sciences, 34*(5), 217–223. https://doi.org/10.1016/j.tibs.2009.02.002

Shukla, A. K., Janmaijaya, M., Abraham, A., & Muhuri, P. K. (2019). Engineering applications of artificial intelligence: A bibliometric analysis of 30 years (1988–2018). *Engineering Applications of Artificial Intelligence, 85*, 517–532. https://doi.org/10.1016/j.engappai.2019.06.010
Stirling, A. (2007). A general framework for analysing diversity in science, technology and society. *Journal of the Royal Society Interface, 4*(15), 707–719. https://doi.org/10.1098/rsif.2007.0213
Tabah, A. N. (1999). Literature dynamics: Studies on growth, diffusion, and epidemics. *Annual Review of Information Science and Technology, 34*, 249–286.
Thomas, J., & Zaytseva, A. (2016). Mapping complexity/human knowledge as a complex adaptive system. *Complexity, 21*(2), 207–234. https://doi.org/10.1002/cplx.21799
Tolcheev, V. O. (2019). Research and analysis of the subject area of deep learning. *Automatic Documentation and Mathematical Linguistics, 53*(3), 103–113. https://doi.org/10.3103/S000510551903004X
Tran, B. X., Nghiem, S., Sahin, O., Vu, T. M., Ha, G. H., Vu, G. T., Pham, H. Q., Do, H. T., Latkin, C. A., Tam, W., & Ho, C. S. (2019). Modeling research topics for artificial intelligence applications in medicine: Latent Dirichlet allocation application study. *Journal of Medical Internet Research, 21*(11), e15511. https://doi.org/10.2196/15511
Tseng, C. Y., & Ting, P. H. (2013). Patent analysis for technology development of artificial intelligence: A country-level comparative study. *Innovation, 15*(4), 463–475. https://doi.org/10.5172/impp.2013.15.4.463
Van den Besselaar, P., & Leydesdorff, L. (1996). Mapping change in scientific specialties: A scientometric reconstruction of the development of artificial intelligence. *Journal of the American Society for Information Science, 47*(6), 415–436. https://doi.org/10.1002/(SICI)1097-4571(199606)47:6%3c415::AID-ASI3%3e3.0.CO;2-Y
Vega-Almeida, R. L. (2010). *Ciencia de la información y paradigma social: Enfoque histórico, epistemológico y bibliométrico para un análisis de dominio*. Universidad de Granada.
Villalba Gómez, J. A. (2016). Problemas bioéticos emergentes de la inteligencia artificial. *Diversitas: Perspectivas En Psicología, 12*(1), 137–147. https://doi.org/10.15332/s1794-9998.2016.0001.10
Wagner, C. S., Roessner, J. D., Bobb, K., Klein, J. T., Boyack, K. W., Keyton, J., et al. (2011). Approaches to understanding and measuring interdisciplinary scientific research (IDR): A review of the literature. *Journal of Informetrics, 5*(1), 14–26. https://doi.org/10.1016/j.joi.2010.06.004
Waltman, L., & van Eck, N. J. (2012). A new methodology for constructing a publication-level classification system of science. *Journal of the American Society for Information Science and Technology, 63*(12), 2378–2392. https://doi.org/10.1002/asi.22748
Waltman, L., van Eck, N. J., van Leeuwen, T. N., Visser, M. S., & Van Raan, A. F. J. (2011). Towards a new crown indicator: Some theoretical considerations. *Journal of Informetrics, 5*(1), 37–47. https://doi.org/10.1016/j.joi.2010.08.001
Wang, P. (2019). On defining artificial intelligence. *Journal of Artificial General Intelligence, 10*(2), 1–37. https://doi.org/10.2478/jagi-2019-0002
West, E., Mutasa, S., Zhu, Z., & Ha, R. (2019). Global trend in artificial intelligence-based publications in radiology from 2000 to 2018. *American Journal of Roentgenology, 213*(6), 1204–1206. https://doi.org/10.2214/AJR.19.21346
Yu, D., Xu, Z., & Fujita, H. (2019). Bibliometric analysis on the evolution of applied intelligence. *Applied Intelligence, 49*(2), 449–462. https://doi.org/10.1007/s10489-018-1278-z
Zhang, X., Wang, X., Zhao, H., de Pablos, P. O., Sun, Y., & Xiong, H. (2019). An effectiveness analysis of altmetrics indices for different levels of artificial intelligence publications. *Scientometrics, 119*(3), 1311–1344. https://doi.org/10.1007/s11192-019-03088-x
Zhang, Y., Chen, H., Lu, J., & Zhang, G. (2017). Detecting and predicting the topic change of Knowledge-based systems: A topic-based bibliometric analysis from 1991 to 2016. *Knowledge-Based Systems, 133*, 255–268. https://doi.org/10.1016/j.knosys.2017.07.011
Zhao, L., Dai, T., Qiao, Z., Sun, P., Hao, J., & Yang, Y. (2020). Application of artificial intelligence to wastewater treatment: A bibliometric analysis and systematic review of technology, economy, management, and wastewater reuse. *Process Safety and Environmental Protection, 133*, 169–182. https://doi.org/10.1016/j.psep.2019.11.014

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