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Are we preparing for a good AI society? A bibliometric review and research agenda

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A R T I C L E I N F O

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A B S T R A C T

Artificial intelligence (AI) may be one of the most disruptive technologies of the 21st century, with the potential to transform every aspect of society. Preparing for a "good AI society" has become a hot topic, with growing public and scientific interest in the principles, policies, incentives, and ethical frameworks necessary for society to enjoy the benefits of AI while minimizing the risks associated with its use. However, despite the renewed interest in artificial intelligence, little is known of the direction in which AI scholarship is moving and whether the field is evolving towards the goal of building a "good AI society". Based on a bibliometric analysis of 40147 documents retrieved from the Web of Science database, this study describes the intellectual, social, and conceptual structure of AI research. It provides 136 evidence-based research questions about how AI research can help understand the social changes brought about by AI and prepare for a "good AI society." The research agenda is organized according to ten social impact domains identified from the literature, including crisis response, economic empowerment, educational challenges, environmental challenges, equality and inclusion, health and hunger, information verification and validation, infrastructure management, public and social sector management, security, and justice.

1. Introduction

Artificial intelligence (AI) is rapidly transforming every aspect of society. Advances in neuroscience, nanotechnologies, computer science, cognitive psychology, and AI-related technologies have renewed interest among both AI scholars and practitioners. Not surprisingly, preparing for a "good AI society" has become a hot topic (Berendt, 2019; Cath et al., 2018; Floridi and Cowls, 2019; Floridi et al., 2018), with growing public and scientific interest in the principles, policies, incentives and ethical frameworks that can help society enjoy the benefits and opportunities created by AI while minimizing the risks associated with its adoption and use.

Today, artificial intelligence is changing the way people interact with technology, assisting users in the execution of both simple and complex tasks (Luger and Sellen, 2016; Pradhan et al., 2018; Schuetz and Venkatesh, 2020), improving business operations, products, and customer services (Davenport and Ronanki, 2018; Roßmann et al., 2018), healthcare services (Szolovits, 2019), transportation (Abduljabbar et al., 2019), disaster prediction and management (Fotovatikhah et al., 2018), agriculture (Jha et al., 2019), and smart cities (Allam and Dhunny, 2019). Artificial intelligence is increasingly seen as an opportunity to address complex societal problems such as sustainability (Nishant et al., 2020) and the COVID-19 pandemic (Sipior, 2020). Current and future developments in artificial intelligence technologies are expected to positively impact both business and society for years to come (Betz et al., 2019; Montes and Goertzel, 2019).

The rapid development of the field has led some scholars to argue that "human-level artificial intelligence" could be achieved within the next half-century (Baum et al., 2011, p. 186), that AI may surpass average human thinking (Simon, 2019), and that we may see the fusion of artificial and human intelligence in the not so distant future (Montes and Goertzel, 2019). Other scholars have expressed concern over how quickly AI is outperforming humans in most tasks (Grace et al., 2018) and an increasing willingness to delegate tasks to AI systems (Taddeo and Floridi, 2018). Several influential politicians, entrepreneurs, and scientists have even warned that AI represents an existential threat to

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mankind (Barrat, 2013). Indeed, eminent scientists such as the late Professor Stephen Hawking have expressed fear that the creation of machines that match or surpass humans could end mankind (Cellan-Jones, 2014).

The challenge for society and organizations is to determine how best to harness AI technologies for good while avoiding its dangers and pitfalls (Makridakis, 2017). Parallel to technological advances, AI research should also consider its economic impacts, legal frameworks, and questions of ethics, transparency, accountability, fairness, and safety (Cath et al., 2018; Russell et al., 2015b). However, despite the renewed scholarly interest in artificial intelligence, little is known of the direction in which AI research is moving.

This study's overarching objective is to evaluate past and current 'AI for social good' scholarship through bibliometric methods and provide guidance for future research efforts into this specific field. Our work follows two stages: Firstly, we review the evolution and structure of overall AI research using bibliometric methods to generate insights into the conceptual, intellectual, and social structure of AI scholarship; Secondly, we narrow our focus to the review of the 'AI for social good' literature and provide evidence-based research directions to expand our knowledge of how AI can benefit society.

We use bibliometric techniques to examine the conceptual, intellectual, and social structure of AI scholarship. Our study complements earlier overviews of AI research (Dwivedi et al., 2019; Frank et al., 2019; Niu et al., 2016) by covering a wider scope of academic sources and taking into account publications up to and including 2019. Most importantly, our work focuses on how well AI research is developing themes necessary to move towards a "good AI society" and in so doing identifies areas requiring more research.

The first section of the paper presents and defines artificial intelligence and identifies the domains where AI can be used for social good. The second section presents the methods used to collect and analyze the AI literature. The current state of the literature is then described, including an analysis of influential works, authors, institutions, and current research patterns and collaborations. The following section considers the evolution of sub-fields where AI could have a positive social impact. The paper concludes with a discussion of avenues for future research.

2. What is artificial intelligence

2.1. A definition of AI

The field of artificial intelligence (AI) strives to understand and build intelligent entities (Russell and Norvig, 2010). In this paper, we define artificial intelligence (AI) as "machines or computer systems capable of learning to perform tasks that normally require human intelligence" (Bawack et al., 2019). In the last five years, AI research and practices have been transformed by advances in AI algorithms, big data, and cloud computing (Borges et al., 2020), and today's AI systems are expected to "correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation" (Kaplan and Haenlein, 2019, p. 15).

Generally speaking, there are two forms of AI: "Strong AI" and "Weak AI" (Kaplan and Haenlein, 2020; Searle, 1980). Strong AI refers to that which can behave in a way that equals or surpasses human intelligence, while weak AI is that which simulates human intelligence in specific problem domains. The latter is the most commonly used form of AI in the world today, and generally, when people discuss AI technologies, they are referring to weak AI. Every AI is expected to have four main capabilities: the ability to perceive, the ability to comprehend, the ability to act, and the ability to learn. These capabilities are enabled by technologies such as sensors and AI techniques, including natural language processing, computer vision, image recognition, machine learning, and deep learning (Bawack et al., 2019; Duan et al., 2019).

2.2. A short history of AI

The AI research field started as a two-month, 10-man research project at Dartmouth College in 1956 "to make machines use language, form abstractions and concepts, solve kinds of problems now reserved for humans, and improve themselves" (McCarthy et al. 2006, pg. 2). Early application of AI took the form of expert systems (ES) and decision support systems (DSS) (Gill, 1995; Remus and Kottemann, 1986). Advances in supercomputing and big data technologies over the past decade have provided AI systems with the ability to perform more complex tasks than traditional DSS and ES. Today, some AI applications can perceive, reason, learn, interact, solve problems, make decisions, and create, allowing them to substitute, augment, or complement humans in task execution (Duan et al., 2019; Rai et al., 2019).

Haenlein and Kaplan (2019) describe how the AI field has evolved using an analogy of the four seasons: spring, summer, fall, and winter. According to the authors, the AI Spring begins with the publication by Isaac Asimov of a short story on robotics and includes the development by Alan Turing of an electro-mechanical computer capable of breaking encrypted German messages during the Second world war, and the Turing Test that is still used today to determine whether a machine is intelligent or not. The AI Summer starts in 1956 with the Dartmouth Summer Research Project on Artificial Intelligence followed by two decades of significant advances in AI technologies and theories. In 1973, the US Congress began criticizing the level of spending on AI research, and the British Science Research Council questioned the optimistic forecasts of AI researchers. Consequently, public funding for AI research by the US and British governments was significantly cut, and the AI field entered a 41 yearlong winter from 1973 to 2014. The success of Google's Alpha Go in 2015 based on advances in artificial neural networks and deep learning heralded the start of the period of AI Fall (or AI Harvest), as the field began to harvest "the fruits of past statistical advances" (p.8). We will use this periodization of AI, illustrated in Fig. 1 to examine the evolution of the field.

2.3. The state of AI scholarship

One of the first reviews of AI scholarship was undertaken by Rajaram (1990) where he summarized technological advances in the field using a taxonomy of AI systems. Other studies have reviewed the AI field since, but most have focused on specific domains and/or AI techniques. For example, Zakhem et al. (2020) conducted a systematic literature review on the use and evolution of AI for skin cancer assessment. Fernandez-Luque and Imran (2018) conducted a narrative literature review on the different applications and challenges of AI in humanitarian health crises. Islam et al. (2020) reviewed AI techniques used to solve drilling problems in the oil and gas industry. McKinnel et al. (2019) conducted a systematic review and meta-analysis of the AI literature to identify research challenges and opportunities related to penetration testing and system vulnerability assessment. Kumar (2017) reviewed the scholarship of AI use in process planning and manufacturing. Similar reviews of AI research have also been conducted for the media industry (Chan-Olmsted, 2019), service delivery (Gursoy et al., 2019), operations management (Grover et al., 2020), accounting (Moudud-Ul-Huq, 2014), the public sector (de Sousa, de Melo, Bermejo, Farias, and Gomes, 2019), marketing (Davenport et al., 2020), employment and work (Wang and Siau, 2019), resulting in the development of several industry or sector-specific research agendas.

Few studies provide a holistic view of AI scholarship. The most comprehensive AI research study was a bibliometric analysis of research published between 1990 and 2014 conducted by Niu et al. (2016). Since then, other studies have been domain-specific, including the use of AI for innovation management (Häfner et al., 2020), engineering (Shukla et al., 2019), national security (Wamba et al., 2019), and health and medicine (Tran et al., 2019). Each of these reviews focused on domain-specific AI applications, and only one study by Wang and Siau

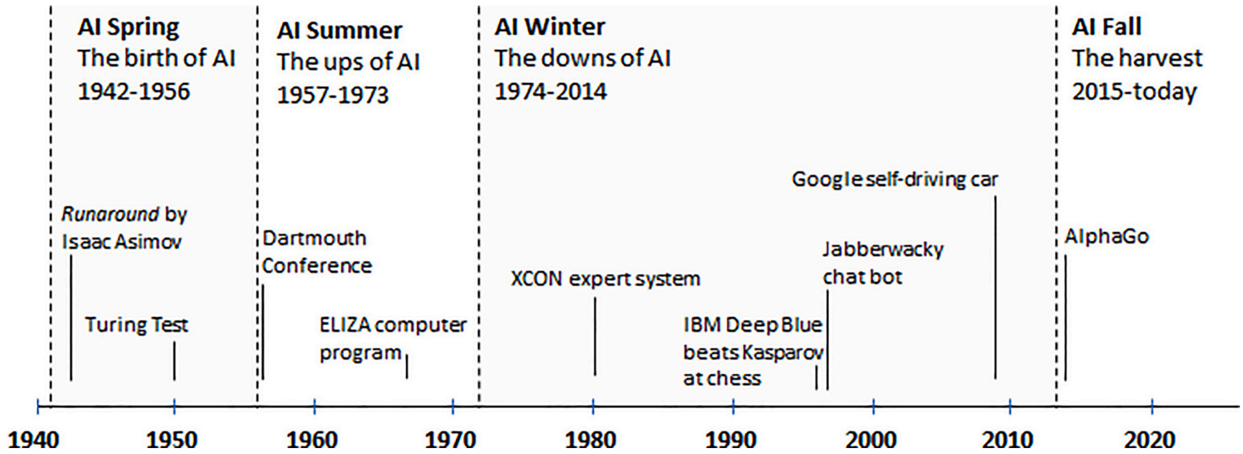

Fig. 1. A brief history of AI - Based on the periodization by Haenlein and Kaplan (2019).

(2019) proposed a research agenda to explore the social implications of AI, with a particular focus on the future of work. Our study addresses this research gap by conducting a bibliometric analysis of four decades of AI literature and by using the results to identify future research directions and formulate questions that focus on developing AI for social good.

2.4. Artificial intelligence for social good

Until the mid-2000s, AI research had productively pursued a research agenda that "focused largely on techniques that are neutral with respect to purpose" (Russell et al., 2015b, p. 3). Faced with the rapidly improving performance of AI, an increase in possible application areas and a "focus of attention, expectation, and concern growing among the general population" (Horvitz and Selman, 2009, p. 5) for AI outcomes and impacts, the Association for the Advancement of Artificial Intelligence (AAAI) brought together a panel of AI scholars "to explore and reflect about societal aspects of advances in machine intelligence (computational procedures for automated sensing, learning, reasoning, and decision making)" (Horvitz and Selman, 2009, p. 1). While social issues concerning robotics (Asimov, 1942; Weld and Etzioni, 1994), algorithms (Mittelstadt et al., 2016) and other artificial intelligence techniques had previously been raised in the literature, the AAAI report created debate in and beyond the AI field and was the first structured attempt at identifying the potential social risks and impacts of AI research and applications.

The work of the AAAI panel led to the launch of the "One Hundred Year Study on Artificial Intelligence" in 2014 by Stanford University to investigate the influence of AI on people and society (Horvitz, 2014). The group's first report in 2016 identified eight sectors or domains where AI could have a distinct impact on society, including transportation, home/service robotics, healthcare, education, low-resource communities, public safety and security, employment and workplace, and entertainment (Stone et al., 2016).

Concurrently, in an open letter to AI Magazine in 2015, over 7000 researchers launched a call for a research agenda to build more "robust and beneficial artificial intelligence" (Russell et al., 2015b, p. 3), and an accompanying paper identified several research directions to "help maximize the societal benefit of AI", including AI's economic impact, legal and ethical issues, and technical studies to develop more robust AI systems (Russell et al., 2015a, p. 106).

In 2016, the White House Office of Science and Technology Policy, the European Parliament's Committee on Legal Affairs, and the UK's House of Commons' Science and Technology Committee each released a report on the social and policy implications of artificial intelligence, machine learning, algorithms, and robotics. The reports each described a "good AI society" with similar key values of "transparency, accountability, and a 'positive impact' on the economy and society" (Cath et al., 2018, p.532).

More recently, the McKinsey Global Institute examined 160 AI use cases and identified ten domains where AI technologies could have a large-scale social impact (Chui et al., 2018). The domains cover the seventeen United Nations Sustainable Development Goals (SDG)[1] and include crisis response, economic empowerment, educational challenges, environmental challenges, equality and inclusion, health and hunger, information verification and validation, infrastructure management, public and social sector management, and security and justice. The study by Chui et al. (2018) is the most complete and recent review of potential areas of AI for social impact and will be used as a framework to describe the state of research in AI for good in Section 4 and to identify opportunities for future research in AI for good in Section 5. The ten social impact domains are presented in Appendix 1.

3. Methodology

3.1. Search strategy

The most relevant documents were extracted from the Web of Science (WoS) database using specific inclusion and exclusion criteria. WoS is widely recognized as a reliable academic database for bibliometric research as it contains a large number of high-profile and high-quality international academic publications (Batistič and der Laken, 2019; Zhang et al., 2019), it offers robust metadata suitable for bibliometric analyses (Gaviria-Marin et al., 2019) and it covers a longer period than alternative databases with equivalent domain coverage such as Scopus or Google Scholar (Harzing and Alakangas, 2016). All document types available in the WoS Core Collection were used for the analysis.

A total of 40 147 unique documents in English were retrieved using the search term "artificial intelligence"[2] covering a forty-four-year period from 1975 to 2019. Table 1 presents the summary statistics for the corpus.

A total of 83 346 authors contributed to the literature between 1975 and 2019. The documents were mainly co-written, with multi-authored documents representing 80% of the corpus. The earliest publication in the corpus was a paper by Jerry Felsen of the University of Southwestern Louisiana entitled "Artificial intelligence techniques applied to reduction of uncertainty in decision analysis through learning" published in *Operational Research Quarterly*[3] in 1975.

[1] https://sustainabledevelopment.un.org/

[2] The search was conducted on February 10 2020, in title, abstract, author keywords, and Keywords Plus.

[3] Renamed the *Journal of the Operational Research Society* in 1978.

Table 1
Main information regarding the collection.

Description	Winter	Fall	Total
Documents	20 300	19 847	40 147
Sources	7 962	7 787	14 480
Period	1975 - 2014	2015 - 2019	1975 - 2019
Annual percentage growth rate	20.7%	14.6%	20.0%
Average citations per document	13.88	4.07	9.03
Average citations per year per document	0.93	1.09	1.01
Authors	38 051	52 562	83 346
Authors of multi-authored documents	34 037	49 849	76 801
Documents per author	0.53	0.378	0.48
Co-authors per document	2.74	3.88	3.32
Multi-authored documents	15 330	16 779	32 109
Collaboration index	2.22	2.97	2.39

The five-year period of AI Fall saw strong growth in per year publications, a larger number of authors, and more collaborations than during the 40-year AI Winter. The collaboration index (i.e., total authors of multi-authored documents divided by total multi-authored documents) increased from 2.22 to 2.97, signaling that a greater number of authors were collaborating on multi-author documents during the later period. Remarkably, the number of publications is almost identical across these two unequal time frames..

3.2. Method of analysis

We used bibliometric techniques to analyze the development and evolution of the AI research field. In the social sciences and management research, bibliometrics has been extensively used to study the evolution of research in areas including big data (Batistič and der Laken, 2019; Zhang et al., 2019), robotics (Goeldner et al., 2015), the internet of things (Nobre and Tavares, 2017), knowledge management (Gaviria-Marin et al., 2019), supply chain management (Fahimnia et al., 2015; Mishra et al., 2016), technological innovation (van Oorschot, Hofman, and Halman, 2018) and social entrepreneurship (Rey-Martí et al., 2016).

The two main categories of bibliometric procedures available are performance analysis and science mapping (Noyons et al., 1999). Performance analysis involves evaluating the production and impact of groups of scientific actors, most often authors, institutions, countries, and journals using bibliographic data. Science mapping is used to represent and analyze the current and evolving cognitive and social structures of a research field. The Bibliomerix[4] R package was used to calculate descriptive statistics, bibliometric measures, and for science mapping (Aria and Cuccurullo, 2017). Bibliometrix was chosen for the analysis as it provides a suite of functions adapted to bibliometric analysis and provides output that can be further manipulated using the open-source R[5] language and environment. In this study, the R language allowed for the tailoring and automation of data analysis scripts calling on Bibliometrix functions and objects and third-party packages for more specific analyses. This was particularly useful for data manipulation, extraction and multiple bibliometric calculations using a large data set (14 480 journals, 40 147 publications, 83 346 authors, 128 countries, 15 542 institutions).

Several statistics are available for bibliometric performance analysis. In this study, following Gaviria-Marin et al. (2019) the main statistics used to evaluate productivity and influence are the h-index and its derivative, the m-index. The h-index is defined as “the number of papers with citation number $\geq h$” (Hirsch, 2005), where h is the number of papers published. For example, an h-index of 20 indicates that an individual has published twenty papers with at least 20 citations. The advantage of the h-index is that it measures both productivity and influence and can be calculated for different bibliometric units of analysis: authors, countries, journals, and institutions. The m-index adjusts the h-index for the “academic age” of the individual (i.e., $m = h/$academic age). Academic age is the number of years since the publication of an individual’s first paper. Other statistics used are derived from yearly research output and citation counts.

The first part of this paper (4.1) examines the current state of the AI literature using performance analysis. The objective is to identify the main themes and contributing disciplines to AI research, the key actors in the field.

The second part of the paper (4.2) focuses on the state of research in the ten social impact domains described by (Chui et al., 2018) (see Appendix 1). We use bibliometric performance measures to summarize the extant research by domain.

4. Results

4.1. The current state of the AI literature

Publications on mainstream AI research in the corpus began in 1975 with 13 publications and that number grew to 7 037 publications per year in 2019, for an annual publication growth rate of 20%. This growth rate is strong compared to the global scientific publication output that is growing at a rate of approximately 3% annually (Bornmann and Mutz, 2015).

A number of production peaks can be observed across this 45-year period in Fig. 2, each corresponding to a technical or conceptual development in the field (Jin et al., 2018). For example, the first period of strong growth in AI research began in the early 1980s, following the XCON expert system’s development. In 1988, probabilistic reasoning was introduced and became a new theoretical foundation for intelligent systems research (Pearl, 2014). In 1997 the first chatbot, “Jabberwacky” was developed (McNeal and Newyear, 2013), and IBM’s Deep Blue beat the reigning world champion, Garry Kasparov, in a game of chess. The next major peak was in 2009 when Google released the first self-driving car that could navigate in urban conditions (Marr, 2018). The dramatic increase in AI publications from 2013 onwards can be explained by the growth in big data in 2012 (Zhang et al., 2019) and deep learning in 2015 (LeCun et al., 2015) with the success of Google’s Alpha Go (Silver et al., 2016), which significantly increased AI research projects and industrial applications.

AI research covered a total of 149 subject areas over the period. Table 2 lists the most frequently observed areas and the number of references per research area. The two dominant disciplines were computer science and engineering. The acronyms for all tables are provided in Appendix 2.

Four application areas exhibited an increase in average annual growth during the AI Fall: *Operations research & management science, Mathematics, Psychology, and Information science & library science*. The average annual growth fell in all other areas between the two periods.

Bibliometric techniques were applied to the corpus to analyze the AI research field’s current state and evolution. The following three sections identify the most influential sources, authors, countries, and institutions in AI research. The conceptual structure of the field is then described, followed by an analysis of its evolution.

4.1.1. The most productive and influential journals in AI

Artificial intelligence research is undertaken in a large variety of areas. Some fields contribute to the development of technologies, models, and algorithms, while others are fields of application. Research is published in a large range of journals. To classify this work, Table 3 presents the 50 most productive and influential journals in AI. The journals are ordered according to the total scholarly production in AI (TPAI) and the h-index computed based on citations by AI publications in the corpus (hAI). Acronyms for all journals are listed below the table.

[4] http://www.bibliometrix.org/index.html
[5] https://www.r-project.org/

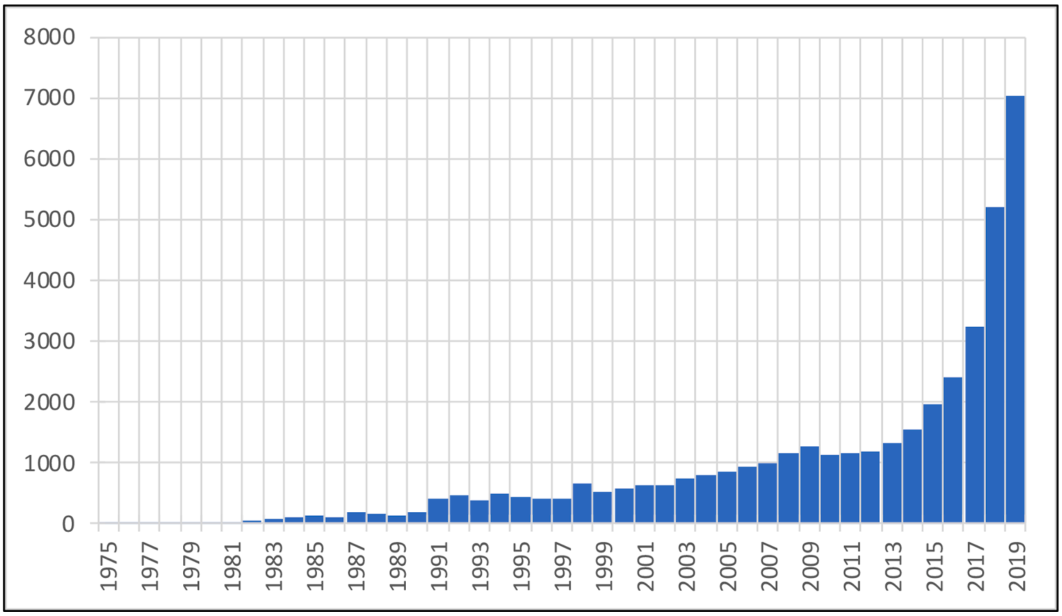

Fig. 2. Number of publications in AI per year: 1975–2019.

Table 2
AI references in different areas (first 30 areas). * Multiple subject areas per publication are possible.

Area	YP	TPAI 1975–2019	CAGR TPAI - Winter	CAGR TPAI - Fall
Computer science	1975	19 176	20.7	20.0
Engineering	1975	13 701	21.8	15.7
Automation & control systems	1983	2 161	23.8	23.4
Telecommunications	1981	1 953	21.7	8.4
Operations research & management science	1975	1 572	14.1	35.6
Science & technology - other topics	1976	1 453	20.1	6.5
Business & economics	1975	1 420	16.2	15.4
Materials science	1983	1 248	23.4	12.8
Mathematics	1981	1 117	18.8	30.3
Energy & fuels	1985	1 104	25.2	10.2
Chemistry	1975	1 079	13.7	12.8
Robotics	1987	1 009	20.2	18.7
Physics	1981	937	21.2	10.3
Education & educational research	1978	913	18.4	15.8
Environmental sciences & ecology	1984	847	22.7	12.6
Instruments & instrumentation	1983	709	20.2	18.6
Psychology	1976	669	13.4	23.4
Neurosciences & neurology	1978	651	14.7	9.4
Medical informatics	1981	643	18.7	17.8
Radiology, nuclear medicine & medical imaging	1982	599	21.1	5.8
Imaging science & photographic technology	1987	533	22.7	16.3
Information science & library science	1975	509	14.7	19.7
Optics	1982	496	16.4	14.0
Water resources	1991	451	19.7	12.7
Social sciences - other topics	1982	445	16.4	11.3
Transportation	1987	417	22.4	12.1
Mathematical & computational biology	1985	395	19.7	16.6
Geology	1984	394	16.4	15.5
Health care sciences & services	1987	377	19.4	9.3
Oncology	1988	355	24.4	4.1

Eleven journals concern application areas of AI with a strong interplay between society and technology, including operations and manufacturing (EJOR, IJAMT, JIM, IJPR), energy and sustainability (EES, SUST, RSER), agriculture (CEA), hydrology (JHYD), chemicals (JACS) and decision making (DSS). The thirty-nine remaining journals all concern either directly or indirectly the development, testing, and analysis of AI models, methods, and technologies.

The most productive journal was ESA, although the percentage of articles on AI (%PAI) in this journal is quite low (3.52%). Two journals with fewer publications but high levels of influence (high h-index and %PAI) are AIMAG and AI. AI has 8 articles with over 200 citations by other AI publications, and two publications in the 50 most cited papers in the field (Table 4). Interestingly, only 8 journals appear in the Top 50 publications by citation count. This result reflects the diverse nature of AI research.

Several journals show an increasing interest in AI research, measured by the TPAI growth rate and the journal space accorded to AI articles. Nine journals exhibited annual growth in AI publications above 70% during the period studied: in order of productivity and influence they are IEEEA (182%), SENS (71%), IFAC (94%), ASB (429%), EES (85%), IET-CV (83%), SUST(193%), SCRP (84%) and JOE (312%). These fast-growing journals are all open access. The outlets that publish the largest proportion of their articles on AI are AIMAG (20.7%), AIR (11.8%), MM (17.6%), and ITCAIG (20.9%).

It is also interesting to examine journal productivity over time. The number of papers published per year by 42 of the top 50 journals increased during the AI Fall compared to the AI Winter but fell for EJOR, AAI, FSS, AMAI, CI, DSS, ITKDE, and ITCIAIG. There are also many young (YP≥2009), influential journals (mAI>1.5) in the field, including IEEEA, SENS, ASB, SUST, RSER, EES and SCRP.

4.1.2. *The most influential publications in the field of AI*

The AI field attracted an increasing number of scholars during the AI Fall, with an equivalent number of papers published over these five years as in the previous 40-year AI Winter. To identify the leading papers in AI research, Table 4 ranks the top 50 publications by total citations in all fields (TC). In the case of a tie, papers are ranked by total citations in AI research (TCAI).

All but two of the top fifty papers were published after 1991, and ten of the most influential papers were published after 2010. Nine of the ten most influential articles present technical or conceptual advances in the

Table 3
The 50 most influential and productive journals in AI research (1975–2019).

R	Journal	TPAI	hAI	TP	TCAI	PCAI	%PAI	CAGR	≥ 500	≥ 200	≥ 100	≥ 50	< 50	T50	IF	5-IF	TPAI-W	TPAI-F	YP	mAI
1	ESA	431	47	12 252	750	1.74	3.52	15.9	0	4	13	26	388	0	5.452	5.448	341	90	1991	1.62
2	IEEEA	358	15	26 586	127	0.35	1.35	182.2	0	0	0	1	357	0	3.745	4.076	2	356	2014	2.50
3	AIMAG	283	21	1 362	366	1.29	20.78	12.8	0	2	1	5	275	0	1.627	1.742	203	80	1987	0.64
4	AI	220	44	2 890	905	4.11	7.61	13	2	6	12	20	180	2	6.628	5.944	178	42	1975	0.98
5	EAAI	208	28	3 234	283	1.36	6.43	11.5	0	1	2	11	194	0	4.201	3.810	159	49	1992	1.00
6	EJOR	149	31	18 612	198	1.33	0.80	14.1	0	3	5	10	131	0	4.213	4.729	137	12	1981	0.79
7	SENS	126	16	23 126	93	0.74	0.54	71.1	0	0	1	2	123	0	3.031	3.302	10	116	2010	1.60
8	AIR	124	20	1 045	139	1.12	11.87	14.2	1	4	0	5	114	2	5.747	5.942	93	31	1988	0.63
9	MM	118	15	667	214	1.81	17.69	16.3	0	0	2	1	115	0	1.855	1.504	94	24	1992	0.54
10	KYBE	114	10	3 506	22	0.19	3.25	11.9	0	0	0	0	114	0	1.754	1.470	98	16	1977	0.23
11	JIFS	106	8	5 376	27	0.25	1.97	22.0	0	0	0	0	106	0	1.851	1.797	22	84	1999	0.38
12	IETIP	105	6	1 495	6	0.06	7.02	52.7	0	0	0	0	105	0	1.995	1.943	3	102	2008	0.50
13	AAI	104	13	1 312	93	0.89	7.93	9.6	0	0	1	4	99	0	1.172	1.242	94	10	1991	0.45
14	AIM	102	27	1 549	284	2.78	6.58	14.5	0	1	1	10	90	0	4.383	4.098	76	26	1993	1.00
15	KBS	98	23	3 975	134	1.37	2.47	13.3	0	1	1	4	92	0	5.921	6.075	80	18	1991	0.79
16	ASC	94	24	5 708	108	1.15	1.65	38.3	0	0	0	7	87	0	5.472	5.390	45	49	2005	1.60
17	NCOM	92	18	13 170	78	0.85	0.70	18.2	0	1	2	2	87	0	4.438	4.010	34	58	1992	0.64
18	IFAC	86	3	11 595	6	0.07	0.74	94.6	0	0	0	0	86	0	0.960	0.990	0	86	2015	0.60
19	IJAMT	84	19	16 773	81	0.96	0.50	18.6	0	0	1	7	76	0	2.633	2.925	60	24	1993	0.70
20	NCA	84	14	4 205	99	1.18	2.00	22.3	0	0	1	1	82	0	4.774	4.627	28	56	1997	0.61
21	ASB	84	7	10 301	36	0.43	0.82	429.2	0	0	0	0	84	0	2.217	2.287	0	84	2017	2.33
22	JIM	81	22	2 148	97	1.20	3.77	12.0	0	0	1	4	76	0	4.311	4.224	67	14	1990	0.73
23	EES	81	13	13 715	54	0.67	0.59	85.3	0	0	0	1	80	0	2.702	2.822	2	79	2013	1.86
24	EL	81	7	46 524	7	0.09	0.17	12.5	0	0	0	0	81	0	1.316	1.279	11	70	1991	0.24
25	AINT	79	14	1 949	57	0.72	4.05	12.2	0	0	0	2	77	0	3.325	3.204	59	20	1993	0.52
26	JETAI	77	12	870	100	1.30	8.85	12.0	0	0	2	2	73	0	2.039	1.881	61	16	1993	0.44
27	IET-CV	77	7	806	10	0.13	9.55	83.8	0	0	0	0	77	0	1.516	1.524	2	75	2013	1.00
28	SUST	76	7	17 769	26	0.34	0.43	193.7	0	0	0	0	76	0	2.576	2.798	0	76	2016	1.75
29	INSC	75	19	10 043	76	1.01	0.75	14.9	1	0	1	4	69	1	5.910	5.563	51	24	1988	0.59
30	SCRP	74	13	103 524	90	1.22	0.07	84.9	0	0	0	0	74	0	3.998	4.576	3	71	2012	1.63
31	ITS	73	10	1 028	64	0.88	7.10	61.1	0	0	2	0	71	0	2.480	2.343	8	65	2010	1.00
32	IJACSA	72	3	3 858	5	0.07	1.87	68.2	0	0	0	0	72	0	1.324	N/A	0	72	2015	0.60
33	JHYD	71	26	15 403	550	7.75	0.46	38.8	0	3	3	8	57	0	4.500	5.080	30	41	2006	1.86
34	IJPR	69	19	10 359	63	0.91	0.67	13.7	0	0	1	5	63	0	4.577	4.145	54	15	1986	0.56
35	AICOM	69	11	8 214	72	1.04	9.61	11.1	0	0	1	0	68	0	1.000	0.729	51	18	1994	0.42
36	FSS	66	22	1 110	47	0.71	0.80	10.1	0	1	3	5	57	1	3.305	2.943	65	1	1987	0.67
37	AMAI	66	13	718	49	0.74	5.95	14.4	0	1	0	1	64	0	0.778	1.000	55	11	1996	0.54
38	RSER	64	32	9 339	316	4.94	0.69	41.4	2	2	6	10	44	2	12.110	12.348	15	49	2009	2.91
39	CI	63	16	2 788	82	1.30	2.26	12.2	0	0	1	4	58	0	3.954	4.069	57	6	1983	0.43
40	DSS	61	22	3 073	152	2.49	1.99	9.3	0	1	3	4	53	1	4.721	5.434	59	2	1991	0.76
41	ES	59	14	1 148	41	0.69	5.14	17.7	0	0	0	1	58	0	1.546	1.697	40	19	1994	0.54
42	CIE	59	13	7 677	47	0.80	0.77	13.2	0	0	0	1	58	0	4.135	4.296	42	17	1986	0.38
43	ITKDE	58	20	3 676	84	1.45	1.58	13.3	0	2	5	2	49	1	4.935	5.201	53	5	1992	0.71
44	CEA	57	16	3 819	77	1.35	1.49	18.3	0	0	2	5	50	0	3.858	4.008	28	29	1995	0.64
45	PLOS	57	12	224 470	67	1.18	0.03	44.4	0	0	1	0	56	0	2.740	3.227	18	39	2008	1.00
46	ITCIAIG	56	13	268	188	3.36	20.90	27.3	1	0	0	2	53	1	1.588	1.211	32	24	2009	1.18
47	SC	53	9	4 386	12	0.23	1.21	24.4	0	0	0	1	52	0	3.050	2.988	18	35	2004	0.56
48	JACS	52	0	531 712	0	0.00	0.01	7.9	0	0	0	0	52	0	14.612	14.549	34	18	1976	0.00
49	JAIR	51	15	1 143	58	1.14	4.46	13.8	0	1	1	4	45	0	2.441	2.678	31	20	1994	0.58
50	JOE	51	2	2 806	1	0.02	1.82	312.3	0	0	0	0	51	0	N/A	N/A	0	51	2017	0.67

AAI, Applied Artificial Intelligence; AI, Artificial Intelligence; AICOM, AI Communications; AIM, Artificial Intelligence in Medicine; AI-MAG, AI Magazine; AINT, Applied Intelligence; AIR, Artificial Intelligence Review; AMAI, Annals of Mathematics and Artificial Intelligence; ASB, Applied Sciences-Basel; ASC, Applied Soft Computing; CEA, Computers and Electronics in Agriculture; CI, Computers in Industry; CIE, Computers & Industrial Engineering; DSS, Decision Support Systems; EAAI, Engineering Applications of Artificial Intelligence; EES, Energies; EJOR, European Journal of Operational Research; EL, Electronics Letters; ES, Expert Systems; ESA, Expert Systems with Applications; FSS, Fuzzy Sets and Systems; IEEEA, IEEE Access; IET-CV, IET Computer Vision; IET-IP, IET Image Processing; IET-ITS, IET Intelligent Transport Systems; IFAC-POL, IFAC Papersonline; IJACSA, International Journal of Advanced Computer Science and Applications; IJAMT, International Journal of Advanced Manufacturing Technology; IJPR, International Journal of Production Research; INSC, Information Sciences; ITCIAIG, IEEE Transactions on Computational Intelligence and AI in Games; ITKDE, IEEE Transactions on Knowledge and Data Engineering; JACS, Abstracts of Papers of the American Chemical Society; JAIR, Journal of Artificial Intelligence Research; JETAI, Journal of Experimental & Theoretical Artificial Intelligence; JHYD, Journal of Hydrology; JIFS, Journal of Intelligent & Fuzzy Systems; JIM, Journal of Intelligent Manufacturing; JOE, Journal of Engineering-Joe; KBS, Knowledge-Based Systems; KYBE, Kybernetes; MM, Minds and Machines; NCA, Neural Computing & Applications; NCOM, Neurocomputing; PLOS, PLOS One; RSER, Renewable & Sustainable Energy Reviews; SC, Soft Computing; SCRP, Scientific Reports; SENS, Sensors; SUST, Sustainability.

Table 4
The 50 most influential publications in AI research (1975–2019).

R	Title	Authors	J	YP	TC	C/Y	TCAI	CAI/Y
1	Perceptual symbol systems	Barsalou, LW	BBS	1999	3 061	145.8	24	1.1
2	Factor graphs and the sum-product algorithm	Kschischang, FR; Frey, BJ; Loeliger, HA	ITIT	2001	3 047	160.4	23	1.2
3	Mastering the game of go with deep neural networks and tree search	Silver, D; Huang, A; Maddison, CJ; Guez, A; Sifre, L; Van, Den, Driessche, G; Schrittwieser, J; Antonoglou, I; Panneershelvam, V; Lanctot, M; Dieleman, S; Grewe, D; Nham, J; Kalchbrenner, N; Sutskever, I; Lillicrap, T; Leach, M; Kavukcuoglu, K; Graepel, T; Hassabis, D	NAT	2016	2 407	601.8	382	95.5
4	Intelligent agents - theory and practice	Wooldridge, M; Jennings, NR	KER	1995	2 387	95.5	137	5.5
5	Toward principles for the design of ontologies used for knowledge sharing	Gruber, TR	IJHCS	1995	2 310	92.4	40	1.6
6	Future paths for integer programming and links to artificial intelligence	Glover, F	COR	1986	1 842	54.2	73	2.1
7	Intelligence without representation	Brooks, RA	AI	1991	1 763	60.8	183	6.3
8	Dermatologist-level classification of skin cancer with deep neural networks	Esteva, A; Kuprel, B; Novoa, RA; Ko, J; Swetter, SM; Blau, HM; Thrun, S	NAT	2017	1 568	522.7	369	123.0
9	Highly sensitive flexible pressure sensors with microstructured rubber dielectric layers	Mannsfeld, SCB; Tee, BCK; Stoltenberg, RM; Chen, CVHH; Barman, S; Muir, BVO; Sokolov, AN; Reese, C; Bao, ZN	NATM	2010	1 435	143.5	0	0.0
10	A review of process fault detection and diagnosis part i: quantitative model-based methods	Venkatsubramanian, V; Rengaswamy, R; Yin, K; Kavuri, SN	CCE	2003	1 311	77.1	24	1.4
11	Rudiments of rough sets	Pawlak, Z; Skowron, A	INSC	2007	1 179	90.7	24	1.8
12	An introduction to multisensor data fusion	Hall, DL; Llinas, J	PIEEE	1997	1 163	50.6	19	0.8
13	Chaff: engineering an efficient sat solver	Moskewicz, MW; Madigan, CF; Zhao, Y; Zhang, LT; Malik, S	DAC	2001	1 100	57.9	0	0.0
14	Neural networks for short-term load forecasting: a review and evaluation	Hippert, HS; Pedreira, CE; Souza, RC	ITPS	2001	1 014	53.4	42	2.2
15	Vibe: a universal background subtraction algorithm for video sequences	Barnich, O; Van, Droogenbroeck, M	ITIP	2011	878	97.6	6	0.7
16	Psychological aspects of natural language use: our words, our selves	Pennebaker, JW; Mehl, MR; Niederhoffer, KG	ARP	2003	873	51.4	5	0.3
17	Mastering the game of go without human knowledge	Silver, D; Schrittwieser, J; Simonyan, K; Antonoglou, I; Huang, A; Guez, A; Hubert, T; Baker, L; Lai, M; Bolton, A; Chen, YT; Lillicrap, T; Hui, F; Sifre, L; Van, Den, Driessche, G; Graepel, T; Hassabis, D	NAT	2017	837	279.0	167	55.7
18	Artificial neural networks (the multilayer perceptron) - a review of applications in the atmospheric sciences	Gardner, MW; Dorling, SR	AE	1998	804	36.5	33	1.5
19	Stanley: the robot that won the DARPA grand challenge	Thrun, S; Montemerlo, M; Dahlkamp, H; Stavens, D; Aron, A; Diebel, J; Fong, P; Gale, J; Halpenny, M; Hoffmann, G; Lau, K; Oakley, C; Palatucci, M; Pratt, V; Stang, P; Strohband, S; Dupont, C; Jendrossek, LE; Koelen, C; Markey, C; Rummel, C; Van, Niekerk, J; Jensen, E; Alessandrini, P; Bradski, G; Davies, B; Ettinger, S; Kaehler, A; Nefian, A; Mahoney, P	JFR	2006	788	56.3	20	1.4
20	Survey of robust residual generation and evaluation methods in observer-based fault detection systems	Frank, PM; Ding, X	JPC	1997	757	32.9	1	0.0
21	Show and tell: a neural image caption generator	Vinyals, O; Toshev, A; Bengio, S; Erhan, D	CVPR	2015	750	150.0	0	0.0
22	On agent-based software engineering	Jennings, NR	AI	2000	746	37.3	35	1.8
23	Serum protein fingerprinting coupled with a pattern-matching algorithm distinguishes prostate cancer from benign prostate hyperplasia and healthy men	Adam, BL; Qu, YS; Davis, JW; Ward, MD; Clements, MA; Cazares, LH; Semmes, OJ; Schellhammer, PF; Yasui, Y; Feng, ZD; Wright, GL	CR	2002	726	40.3	10	0.6
24	Tackling real-coded genetic algorithms: operators and tools for behavioural analysis	Herrera, F; Lozano, M; Verdegay, JL	AIR	1998	695	31.6	9	0.4
25	The multiple-demand (md) system of the primate brain: mental programs for intelligent behavior	Duncan, J	TCS	2010	635	63.5	3	0.3
26	Advances in diagnostic techniques for induction machines	Bellini, A; Filippetti, F; Tassoni, C; Capolino, GA	ITIE	2008	626	52.2	15	1.3
27	Constructing free-energy approximations and generalized belief propagation algorithms	Yedidia, JS; Freeman, WT; Weiss, Y	ITIT	2005	622	41.5	9	0.6
28	Machine learning: trends, perspectives, and prospects	Jordan, MI; Mitchell, TM	SCI	2015	620	124.0	92	18.4
29	Carotenoid content of fruits and vegetables - an evaluation of analytic data	Mangels, AR; Holden, JM; Beecher, GR; Forman, MR; Lanza, E	JADA	1993	617	22.9	0	0.0
30	A review on the prediction of building energy consumption	Zhao, HX; Magoules, F	RSER	2012	601	75.1	31	3.9
31	Word sense disambiguation: a survey	Navigli, R	ACS	2009	600	54.5	12	1.1
32	A survey of monte carlo tree search methods		ITCIAIG	2012	591	73.9	79	9.9

(continued on next page)

Table 4 (*continued*)

R	Title	Authors	J	YP	TC	C/Y	TCAI	CAI/Y
		Browne, CB; Powley, E; Whitehouse, D; Lucas, SM; Cowling, PI; Rohlfshagen, P; Tavener, S; Perez, D; Samothrakis, S; Colton, S						
33	Is imitation learning the route to humanoid robots?	Schaal, S	TCS	1999	582	27.7	10	0.5
34	Managerial applications of neural networks - the case of bank failure predictions	Tam, KY; Kiang, MY	MSCI	1992	552	19.7	47	1.7
35	Grasp: a search algorithm for propositional satisfiability	Marques-Silva, JP; Sakallah, KA	ITC	1999	545	26.0	14	0.7
36	A review on the forecasting of wind speed and generated power	Ma, L; Luan, SY; Jiang, CW; Liu, HL; Zhang, Y	RSER	2009	544	49.5	26	2.4
37	Cooperative mobile robotics: antecedents and directions	Cao, YU; Fukunaga, AS; Kahng, AB	AR	1997	544	23.7	14	0.6
38	FOG and IOT: an overview of research opportunities	Chiang, M; Zhang, T	IITJ	2016	528	132.0	13	3.3
39	A review of vessel extraction techniques and algorithms	Kirbas, C; Quek, F	ACS	2004	527	32.9	2	0.1
40	Symbolic boolean manipulation with ordered binary-decision diagrams	Bryant, RE	ACS	1992	518	18.5	3	0.1
41	Genetic algorithms in astronomy and astrophysics	Charbonneau, P	AJSS	1995	512	20.5	2	0.1
42	Fuzzy-sets in approximate reasoning 0.1. Inference with possibility distributions	Dubois, D; Prade, H	FSS	1991	489	16.9	13	0.4
43	Credit rating analysis with support vector machines and neural networks: a market comparative study	Huang, Z; Chen, HC; Hsu, CJ; Chen, WH; Wu, SS	DSS	2004	468	29.3	41	2.6
44	Neural networks - a review from a statistical perspective	Cheng, B; Titterington, DM	SSCI	1994	468	18.0	11	0.4
45	An approach for measuring semantic similarity between words using multiple information sources	Li, YH; Bandar, ZA; Mclean, D	ITKDE	2003	466	27.4	0	0.0
46	Ant colony optimization: introduction and recent trends	Blum, C	PLR	2005	464	30.9	14	0.9
47	Psychophysical support for a 2-dimensional view interpolation theory of object recognition	Bulthoff, HH; Edelman, S	PNAS	1992	461	16.5	1	0.0
48	Review on computational trust and reputation models	Sabater, J; Sierra, C	AIR	2005	443	29.5	14	0.9
49	Bayesian graphical models for discrete-data	Madigan, D; York, J	ISR	1995	442	17.7	2	0.1
50	Predicting surface roughness in machining: a review	Benardos, PG; Vosniakos, GC	IJMTM	2003	436	25.6	11	0.6

CVPR, 2015 IEEE Conference On Computer Vision And Pattern Recognition; DAC, 38th Design Automation Conference Proceedings 2001; ACS, ACM Computing Surveys; ARP, Annual Review of Psychology; AJSS, Astrophysical Journal Supplement Series; AE, Atmospheric Environment; AR, Autonomous Robots; BBS, Behavioral and Brain Sciences; CR, Cancer Research; CCE, Computers & Chemical Engineering; COR, Computers & Operations Research; ACS, Computing Surveys; IITJ, IEEE Internet of Things Journal; ITC, IEEE Transactions on Computers; ITIP, IEEE Transactions On Image Processing; ITIE, IEEE Transactions on Industrial Electronics; ITIT, IEEE Transactions On Information Theory; ITPS, IEEE Transactions On Power Systems; IJHCS, International Journal of Human-Computer Studies; IJMTM, International Journal of Machine Tools & Manufacture; ISR, International Statistical Review; JFR, Journal of Field Robotics; JPC, Journal of Process Control; JADA, Journal of The American Dietetic Association; KER, Knowledge Engineering Review; MSCI, Management Science; NAT, Nature; NATM, Nature Materials; PLR, Physics of Life Reviews; PIEEE, Proceedings of the IEEE; PNAS, Proceedings of The National Academy of Sciences of the United States Of America; SCI, Science; SSCI, Statistical Science; TCS, Trends in Cognitive Sciences.

development of AI technologies. The most cited study is a paper by Barsalou (1999) entitled “Perceptual symbol systems” in which he presents a theory of perceptual symbols with implications for neuroscience and artificial intelligence. One explanation for this paper’s influence is that it provides a theoretical foundation of many studies on cognition, be it in AI or cognitive psychology. Given that perception is a key capability of AI systems, the perceptual theory of knowledge developed in this paper has been used to guide research and development of the perceptual components of AI systems, including research on sensors that enable AI systems to capture information from their environment to simulate human behavior.

The second most cited paper is Kschischang et al. (2001) on “Factor graphs and the sum-product algorithm”. This paper underlies the development of several AI algorithms used today, such as Bayesian networks, Markov networks, and random forests, due to the improved accuracy they provides when computing message-passing algorithms.

The paper entitled “Mastering the game of Go with deep neural networks and tree search” by Silver et al. (2016) is the third most cited paper. It reports on how deep neural networks trained in the game of Go achieved a near-perfect winning rate against other Go programs and defeated the human European Go champion. This paper marks a major achievement in the field of artificial intelligence as Go is considered a difficult game to master owing to its vast search space and the difficulty evaluating the value of board positions and moves.

The fourth most cited paper by Wooldridge and Jennings (1995) entitled “Intelligent agents: Theory and practice” presents the theoretical and practical issues in the design and construction of intelligent agents. The paper discusses agent theory, agent architectures, and agent languages, and is relevant to the growing number of intelligent agent applications. Today’s most popular intelligent agents are Google’s Google Assistant, Amazon’s Alexa, Apple’s Siri, and Microsoft’s Cortana. The growth of business and domestic applications of these technologies has increased research interest in the fundamentals of this AI technology.

The fifth and six most cited papers also developed theoretical underpinnings for AI applications: Gruber (1995) published “Toward principles for the design of ontologies used for knowledge sharing?” on the role and development of formal ontologies as a way of sharing and reusing knowledge among software entities; Glover (1986) published “Future paths for integer programming and links to artificial intelligence” summarizing recent developments that offer promise to enhance the solving of combinatorial optimization problems

Brooks (1991) paper entitled "Intelligence without representation" presents an approach to building complete intelligent creatures, such as mobile robots that can operate without supervision. The importance of this paper can be explained by the increasing use of AI in robotics.

Esteva et al. (2017) published "Dermatologist-level classification of skin cancer with deep neural networks" that reports on the use of deep convolutional neural networks, trained using a dataset of clinical images to automatically classify skin lesions.

Mannsfeld et al. (2010) report on the development of an electronic skin that can be used as an active sensory device by artificial intelligence that comes into direct contact with humans in their paper "Highly sensitive flexible pressure sensors with microstructured rubber dielectric layers".

The tenth article in the list is by Venkatasubramanian et al. (2003) entitled "A review of process fault detection and diagnosis: Part I: Quantitative model-based methods", a review paper of fault detection and diagnosis methods for process engineering. Artificial intelligence techniques are increasingly employed for process fault diagnosis.

Only seven of the top 50 papers present a concrete application of AI that could be considered to have a societal impact, according to the classification by Chui et al. (2018). The paper by Esteva et al. (2017) on the detection of skin cancers can be classified in social impact domain 6 "Health and hunger". Adam et al. (2002) develop a protein profiling system for the early detection of prostate cancer using an artificial intelligence learning algorithm to differentiate cancerous from noncancerous proteomic patterns. This article can also be classified in social impact domain 6 "Health and hunger". Zhao and Magoulès (2012) review recently developed engineering, statistical, and artificial intelligence models and methods for predicting building energy consumption. Lei et al. (2009) review and assess wind power forecasting models, including new methods based on artificial intelligence. These two articles can be classified in social impact domain 8 "Infrastructure management". Pennebaker et al. (2003) explore the psychological aspects of natural language use and can be classified in social impact domain 6 "Health and hunger" under the mental health theme. Tam and Kiang (1992) study of how neural networks can be used to predict bank failures can be classified under social impact domain 9 "Public and social sector management". And finally, Mangels et al. (1993) used artificial intelligence to measure the carotenoid content of fruit and vegetables and generate a database that can be used to examine the association between dietary carotenoids and disease incidence. This paper can also be classified in impact domain 6 "Health and hunger".

4.1.3. The most productive and influential authors in AI research

Over 80 000 authors contributed to the papers in our corpus, of which 52 562 published their work during the AI Fall. Ranking of authors by productivity and influence helps describe the intellectual dynamics of the field. Table 5 ranks authors according to their AI adjusted h-index (hAI) and total citations (TCAI). Statistics in the table are based on all publications, including both first and co-authorships.

The most published and influential author in the corpus is Ozgur Kisi from Iran, with an h-index of 19 and the majority of his production during the AI Fall. The author works in the areas of engineering and water resources, and his most cited paper (TC 203, TCAI 47) as first author is "Forecasting daily lake levels using artificial intelligence approaches" published in *Computers & Geosciences* (Kisi et al., 2012). This paper tests and compares three artificial intelligence approaches to predict lake-level variations.

The second-ranked author is Gilles Klopman, publishing in the areas of genetics, heredity, and toxicology. The author's most cited paper is "Artificial intelligence approach to structure-activity studies. Computer automated structure evaluation of biological activity of organic molecules" published in *Journal of the American Chemical Society* (Klopman, 1984). All of Klopman's publications appeared during the AI Winter.

There are also seven young (YP > 2016) and influential authors (mAI > 3) on the list: H. Shahabi and K. Chapi (Iran) working in engineering and geology, A Shirzadi (Vietnam) in environmental sciences, ecology and engineering, BT. Pham (Norway) in engineering and materials science, M. Panahi (Iran), K. Khosravi (Vietnam), and B. Bin Ahmad (Malaysia) in engineering and chemistry.

The most productive and influential authors publish in a wide variety of fields. The most frequently observed areas are engineering (21% of total areas provided) and computer science (20%). This is not surprising given the technical nature of the field. It is interesting to note the diversity of the 22 other, often secondary areas, including geology (8% of total areas), water resources (5%), and materials science (4%). Table 6 presents the frequency of all 85 areas cited by the top 50 ranked authors.

While engineering and computer science dominate the list, closer inspection reveals a "long tail" of 83 other research areas within the AI field. This result illustrates the large variety of application areas for AI research, and the potential for AI research to have a social impact.

4.1.4. The most productive and influential institutions in AI research

Over 15 000 institutions contributed to AI research over the 45-year period. The 50 most productive and influential author affiliations are presented in table 7, ordered by the h-index (HAI) and total citations in AI research (TCAI).

Institutions in the USA, China, and the UK dominate the table. Two in three of the top 50 institutions are based in one of these three countries. The remaining 17 institutions are spread across 8 countries: Canada, Iran, Singapore, Greece, Malaysia, India, Netherlands, and France. All of the 50 top-ranked institutions began publishing in AI during the AI Winter, with a median start year of 1986.

Stanford University (USA) is the most productive and influential institution, accounting for 3 articles amongst the top 50 publications, and 8 publications with over 200 citations. The second most productive institution is Carnegie Mellon University (USA), with 1 article in the top 50 and 7 with over 200 citations. The University of London (UK) and Hong Kong Polytechnical University (China) are in third and fourth position with a slightly lower h-index than CMU but a higher number of average citations per article in AI research. Despite the dominance of North American institutions, four of the five fastest-growing institutions are in Iran and China: Islamic Azad University (48%), University of Tehran (51%), University of Tabriz (53%), Tsinghua University (38%) and Harvard Medical School (100%)

Several institutions have maintained their influence over time, as highlighted by their m-index in AI research (mAI > 1.5), including Islamic Azad University (Iran), University of Malaya (Malaysia), University of Tehran (Iran), University of Tabriz (Iran) and Harvard Medical School (USA). The University of Illinois publishes the highest proportion of research in AI compared to all other institutions on the list.

4.1.5. The most productive and influential countries in AI research

We can also identify the most productive and influential countries in AI research. From the 128 countries that contributed to AI scholarship between 1975 and 2019, Table 8 presents the top 50 countries based on their h-index and total citations in AI research. The table is based on publications where the country appears as the main affiliation of the first author.

Consistent with the result presented previously, the USA, the United Kingdom, China, and Canada are the four most productive and influential countries in AI research. The USA dominates the rankings with a significantly higher h-index (HAI), research output (TPAI), and total citations (TCAI) than second-place United Kingdom. American researchers also contribute close to half of all top 50 publications in AI, compared to 9 from the UK. On the other hand, the UK demonstrates a greater intercountry collaboration (MCP) level than the USA and higher per-capita AI research output and number of citations.

High production volumes but low average citations raise the issue of the relative visibility of publications from countries such as China, Italy, India, France, and Germany compared to the USA, the UK, Canada, and Iran. This is also the case for countries with high annual growth rates in

Table 5
The 50 most productive and influential authors in AI research (1975–2019).

R	Name	C	hAI	TCAI	TC	TPAI	PCAI	TPAI-W	TPAI-F	T50	mAI	YP	Main area	Secondary area
1	Kisi O	Iran	19	294	1 381	43	6.84	18	25	0	1.73	2009	Engineering	Water Resources
2	Klopman G	USA	19	208	1 519	33	6.30	33	0	0	0.53	1984	Toxicology	Genetics & Heredity
3	Chau KW	China	18	241	1 469	37	6.51	25	12	0	0.64	1992	Engineering	Computer Science
4	Smith DH	USA	17	247	612	27	9.15	26	1	0	0.38	1975	Chemistry	Computer Science
5	Cheng MY	China	17	77	851	38	2.03	26	12	0	1.13	2005	Engineering	Computer Science
6	El-Shafie A	Malaysia	15	123	682	28	4.39	10	18	0	1.15	2007	Engineering	Water Resources
7	Shahabi H	Iran	14	223	568	23	9.70	0	23	0	4.67	2017	Engineering	Geology
8	Chen CY	China	14	211	477	38	5.55	30	8	0	0.82	2003	Engineering	Mechanics
9	Chen W	China	14	147	535	35	4.20	10	25	0	0.74	2001	Engineering	Computer Science
10	Rosenkranz HS	USA	14	88	577	21	4.19	21	0	0	0.40	1985	Toxicology	Genetics & Heredity
11	Zhang J	China	14	45	676	91	0.49	24	67	0	0.67	1999	Engineering	Computer Science
12	Djerassi C	USA	13	217	610	17	12.76	17	0	0	0.29	1975	Chemistry	Spectroscopy
13	Bui DT	Iran	13	204	1 169	33	6.18	0	33	0	3.25	2016	Environmental Sciences & Ecology	Engineering
14	Dubois D	France	13	37	660	22	1.68	19	3	1	0.45	1991	Computer science	Mathematics
15	Nourani V	Iran	12	202	808	42	4.81	11	31	0	1.09	2009	Engineering	Water Resources
16	Shirzadi A	Vietnam	12	202	1 106	21	9.62	0	21	0	4.00	2017	Engineering	Environmental Sciences & Ecology
17	Shiri J	Iran	12	154	455	15	10.27	12	3	0	1.20	2010	Geology	Water Resources
18	Shih BY	China	12	134	519	17	7.88	17	0	0	1.20	2010	Engineering	Mechanics
19	Wang JZ	China	12	49	312	25	1.96	5	20	0	0.71	2003	Energy & Fuels	Computer Science
20	Prade H	France	12	37	765	32	1.16	23	9	1	0.41	1991	Computer Science	Mathematics
21	Chapi K	Iran	11	154	612	13	11.85	0	13	0	3.67	2017	Engineering	Geology
22	Pham BT	Norway	11	138	486	22	6.27	0	22	0	3.67	2017	Engineering	Materials Science
23	Yaseen ZM	Malaysia	11	85	547	20	4.25	0	20	0	2.20	2015	Engineering	Water Resources
24	Moghaddam AA	Iran	11	85	737	11	7.73	4	7	0	1.57	2013	Environmental Sciences & Ecology	Water Resources
25	King RD	UK	11	75	375	15	5.00	12	3	0	0.39	1992	Computer Science	Science & Technology - Other Topics
26	Li Y	China	11	58	327	84	0.69	33	51	0	0.46	1996	Computer Science	Engineering
27	Wang ZL	China	11	38	837	33	1.15	8	25	0	0.61	2002	Materials Science	Chemistry
28	Yang J	China	11	35	371	49	0.71	14	35	0	0.50	1998	Engineering	Computer Science
29	Wang H	China	11	24	277	68	0.35	32	36	0	0.55	2000	Computer Science	Engineering
30	Khosravi K	Vietnam	10	129	914	14	9.21	0	14	0	3.33	2017	Engineering	Chemistry
31	Bin Ahmad B	Malaysia	10	106	776	14	7.57	0	14	0	3.33	2017	Engineering	Chemistry
32	Panahi M	Iran	10	98	571	13	7.54	0	13	0	5.00	2018	Chemistry	Engineering
33	Liu Y	China	10	88	337	81	1.09	25	56	0	0.53	2001	Computer Science	Engineering
34	Chou JS	China	10	72	448	22	3.27	8	14	0	1.00	2010	Engineering	Computer Science
35	Wang Y	China	10	57	476	74	0.77	12	62	0	0.63	2004	Engineering	Computer Science
36	Zhang Y	China	10	52	348	96	0.54	30	66	1	0.53	2001	Computer Science	Engineering
37	Li X	China	10	49	695	50	0.98	17	33	0	0.53	2001	Computer Science	Engineering
38	Li L	China	10	31	296	52	0.60	15	37	0	0.59	2003	Computer Science	Engineering
39	Corchado JM	Spain	10	30	358	33	0.91	13	20	0	0.53	2001	Computer Science	Engineering
40	Wang YX	Canada	10	30	289	32	0.94	14	18	0	0.45	1998	Computer Science	Engineering
41	Tadeusiewicz R	Poland	10	29	473	25	1.16	24	1	0	0.50	2000	Computer Science	Engineering
42	Zha XF	Singapore	10	29	341	11	2.64	11	0	0	0.45	1998	Engineering	Computer Science
43	Wang J	China	10	24	314	71	0.34	14	57	0	0.31	1988	Engineering	Computer Science
44	Chan FTS	China	10	22	428	14	1.57	11	3	0	0.50	2000	Engineering	Computer Science
45	Hsu YY	China	10	20	338	12	1.67	12	0	0	0.34	1991	Engineering	Computer Science
46	Chan CW	Canada	9	42	378	21	2.00	19	2	0	0.36	1995	Computer Science	Engineering
47	Neves J	Portugal	9	39	228	42	0.93	31	11	0	0.41	1998	Computer Science	Engineering
48	Chen J	China	9	34	227	47	0.72	15	32	0	0.33	1993	Computer Science	Engineering
49	Kim S	Korea	9	32	267	42	0.76	8	34	0	0.47	2001	Engineering	Computer Science
50	Zhang D	China	9	24	317	26	0.92	15	11	0	0.64	2006	Computer Science	Engineering

research output (CAGR > 20%), including Korea, Saudi Arabia, Vietnam, Pakistan, and Indonesia.

Several smaller, less known countries are also productive and influential in the field. The three countries with the highest per capita level of publications and citations are Singapore, Ireland, and Slovenia. As a share of national research output over the same period, AI publications are highest in Algeria, Romania, and Indonesia. This result confirms previous research into the “long tail” in scientific production: a large number of lesser-known outlets collectively contribute significantly to scientific production (Wu et al., 2009).

The AI field is collaborative by nature, with over 80% of documents between 1975 and 2019 published by multiple authors, increasing to 84.5% during the AI Fall. Intercountry collaborations are measured by the MCP ratio, the fraction of articles where co-authors belong to different countries (i.e. multi-country papers/total papers). As a reference point, the USA had an average MCP of 0.12 over the period, indicating that 12% of papers were authored with scholars with affiliations in other countries than the USA. Fifteen countries had MCP ratios equal to or above 0.25, reflecting a strong level of intercountry collaboration: Australia, Malaysia, Singapore, Switzerland, Belgium, Portugal, Sweden, Saudi Arabia, New Zealand, Vietnam, Denmark, Finland, Norway, Pakistan, and Tunisia.

Table 6
Frequency of all areas cited by the top 50 authors in AI research.

Area		Area	
Engineering	717	Health care sciences & services	7
Computer science	680	Life sciences & biomedicine - other topics	7
Water resources	155	Oceanography	7
Chemistry	152	Physical geography	7
Environmental sciences & ecology	128	Respiratory system	7
Geology	115	Spectroscopy	7
Telecommunications	110	General & internal medicine	6
Materials science	104	Nuclear science & technology	6
Automation & control systems	92	Urology & nephrology	6
Science & technology - other topics	92	Astronomy & astrophysics	5
Physics	70	Biophysics	5
Energy & fuels	67	Metallurgy & metallurgical engineering	5
Operations research & management science	59	Cell biology	4
Mathematics	57	Food science & technology	4
Instruments & instrumentation	47	Geochemistry & geophysics	4
Mechanics	46	Geography	4
Toxicology	42	Public, environmental & occupational health	4
Remote sensing	40	Social sciences - other topics	4
Imaging science & photographic technology	35	Developmental biology	3
Genetics & heredity	32	Legal medicine	3
Robotics	30	Marine & freshwater biology	3
Meteorology & atmospheric sciences	29	Pathology	3
Oncology	28	Polymer science	3
Agriculture	27	Public administration	3
Radiology, nuclear medicine & medical imaging	24	Surgery	3
Acoustics	21	Arts & humanities - other topics	2
Construction & building technology	21	Cardiovascular system & cardiology	2
Optics	21	Government & law	2
Business & economics	20	Mining & mineral processing	2
Thermodynamics	20	Ophthalmology	2
Biochemistry & molecular biology	19	Architecture	1
Pharmacology & pharmacy	18	Biodiversity & conservation	1
Transportation	16	Electrochemistry	1
Biotechnology & applied microbiology	15	Mathematical methods in social sciences	1
Medical informatics	14	Medical laboratory technology	1
Mathematical & computational biology	13	Nursing	1
Neurosciences & neurology	11	Obstetrics & gynecology	1
Education & educational research	10	Otorhinolaryngology	1
Forestry	9	Physiology	1
Research & experimental medicine	9	Psychiatry	1
Information science & library science	8	Psychology	1
Gastroenterology & hepatology	7	Reproductive biology	1

The preceding bibliometric analysis shows that although dominated by North American scholars, the AI research field is internationally diverse, with a main focus on technical or conceptual advances in the development of AI models and technologies. The "long tail" of subject areas and lower ranked journals underscores the richness of scholarship in the AI field. The following section further explores the conceptual structure of AI scholarship.

4.1.6. Thematic evolution of the field

The thematic evolution of a scientific field can be quantified and visualized (Cobo et al., 2011) using co-word analysis. Co-word analysis identifies groups or clusters of keywords that represent the different conceptual themes developed within a research field for the subperiod under study. Each cluster can be described according to its *centrality* and *density*. Centrality measures the strength of the links between a cluster and other clusters. According to Callon et al., 164, "the more numerous and stronger are these links, the more this cluster designates a set of research problems considered crucial by the scientific or technological community". A cluster with a high degree of centrality occupies a strategic position in a research field. Density measures the strength of the links between the keywords within a cluster and describes "the cluster's capacity to maintain itself and to develop over the course of time in the field under consideration" (Callon et al., 1991, p. 165).

Research subfields can be mapped to a two-dimensional space, called a "strategical graph" (Callon et al., 1991) or "strategic diagram" (Cobo et al., 2011) according to the level of centrality and density of each cluster. An example of a strategic diagram is presented in Fig. 3.

Quadrant 1 is made up of clusters central to the research domain (high centrality) and highly developed, exhibiting strong internal links (high density). These clusters often represent core fields of study and have been developed over time by a well-defined group of researchers. Clusters in quadrant 2 are also important to the field but they are generally less developed than clusters in quadrant 1. These clusters may represent themes that are growing in importance, but that require more significant investment before they mature. Quadrant 3 clusters are well developed but not well connected to other themes within the field. Typically, these themes are specialized and peripheral in nature, and while they may have been central at one point, they have been thoroughly investigated and today are less relevant to the field. Clusters in quadrant 4 are peripheral and little developed, representing either emerging or declining themes.

We analyzed the evolution of AI research themes across two time periods: the "AI Winter" from 1975 to 2014 and the "AI Fall" from 2015 to 2019. Figs. 4 and 5 present the strategic maps of the main AI research themes and trends for each period based on the 250 most frequent keywords provided by authors. Each circle's size represents the number of occurrences of cluster keywords, and the label represents the most frequent keyword in that cluster over the period. Tables 9 and 10 list the keywords per cluster by their frequency.

The central, motor themes during the AI Winter were "expert systems" and "knowledge representation". During this period, the focus of AI research was mainly on expert systems. An expert system are knowledge-based systems that emulate expert thought to solve significant problems in a particular domain of expertise (Sell, 1986, p. 25). "Knowledge representation" was also a motor theme during the AI Winter because knowledge was such an important input into rule-based AI algorithms. Accordingly, the representation of knowledge became "one of Al's top research priorities" (Patterson, 1990) during the period. Research in expert systems and knowledge representation had several successful applications during the period, such as IBM's Deep Blue computer that defeated the reigning world champion Garry Kasparov in a game of chess in 1997 (Newborn, 2000).

An emerging theme that also attracted significant scholarly attention during the period was neural networks. This large cluster grouped several themes, including artificial neural networks, genetic algorithms, and fuzzy logic, and reflects the search for alternative models of human reasoning by AI scholars. Since the start of the AI Spring, artificial neural networks have been at the very core of artificial intelligence research. In the 1940s, the first computational model for neural networks was introduced by Warren McCulloch and Walter Pitts (1943) while artificial intelligence scientists started applying the neural plasticity principles developed by Donald Hebb (1949) to computational models. AI research on artificial neural networks stagnated until the beginning of the AI Winter as influential AI researchers pointed out the limits of the use of neural networks in computational machines (Minsky and Papert, 1969), mainly due to the overall lack of processing power. Hopes were revived and interest renewed at the start of the AI Winter with a general increase in the processing power of machines but also with significant algorithmic advances such as Werbos's (1974) backpropagation algorithm and the introduction of parallel distributed processing algorithms when simulating neural processes (Rumelhart and McClelland, 1986).

A smaller emerging cluster focused on machine learning, data mining, and classification. Machine learning and data mining are closely

Table 7
The 50 most productive and influential institutions in AI research (1975–2019).

R	Institution	C	hAI	TCAI	TPAI	PCAI	CAGR	T50	≥ 500	≥ 200	≥ 100	≥ 50	< 50	TPAI-W	TPAI-F	TP	PAI/th	YP	mAI
1	Stanford University	USA	34	1 165	287	4.06	10.2	3	3	5	9	10	260	149	138	314 990	0.91	1975	0.76
2	Carnegie Mellon University	USA	31	376	219	1.72	11.8	1	2	5	2	9	201	136	83	74 006	2.96	1977	0.72
3	University of London	UK	30	491	231	2.13	15.5	2	2	3	5	7	214	133	98	779 038	0.30	1986	0.88
4	Hong Kong Polytechnic University	China	30	327	171	1.91	23.9	0	0	3	1	14	153	104	67	54 730	3.12	1995	1.20
5	University of Texas	USA	30	294	278	1.06	13.6	2	2	3	5	13	255	125	153	642 835	0.43	1975	0.67
6	Nanyang Technological University	Singapore	29	210	197	1.07	18.5	0	0	1	3	9	184	103	94	94 606	2.08	1992	1.04
7	Islamic Azad University	Iran	28	364	247	1.47	48.2	0	0	0	0	10	237	81	166	82 961	2.98	2005	1.87
8	National Taiwan University	China	27	281	173	1.62	16.6	1	0	1	3	5	164	83	90	121 318	1.43	1990	0.90
9	University of Pittsburgh	USA	27	195	122	1.60	12.4	0	0	3	3	8	108	77	45	235 755	0.52	1978	0.64
10	University of Hong Kong	China	27	146	187	0.78	15.6	0	0	0	4	8	175	89	98	91 072	2.05	1983	0.73
11	University of Toronto	Canada	26	229	186	1.23	11.4	1	1	0	3	12	170	76	110	415 797	0.45	1977	0.60
12	University of Malaya	Malaysia	26	201	104	1.93	33.7	0	0	1	4	6	93	27	77	46 968	2.21	2003	1.53
13	University of Tehran	Iran	26	182	142	1.28	51.1	0	0	0	0	9	133	53	89	46 749	3.04	2007	2.00
14	Indian Inst of Tech System	India	26	157	192	0.82	20.7	0	0	0	3	4	185	96	96	215 976	0.89	1991	0.90
15	University of Tabriz	Iran	25	480	115	4.17	53.9	0	0	1	1	10	103	37	78	13 553	8.49	2008	2.08
16	Harvard University	USA	25	230	123	1.87	10.1	0	0	1	4	6	112	45	78	766 420	0.16	1976	0.57
17	Chinese Academy of Science	China	25	154	260	0.59	24.4	0	0	1	0	6	253	205	55	710 196	0.37	1995	1.00
18	University of Oxford	UK	23	389	186	2.09	14.3	0	0	1	4	3	178	55	131	319 156	0.58	1980	0.58
19	University of California Berkeley	USA	22	255	125	2.04	12.5	2	2	1	4	7	111	61	64	270 367	0.46	1984	0.61
20	Case Western Reserve University	USA	22	236	54	4.37	12.1	0	0	2	1	5	46	43	11	125 441	0.43	1984	0.61
21	Texas AANDM University	USA	22	207	99	2.09	14.5	0	0	1	2	8	88	55	44	184 364	0.54	1985	0.63
22	National University of Singapore	Singapore	22	171	177	0.97	19.5	0	0	0	2	5	170	76	101	145 947	1.21	1990	0.73
23	National and Kapodistrian University of Athens	Greece	22	165	128	1.29	18.2	1	0	2	1	5	120	91	37	80 175	1.60	1990	0.73
24	National Tech. University Athens	Greece	22	121	89	1.36	16.7	1	0	2	1	5	81	68	21	32 346	2.75	1990	0.73
25	Tsinghua University	China	22	115	177	0.65	38.2	0	0	1	2	4	170	33	144	153 792	1.15	2003	1.29
26	University of Illinois	USA	22	89	154	0.58	13.1	1	1	0	0	9	144	92	62	13 456	11.44	1978	0.52
27	University Colorado	USA	21	300	108	2.78	15.2	0	1	0	3	3	101	49	59	228 646	0.47	1986	0.62
28	McGill University	Canada	21	200	118	1.69	15.1	0	0	1	2	4	111	47	71	206 295	0.57	1985	0.60
29	Huazhong University of Science & Tech	China	21	135	126	1.07	17.6	0	0	1	1	4	120	41	85	92 525	1.36	1996	0.88
30	University of Exeter	UK	21	77	60	1.28	12.8	0	0	0	1	1	58	42	18	55 714	1.08	1985	0.60
31	University of Alberta	Canada	20	248	118	2.10	15.1	0	0	0	3	5	110	67	51	167 517	0.70	1985	0.57
32	University of Michigan	USA	20	200	138	1.45	12.9	1	1	2	0	5	130	60	78	340 732	0.41	1984	0.56
33	University of British Columbia	Canada	20	160	112	1.43	18.4	0	0	2	0	6	104	52	60	221 833	0.50	1991	0.69
34	University of Manchester	UK	20	104	93	1.12	12.6	1	0	2	1	6	84	44	49	194 211	0.48	1990	0.67
35	Purdue University	USA	20	75	118	0.64	13.0	1	1	0	1	3	113	71	47	151 303	0.78	1980	0.50
36	Arizona State University	USA	19	258	99	2.61	16.0	1	1	0	4	3	91	44	55	100 597	0.98	1988	0.59
37	National Cheng Kung University	China	19	202	83	2.43	17.8	0	0	1	0	2	80	56	27	64 267	1.29	1992	0.68
38	University of Maryland	USA	19	177	135	1.31	13.0	0	0	1	2	6	126	76	59	97 077	1.39	1979	0.46
39	University of Cambridge	UK	19	169	83	2.04	13.1	0	0	3	3	4	73	24	59	287 765	0.29	1983	0.51
40	Natl Taiwan University of Science & Tech	China	19	143	89	1.61	23.8	0	0	0	1	2	86	45	44	20 269	4.39	1998	0.86
41	Harvard Medical School	USA	18	417	129	3.23	100.2	0	0	1	1	3	124	1	128	76 381	1.69	2012	2.25
42	University of Southern California	USA	18	167	84	1.99	12.0	0	0	0	3	7	74	80	4	175 434	0.48	1980	0.45
43	University of Arizona	USA	18	157	90	1.74	15.1	1	0	1	2	3	84	64	26	162 491	0.55	1987	0.55
44	Columbia University	USA	18	123	104	1.18	15.1	0	0	0	4	1	99	34	70	268 664	0.39	1986	0.53
45	University of Amsterdam	Netherlands	18	115	127	0.91	14.3	0	0	0	2	6	119	81	46	156 239	0.81	1988	0.56
46	University of Sheffield	UK	18	106	76	1.39	16.7	0	0	0	2	7	67	47	29	116 880	0.65	1991	0.62
47	Universiti Teknologi Malaysia	Malaysia	18	105	122	0.86	21.6	0	0	0	1	1	120	30	92	27 425	4.45	1998	0.82
48	University of Washington	USA	18	105	105	1.00	13.8	0	0	1	1	3	100	46	59	309 461	0.34	1983	0.49
49	University of Chicago	USA	18	104	46	2.26	9.8	0	0	0	1	6	39	21	25	242 873	0.19	1978	0.43
50	CNRS	France	18	69	116	0.59	13.7	0	0	1	2	3	110	69	47	935 610	0.12	1982	0.47

Table 8
The 50 most productive and influential countries in AI research (1975–2019).

R	Country	hAI	TCAI	TPAI	PCAI	CAGR	TP	PAI/th	≥ 500	≥ 200	≥ 100	≥ 50	< 50	T50	TPAI-W	TCAI-F	TPAI/PMH	TCAI/PMH	YP	MCP
1	USA	131	8 811	7 340	1.20	22.4	19 640 032	0.37	20	66	114	240	6900	23	4 130	3 210	22.4	26.8	1975	0.12
2	United Kingdom	80	3 040	2 328	1.31	15.6	1 177 471	1.98	7	22	32	71	2196	9	1 382	946	34.8	45.5	1978	0.21
3	China	70	2 765	6 141	0.45	25.8	5 175 367	1.19	1	15	22	76	6027	1	2 415	3 726	4.4	2.0	1981	0.15
4	Canada	52	1 048	1 163	0.90	18.3	2 589 186	0.45	1	5	15	35	1107	1	677	486	30.9	27.9	1977	0.23
5	Spain	46	1 104	1 477	0.75	25.6	1 605 418	0.92	1	4	9	26	1437	3	911	566	31.4	23.5	1987	0.20
6	Iran	43	1 155	892	1.29	42.8	504 915	1.77	0	1	2	32	857	0	327	565	10.8	13.9	2003	0.24
7	Italy	43	667	1 076	0.62	20.8	2 141 316	0.50	2	4	6	27	1037	2	596	480	17.8	11.1	1982	0.20
8	Australia	41	612	836	0.73	21.2	1 727 324	0.48	0	0	8	22	806	0	412	424	33.0	24.1	1984	0.26
9	India	40	633	1 774	0.36	25.4	1 705 320	1.04	0	1	10	18	1745	0	585	1 189	1.3	0.5	1986	0.07
10	France	40	580	990	0.59	20.5	2 803 167	0.35	1	4	9	16	960	2	628	362	14.8	8.6	1982	0.22
11	Germany	39	519	1 045	0.50	23.4	3 398 906	0.31	1	0	4	22	1018	1	533	512	12.6	6.2	1986	0.18
12	Turkey	38	536	596	0.90	22.6	642 730	0.93	0	1	3	20	572	0	268	328	7.1	6.4	1991	0.12
13	Greece	34	359	371	0.97	22.6	357 360	1.04	0	3	2	17	349	1	244	127	34.6	33.5	1990	0.16
14	Malaysia	34	344	539	0.64	28.0	245 822	2.19	0	1	11	11	516	0	223	316	16.9	10.8	1998	0.29
15	Korea	33	543	771	0.70	26.8	1 165 088	0.66	0	1	5	14	751	0	238	533	14.9	10.5	1991	0.13
16	Netherlands	33	325	362	0.90	14.2	1 275 164	0.28	0	1	6	13	342	0	233	129	20.9	18.8	1985	0.22
17	Brazil	32	380	836	0.45	24.1	999 008	0.84	1	0	4	6	825	1	431	405	4.0	1.8	1991	0.19
18	Singapore	31	282	315	0.90	17.7	304 245	1.04	0	1	4	12	298	0	181	134	55.2	49.4	1988	0.31
19	Japan	30	517	923	0.56	19.7	3 464 402	0.27	0	4	6	8	905	0	437	486	7.3	4.1	1981	0.12
20	Poland	29	312	691	0.45	18.8	747 556	0.92	1	0	3	4	683	1	354	337	18.2	8.2	1981	0.08
21	Switzerland	27	232	227	1.02	17.3	943 749	0.24	0	1	7	9	210	0	114	113	26.5	27.1	1985	0.29
22	Belgium	24	115	194	0.59	16.8	288 637	0.67	1	0	2	11	180	1	114	80	16.9	10.0	1985	0.38
23	Portugal	22	168	333	0.50	23.1	124 ,621	2.67	1	1	2	3	326	1	189	144	32.4	16.4	1991	0.25
24	Austria	22	167	251	0.67	17.6	198 169	1.27	0	1	1	4	245	0	144	107	28.3	18.8	1985	0.23
25	Ireland	22	154	205	0.75	21.8	78 716	2.60	0	2	3	5	195	0	133	72	41.5	31.2	1992	0.18
26	Sweden	20	163	181	0.90	18.9	294 165	0.62	0	0	1	4	176	0	92	89	17.6	15.8	1989	0.25
27	Israel	19	100	159	0.63	14.3	180 440	0.88	0	1	3	1	154	0	95	64	17.6	11.0	1981	0.22
28	Mexico	18	124	356	0.35	16.3	110 878	3.21	0	1	1	1	353	0	199	157	2.8	1.0	1980	0.17
29	Czech Republic	17	123	315	0.39	15.9	101 195	3.11	0	1	1	2	311	0	181	134	29.5	11.5	1980	0.14
30	Saudi Arabia	17	94	182	0.52	28.1	79 980	2.28	0	0	2	2	178	0	51	131	5.3	2.7	1998	0.29
31	Algeria	17	75	179	0.42	23.9	27 045	6.62	0	0	0	5	174	0	74	105	4.2	1.7	1998	0.22
32	New Zealand	16	70	102	0.69	15.1	100 707	1.01	0	1	0	3	98	0	55	47	20.7	14.2	1991	0.25
33	Vietnam	15	180	96	1.88	30.8	32 208	2.98	0	0	0	2	94	0	10	86	1.0	1.9	2002	0.59
34	Serbia	15	86	128	0.67	18.9	28 292	4.52	0	0	0	2	126	0	70	58	18.4	12.4	1991	0.20
35	Denmark	15	54	111	0.49	11.5	187 749	0.59	0	2	0	1	108	0	57	54	19.1	9.3	1982	0.38
36	South Africa	15	53	172	0.31	18.7	95 580	1.80	0	0	2	3	167	0	60	112	2.9	0.9	1989	0.13
37	Egypt	14	95	189	0.50	17.6	58 933	3.21	0	0	0	2	187	0	74	115	1.9	0.9	1991	0.21
38	Russia	14	93	554	0.17	23.2	233 929	2.37	0	0	0	0	554	0	151	403	3.8	0.6	1992	0.11
39	Slovenia	14	80	91	0.88	18.9	28 003	3.25	0	1	0	3	87	0	59	32	43.6	38.3	1993	0.16
40	Finland	14	57	168	0.34	15.4	126 121	1.33	0	1	1	3	163	0	79	89	30.4	10.3	1988	0.26
41	Norway	13	89	133	0.67	16.2	120 330	1.11	0	0	0	2	131	0	48	85	24.9	16.6	1991	0.27
42	Pakistan	13	55	210	0.26	39.7	52 190	4.02	0	0	0	1	209	0	55	155	1.0	0.3	2003	0.32
43	Romania	12	104	531	0.20	28.5	54 849	9.68	0	0	2	1	528	0	270	261	27.4	5.4	1994	0.08
44	Hungary	12	56	117	0.48	14.0	80 533	1.45	0	0	0	3	114	0	71	46	12.0	5.7	1988	0.15
45	Tunisia	9	45	119	0.38	30.4	33 475	3.55	0	0	0	1	118	0	34	85	10.2	3.8	2001	0.30
46	Colombia	8	15	87	0.17	28.2	41 403	2.10	0	0	0	0	87	0	36	51	1.7	0.3	2001	0.23
47	Thailand	7	21	101	0.21	19.4	64 432	1.57	0	1	1	1	98	0	47	54	1.5	0.3	1993	0.11
48	Indonesia	7	12	179	0.07	38.3	32 898	5.44	0	0	0	0	179	0	17	162	0.7	0.0	2003	0.11
49	Slovakia	7	9	112	0.08	18.4	29 485	3.80	0	0	0	0	112	0	53	59	20.5	1.7	1991	0.13
50	Morocco	6	13	84	0.15	36.5	25 220	3.33	0	0	0	0	84	0	19	65	2.3	0.4	2007	0.08
	EU countries	94	5116	8621	0.59	16.16	13 921 130	0.62	8	25	52	165	8371	12	4941	3680	20.1	11.9	1980	0.23

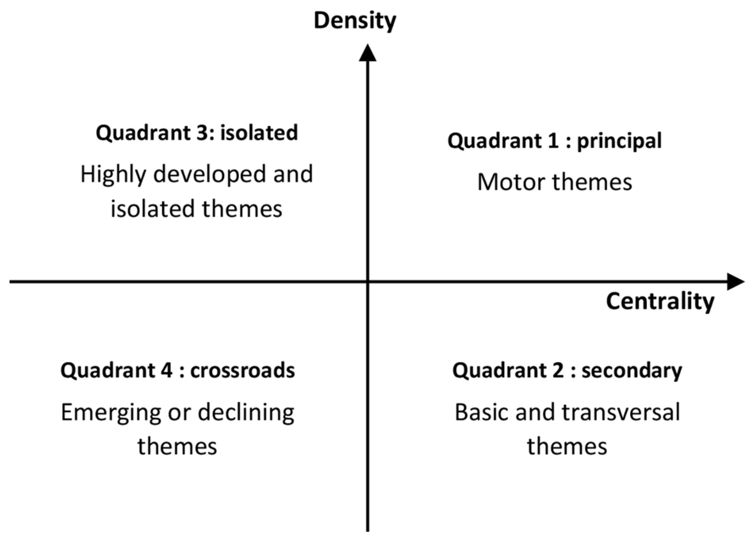

Fig. 3. The strategic diagram (adapted from Cobo et al. (2011) and Callon et al. (1991)).

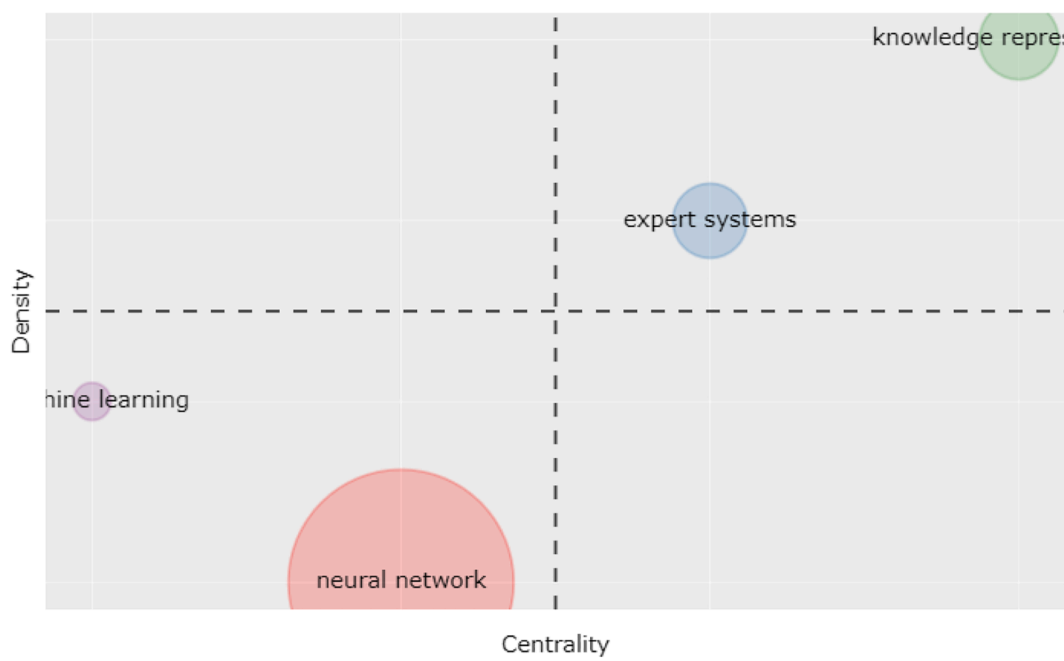

Fig. 4. Strategic map of research during the AI Winter (1975 to 2014).

related, as they often employ similar methods. However, while machine learning's main focus is to make predictions based on known properties learned from training data, data mining is more about discovering unknown properties from data. In the 1970s and 1980s, a substantial substream of AI research was dedicated to pattern recognition (e.g. Duda and Hart, 1973). As companies and scientists began capturing huge volumes of historical data during the 1990s, more and more data mining, classification techniques, and machine learning algorithms were used by both scientists and businesses (Mitchell, 1999). Meanwhile, machine learning research evolved significantly with the introduction of 'boosting', a concept that helped reduce inherent supervised learning biases by relying on the principle that a set of weak learners can create one single strong learner (Schapire, 1990).

We can observe from Fig. 5 that expert systems were no longer a significant AI research area during the AI Fall. This thematic evolution can be explained by the limits of such systems. Expert systems perform well in areas that lend themselves to the formalisation of human intelligence but perform poorly when interpreting and learning from external data, and thus technically speaking are "not true AI" (Haenlein and Kaplan, 2019).

The principal theme during this period was learning, including feature extraction, computer vision, and image classification revealing a growing interest in using AI to learn about real-world phenomena through image processing. The keywords per cluster are listed in Table 10 by order of importance.

Today, AI research focuses mostly on the learning and adaptive capabilities of AI. A number of other AI technologies including speech and pattern recognition are also important for industrial AI systems but are so far more developed in practice than in research (Bawack et al., 2019). The emergence of the learning cluster coincides with a growing interest in image recognition techniques and increased investment in computer vision and face recognition technologies by large organizations such as Google, Facebook, Amazon, Apple, and Tesla. For example, the launch of DeepFace by Facebook in 2015, a deep learning facial recognition

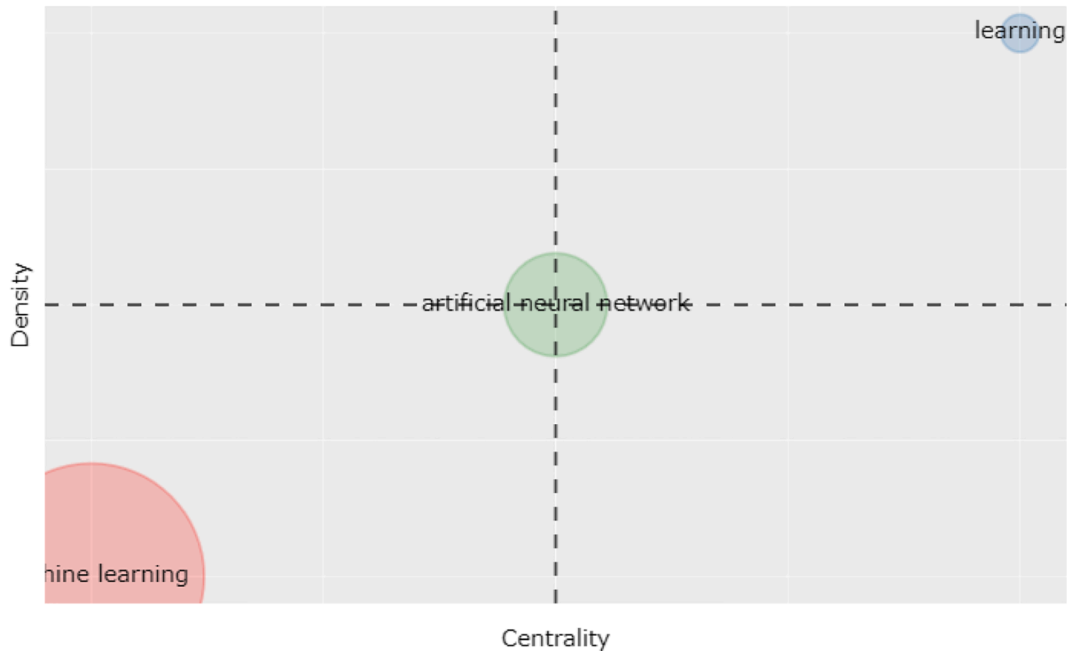

Fig. 5. Strategic map of research during the AI Fall (2015 to 2019).

Table 9
Cluster keywords and quadrant (1975 to 2014 – AI Winter).

	Cluster	Keywords	Position
1	Machine learning	machine learning; data mining; classification	Crossroads
2	Neural network	neural network; artificial neural network; genetic algorithm; fuzzy logic; simulation; optimization; pattern recognition; support vector machine; modeling; fault diagnosis; image processing	Crossroads
3	Expert systems	expert system; case-based reasoning; decision support systems; knowledge-based systems	Motor
4	Knowledge representation	knowledge representation; robotics; learning; multi-agent systems; planning; ontology; reinforcement learning; decision making	Motor

Table 10
Cluster keywords and quadrant (2015 to 2019 – AI Fall).

	Cluster	Keywords	Position
1	Machine learning	machine learning; deep learning; neural network; big data; convolutional neural network; data mining; internet of things; natural language processing; classification; reinforcement learning; robotics; prediction; image processing; automation; cloud computing; pattern recognition; technology; deep neural network; ethics	Crossroads
2	Learning	learning; feature extraction; computer vision; image classification; neural nets	Motor
3	Artificial neural network	artificial neural network; support vector machine; fuzzy logic; genetic algorithm; optimization; ANFIS; ANN; fault diagnosis; particle swarm optimization; simulation; decision making	Mixed

system, has raised a lot of public attention but also substantial research efforts.

The emerging, although loosely linked machine learning cluster continued to develop during the period, attracting research on robotics, neural networks, big data, deep learning, and convolutional neural networks from other clusters. The fall in density from the first period indicates that while the cluster grew, the links between keywords within the cluster are weaker prefiguring a splintering of the cluster over time. One way to explain such evolution could be in the tumultuous and intertwined history of the artificial intelligence and machine learning fields. Around the early 1980s, the artificial intelligence and machine learning industries took separate paths while machine learning continued to be used as training programs for AI. Recent advances in deep learning, neural networks, and natural language processing techniques have created multiple links between the two domains. As Christopher D. Manning notes: “Deep Learning waves have lapped at the shores of computational linguistics for several years now, but 2015 seems like the year when the full force of the tsunami hit the major Natural Language Processing (NLP) conferences.” (Manning, 2015, p. 701).

Research in the large, emerging cluster on neural networks during the AI Winter shed the keyword “neural network” and transformed into a denser and central artificial neural networks cluster. Today, artificial neural networks are one of the most important areas in both AI research and the application of AI technologies in business. Neural networks are used by organizations for a range of tasks including social network filtering, marketing campaign optimization, financial trading system design, and improved disease identification and diagnosis.

4.2. State of research into AI for social good

The main themes, journals, and articles that have dominated the AI literature over the past 45 years have been technical in nature. To explore the extent of research in areas where AI could be applied for social good, we searched for papers in the corpus developing each of the ten social impact domains identified by Chui et al. (2018). The domain-specific research queries are provided in Appendix 3. Table 11 presents the descriptive statistics for the papers in the reduced corpus.

A total of 1048 documents were published across the ten AI for social

Table 11
Main information regarding the "AI for social good" collection.

Description	AI for good	Total corpus
Documents	1 048	40 147
Sources	792	14 480
Period	1991 - 2019	1975 - 2019
Annual percentage growth rate	25.1%	20.0%
Average citations per document	9.74	9.03
Average citations per year per document	1.58	1.01
Authors	4 010	83 346
Authors of multi-authored documents	3 907	76 801
Documents per author	0.27	0.48
Authors per document	3.73	2.08
Co-authors per document	4.1	3.32
Multi-authored documents	944	32 109
Collaboration index	4.14	2.39

good domains, representing 2.6% of all AI research in the corpus. The collaboration index was higher than for the entire corpus indicating that research on AI for social good more often involves multiple authors. The growth rate for this subset was also higher as was the number of citations per document.

The publication period is shorter than that of the AI corpus, covering twenty-nine years from 1991 to 2019. Fig. 6 presents the publications per year across the period.

The two earliest publications appeared in 1991: a case study by Bijoch et al. (1991) on an intelligent power system alarm processor at Northern States Power Co. published in *IEEE Transactions on Power systems* and an editorial by Batty and Yeh (1991) on the promise of expert systems for urban planning published in *Computers, Environment and Urban Systems*.

AI research covered a total of 106 subject areas over the period. The two dominant areas were computer science and engineering. The number of references per research area is provided in Table 12.

Three application areas exhibited an increase in average annual growth during the AI Fall, including *Operations research & management science, Robotics*, and *Radiology, nuclear medicine & medical imaging*. The average annual growth rate fell in all other areas between the two periods.

We used Chui et al. (2018)'s review of potential areas of AI for social impact as a framework to describe and analyze the state of research in AI for social good and to identify opportunities for future research. The authors present a study by the McKinsey Global Institute of 160 AI use cases and ten domains where AI technologies could have a large-scale

Table 12
AI references in different areas (first 30 areas).

Area	YP	TPAI 1975–2019	CAGR TPAI - Winter	CAGR TPAI - Fall
Computer science	1991	308	25.6	10.3
Engineering	1991	308	22.5	7.8
Environmental sciences & ecology	1991	91	19.2	9.8
Medical informatics	1993	66	19.7	8.4
Energy & fuels	1992	65	19.9	3.8
Science & technology - other topics	2002	59	38.5	3.4
Telecommunications	1996	50	22.4	5.6
Health care sciences & services	1993	49	18.9	5.2
Water resources	1998	48	23.7	9.9
Chemistry	2010	35	141.5	0.6
Operations research & management science	1991	32	10.5	26.2
Automation & control systems	1996	30	16.2	14.9
General & internal medicine	2004	29	38.5	2.2
Psychiatry	2013	27	2500.0	0.8
Materials science	2006	25	46.3	3.5
Business & economics	1992	24	9.9	8.4
Physics	2003	22	28.7	6.6
Oncology	2001	21	24.4	4.3
Public, environmental & occupational health	1996	21	17.0	4.3
Construction & building technology	2006	20	40.3	5.9
Instruments & instrumentation	1996	20	16.7	4.6
Robotics	2001	20	8.8	27.2
Agriculture	2000	19	20.1	7.9
Education & educational research	2000	17	17.9	11.2
Geology	2008	16	49.1	7.8
Radiology, nuclear medicine & medical imaging	2017	16	0	130.9
Transportation	1998	15	14.7	10.8
Cardiovascular system & cardiology	2005	14	30.5	4.9
Neurosciences & neurology	2013	14	1200.0	1.5
Psychology	1992	14	12.0	3.1

Multiple subject areas per publication are possible.

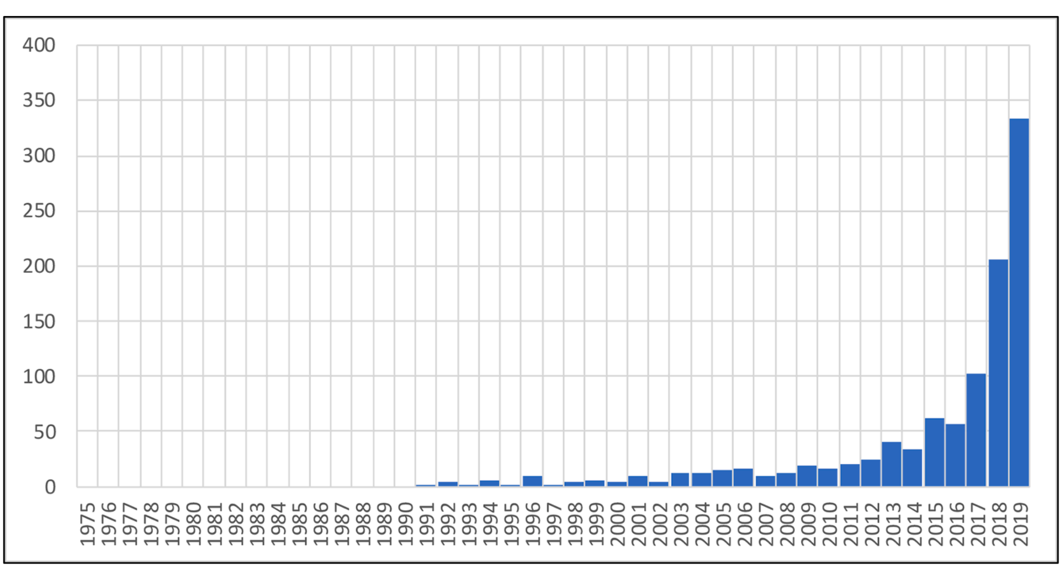

Fig. 6. Number of AI for social good publications per year: 1975–2019.

social impact. The domains cover the seventeen United Nations Sustainable Development Goals and include crisis response, economic empowerment, educational challenges, environmental challenges, equality and inclusion, health and hunger, information verification and validation, infrastructure management, public and social sector management, security and justice. The ten social impact domains are presented in Appendix 2.

The percentages of papers in the AI for social good corpus that have been published in each domain are presented in Fig. 7. Three social impact domains have attracted over three quarters of research interest: health and hunger (47% of publications), infrastructure management (26%), and environmental concerns (11%).

Six domains accounted for less than 10% of publications including social equality and inclusion (1.7%), economic empowerment (0.6%), security and justice (1.3%), educational challenges (2%), information verification and validation (1.3%), and public and social sector management (0.8%).

Table 13 ranks AI social domain output according to average document global citations. The most cited domain is security and justice, followed by equality and inclusion and environmental challenges. Five domains have below-average citations: health and hunger, educational challenges, economic empowerment, public and social sector management, and information verification and validation. One explanation for the last three domains may be that they are relatively recent, as shown by the narrow date ranges. However, health and hunger is one of the oldest domains with the highest publication count but low average citations.

Bibliographic statistics by domain and key issues are provided in Appendix 4. The following section examines the production in each of the ten social impact domains, according to issue types addressed or ignored by AI research.

4.2.1. Crisis response

Crisis response refers to the management of crises such as man-made and natural disasters, disease outbreaks, search and rescue missions, and humanitarian crises. A total of eighty-four publications in the corpus concern this domain, written between 1996 and 2019, with half of all documents published from 2016 onwards. Most publications concern responses to natural and man-made disasters ($n = 34$) and search and rescue efforts (39), whereas few address disease outbreaks (10) and humanitarian or migration crises (2). Keyword analysis reveals that the main topics covered in papers on disaster response are artificial neural networks, geographical information systems, and ANFIS. Research on search and rescue has focused on robotics, multi-agent systems, and computer vision.

Table 13
Production and citations by domain.

Domain	Articles	Average citations per document	Date range
Security and justice	13	69.6	1996–2019
Equality and inclusion	18	15.5	2005–2019
Environmental challenges	113	9.8	1994–2019
Crisis response	84	11.3	1996–2019
Infrastructure management	272	11.6	1991–2019
Health and hunger	477	6.9	1992–2019
Educational challenges	21	2.5	2000–2019
Economic empowerment	6	2	2013–2018
Public and social sector management	8	1.4	2014–2019
Information verification and validation	13	1.1	2015–2019

The most cited paper in this domain is an article entitled “Human-robot interaction in rescue robotics” published in *IEEE Transactions on Systems, Man, and Cybernetics* by Murphy (2004). It is a tutorial paper on how robots are currently used in urban search and rescue and the human-robot integration issues encountered.

4.2.2. Economic empowerment

Economic empowerment involves providing access to resources and opportunities, in particular for vulnerable populations. This was the most under-researched domain with only six articles identified in the corpus that were written between 2013 and 2018: three papers pertained to agricultural quality and yield and three concerned the use of AI to stimulate economic growth for vulnerable populations. No papers were found to address financial inclusion or labor supply and demand matching. Keyword analysis revealed that research into agricultural quality and yield concerned classification and plant disease analysis. No common keywords were found between the publications on economic growth initiatives.

The most cited paper in this area is “Artificial intelligence policy in India: a framework for engaging the limits of data-driven decision-making” published in *Philosophical Transactions of the Royal Society A* by

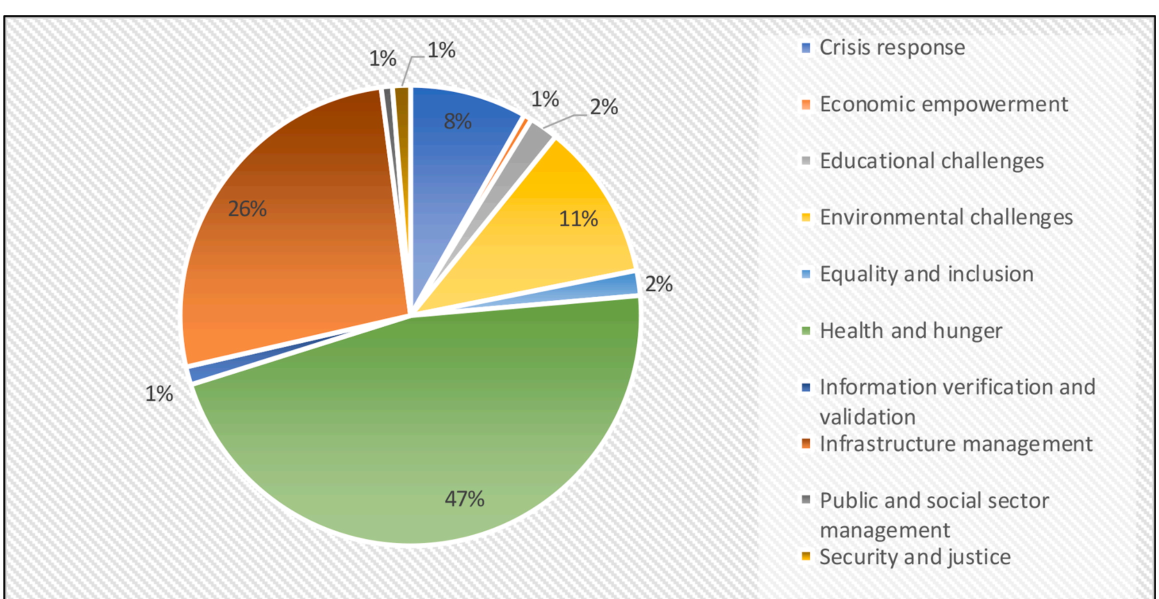

Fig. 7. AI research publications by social impact domain.

Marda (2018). The article proposes a framework for AI-based policy deliberations using India's current AI policy landscape as a backdrop. According to the author, AI policy in India is particularly oriented towards AI for economic growth and social good.

Today, a new generation of AI that could impact economic empowerment is emerging. For example, Montes and Goertzel (2019) propose an AI approach that operates in a decentralized, distributed, and more democratized manner, potentially improving services and addressing ethical issues in some markets.

4.2.3. Educational challenges

Educational challenges include improving student achievement and increasing teacher and administrative productivity. A total of 21 publications were found in the corpus dealing with this social domain. Most papers involved maximizing student achievement and performance ($n = 19$) and focus on machine learning, assessment, autism, fuzzy logic, and prediction. Only two publications dealt with access to and completion of education, and no papers were found addressing AI for teacher and administrative productivity. According to author-provided keywords, the two papers on education access dealt with online education, the theory of mind, the Turing test, and virtual teaching assistants.

A sample paper from this domain is entitled "Evaluation of student performance in laboratory applications using fuzzy logic" published in *Procedia - Social and Behavioral Sciences* by Gokmen et al. (2010). The paper proposes and tests a new performance evaluation method based on fuzzy logic systems.

4.2.4. Environmental challenges

Environmental challenges involve protecting natural resources and biodiversity, improving energy efficiency, and combatting climate change. A total of 113 papers concerning AI and environmental issues were identified in the corpus, published between 1994 and 2019, with one-half of all publications appearing from 2018 onwards. The majority of papers concerned global warming, climate change, and adaptation ($n = 105$), with a focus on deep learning, artificial neural networks, and smart grids. One in four papers on environmental challenges answered questions of animal and plant conservation and biodiversity, with a particular focus on ARtificial Intelligence for Ecosystem Services (ARIES) technology and machine learning. Few papers were found to have addressed energy efficiency and sustainability (2) or land, air, and water conservation (5).

The most cited paper in this collection is entitled "It's about time: A conceptual framework for the representation of temporal dynamics in geographic information systems" published in *Annals of the Association of American Geographers* by Peuquet (1994). The article proposes an integrated approach for representing spatiotemporal data in geographic information systems.

4.2.5. Equality and inclusion

Equality and inclusion involve reducing biases based on gender, disability, community, or race. This was one of the least researched areas in the corpus, with only 18 papers published between 2005 and 2019. The majority of papers concerned exploitation or discrimination on the basis of race, gender, handicap, religion, or sexual orientation (12), with a particular focus on conversational agents, game theory, and natural language processing. Six papers were published on accessibility and disabilities and no papers were found on AI and marginalized communities.

The most cited paper in this domain is "Smart wheelchairs: A literature review" published in the *Journal of rehabilitation research and development* by (Simpson, 2005).

4.2.6. Health and hunger

Health and hunger is one of the oldest and most productive AI for social good impact domains. It covers early-stage diagnosis and improved treatment of illness, as well as optimized food distribution to avoid hunger. A total of 477 documents were published in this domain between 1992 and 2019, with half of all publications appearing over the last five years. One researched theme was health prevention and prediction ($n = 219$). Analysis of co-occurring keywords identified three thematic groups: big data and precision medicine, prognosis and prediction, and AI techniques for various health conditions.

Another published theme around health was treatment and long-term care (269). Keyword analysis revealed three areas of interest: psychiatric care, diagnosis using chatbots and conversational agents, and the use of AI technologies for health care in general.

Mental wellness and health was a third theme that attracted research attention across the period (76). Keyword analysis revealed a particular focus on natural language processing, chatbots, and mental health. A small number of documents were published on treatment delivery (6) and hunger (3).

The most cited paper in this area is "Harnessing context sensing to develop a mobile intervention for depression" published in *Journal of medical Internet research* (Burns et al., 2011). The authors report on the experimental use of mobile phone sensors and machine learning algorithms to detect unipolar depression in patients. Four papers on health issues are also ranked amongst the top 50 most influential publications in AI (see Table 4).

4.2.7. Information verification and validation

Information verification and validation involves the detection, filtering, and negating of false, misleading, or polarizing content. This domain is the youngest of the ten AI for social good domains, recently gaining attention with the increasing diffusion of "fake news" across social media. A total of 13 publications on this topic were identified in the corpus since 2015. The majority of publications concern fake or false news (11), with a main focus on deep learning, deception detection, and natural language processing. Only two articles have dealt with the polarization of opinion.

The most cited document in this collection is a conference paper entitled "Fake news detection using naive Bayes classifier" by Granik and Mesyura (2017) that was presented at the *2017 IEEE First Ukraine Conference on Electrical and Computer Engineering (UKRCON)*. Using Facebook data, the article demonstrates how artificial intelligence can be used for fake news detection.

4.2.8. Infrastructure management

Infrastructure management involves improving the use and management of energy, water and waste, and optimizing transportation, real estate development, and urban planning for social good. This is the second most productive and oldest domain of AI research for social good with 272 publications appearing between 1991 and 2019. Most publications in this area are on energy management (153), with a particular focus on distributed power generation, machine learning, and energy management. A large number of publications also deal with water and waste management (76), often using deep learning and fuzzy logic. Publications on both of these themes also use neural networks. Urban planning has also received attention from researchers (31), most often addressing questions of smart cities and climate change. Some publications on real estate (20) and transportation management (12) also appeared during the period.

The most cited paper in this area is "Multiobjective intelligent energy management for a microgrid" published in *IEEE transactions on Industrial Electronics* by Chaouachi et al. (2012). The authors investigated online energy management using intelligent microgrids under cost and emission minimization constraints. Two papers on infrastructure management are ranked amongst the top 50 most influential publications in AI.

4.2.9. Public and social sector management

This domain includes all activities that seek to improve the performance of public and social bodies, their financial management, and the delivery of services to citizens. Only eight publications concerned this domain between 2014 and 2019, mainly dealing with government services to citizens (9) and the effective management of the public sector (2). No publications in the corpus treated the use of AI for fundraising, the management of the social sector, or public finances.

The most cited article in this domain is “IoT and AI for smart government: A research agenda” published in *Government Information Quarterly* by Kankanhalli et al. (2019). A second example of the possible role of AI in public and social sector management is provided by de Sousa et al. (2019) in their review of AI use in the public sector. One paper from this domain is ranked amongst the top 50 most influential publications in AI

4.2.10. Security and justice

The security and justice domain includes activities seeking to reduce crime and physical harm, improve policing, and ensure a fair judiciary. A small number of publications (13) addressed this domain between 1996 and 2019, most on the theme of policing (10). Few publications addressed the use of AI for harm prevention (1) and fair prosecution (2).

A representative and highly cited article in this area is “A data-driven software tool for enabling cooperative information sharing among police departments” and was published in the *European Journal of Operational Research* by Redmond and Baveja (2002). The authors present a police department decision support system that uses artificial Intelligence software.

Table 14 presents a breakdown of the ten social impact domains by journal, institution, and country.

Once again, the USA, the UK, and China lead AI research in the majority of social impact domains. However, several smaller countries also participate in specific areas, such as Turkey on environmental challenges, Italy on information verification and validation, and Spain in infrastructure management. Many lower-ranked institutions also work on these issues, and most publications are in conferences rather than journals.

5. Discussion

This paper reviews the evolution and structure of AI research using bibliometric methods. The results provide insights into the conceptual, intellectual, and social structure of AI scholarship, as well as its past and emerging themes. The number of publications on AI has risen rapidly these past five years, with as many publications appearing since 2015 as over the preceding 40 years. The influence of publications has also increased, lending support to Haenlein and Kaplan’s periodization of AI research using the seasons: since 2015, scholars appear to be reaping the harvest of several past decades of conceptual and technical development and experimentation.

The fastest-growing publication outlets are open access journals and in particular IEEE Access, Applied Sciences (Basel), Sensors, Energies, IET Computer Vision, Scientific Reports, Sustainability, IFAC Papersonline and Journal of Engineering (JOE). Articles are accessible to all from their online publication date, giving authors a better chance to diffuse their research and make an impact in the field (Eysenbach, 2006; van Vlokhoven, 2019). Given the rapid evolution of AI, it is easy to understand why researchers feel the need to publish their research as quickly as possible. The quality and reputation of journals are also a consideration for authors, with IEEE Access the 2015 winner of the PROSE Award for the best new journal in science, technology, engineering, and mathematics.[6]

Several dominant research themes were found to characterize contemporary AI research, notably learning for feature extraction and image classification and machine learning using neural networks and big data. These themes have evolved from early, highly developed fields such as expert systems, knowledge representation, and neural networks. Our analysis shows that AI technologies, models, and applications are still at the center of AI research, with little or no influence from the social sciences, thus confirming previous work by Frank et al. (2019). However, the development of a large, emerging cluster on machine learning that notably includes research on big data and AI, and a smaller motor research cluster on AI learning and feature extraction reveals a growing interest in using AI to learn about real-world phenomena through image processing.

We can observe a clear shift in AI research paradigms, from genetic algorithms, machine learning, and fuzzy sets to deep learning and convolutional neural networks. One explanation is that modeling using deep learning and convolutional neural networks, and possibly a combination of their capabilities to form deep convolutional networks is more appropriate in complex environments than were previous techniques, making them suited for complex learning tasks, especially those involving detecting, identifying, and processing images, videos, speech, text, and audio (Krizhevsky et al., 2012; LeCun et al., 2015). The volume of AI research applying these techniques is expected to increase over the coming years.

Our findings show a growing emphasis on AI’s technical aspects and little research on the social and societal aspects that would shape a good AI society. Research on the ten AI for social good domains accounted for less than 3% of publications in the corpus. The most productive areas were health and hunger, infrastructure management, and environmental challenges. Unequal interest has been paid to research themes within these domains: three-quarters of research on environmental challenges has addressed global warming and climate change; most research on health and hunger has studied two themes (prediction and prevention, treatment and long-term care); and 80% of publications on an infrastructure management deal with energy, water, and waste.

Given the rapid technological evolution of the AI domain, a number of research questions remain unanswered about the possible positive impacts of AI on society and people. Drawing from the bibliometric analysis, the in-depth analysis of the professional literature, the discussion sessions between the researchers and the emerging literature on AI for good, a list of potential future research questions have been identified. Table 15 lists research questions in each of the ten social impact domains identified by Chui et al. (2018) that could guide scholars as they explore how AI can be developed for the good of society.

These research questions complete and complement suggestions made by other studies (Cath et al., 2018; Duan et al., 2019; Russell et al., 2015a). Scholars could further explore these domains through literature reviews and case studies to refine research questions and contribute to the knowledge base of AI for good.

The results of our study should be read in light of their limitations. Firstly, some publications might have not been considered in our analysis if they were not present in the WoS Core Collection database. Secondly, while we use several well-established bibliometric tools for data analysis, insights are based on the authors’ expertise. A meta-analytical review of the literature may provide other insights the authors may have overlooked. This may be an avenue for future research. With these limitations in mind, we believe we have provided a comprehensive review of AI scholarship, highlighted its evolution and knowledge structure, and suggested evidence-based research directions to develop AI for the good of society.

6. Conclusion

Our study has answered the call for greater research into how public and private actors should best harness AI technologies for good. Using a typology of domains where AI technologies could have an important social impact as a framework, we critically appraised 45 years of AI scholarship, described the current state of research, and identified many opportunities and directions for future research.

[6] https://proseawards.com/winners/2015-award-winners/ Retrieved September 19, 2019

Table 14
Main outlets, countries and institutions by social impact domain.

Domain	Main journals	Main countries	Main institutions	Highest TC	Papers in top 50
Security and justice	RS (3), AI-MAG (2), EAAI (2)	USA (25), China (7), Iran (5)	Univ S Florida (4), Colorado Sch Mines (2), Gh Asachi Tech Univ Iasi (2)	155	
Equality and inclusion	IS18 (1), GHTC (1), PHILT (1)	India (1), Japan (1), Norway (1)	Chandigarh Univ (1), Inst Hyper Network Soc (1), Norwegian Univ Sci And Technol (1)	17 162	
Environmental challenges	IJEE (2), AIES18 (2), INTED (1)	USA (9), Turkey (2), Austria (1)	Georgia Inst Technol (2), Near East Univ (2), Smith Coll (2), Comp Res Inst (1)	4 055	
Crisis response	STE (4), WAT (4), EES (3)	China (18), USA (18), Korea (8)	Cyber Univ Korea (3), Univ Regina (3), Chaoyang Univ Technol (2)	123	
Infrastructure management	SII13 (1), CCWC (1), AI-EDAM (1)	Spain (5), USA (5), United Kingdom (3)	Univ Deusto (2), Atilim Univ (1), Brookings Inst (1), Cardiff Univ (1)	145	2
Health and hunger	AIM (12), ESA (9), JMIR (9)	USA (119), China (45), United Kingdom (33)	Univ Toronto (6), Hong Kong Polytech Univ (5), Iuliu Hatieganu Univ (4)	149	4
Educational challenges	JIPS (2), KBEI (1), UKRCON (1)	USA (3), Korea (2), Ukraine (2)	Vinnytsia Natl Tech Univ (2), Azad Univ (1), Carleton Univ (1), Columbia Univ;Columbia Univ	7 100	
Economic empowerment	EES (7), SENS (7), E&B (6)	China (40), USA (25), United Kingdom (21)	Cardiff Univ (4), Comsats Inst Informat Technol (4), Univ Tehran (4)	98	
Public and social sector management	ICEDEG (1), SITA (1), ALR (1)	United Kingdom (3), Australia (1), Canada (1)	Dept Comp Sci (1), Integral Mind Technol (1), Interdisciplinary Ctr Herzliya;Osgoode Hall Law Sch (1), King Khalid Univ (1)	9 248	1
Information verification and validation	AI&S (1), AT (1), CHI19 (1)	USA (7), Italy (2), Germany (1)	Univ Catania (2), Rutgers State Univ (1), San Jose State Univ (1)	28	

AI&S, AI & Society; AI-EDAM, Ai Edam-Artificial Intelligence For Engineering Design Analysis and Manufacturing; AIES18, 2018 AAAI/ACM Conference on AI, Ethics, and Society; ALR, Alberta Law Review; AT, Anthropology Today; CCWC, 2018 IEEE 8th Annual Computing and Communication Workshop and Conference; CHI19, 2019 CHI Conference on Human Factors In Computing Systems; E&B, Energy and Buildings; GHTC, 2018 IEEE Global Humanitarian Technology Conference; ICEDEG, 2014 First International Conference on e-Democracy & e-Government; IJEE, International Journal of Engineering Education; INTED, 12th International Technology, Education and Development Conference; IS18, 2018 9th International Conference on Intelligent Systems; JIPS, Journal of Information Processing Systems; JMIR, Journal of Medical Internet Research; KBEI, 2015 2nd International Conference on Knowledge-Based Engineering and Innovation; PHILT, Philosophical Transactions of The Royal Society A-Mathematical Physical and Engineering Sciences; RS, Remote Sensing; SII13, 2013 IEEE/Sice International Symposium on System Integration; SITA, 2015 10th International Conference on Intelligent Systems: Theories and Applications; STE, Science of The Total Environment; UKRCON, 2017 IEEE First Ukraine Conference on Electrical and Computer Engineering; WAT, Water.

We now invite researchers to extend and complement this study through domain and issue-specific research and, in so doing, help shape the directions in which AI will transform our societies.

Author statement

Author	Contribution
Samuel Fosso Wamba	• Idea generation and formulation • Research goals and aims • Guide for literature review • Conduct the first search for articles • Download all articles for the bibliometric analysis • Conduct the initial data analysis and interpretation • Co-writing of the first draft, advanced draft, and final paper • Finalize the paper • Participate in the whole revision process of the manuscript • Coordinate the team during the entire process
Ransome Epie Bawack	• Conduct a more elaborate data analysis and interpretation • Co-writing of the first draft, advanced draft, and final paper • Participate to the literature review process • Participate in the whole revision process of the manuscript
Kevin Carillo	• Co-writing of the first draft, advanced draft, and final paper • Participate in the whole revision process of the manuscript
Cameron Guthrie	• Conduct the second data collection required during the review process • Conduct all new required analysis requested during the review process • Lead the revision process • Put together all parts of the revised paper • Co-writing of the revised draft, advanced draft, and final paper
Maciel M. Queiroz	• Co-writing of the first draft, advanced draft, and final paper • Participate in the whole revision process of the manuscript

Table 15
Research questions on developing, adopting, and implementing AI for social good.

Social impact domains and research questions on AI

1. Crisis response
Issue 1.1 - Disease outbreak
- How can AI predict disease outbreaks and support emergence response planning?
- How can AI techniques detect disease local outbreak diffusion patterns?
- How can AI help avoid supply shortages and optimize resource allocation?
- How can AI systems detect and identify salient symptoms (fever, blood pressure, heart rate pulse, pupil dilatation)?
- How can AI systems interact with patients to identify specific disease pathologies?

Issue 1.2 - Migration crises
- How can AI be used to analyze geo satellite data to identify and monitor migration flows during social/political conflicts or wars?
- How can AI assist migrants in the social reestablishment process?
- Will AI provide a basis for policymakers to developing social policies to minimize the effects of the migration crisis?

Issue 1.3 - Natural and man-made disasters
- How can AI help reduce uncertainty in decision-making during disaster management?
- How can AI support social resilience during natural disasters?
- How can AI be used to analyze social media to detect, monitor, and manage disasters?
- How can AI be used to assessing disaster damage and optimize aid delivery?
- How can AI be used with other new technologies such as drones, driverless cars, and nanosatellites to enhance disaster response?
- How can aid organizations use AI to improve decision making, resource utilization, and allocation, coordination, and collaboration between disaster management stakeholders?

Issue 1.4 - Search and rescue
- What is the role of AI in helping search and rescue in difficult regions?
- How can AI autonomous agents (robots) be used to help and rescue individuals in areas with extreme conditions?
- How can AI be used to optimize the rescue strategy for a given mission under strict time constraints pertaining to the life of individuals?
- How can AI systems use satellite data to identify individuals, lost ships, or airplane wreckages (in the middle of oceans, deserts…)?

2. Economic empowerment
Issue 2.1 - Agricultural quality and yield
- What is the economic value of integrating AI solutions into farming processes (e.g., real-time monitoring of livestock and crops)?
- Which are the enablers and barriers of AI adoption by farmers?
- How can AI be used by farmers to optimize harvesting and overall profit?
- How can AI systems be used to visually identify crop and soil-borne diseases?
- How can AI systems assist farmers to optimize the growth of cereals (plot location, seeding, watering, fertilizing)?

Issue 2.2 - Financial inclusion
- How can AI promote financial inclusion by using smart devices?
- How could an AI system be designed to provide an accurate credit risk assessment of an individual based on their digital footprint and online interactions?
- How can AI help in developing AI-based micro-credit services in developing countries?
- How can AI help empower vulnerable people in developing countries?
- Will AI contribute to accelerating financial inclusion in both developed and developing countries?

Issue 2.3 - Initiatives for economic growth
- How can AI help monitor and predict the evolution of financial markets to prevent financial crises?
- How should AI systems be designed and used to detect weak signals that characterize the advent of a financial crisis?
- What are the impacts of AI solutions on manufacturing processes in terms of personalized products at the individual, group, city, state levels?

Issue 2.4 - Labor supply and demand matching
- How can AI help optimize the labor market and reduce unemployment?
- How can AI be used to identify the best candidate for a given job offer?

3. Educational challenges
Issue 3.1 - Access and completion of education
- Will AI improve the societal indicators for education in emerging economies?
- How can AI be used as a tool to democratize and leverage high-quality education?
- How can AI be used to improve the learning experience of students by matching the content and courses to the specific profiles and needs of students?
- How can an AI system help candidates identify educational programs that match their needs and specificities?

Issue 3.2 - Maximizing student achievement
- What are the potential impacts of AI on learning outcomes?
- How can AI be used by students to improve their performance?

Table 15 (*continued*)

Social impact domains and research questions on AI

- How should an AI-based virtual assistant be designed and used to help students during schooling?
- Will AI contribute to reducing the educational divide?

Issue 3.3 - Teacher and administration productivity
- How can teachers enhance their classroom performance with AI?
- How can AI systems help teachers in the pedagogy and delivery of their courses?
- Will AI enable personalize learning?
- Will AI facilitate the work of all actors of the education ecosystem and improve their productivity?

4. Environmental challenges
Issue 4.1 - Animal and plant conservation
- Can AI techniques support biodiversity conservation by predicting plant and animal extinction?
- How can the use of IoT devices and AI systems be designed and used to monitor endangered animals and species?
- How can AI applications improve the protection of endangered species or exhausted populations?

Issue 4.2 - Climate change and adaptation
- Will AI improve the societal indicators for the environment in emerging economies?
- How can AI help discover unanticipated climate change events?
- How can AI help develop response, contingency, and continuation planning before a climate change event?
- How can IoT and AI systems be used to more precisely monitor and control global warming?
- To what extent can companies use IoT and AI systems to precisely evaluate and monitor their carbon imprint?
- How can AI applications contribute to combating climate change?

Issue 4.3 - Energy efficiency and sustainability
- Are countries ready to adopt robots to enable a sustainable “good AI society”?
- How can AI optimize energy distribution and pricing to patterns of energy consumption?
- How can AI techniques be used to optimize energy consumption on smart grids?
- How should an AI tool be designed to help cities optimize energy supply and demand?
- How can AI applications contribute to sustainable production?
- What is the contribution of AI to sustainable resource management?

Issue 4.4 - Land, air, and water conservation
- How can AI applications contribute to minimizing air pollution?
- How can AI help anticipate air pollution?
- How can the combination of IoT, analytics, and AI help in maintaining good air quality in large cities?

5. Equality and inclusion
Issue 5.1 - Accessibility and disabilities
- How can AI help people with visual, hearing, and physical disabilities?
- How can AI-enabled robots be used to assist individuals with physical disabilities?
- How can AI systems detect individuals with disabilities and provide them with real-time assistance (in the streets, at pedestrian crossings, in shops and offices)?

Issue 5.2 - Exploitation
- How can AI be used to identify victims of exploitation?
- How can AI be used to analyze social media data to detect potential exploitation threats?
- How can AI applications contribute to combating discrimination?
- How can AI applications enhance social diversity and inclusion?

Issue 5.3 - Marginalized communities
- What is the role of AI in transforming social well-being in marginalized communities?
- How can AI systems be used to help monitor and control the health and sustainability of marginal communities?

6. Health and hunger
Issue 6.1 - Treatment delivery
- Will AI improve the societal indicators for public health systems in emerging economies?
- How can better image processing improve government decisions related to health in society?
- How can AI be used to identify the best possible medical treatment for a given medical case or pathology?
- To what extent will it be possible to design an AI system that helps assist individuals in their daily medication and treatment?
- Will AI improve the societal indicators for public health systems in emerging economies?
- How can AI applications help reduce operating costs and improve quality in healthcare systems?

Issue 6.2 - Prediction and prevention
- To what extent will AI transform traditional medicine into predictive medicine?
- To what extent will AI transform traditional medicine into preventive medicine?
- How can AI applications help to prevent and solve malnutrition issues?

(*continued on next page*)

Table 15 (*continued*)

Social impact domains and research questions on AI
• How can AI applications help to prevent diseases?
Issue 6.3 - Treatment and long-term care
• How should AI agents be designed to help individuals monitor their current health?
• How can AI be used to ensure the long-term health and well-being of patients and individuals?
Issue 6.4 - Mental wellness
• How can AI agents help in interacting with individuals suffering from mental illnesses?
• Should AI use an individual's digital footprint to assess their level of mental wellness?
Issue 6.5 - Hunger
• How can AI be used to combat food waste?
• How can AI be used to optimize the distribution of surplus food to needy populations?
• How can AI contribute to reducing hunger?
• Can AI systems help in predicting food crises based on past and current weather and harvest data?
7. Information verification and validation
Issue 7.1 - False news
• What are the technological and ethical issues in monitoring customer's behavior in social media with AI?
• How can AI techniques be used to distinguish fake news from real news?
• How should AI agents be designed to help individuals detect and report fake news to legal entities?
• How can AI applications contribute to combating fake news?
• What is the contribution of AI applications to real-time fact-checking?
Issue 7.2 - Polarization
• How can AI prevent the polarization of information in broadcast, online, and social media?
8. Infrastructure management
Issue 8.1 - Energy
• To what extent could AI be used to provide real-time analysis of public transportation to optimize energy consumption?
• How can AI be used by cities and countries to optimize energy consumption based on traffic and weather data?
Issue 8.2 - Real estate
• How can AI be used to optimize real estate investments?
• How can AI be used to track, monitor, and manage the real estate projects of cities?
Issue 8.3 - Transportation
• How can better image processing improve government decisions related to transportation services?
• How can AI be combined with geographic information systems to improve transport services and experience?
• How can AI be used for the predictive maintenance of public transport systems?
• How can better image processing be used in automated transportation systems and robots for the benefit of society?
Issue 8.4 - Urban planning
• How can AI systems be used to optimize and predict urban planning in large cities?
• How can AI applications help build more efficient and sustainable public infrastructure?
• What is the impact of AI on urban planning?
Issue 8.5 - Water and waste management
• How can AI help improve waste management in urban areas?
• How can AI support a circular economy in water distribution and waste management?
• How can AI be used to manage and predict water consumption based on weather data?
• How can AI be used with IoT devices to monitor groundwater levels?
9. Public and social sector management
Issue 9.1 - Effective management of the public sector
• What skills are required to use AI productively in public sector management?
• How will AI transform public sector service delivery and management?
• To what extent is the public sector ready to interact with AI systems and agents?
Issue 9.2 - Effective management of the social sector
• How can AI be used to assist social sector operations?
• How can AI virtual agents help workers in the social sector?
Issue 9.3 - Fundraising
• How can fundraising campaigns be improved through the use of AI systems?
Issue 9.4 - Public finance management
• To what extent can AI optimize the management of public finances?
Issue 9.5 - Services to citizens
• How could AI be used to identify and provide customized services to citizens?
• What new kinds of AI-based services could be provided to citizens?
• How can AI improve citizen experiences in cities?
• How can AI applications enhance public safety?
• How can AI applications help identify high-risk urban areas for better government interventions?
• How can AI applications help improve resource allocation within a city, region, or country?
10. Security and justice
Issue 10.1 - Harm prevention
• To what extent can AI allow for a predictive or preventive justice system?
• How are governments across the globe deploying AI surveillance technologies?
Issue 10.2 - Fair prosecution
• How should we design AI-based diagnosis and evaluation systems to help the justice system analyze evidence?
• Will AI be able to assist lawyers and judges in ensuring fair trials?
• What is the impact of AI applications on citizens' rights (e.g., freedom of speech, association, movement, strike, etc.)?
• How can AI applications facilitate social justice?
Issue 10.3 - Policing
• How can better image processing improve government decisions related to security in society?
• What are the ethical issues of AI for monitoring the population?
• Can AI systems help police forces detect potential criminals through the real-time analysis of social media data?
• How can computer vision help detect and identify potential crimes?
• Will AI be capable of assisting the police in preventing crimes?
• Is AI going to lead to a surveillance society, and if so how can we protect citizens' rights?

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.techfore.2020.120482.

Appendix 1. AI for social good framework: based on from Chui et al. (2018)

	Social impact domain	Description	Example use of AI
1	Crisis response	Specific crisis-related challenges, such as responding to natural and man-made disasters in search and rescue missions and at times of disease outbreak	Using AI on satellite data to map and predict wildfire progression to optimize firefighter response.
2	Economic empowerment	Opening access to economic resources and opportunities, including jobs, skills development, and market information, with an emphasis on currently vulnerable populations.	Early detection of plant damage through low-altitude sensors, including smartphones and drones, to improve yield in small farms.
	Educational challenges	Maximizing student achievement and improving teacher productivity	Adaptive learning technology used to recommend content to students based on past success and engagement with the material.
4	Environmental challenges	These include sustaining biodiversity and combating natural resource depletion, pollution, and climate change.	Robots with AI capabilities can be used to sort recyclable material from waste.
5	Equality and inclusion	Addressing equality, inclusion, and self-determination challenges, such as reducing or eliminating bias based on race, sexual orientation, religion, citizenship, and disabilities.	Use of AI to automate emotion recognition and provide social cues to help individuals along the autism spectrum interact in social environments.

(continued on next page)

(*continued*)

	Social impact domain	Description	Example use of AI
6	Health and hunger	Addressing health and hunger challenges, including early-stage diagnosis and optimized food distribution.	Disease detection AI system using the visual diagnosis of natural images.
7	Information verification and validation	The challenge of facilitating provision, validation, and recommendation of helpful, valuable, and reliable information to all.	Actively presenting opposing views to ideologically isolated pockets in social media.
8	Infrastructure management	Infrastructure challenges that could provide public good in the categories of energy, water, and waste management, transportation, real estate, and urban planning.	Predictive maintenance of public transportation systems such as trains and public infrastructure.
9	Public and social sector management	Initiatives that are related to the efficiency and effective management of public- and social-sector entities, including strong institutions, transparency, and financial management.	Identify tax fraud using alternative data such as browsing data, retail data, and payment history. Providing automated question answering via email to improve government interaction with citizens.
10	Security and justice	Challenges in society include harm prevention, tracking criminals, and mitigating bias of police forces.	Using AI to create solutions that help firefighters determine safe paths through burning buildings using data from IoT devices.

Appendix 2. Acronyms used in tables

Acronym	Description
≥ 500, ≥ 200, ≥ 100, ≥ 50	Documents with greater than or equal to 500, 200, 100 and 50 citations
<50	Documents with less than 50 citations
C	Country name
C/Y	Citations per year (TC/number of years)
CAI/Y	Citations in artificial intelligence per year (TCAI/number of years)
CAGR	Compound annual average growth rate of research output
hAI	H-index based exclusively on artificial intelligence publications
IF	Impact Factor (published by Clarivate)
IF-5Y	Impact Factor for the past 5 years
J	Abbreviated journal names
mAI	M-index based exclusively on artificial intelligence publications
Main area	Main research area of publication based on WoS schema
PCAI	Average citations by artificial intelligence publications
%PAI	Percentage of documents published in artificial intelligence (TPAI/TP)
PAI/th	Total publications in artificial intelligence per thousands of total publications
Secondary area	Secondary research area of publication based on WoS schema
T50	Articles in the top 50
TC	Total citations in all areas
TCAI	Total citations in artificial intelligence research
TP	Total publications in all areas
TPAI	Total publications in artificial intelligence
TPAI-W	Total publications in artificial intelligence during the AI Winter period
TPAI-F	Total publications in artificial intelligence during the AI Fall period
TPAI/PMH	Total publications in artificial intelligence per million inhabitants
TCAI/PMH	Total citations in artificial intelligence research per million inhabitants
YP	Year of publication: first year of publication in the case of a journal or an author; exact year of publication in the case of a document

Note: CAI/Y, hAI, mAI, TCAI are based on local citations, that is citations by other publications in the corpus.

Appendix 3. Queries used by social impact domain

	Social impact domain	Query
1	Crisis response	disease outbreak OR migration crisis OR humanitarian cris* OR natural disaster OR man-made disaster OR search and rescue
2	Economic empowerment	agricultural yield OR agricultural quality OR financial inclusion OR economic growth.*initiative OR initiative.*economic growth OR economic growth.*empowerment OR empowerment.*economic growth OR economic growth.*inclusion OR inclusion.*economic growth OR labor supply OR labor demand
3	Educational challenges	education access OR education completion OR student performance OR student achievement OR teacher productivity OR administration productivity OR education productivity
4	Environmental challenges	animal conservation OR plant conservation OR climate change OR global warming OR energy sustainability OR energy efficiency OR land conservation OR air conservation OR water conservation
5	Equality and inclusion	access*.*disabilit* OR disabilit*.*access* OR exploitation.*handicap OR exploitation.*gender OR exploitation.*race OR exploitation.*sexual OR exploitation.*religio* OR handicap.*exploitation OR gender.*exploitation OR race.*exploitation OR sexual.*exploitation OR religio*.*exploitation OR discrimination.*handicap OR discrimination.*gender OR discrimination.*race OR discrimination.*sexual OR discrimination.*religion OR handicap.*discrimination OR gender.*discrimination OR race.*discrimination OR sexual.*discrimination OR religio*.*discrimination OR marginalized communities
6	Health and hunger	treatment delivery OR health.*prediction OR health.*prevention OR prevention.*health OR prediction.*health OR health.*treatment OR health.*long-term care OR treatment.*health OR long-term care.*health OR mental wellness OR mental health OR hunger
7	Information verification and validation	fake news OR false news OR polarization
8	Infrastructure management	energy management OR real estate management OR transportation management OR transport management OR urban planning OR water management OR waste management
9	Public and social sector management	public sector.*management OR social sector.*management OR fundraising OR public finance.*management OR management.*public finance OR citizen service OR services to citizens OR services for citizens OR government services
10	Security and justice	harm prevention OR fair prosecution OR policing

Appendix 4. Productivity and influence statistics by domain and key issue

Domain	Count	Average citations	Date range
Crisis response	*84*	*11.3*	*1996–2019*
Disease outbreak	10	3.7	2008–2019
Migration crises	2	0	2018–2018
Natural and man-made disasters	34	7.4	1996–2019
Search and rescue	39	16.9	1996–2019
Economic empowerment	*6*	*2*	*2013–2018*
Agricultural quality and yield	3	2.7	2013–2018
Financial inclusion	0	0	–
Initiatives for economic growth	3	1.3	2016–2018
Labor supply and demand matching	0	0	–
Educational challenges	*21*	*2.5*	*2000–2019*
Access and completion of education	2	0.5	2018–2018
Maximizing student achievement	19	2.7	2000–2019
Teacher and administration productivity	0	0	–
Environmental challenges	*113*	*9.8*	*1994–2019*
Animal and plant conservation	31	22.7	2001–2019
Climate change and adaptation	105	9.9	1994–2019
Energy efficiency and sustainability	2	6	2018–2019
Land, air, and water conservation	5	12	2003–2019
Equality and inclusion	*18*	*15.5*	*2005–2019*
Accessibility and disabilities	6	42.1	2005–2019
Exploitation	12	1.5	2013–2019
Marginalized communities	0	0	–
Health and hunger	*477*	*6.9*	*1992–2019*
Treatment delivery	6	1.8	2018–2019
Prediction and prevention	219	5.4	1992–2019
Treatment and long-term care	269	6.9	1992–2019
Mental wellness	76	11.2	1992–2019
Hunger	3	4	2009–2018
Information verification and validation	*13*	*1.1*	*2015–2019*
False news	11	1.3	2017–2019
Polarization	2	0	2015–2018
Infrastructure	*272*	*11.6*	1991–2019
Energy	153	12.9	1991–2019
Real estate	20	1.6	1997–2019
Transportation	12	9.4	1996–2018
Urban planning	31	4	1991–2019
Water and waste management	76	12.7	1994–2019
Public and social sector	*8*	*1.4*	2014–2019
Effective management of the public sector	2	2	2018–2019
Effective management of the social sector	0	0	–
Fundraising	0	0	–
Public finance management	0	0	–
Services to citizens	9	1.2	2014–2019
Security and justice	*13*	*69.6*	1996–2019
Harm prevention	1	3	2019
Fair prosecution	2	0.5	2019–2019
Policing	10	69.4	1996–2019

Note: Domain summary measures in italics.

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