Annals of Operations Research
https://doi.org/10.1007/s10479-022-05006-6

ORIGINAL RESEARCH

Adoption of Industry 4.0 technologies by organizations: a maturity levels perspective

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Accepted: 21 September 2022

Abstract

This study employs a structured literature analysis considering Industry 4.0 technologies and their adoption stages (intention, adoption, implementation, routinization, continuance, and diffusion). We identify the technology adoption stage for each technology type, which in turn supports a maturity level categorization, as well as future research suggestions and challenging open research questions. By considering an integrated view of all the adoption stages of Industry 4.0 key technologies, we reveal the key technologies and their development stages, as well as a novel maturity level categorization perspective. The proposed categorization brings valuable research insights in the form of guidelines for practitioners and decision-makers interested in gaining a deeper understanding of the maturity level of key Industry 4.0 technologies.

Keywords Industry 4.0 · Digitalization · Digital technologies · Production systems · Supply networks

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Published online: 06 October 2022

1 Introduction

Industry 4.0 has come to be considered one of the most disruptive approaches for organizations in recent years (Ivanov et al., 2021; Lee & Lim, 2021; Lin et al., 2019; Lopes et al., 2021; Neumann et al., 2021; Queiroz et al., 2020a; Rosin et al., 2020; Shayganmehr et al., 2021; Zhang et al., 2022). By combining cutting-edge technologies [e.g. blockchain, digital twin, the Internet of things (IoT), cyber-physical systems (CPS), big data analytics (BDA), cloud computing, and artificial intelligence (AI), among others], Industry 4.0 has been bringing about unprecedented changes in organizations (Xu et al., 2018), business processes (Queiroz et al., 2020a), product development (Dubey et al., 2021), and workers' activities (Garrido-Hidalgo et al., 2018; Kazancoglu & Ozkan-Ozen, 2018; Sivathanu & Pillai, 2018). Since its introduction by the German government in 2011 as a project to develop its high-tech industry (Xu et al., 2018), Industry 4.0 has been considered both by scholars and practitioners around the world as a hot topic. Industry 4.0 technologies are also transforming the dynamics of society, organizations, production systems, and supply networks (Calış Duman & Akdemir, 2021; Cugno et al., 2021; Fragapane et al., 2022; Kumar & Singh, 2021; Shao et al., 2021; Sharma et al., 2021).

As a combination of several cutting-edge technologies, Industry 4.0 has benefited from several studies (Culot et al., 2020; Narayanamurthy & Tortorella, 2021; Queiroz et al., 2020a; Saucedo-Martínez et al., 2018; Xu et al., 2018) that clearly illustrate the significant efforts made to report the latest advances and disseminate resourceful insights and trends for scholars, practitioners, and decision-makers (Ivanov et al., 2019, 2021; Koh et al., 2019). One of scholars' and practitioners' main interests in the context of cutting-edge technologies is the adoption and post-adoption stages of such technologies (Chan & Chong, 2013; Fosso Wamba & Queiroz, 2022; Martins et al., 2016). It is in this context that the relevant literature has recently made significant advances in reporting different Industry 4.0 technologies and their adoption dynamics (Fosso Wamba & Queiroz, 2022; Frank et al., 2019; Ivanov et al., 2021; Tortorella et al., 2019).

For instance, the adoption behavior towards a number of technologies has so far been reported adequately. This includes radio frequency identification (RFID) (Hossain & Quaddus, 2011), mobile health (Miao et al., 2017), big data (Raguseo, 2018), blockchain (Fosso Wamba et al., 2020; Wong et al., 2020), the IoT (Mital et al., 2018), mobile wallets (Singh & Sinha, 2020), smartwatches (Chuah et al., 2016), cloud computing (Low et al., 2011), and virtual reality (Laurell et al., 2019), among others. Similar to the analysis of the technology adoption stages, post-adoption analysis also plays a fundamental role in the understanding the diffusion of these technologies (Junior et al., 2019; Karahanna et al., 1999; Thong et al., 2006), the continuing interest of organizations in using these technologies (Bhattacherjee, 2001a; Bölen, 2020; Hsu & Lin, 2019; Kaba, 2018; Zhou, 2011, 2014), and users' continuing intention to use them.

While the Industry 4.0 adoption literature has adequately disseminated significant advances in the related technologies, there remains a scarcity of studies employing review approaches (Ivanov et al., 2021; Lee & Lim, 2021; Machado et al., 2019), especially structured literature analyses, to explore the various adoption stages of these technologies (intention; adoption; implementation; routinization; continuance; and diffusion). Thus, there is an important gap in the literature concerning structured literature studies, including a robust analysis, in relation to reporting and organizing advances in this research field. In this regard, in an attempt to address this gap, the research questions (RQs) of this work are as follows:

RQ1: What are the main dynamics of the literature on the adoption stages of Industry 4.0 technologies from 2011 to 2019?
RQ2: Which are the most popular technologies and what is their respective maturity level?

Accordingly, this study has the following research objectives: (i) to identify and analyze the most relevant literature on the adoption stages of Industry 4.0 technologies from 2011 to 2019; (ii) to provide insights into the most influential studies, supported by a bibliometric analysis approach; (iii) to identify the adoption stages of the primary Industry-4.0-related technologies; and (iv) to provide scholars and practitioners with valuable insights obtained through a well-articulated research agenda.

Our literature analysis, supported by a network approach, used the "Industry 4.0" term and its combination with the adoption stages (intention, adoption, implementation, routinization, continuance, and diffusion) to obtain 788 articles. Using Biblioshiny software (Aria & Cuccurullo, 2017; Shonhe, 2020), we filtered and analyzed the articles from the Scopus database to understand the interplay between these papers' themes. This study provides essential contributions to scholars and practitioners, as well as to the operations literature, by categorizing the main Industry 4.0 technologies in terms of their adoption stage, as well as by identifying critical hot topics and proposing a well-articulated research agenda.

The remainder of this paper is organized as follows. Section 2 highlights the basic concepts of Industry 4.0 and its recent advances. Section 3 presents the methodological approach, following which the results are presented in Sect. 4. In Sect. 5, we highlight the main Industry 4.0 technologies and their related adoption stage, followed by the identification of trends, challenges, emerging topics, and categorization in Sect. 6. Section 7 presents an insightful research agenda, and, finally, Sect. 8 provides the concluding remarks, including limitations and contributions.

2 Related literature

2.1 Industry 4.0: recent advances

The extant literature has no unique conception of Industry 4.0, as it has only recently emerged (in 2011) and has since been a hot topic (Bag et al., 2021; Bai et al., 2020; Benitez et al., 2020; Guzmán et al., 2020; Queiroz et al., 2021). However, for the majority of scholars, Industry 4.0 refers to information and communication technologies (ICTs) integrated with leading-edge industrial technology (Ben-Daya et al., 2017; Stock & Seliger, 2016; Zhong et al., 2017). In this regard, Industry 4.0 comprises several technologies, including CPS, the IoT, BDA, and cloud computing (Queiroz et al., 2021; Zhong et al., 2017), among others. One of the key characteristics of Industry 4.0 is that it enables the combination of production systems with machines in an intelligent and autonomous environment (Qin et al., 2016), thus enabling real-time communication exchange between the components while providing feedback to the production system (Qin et al., 2016). Several scholars have made a significant effort to establish a relevant categorization of Industry 4.0 frameworks (Koh et al., 2019; Liao et al., 2017; Qin et al., 2016; Queiroz et al., 2020a; Saucedo-Martínez et al., 2018).

Despite a new generation of smart products based on advances in machinery and the IoT, which provide significant feedback for business process management (e.g. smartwatches, smart clothing, smart TVs, etc.), the role of human beings cannot be underestimated. However, several challenges will have to be faced in order to acquire the new competencies required

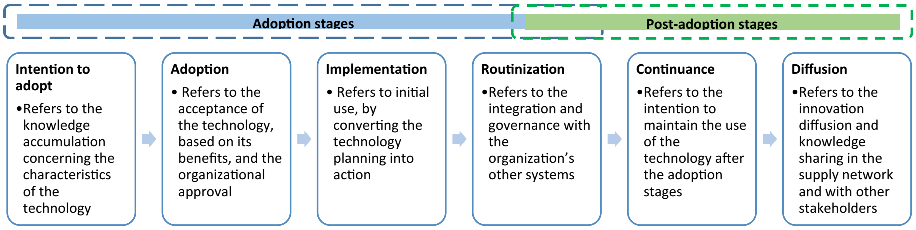

Fig. 1 Adoption stages of Industry 4.0 technologies

to meet Industry 4.0 demands (Bibby & Dehe, 2018; Hecklau et al., 2016). Thus, workers' activities need to be integrated and interconnected with many ICTs (Gawankar et al., 2020; Liao et al., 2017; Zezulka et al., 2016). In this vein, in the Industry 4.0 context, there is an integrated network that supports the communication of the elements. In other words, the physical resources (machines, products, and conveyors) supported by the IoT are able to optimize production by operating in response to the demand.

Researchers have made great efforts to understand the dynamics behind the adoption of Industry-4.0-related technologies (Fosso Wamba & Queiroz, 2022; Kamble et al., 2019; Lai et al., 2018; Lee et al., 2019; Rauschnabel et al., 2018; Yeh & Chen, 2018). Several contributions concerning Industry 4.0 adoption dynamics are notable. For example, Queiroz and Fosso Wamba (2019) investigated blockchain adoption in the Indian and US supply chain context. These authors found that, among the variables influencing technology adoption, there are behavioral differences from one country to the other. Laurell et al. (2019) investigated the barriers to virtual reality adoption and reported that technological performance is one of the most significant adoption impediments. Regarding Industry 4.0 adoption in small and medium-sized enterprises (SMEs), Masood and Sonntag (2020) identified efficiency, flexibility, quality, cost, and competitive advantage as the main adoption benefits, while knowledge and financial aspects were found to be the main barriers to adoption.

As we intend to examine Industry 4.0 technologies in terms of their different adoption stages (intention, adoption, implementation, routinization, and continuance), we believe it is necessary to provide an integrated view of these different stages. From this perspective, based on the technology-adoption-related literature (Bhattacherjee, 2001b; Davis et al., 1989; Fosso Wamba & Queiroz, 2022; Martins et al., 2016; Venkatesh & Bala, 2008), we build Fig. 1, which shows a brief contextualization of the adoption stages considered in this work.

3 Methodology

In this study, we employed a structured literature review approach (Queiroz et al., 2020b), integrated with bibliometric techniques (Caviggioli & Ughetto, 2019; Kazemi et al., 2019; Mishra et al., 2018a, 2018b) in order to support the collection, organization, and analysis of the papers. We performed a search (on September 1, 2020) in the Scopus database (Mishra et al., 2018a; Nobre & Tavares, 2017). Scopus is one of the largest abstract and citation databases of peer-reviewed publications, with more than 24,600 titles from 5,000 publishers (Elsevier, 2020). With this in mind, we used the "Industry 4.0" keyword combined with the different adoption stages. In order to ensure the reliability and replicability of this study, we present the research protocol in Fig. 2.

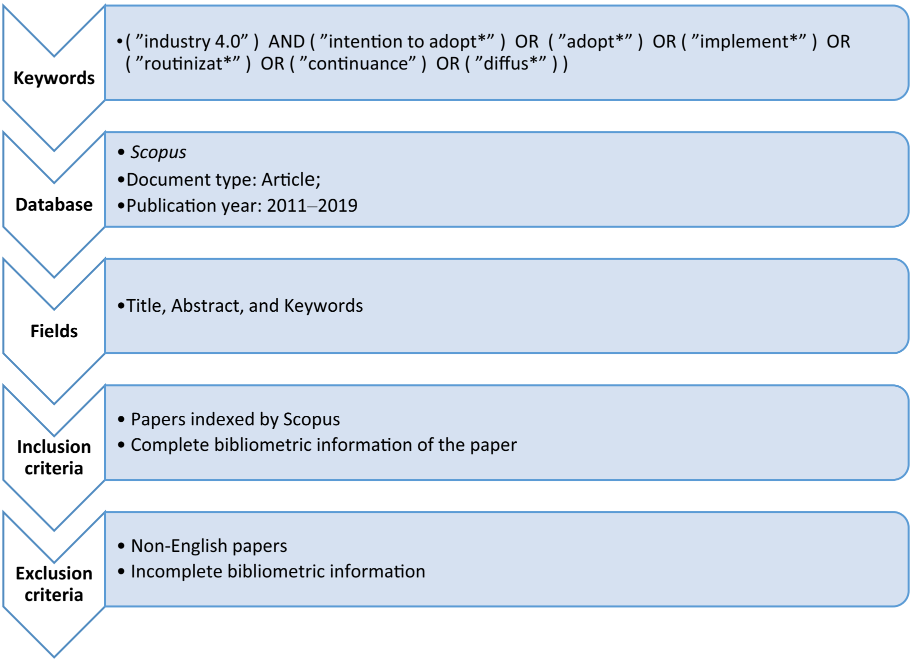

Fig. 2 Research protocol

In our search, we considered the titles, keywords, and abstracts of articles published in English between 2011 and 2019. We determined 2019 as the limit to avoid some bias generated by the COVID-19 pandemic. The search enabled us to retrieve 788 articles that were analyzed following the best practices in bibliometrics, thus using an R-tool [namely (https://bibliometrix.org/) Biblioshiny (Aria & Cuccurullo, 2017; Camarasa et al., 2019; Shonhe, 2020)], the Scopus database (Elsevier, 2020), and an Excel spreadsheet (Blažun Vošner et al., 2017).

4 Results

4.1 Papers by year and top 20 journals

Figure 3 shows the number of articles retrieved for each year of the period considered. Using the agreed criteria for the search (Industry 4.0 combined with related adoption stage terms). Although the Industry 4.0 term was introduced only recently (in 2011), we found the first articles related to its stages only in 2014 (3 papers). And a significant increase of publications from 2015, with 15 papers being published in that year. From there on, the publication output virtually doubled every year, reaching 419 papers in 2019. This shows how Industry-4.0-related topics have rapidly gained popularity around the globe and are being considered hot topics in academia. Thus, this massive growth of published papers between 2015 and 2019 represents an important milestone not only for any organization's digital transformation but also for the interest of scholars in gaining a better understanding of this phenomenon.

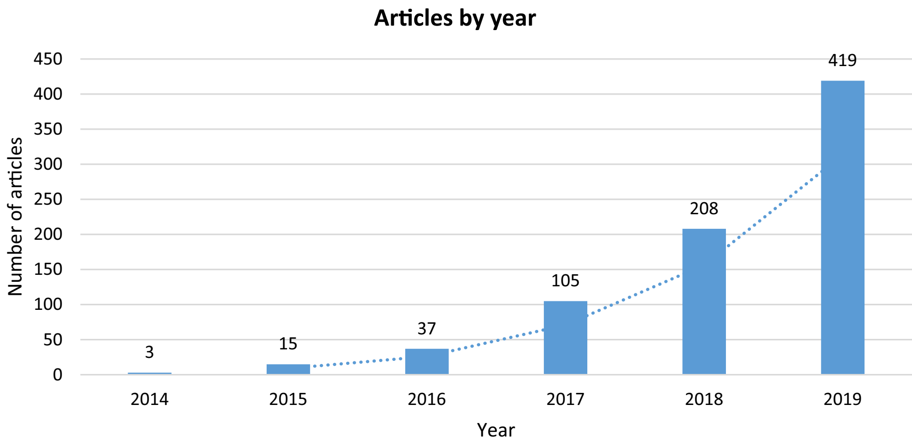

Fig. 3 Frequency of articles published (2014–2019). *Note*: Although our research period started in 2011, the first relevant published papers considering the criteria of the search were found only from 2014 onwards

Table 1 highlights the top 20 journals (considering also proceedings journals) that published the most output on the studied theme during the selected period. The first position is occupied by *IFAC-PapersOnLine*, followed by *IEEE Access* and *Procedia Manufacturing*. It is interesting to note the diversity among the journals in terms of scope. For instance, the journals display a variety of specialization fields: conference proceedings (e.g. *IFAC-PapersOnLine* and *Procedia Manufacturing*); environmental issues (*Sustainability*); information and communication technologies (*Computers in Industry*); social sciences and business (*Applied Sciences* and *Social Sciences*); engineering and manufacturing (*International Journal of Advanced Manufacturing Technology*, *International Journal of Computer Integrated Manufacturing*, *Sensors*, *Journal of Manufacturing Technology Management*, *International Journal of Innovative Technology and Exploring Engineering*, *Manufacturing Letters and Processes*); operations, supply chain, and production management (*International Journal of Supply Chain Management*, *International Journal of Production Research*, *Computers and Industrial Engineering*, and *Benchmarking*); and the interplay between technology, the environment, and society (*Technological Forecasting and Social Change*). It can be seen that the fields of engineering and manufacturing abound while those of production management and supply chain have only a few representative journals. Other characteristics can be highlighted, including that *IFAC-PapersOnLine* is the most productive outlet (49 papers), although it has achieved only 303 citations. Furthermore, *Manufacturing Letters* is shown to have a strong influence in this field, with only eight papers but achieving 1,748 citations.

4.2 Authors' and papers' influence

Table 2 highlights the most influential authors based on their total citation output and the total citations per year. It can be seen that the top three papers are focused on "basic" or "first-generation" Industry-4.0-related technologies, namely CPS, big data, and the IoT, respectively. In this vein, these technologies can be understood as the foundation of Industry 4.0. Moreover, the paper holding the first rank ("A cyber-physical systems architecture for

Table 1 Top 20 sources based on article output

Source	NP	TC
IFAC-PapersOnLine	49	303
IEEE access	23	739
Procedia manufacturing	22	392
Sustainability	20	481
Computers in industry	19	514
International journal of advanced manufacturing technology	16	93
International journal of computer integrated manufacturing	13	146
Sensors	12	140
Social sciences	12	264
International journal of supply chain management	11	65
Journal of manufacturing technology management	11	193
Applied sciences	10	44
IEEE transactions on industrial informatics	10	357
International journal of production research	9	364
International journal of innovative technology and exploring engineering	8	5
Manufacturing Letters	8	1748
Processes	8	68
Technological Forecasting and Social Change	8	566
Computers and Industrial Engineering	7	92
Benchmarking	6	27

NP number of papers, *TC* total citations

Industry 4.0-based manufacturing systems") has achieved an incredible number of citations (1,595 total citations), equal to 265.83 citations per year. It is also important to highlight other cutting-edge approaches, such as big data, the IoT, blockchain, smart factory, and digital twin, which ranked from second to sixth positions, respectively.

Considering the influence of citations, we can see other interesting dynamics. For example, sustainability issues, SMEs, manufacturing, performance, and costs are other topics of interest. Furthermore, considering the journal dynamics, we can see the significant performance of *IEEE* journals and other engineering/computer/manufacturing journals.

It should be noted that *Technological Forecasting and Social Change* shows a good citation performance, with three papers (ranked in 9th, 10th, and 20th positions), obtaining 163, 151, and 112 citations, respectively. The *International Journal of Production Economics* also shows good performance, with two papers in the ranking (14th and 15th positions), obtaining 141 and 137 citations, respectively. Such dynamics clearly illustrate the importance of these journals in the field, with some significant outcomes.

The *International Journal of Production Research* is ranked 8th with a paper entitled "The industrial management of SMEs in the era of Industry 4.0" that received 169 citations. Despite the excellent performance of the *International Journal of Production Research* and the *International Journal of Production Economics*, more effort is still needed in terms of participation in the production, operations and supply chain management (PO&SCM) field.

Table 2 Top 20 papers based on the total number of citations

Rank	AU	TI	SO	TC	DOI	TCpY
1	Lee et al. (2015)	A cyber-physical systems architecture for Industry 4.0-based manufacturing systems	Manufacturing letters	1595	10.1016/J.MFGLET.2014.12.001	265.83
2	Wang et al. (2016)	Towards smart factory for Industry 4.0: a self-organized multi-agent system with big data based feedback and coordination	Computer networks	463	10.1016/J.COMNET.2015.12.017	92.60
3	Wan et al. (2016)	Software-defined industrial internet of things in the context of Industry 4.0	IEEE sensors journal	300	10.1109/JSEN.2016.2565621	60.00
4	Sikorski et al. (2017)	Blockchain technology in the chemical industry: machine-to-machine electricity market	Applied energy	247	10.1016/J.APENERGY.2017.03.039	61.75
5	Chen et al. (2017)	Smart factory of Industry 4.0: key technologies, application case, and challenges	IEEE access	199	10.1109/ACCESS.2017.2783682	49.75
6	Tao and Zhang (2017)	Digital twin shop-floor: a new shop-floor paradigm towards smart manufacturing	IEEE Access	197	10.1109/ACCESS.2017.2756069	49.25
7	Sanders et al. (2016)	Industry 4.0 implies lean manufacturing: research activities in Industry 4.0 function as enablers for lean manufacturing	Journal of industrial engineering and management	180	10.3926/JIEM.1940	36.00
8	Moeuf et al. (2018)	The industrial management of SMEs in the era of Industry 4.0	International journal of production research	169	10.1080/00207543.2017.1372647	56.33
9	Li (2018)	China's manufacturing locus in 2025: with a comparison of made-in-China 2025 and Industry 4.0	Technological forecasting and social change	163	10.1016/J.TECHFORE.2017.05.028	54.33

Table 2 (continued)

Rank	AU	TI	SO	TC	DOI	TCpY
10	Müller et al. (2018a)	Fortune favors the prepared: how SMEs approach business model innovations in Industry 4.0	Technological forecasting and social change	151	10.1016/J.TECHFORE.2017.12.019	50.33
11	Müller et al. (2018b)	What drives the implementation of Industry 4.0? The role of opportunities and challenges in the context of sustainability	Sustainability	150	10.3390/SU10010247	50.00
12	Haseeb et al. (2019)	Industry 4.0: a solution towards technology challenges of sustainable business performance	Social sciences	144	10.3390/SOCSCI8050154	72.00
13	Wan et al. (2017)	A manufacturing big data solution for active preventive maintenance	IEEE transactions on industrial informatics	144	10.1109/TII.2017.2670505	36.00
14	Dalenogare et al. (2018)	The expected contribution of Industry 4.0 technologies for industrial performance	International journal of production economics	141	10.1016/J.IJPE.2018.08.019	47.00
15	Frank et al. (2019)	Industry 4.0 technologies: implementation patterns in manufacturing companies	International journal of production economics	137	10.1016/J.IJPE.2019.01.004	68.50
16	Rojko (2017)	Industry 4.0 concept: background and overview	International journal of interactive mobile technologies	129	10.3991/ijim.v11i5.7072	32.25
17	Boyes et al. (2018)	The industrial Internet of things (IIoT): an analysis framework	computers in industry	126	10.1016/J.COMPIND.2018.04.015	42.00
18	Ghobakhloo (2018)	The future of manufacturing industry: A strategic roadmap toward Industry 4.0	Journal of manufacturing technology management	121	10.1108/JMTM-02-2018-0057	40.33

Table 2 (continued)

Rank	AU	TI	SO	TC	DOI	TCpY
19	Zezulka et al. (2016)	Industry 4.0 – An introduction in the phenomenon	IFAC-PapersOnLine	120	10.1016/J.IFACOL.2016.12.002	24.00
20	Lopes de Sousa Jabbour et al. (2018)	When titans meet – Can Industry 4.0 revolutionize the environmentally-sustainable manufacturing wave? The role of critical success factors	Technological forecasting and social change	112	10.1016/j.techfore.2018.01.017	37.33

TI title, *SO* source, *DOI* digital object identifier, *TC* total citations, *TCpY* total citations per year

4.3 Publications and citations by country

Table 3 presents the top 20 countries based on publication output, while Table 4 shows the top 20 countries according to the citations. In terms of publication output, China is in the first position, followed by European countries (Italy, Germany, Spain, and the UK) in 2nd–5th positions, respectively. Regarding Asian countries, China is ranked 1st, followed by India (6th), Malaysia (7th), South Korea (11th), Taiwan (13th), and Indonesia (14th). Notably, we can see that the USA is ranked only 8th. Although Brazil (a Latin American emerging economy) is ranked 9th, the low level of participation of other emerging economies, especially Latin American and African countries, is quite obvious. These findings have key implications both from the theoretical and managerial perspectives, thus emphasizing the need for the countries concerned to make more efforts to address the Industry 4.0 phenomenon.

Regarding the citation output per country, as highlighted in Table 4, we can see that China (1,065 citations) had nearly double the citations of the country ranked 2nd (Germany,

Table 3 Publications by country

Rank	Country	Papers	Rank	Country	Papers
1	China	173	11	South Korea	52
2	Italy	170	12	Portugal	47
3	Germany	122	13	Taiwan	46
4	Spain	104	14	Indonesia	40
5	UK	97	15	Czech republic	36
6	India	94	16	France	33
7	Malaysia	93	17	Sweden	32
8	USA	93	18	South Africa	27
9	Brazil	86	19	Canada	25
10	Poland	53	20	Romania	25

Table 4 Citations by country

Rank	Country	TC	AAC	Rank	Country	TC	AAC
1	China	1065	53.25	11	India	151	7.95
2	Germany	603	14.71	12	Taiwan	112	8.62
3	UK	544	45.33	13	South Korea	107	6.29
4	Brazil	396	22.00	14	Portugal	106	9.64
5	USA	388	22.00	15	Slovenia	87	17.40
6	Italy	353	7.35	16	Singapore	80	40.00
7	Spain	253	9.73	17	Poland	72	5.54
8	Czech Republic	176	16.00	18	Mexico	68	17.00
9	Austria	174	19.33	19	Hong Kong	62	32.00
10	South Africa	169	84.50	20	Denmark	60	15.00

TC total citations, *AAC* average article citations with 603 citations). Further, only the top three countries (China, Germany, and the UK) have achieved more than 500 citations. Surprisingly, a highly representative Latin American emerging economy, namely Brazil, is ranked 4th, with 396 citations, which illustrates not only Brazil's influence but also the emergence of Industry 4.0 technologies in that country. Further, the USA is ranked only 5th.

4.4 Network analysis

4.4.1 Keyword analysis

In order to gain an in-depth understanding of the relationships between the selected terms, we adopted a network analysis approach (Mishra et al., 2018a). Table 5 presents the top 20 keywords based on their occurrence. The left side of the table shows the keywords provided by the authors, while the right side shows the KeyWords Plus (generated by an algorithm, based on words and phrases used in the paper and therefore not necessarily the same as those provided by the authors).

Table 5 shows that "Industry 4.0" and "Internet of things" are the top two keywords in both cases. Regarding the authors' keywords, other cutting-edge technologies, such as "cyber physical systems," "big data," "cloud computing," "machine learning," and "artificial intelligence," appear. Moreover, other terms, including "smart manufacturing," "digitalization,"

Table 5 Top 20 keywords (authors' keywords vs. KeyWords Plus)

Rank	Authors' keywords	Occurrences	KeyWords Plus	Occurrences
1	Industry 4 0	498	Industry 4 0	266
2	Internet of things	64	Internet of things	102
3	Cyber physical systems	56	Embedded systems	100
4	Smart manufacturing	38	Manufacture	84
5	Smart factory	36	Cyber physical system	72
6	Big data	32	Decision making	52
7	IoT	29	Industrial revolutions	44
8	Cyber physical system	23	Industrial research	42
9	Manufacturing	23	Big data	41
10	Cloud computing	21	Internet of things (IoT)	39
11	Digitalization	19	Automation	35
12	Industrial Internet of things	19	Smart manufacturing	35
13	Internet of things (IoT)	19	Manufacturing industries	32
14	Digital transformation	17	Artificial intelligence	25
15	Sustainability	16	Cloud computing	21
16	Machine learning	14	Competition	21
17	Artificial intelligence	12	Distributed computer systems	21
18	Digitization	12	Maintenance	21
19	SME	12	Network architecture	20
20	Supply chain	12	Virtual reality	20

"digital transformation," "digitization," "supply chain," and "sustainability" can be found. Regarding the KeyWords Plus, we observe some other important words. These include "decision making," "automation," "artificial intelligence," "competition," and "virtual reality."

4.4.2 Co-occurrence network analysis

In Table 6, we present out the co-occurrence network of the terms. We measured the betweenness centrality, which "measures brokerage or gatekeeping potential. It is (approximately) the number of shortest paths between vertices that pass through a particular vertex" (Aria & Cuccurullo, 2020). Accordingly, we found four clusters. The term with the most betweenness centrality in cluster 1 is "Industry 4.0." It should be noted that this cluster mainly comprises approaches to manufacturing and production, as well as supply chains. In cluster 2, the element with most betweenness centrality is "embedded systems," which implies that this cluster is focused on "industrial network architecture." It is interesting to note that the third cluster is dedicated to "objects communication," including "IoT" and "real time systems." Finally, cluster 4 is devoted to decision-making approaches, including "information systems," "data analytics," and "artificial intelligence."

5 Key Industry-4.0-related technologies and their adoption stage

Based on the assessment of the adoption stage of each key Industry 4.0 technology, we created a categorization using bibliometric analysis. Table 7 highlights the main technologies and their maturity in each adoption stage. Accordingly, we considered the technology's popularity and importance in related adoption contexts. The symbols in Table 7 refer to the level of adoption for each technology at each stage (Ω = very low; ● = low; Δ = moderate; ▲ = high; ☼ = very high). It can be clearly seen that the IoT, CPS, machine to machine, and big data are technologies with very high levels of adoption and implementation. However, their routinization, continuance, and diffusion are ongoing (moderate level). Next, the level of adoption and implementation of cloud manufacturing, cloud computing, AI, simulation, and machine learning are high, while their level of routinization, continuance, and diffusion remains moderate. Regarding intelligent robots, virtual reality, augmented reality, and additive manufacturing, they present moderate levels of adoption and implementation, while it is difficult to observe their level of routinization and continuance intention (very low level). Nonetheless, the diffusion of these technologies in the supply network is still embryonic (low level). Finally, technologies such as edge computing, digital twin, blockchain, cybersecurity, and quantum computing are at their infancy stage when it comes to adoption and implementation (low or very low level), with the exception of blockchain and cybersecurity, in which the adoption and implementation stages are at a moderate level. The other technologies, namely digital twin, quantum computing, and edge computing, remain poorly explored in all stages (low or very low level).

6 Discussion, trends, challenges, and emerging topics

The main findings of this study provide important theoretical and practical contributions. First, we have identified that Industry 4.0, and its combination with the adoption stages (e.g. intention, adoption, implementation, routinization, continuance, and diffusion), has been

Table 6 Co-occurrence network

Term	Cluster	Betweenness centrality	Term	Cluster	Betweenness centrality
Industry 4.0	1	422.22	Distributed computer systems	2	5.47
Manufacture	1	48.51	Cloud computing	2	4.24
Industrial research	1	11.94	Network architecture	2	1.30
Manufacturing industries	1	5.27	Data handling	2	0.95
Industrial revolutions	1	2.88	Computer architecture	2	0.53
Smart manufacturing	1	2.45	Intelligent manufacturing	2	0.30
Life cycle	1	1.01	Cyber physical systems (CPSs)	2	0.03
Virtual reality	1	0.70	Internet of things	3	58.31
Costs	1	0.70	Automation	3	3.01
Robotics	1	0.57	Internet of things (IoT)	3	2.88
Surveys	1	0.44	Real-time systems	3	0.89
Product design	1	0.39	Industry	3	0.64
Competition	1	0.34	Digital storage	3	0.23
Sustainable development	1	0.33	Quality control	3	0.18
Supply chains	1	0.27	Article	3	0.00
Manufacturing	1	0.27	Information management	4	1.01
Production control	1	0.18	Maintenance	4	3.83
Assembly	1	0.12	Manufacturing environments	4	0.32
Optimization	1	0.09	Predictive maintenance	4	0.59
Manufacturing process	1	0.09	Decision making	4	15.01
Economics	1	0.08	Artificial intelligence	4	2.77
Design/methodology/approach	1	0.05	Learning systems	4	1.07

Table 6 (continued)

Term	Cluster	Betweenness centrality	Term	Cluster	Betweenness centrality
Embedded systems	2	54.24	Information analysis	4	0.56
Cyber physical system	2	34.70	Data analytics	4	1.19
Big data	2	14.73	Decision support systems	4	0.14

Table 7 Key technologies and their adoption stage in the context of Industry 4.0

Key Industry 4.0 technologies	Adoption stage					
	Intention to adopt	Adoption	Implementation	Routinization	Continuance	Diffusion
Internet of things	☼	☼	☼	Δ	Δ	Δ
Cyber-physical systems	☼	☼	☼	Δ	Δ	Δ
Machine to machine	☼	☼	☼	Δ	Δ	Δ
Big data	☼	☼	☼	Δ	Δ	Δ
Cloud manufacturing	▲	▲	▲	Δ	Δ	Δ
Cloud computing	▲	▲	▲	Δ	Δ	Δ
Artificial intelligence	▲	▲	▲	Δ	Δ	Δ
Simulation	▲	▲	▲	Δ	Δ	Δ
Machine learning	▲	▲	▲	Δ	Δ	Δ
Intelligent robots	Δ	Δ	Δ	Ω	Ω	●
Virtual reality	Δ	Δ	Δ	Ω	Ω	●
Augmented reality	Δ	Δ	Δ	Ω	Ω	●
Additive manufacturing	Δ	Δ	Δ	Ω	Ω	●
Blockchain	Δ	Δ	Δ	●	Ω	Δ
Cybersecurity	Δ	Δ	Δ	●	Ω	Δ
Digital twin	●	●	Ω	Ω	Ω	●
Quantum computing	Ω	Ω	Ω	Ω	Ω	Ω
Edge computing	Ω	Ω	Ω	Ω	Ω	Ω

Symbols refer to the level of adoption of the technology at each stage: Ω = very low; ● = low; Δ = moderate; ▲ = high; ☼ = very high increasingly investigated and reported in publications since 2014. This means that it has become a hot topic for scholars from that time, while also arousing interest among managers and decision-makers seeking to improve their organization's performance. In addition, our bibliometric analysis has identified the top 20 journals that have published the most papers during the period under study.

Apart from the interesting output of the journals specializing in conference proceedings (*IFAC-PapersOnLine, Procedia Manufacturing*), we identified that the list is dominated by manufacturing/engineering/computers journals (*IEEE Access*, *Computers in Industry*, *International Journal of Advanced Manufacturing Technology*, *International Journal of Computer Integrated Manufacturing*, *Sensors*, *IEEE Transactions on Industrial Informatics*, *International Journal of Innovative Technology and Exploring Engineering*, *Manufacturing Letters*, etc.). Surprisingly, considering traditional fields related to the production, operations and supply chain management (PO&SCM), only one highly representative journal appeared in the list of the most productive (output) journals, namely the *International Journal of Production Research*.

However, other traditional PO&SCM journals emerged (e.g. *International Journal of Production Economics*) when the citation output was taken into account. It is important to note that other journals encompassing PO&SCM show a good performance. For instance, in Table 1 (top 20 sources based on article output), the journals *Benchmarking* and *Computers and Industrial Engineering* display a good performance. Further, among the top 20 papers selected based on their citations (Table 2), the *International Journal of Production Research* is ranked 8th. Further, the journal *Technological Forecasting and Social Changes* has three papers in the top 20 most cited.

Regarding the scientific productivity by country, we found that China is ranked in the first place, followed by European countries (Italy, Germany, Spain, and the UK). Surprisingly, the USA did not appear in the top-three list. In addition, the high productivity of other Asian countries (India, Malaysia, South Korea, Taiwan, and Indonesia) should be noted. Brazil, the best performer in Latin America, is ranked in 9th.

In relation to the number of citations by country, other unexpected results emerged. For example, China has achieved practically double Germany's number of citations. Regarding Brazil, it is worthwhile noting that its contribution to the field is high (ranked 4th), which is higher than that of the USA (5th). Furthermore, South Africa achieved good performance in both ranks, publications (18th) and citations by country (10th).

The network analysis showed that, beyond traditional Industry-4.0-related technologies, such as the IoT, CPS, and smart factory/manufacturing, other related approaches are gaining importance. These include "digital transformation," "sustainability," "machine learning," "industrial research," "artificial intelligence," "competition," "virtual reality," etc. Finally, we created four representative clusters. Cluster 1 is dedicated to "industrial operations," cluster 2 to "industrial network architecture," cluster 3 to "objects communication," and cluster 4 to "intelligence tools" (including "data analytics" and "artificial intelligence").

Through this robust and clear identification of clusters, scholars and managers can improve their understanding of the dynamics and turn their efforts toward one or more specific technologies. The challenge for managers is to adopt these cutting-edge technologies as much as, and as effectively as, possible. For scholars, it is important to understand and identify the main trends in these related topics. For decision-makers, the cluster identification can help generate insights into related technologies, the relationships between them, and their different benefits. Table 8 highlights the cluster classification, with suggestions for future research.

Table 8 Cluster classification and future research suggestions

Cluster	Main topic	Current research (secondary topic)	Emerging topics	Suggestions for future research
1	Industry 4.0	Industrial operations	Virtual reality (VR), Product design, Industrial research	(i) Empirical studies about VR adoption in different segments and industry sizes. (ii) Quantitative/qualitative studies examining the improvement of product design by industrial research and VR tools
2		Industrial network architecture	Network architecture, Intelligent manufacturing	(i) Models and frameworks to understand the dynamics of intelligent manufacturing and the role of human and nonhuman interactions in production systems and supply chains. (ii) Frameworks to explore the procedures concerning optimized human–machine interactions in industrial networks
3		Objects communication	Real-time systems, Quality control	(i) Empirical studies concerning trust in the network architecture. (ii) Exploration of real-time approaches, such as the digital twin for production systems' improvement. (iii) Big data analytics techniques and contributions to production systems efficiency
4		Intelligence tools	Data analytics, Artificial intelligence, Information management	(i) Investigation of how data analytics and artificial intelligence techniques could contribute to a more resilient production and supply chain systems. (ii) Investigation of the role of information management in enhancing the adoption, implementation, routinization, and diffusion of Industry 4.0 technologies in production systems

6.1 Categorization of Industry-4.0-related technologies

Based on the above findings, Table 9 highlights the maturity level of Industry 4.0 technologies in relation to their technology adoption stage. In the first place, we have the "early stage of experimentation" maturity level, which is focused on technologies whose adoption is at the first level (the intention to adopt stage). This category is represented by highly disruptive technologies, such as edge computing, digital twin, blockchain technologies, cybersecurity, and quantum computing. The second maturity level is concerned with "performance viability proof," which therefore encompasses technologies already adopted but at a low level, and thus needing further cost–benefit analysis. The main representative technologies of this category are intelligent robots, virtual reality, augmented reality, and additive manufacturing. The third maturity level concerns technology knowledge sharing in the networks. This category presents medium adoption and diffusion levels, incorporating technologies such as cloud manufacturing, cloud computing, artificial intelligence, simulation, and machine learning. Finally, in the fourth maturity level, we have highly adopted and implemented technologies, including the IoT, CPS, machine to machine, and big data. However, there is a need to consider a fifth maturity level for "highly-diffused technologies," which could consider all the adoption stages (intention, adoption, implementation, routinization, continuance, and diffusion).

7 Proposed research agenda

The main findings of this work have enabled us to identify interesting literature gaps and possible open research questions. Table 10 highlights these gaps and the corresponding open research questions. It can be seen that organizations are still failing to adequately consider the routinization and continuance stages of the main Industry 4.0 technologies. This represents an interesting research agenda, as does the exploration of the enablers of, and critical constraints to, the other adoption stages. Moreover, an in-depth understanding of the differences between technologies and their related stages needs to be gained, and this

Table 9 Technology adoption stage for each type of Industry 4.0 technology

Maturity level	Technology adoption stage	Brief description	Technologies
4	Consolidated technologies (CTE)	Very high adoption level and implementation in several industries globally	IoT, CPS, M2M, and BD
3	Knowledge sharing (KNS)	High adoption level in different types of industries, but needing more diffusion efforts	CM, CC, AI, SI, and ML
2	Performance viability proof (PVP)	Moderate adoption level and implementation, requiring further cost–benefit analysis	IR, VR, AR, and AM
1	Early-stage of experimentation (ESE)	First adoption level: intention and adoption decisions	EC, DT, BT, CS, and QC

IoT the Internet of things, *CPS* cyber-physical systems, *M2M* machine to machine, *BD* big data, *CM* cloud manufacturing, *CC* cloud computing, *AI* artificial intelligence, *SI* simulation, *ML* machine learning, *IR* intelligent robots, *VR* virtual reality, *AR* augmented reality, *AM* additive manufacturing, *EC* edge computing, *DT* digital twin, *BT* blockchain technologies, *CS* cybersecurity, *QC* quantum computing

Table 10 Literature gaps and open research questions

Literature gaps	Open research questions	Related literature
Main barriers to the routinization stage	What are the barriers to the routinization stage of Industry 4.0 technologies?	Senna et al. (2022), Fosso Wamba and Queiroz (2022), Martins et al. (2016)
Continuance intention barriers	What are the constraints to the continuance intention stage of Industry 4.0 technologies?	Liébana-Cabanillas et al. (2021), Raj et al. (2020), Liao et al. (2009)
Primary barriers to the diffusion stage	What are the barriers to the diffusion stage of Industry 4.0 technologies?	Majumdar et al. (2021), Stentoft et al. (2021), Laurell et al. (2019)
Enablers and critical success factors for the diffusion stage of technologies	What are the enablers and critical success factors for the adoption, implementation, routinization, continuance, and diffusion of Industry 4.0 technologies?	Sony et al. (2021), Moeuf et al. (2020), Sony and Naik (2020)
Diffusion stage differences between technologies	Which are the main differences between the various types of Industry 4.0 technologies at the diffusion stage?	Fosso Wamba and Queiroz (2022), Raj et al. (2020)
Enablers, barriers, and critical success factors in play at different stages of the technologies	Which are the main enablers/barriers/critical success factors in play at the diffusion stage of Industry 4.0 technologies?	Samad et al. (2022), Luthra et al. (2020), Moeuf et al. (2020)
Differences between countries at the technology diffusion stage	What are the differences between country related to the development levels and stages of Industry 4.0 technologies?	Fosso Wamba and Queiroz (2022), Raj et al. (2020)
Technologies that are more effective in the face of disruptive events (e.g. pandemic outbreaks, climate change, etc.)	How could Industry 4.0 technologies fight against disruptive events and support the supply network's continuance?	Queiroz et al. (2020b), Queiroz & Fosso Wamba, 2021, Hosseini and Ivanov (2020) (2020, Ivanov (2020), Ivanov and Dolgui (2020)
Contribution in terms of efficiency, performance, and business value generated by Industry 4.0 technologies in operations and production systems	What are the main benefits of Industry 4.0 technologies for operations and production systems?	Mujahid Ghouri et al. (2021), Tortorella et al. (2019), Dalenogare et al. (2018)
Industry 4.0 technologies and human skills	What are the main challenges in terms of workers' and production managers' skills needed to get the most out of these technologies?	Saniuk et al. (2021), Wagire et al. (2021), Koh et al. (2019)

will be only possible through research; this, therefore, constitutes another exciting research stream. It would also be interesting to examine countries' cultural differences that influence the adoption of Industry 4.0 technologies.

Other notable literature gaps leading to open research questions have been identified. For instance, it is essential to gain a profound understanding of the most effective technologies to better support firms during disruptive events such pandemic outbreaks, war risks, climate changes, etc. Similarly, the role of each Industry 4.0 technology in the enhancement of the efficiency and performance of production systems and supply networks represents another interesting research avenue. Finally, more research concerning the interplay between technologies and humans, especially workers' and management's skills, is urgently required.

8 Concluding remarks and contributions

This study has utilized a bibliometric approach to explore Industry-4.0-related technologies and their various development stages (intention, adoption, implementation, routinization, continuance, and diffusion). We used one of the leading journal databases (Scopus) to retrieve relevant data covering the period 2011–2019. Through a well-articulated research agenda derived from the literature review and analysis, our study has presented significant findings and insights regarding this issue that are of interest to scholars, managers, and decision-makers.

First, we identified the most productive journals (output and citation) and the most influential authors in the area of Industry 4.0 technologies. The findings showed that the top-20 list is dominated by engineering/manufacturing/computer journals, with many journals specializing in conference proceedings ranked at the top. Second, only few journals in the area of PO&SCM appear in the top-20 list as the most productive journals (output), as well as in the citation output.

Third, regarding publication output by country, the list is dominated by China, European countries (Italy, Germany, Spain, the UK, etc.) and Asian countries (India, Malaysia, South Korea, Taiwan, and Indonesia). With regard to citations per country, similar dynamics were observed, with China being ranked first. Surprisingly, while Brazil shows good performance in the two rankings, the USA does not appear among the top three in any of the rankings. Regarding the performance of African economies, South Africa achieved important productivity and performance.

8.1 Contributions

We identified four clusters concerning the interplay of Industry-4.0-related technologies: cluster 1 ("industrial operations"); cluster 2 ("industrial network architecture"); cluster 3 ("objects communication"); and cluster 4 ("intelligence tools"). We also formulated an interesting categorization regarding the key Industry 4.0 technologies and their various development stages. We observed the low development of stages such as routinization and continuance.

A valuable categorization taking into account the maturity level of each technology was also presented, in which four main levels (early stage of experimentation, performance viability proof, knowledge sharing, and consolidated technologies) were proposed according to the adoption stage of the technology. Finally, a stimulating research agenda was developed.

8.2 Limitations

The present study has three main limitations, which represent interesting opportunities for further research in the domain by scholars. First, we focused only on the Scopus database. Future studies can consider other databases, such as Web of Science (WoS). Second, the number of keywords used for the search was limited; thus, other combinations of keywords may generate different insights. Third, we focused only on the period from 2011 to 2019 (before COVID-19).

Funding This study was partially funded by Conselho Nacional de Desenvolvimento Científico e Tecnológico—CNPq (grant number 11037/2021–6).

Declarations

Conflict of interest The authors have no conflicts of interest to declare.

Ethical approval This article does not contain any studies with human participants or animals performed by any of the authors.

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