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Systematic Review

Bibliometric Analysis of Fourth Industrial Revolution Applied to Material Sciences Based on Web of Science and Scopus Databases from 2017 to 2021

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Abstract: Material science is a broad discipline focused on subjects such as metals, ceramics, polymers, electronics, and composite materials. Each of these fields covers areas associated with designing, synthesizing, and manufacturing, materials. These are tasks in which the use of technology may constitute paramount importance, reducing cost and time to develop new materials and substituting try-and-error standard procedures. This study aimed to analyze, quantify and map the scientific production of research on the fourth industrial revolution linked to material science studies in Scopus and Web of Science databases from 2017 to 2021. For this bibliometric analysis, the Biblioshiny software from RStudio was employed to categorize and evaluate the contribution of authors, countries, institutions, and journals. VOSviewer was used to visualize their collaboration networks. As a result, we found that artificial intelligence represents a hotspot technology used in material science, which has become usual in molecular simulations and manufacturing industries. Recent studies aim to provide possible avenues in the discovery and design of new high-entropy alloys as well as to detect and classify corrosion in the industrial sector. This bibliometric analysis releases an updated perspective on the implementations of technologies in material science as a possible guideline for future worldwide research.

Keywords: bibliometric; material science; industry 4.0; Scopus; Web of Science; Biblioshiny; VOSviewer

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1. Introduction

Material science is fundamental for discovering, designing, and casting the human world. It encompasses diverse disciplines such as chemistry, metallurgy, and solid-state physics, among others, to correlate materials' properties with their composition and structure. These efforts serve as raw materials for engineers to develop applications in electronics, nuclear, construction, communications, food, and other industries. However, successful results are troublesome since try-and-error methodologies take time and resources. Hence, material science relies on computational techniques to increase design reliability and precision, opening space for a new industrial automatization era [1–3].

The fourth industrial revolution, also known as Industry 4.0, is composed of many technologies from which data mining [4] and artificial intelligence (AI) stands out in material science [5], which can be incorporated together [6]. Machine learning [7,8] and its deep learning branch [9,10] are the most used algorithms from AI. For these emerging tools to function, having data of quality is essential. Therefore, pretreatment steps are always required regardless of the data source; experimental, computational, or industrial [11]. Experimental data supply information about the chemical composition, material properties, testing conditions, processing parameters, etc. Computational data provide algorithm types, chemical details, computation constraints, etc. Industrial data cover property information, equipment applied, brand names, material names, and others. The stages necessary for introducing an AI model in industrial production include data management, model learning, model verification, model deployment, and cross-cutting aspects [12].

The application of technologies from industry 4.0 in material science is diverse, as shown in the following research works. Data mining has been used to classify martensite, pearlite, and bainite microstructures from their morphological parameters [13]. Machine learning algorithms have been introduced to predict stable lead-free hybrid organic-inorganic perovskites from unexplored perovskite data, identifying new stable compounds [14]. Deep learning -a preferred algorithm from machine learning- is gaining relevance in the design of photonic devices through deep neural networks, synthesizing multilayer structures based on the thickness of each layer as input parameters [15].

Bibliometrics has been found very useful to describe the impact and growth of a research field and determine its protagonists. It can be used with short or wide timeframes as observed in the work of Nandiyanto et al. [16], Vukić et al. [17], and Modak et al. [18] regarding chemical engineering issues. Likewise, the scientific community recommends using Scopus and WoS databases to carry out this type of review due to their known quality and flexibility to elaborate a robust query equation [19,20].

Few articles deal with the bibliometric analysis of industry 4.0 applied to material science. Advanced and smart manufacturing have been studied separately based on Scopus or Web of Science (WoS) databases, proving that industry 4.0 is exponentially increasing and just emerging, correspondingly [21,22]. Artificial neural network applications have been explored through Scopus, highlighting their importance in engineering fields [23]. Other studies have focused on quantifying the use of deep learning in structural crack detection [24] and AI in the textile industry [25] through WoS. These bibliometric studies have only covered certain areas of material science or industry 4.0 and have mainly employed only one database. This research aims to provide a wider and complete scientometric vision of industry 4.0 applied to material science. We took the recent 2017–2021 period, Scopus and WoS databases, covering several emerging topics, and utilized bibliometrix from RStudio for data mining. The following research questions were addressed:

- Q1: How many research articles were annually published between 2017 and 2021 in material science linked to industry 4.0?
- Q2: Who are the most cited authors in studies associated with industry 4.0?
- Q3: Which papers are the most cited in material science combined with industry 4.0?
- Q4: What journals host the highest quantities of papers in this research area?
- Q5: What are the leaders' institutions in the focused research field?
- Q6: What are the most active sponsor institutions in the selected period?
- Q7: What are the top ten countries publishing on this subject?

Bibliometric research can lead to the development and discovery of trends in a field, helping the scientific community to identify new hotbeds of innovation based on a recent window of observation [26]. This bibliometric analysis provides an updated perspective of the implementations of technologies from industry 4.0 in material science as a scientific reference for subsequent research.

2. Materials and Methods

2.1. Study Design

We opted for a bibliometric analysis to numerically measure the scientific activity of industry 4.0 as it is applied to materials science. This decision was made based on the high number of scientific articles collected from Scopus and WoS between 2017 and 2021.

2.2. Data Source

The Scopus and Web of Science databases were selected due to their widespread reputation for hosting high-quality journals and research documents. Institutional access was required to download and corroborate the content of the study files.

2.3. Search Strategy

We introduced an extended list of keywords in both databases, covering material science and industry 4.0 topics (see Figure 1). In search of articles that are relevant to industry 4.0, the words used were the following: data science, industry 4.0, augmented reality, computer science, remote sensing, artificial intelligence, 3D scanning, data mining, data analytics, data handling, data processing, big data, data visualization, internet of things, and machine learning. The selected words to represent material science were: material, alloys, polymers, metals, nanomaterials, minerals, plastics, ceramics, catalyst, biomaterials, molecular, organic materials, inorganic materials, corrosion, material synthesis, and manufacturing. These keywords were obtained in a cyclical process in which, starting from the articles returned by the databases, more words were incorporated, covering the initially unforeseen topics. The established timeline covered data between 2017 and 2021, while the search was narrowed down to titles and keywords to increase the effectiveness of the search equation. Besides, only original articles were considered as the document type. Both web pages were consulted for the last time on 9 September 2022.

2.4. Bibliometric Analysis

Plots and tables combined the separately processed and analyzed data downloaded in BibTeX files from the Scopus and WoS databases. The Biblioshiny app from the RStudio cloud was used as a tool to obtain and organize both databases before manual manipulation. Biblioshiny offers data about the most productive countries, institutions, authors, research fields, and journals, as well as about keywords, h-index, impact factor, total citations, etc. [27]. Moreover, VOSviewer was included for data mining, mapping, and visualization of collaborative networks [28].

2.5. Limitations

The Scopus and WoS databases are not perfectly adapted to bibliometric analyses; therefore, they tend to return a certain amount of erroneous data that limits the conclusions to be drawn from them. In bibliometric studies, qualitative statements tend to be subjective since these analyses are essentially quantitative [29]. This type of review offers a short-term forecast of the area under investigation [30].

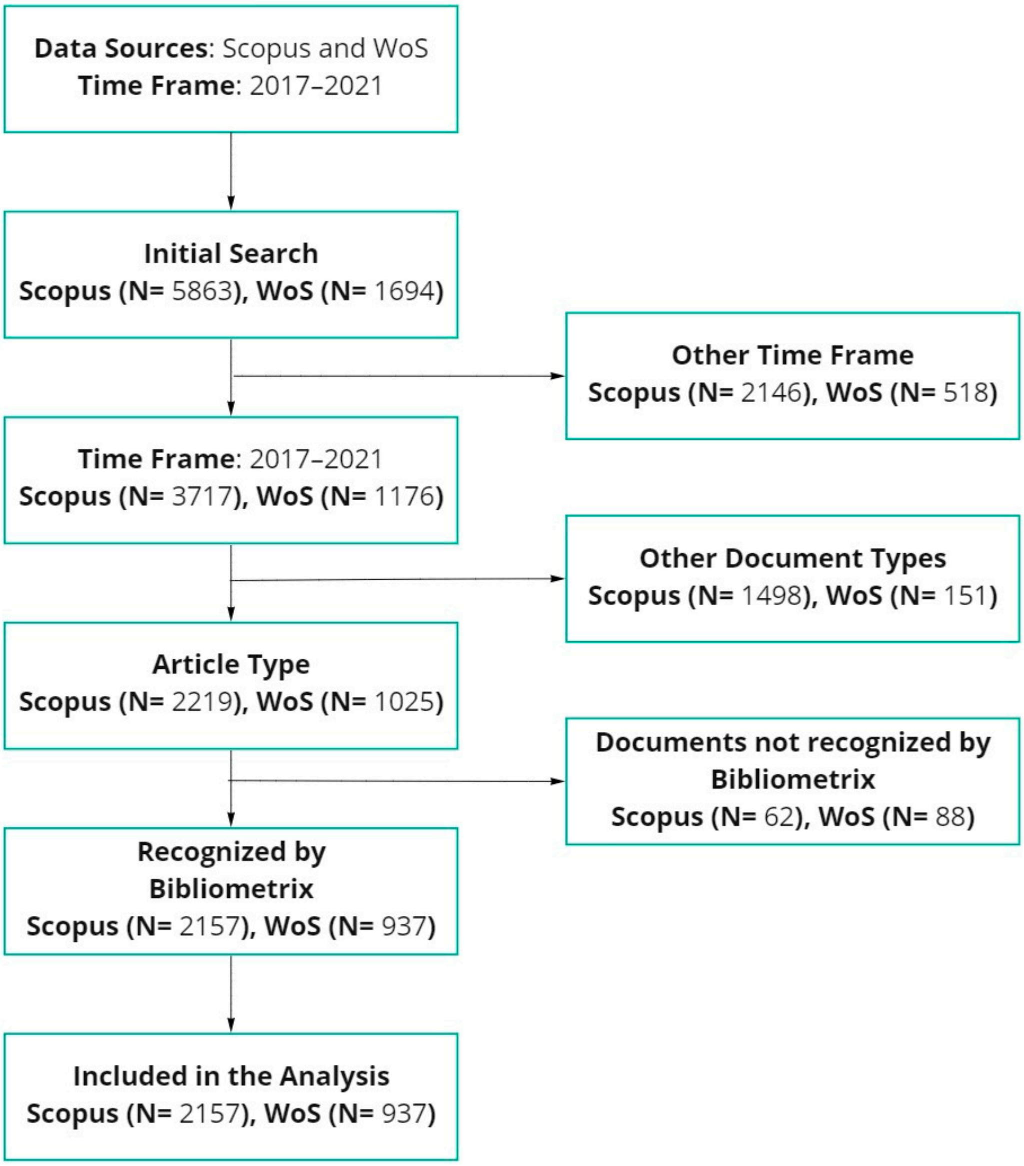


Figure 1. Flowchart of used bibliometric methodology.

3. Results and Discussion

The findings delivered from each of the previously mentioned objectives will be presented in the following subsections based on the data taken from WoS and Scopus. Figure 1 shows that Scopus is the most used database to publish articles related to industry 4.0 in material science, more than doubling the number of documents hosted in WoS.

3.1. Trends in the Annual Production of Original Papers

Figure 2a shows that the introduction of technologies from industry 4.0 within material science areas slightly increased from 2017 to 2019; however, it showed sharp growth after this point. One of the technologies that has presented an important increase in recent years is machine learning; however, it is still a developing tool that requires a higher degree of fine-tuning before we can see its complete potential [31].

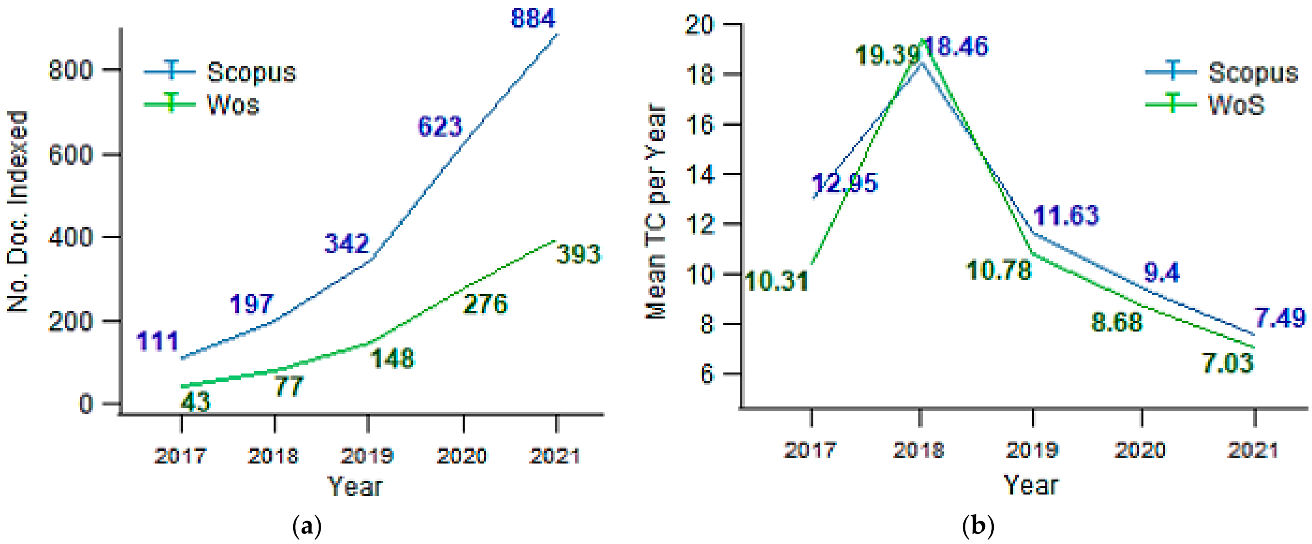


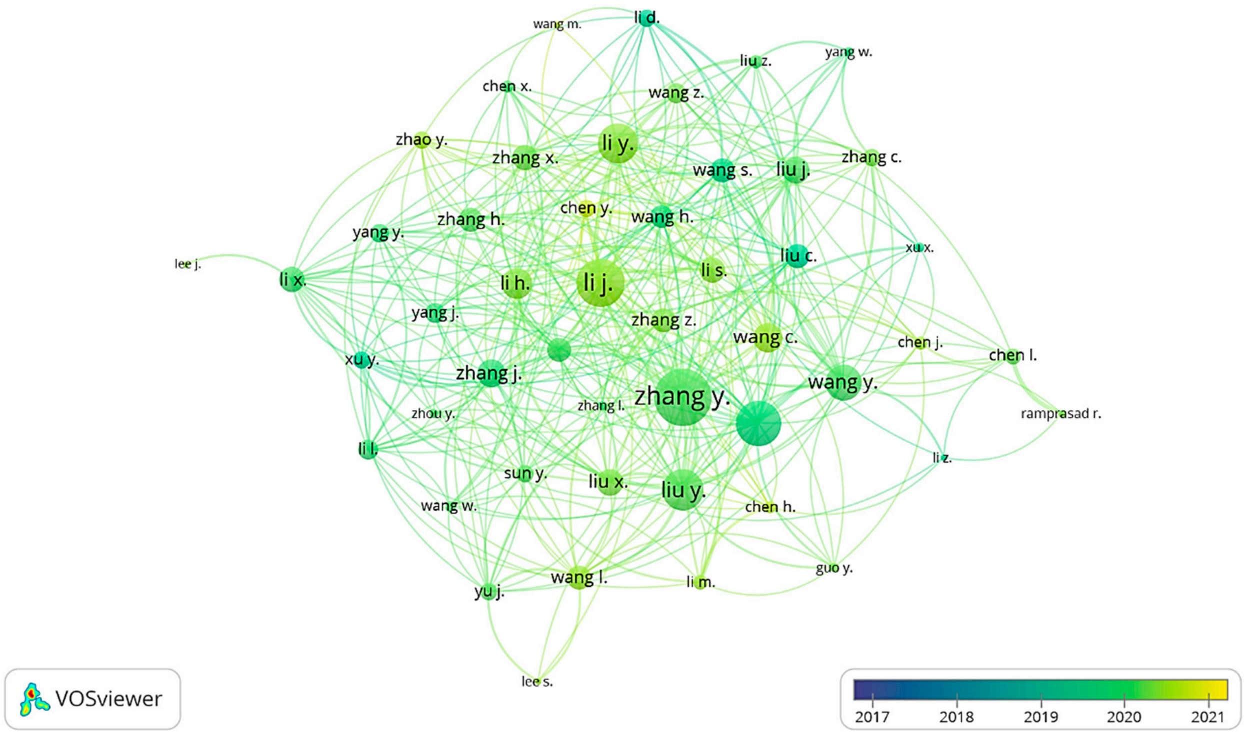
Figure 2. The year-wise of publication (**a**) and total citation (TC) (**b**) from WoS and Scopus from 2017 to 2021.

There has been rapid adoption of digital technologies during the COVID-19 pandemic, triggering the additional implementation of artificial intelligence in material science [32]. As seen in Figure 2a, the number of published papers pertaining to the assessed subjects has grown exponentially in the past five years.

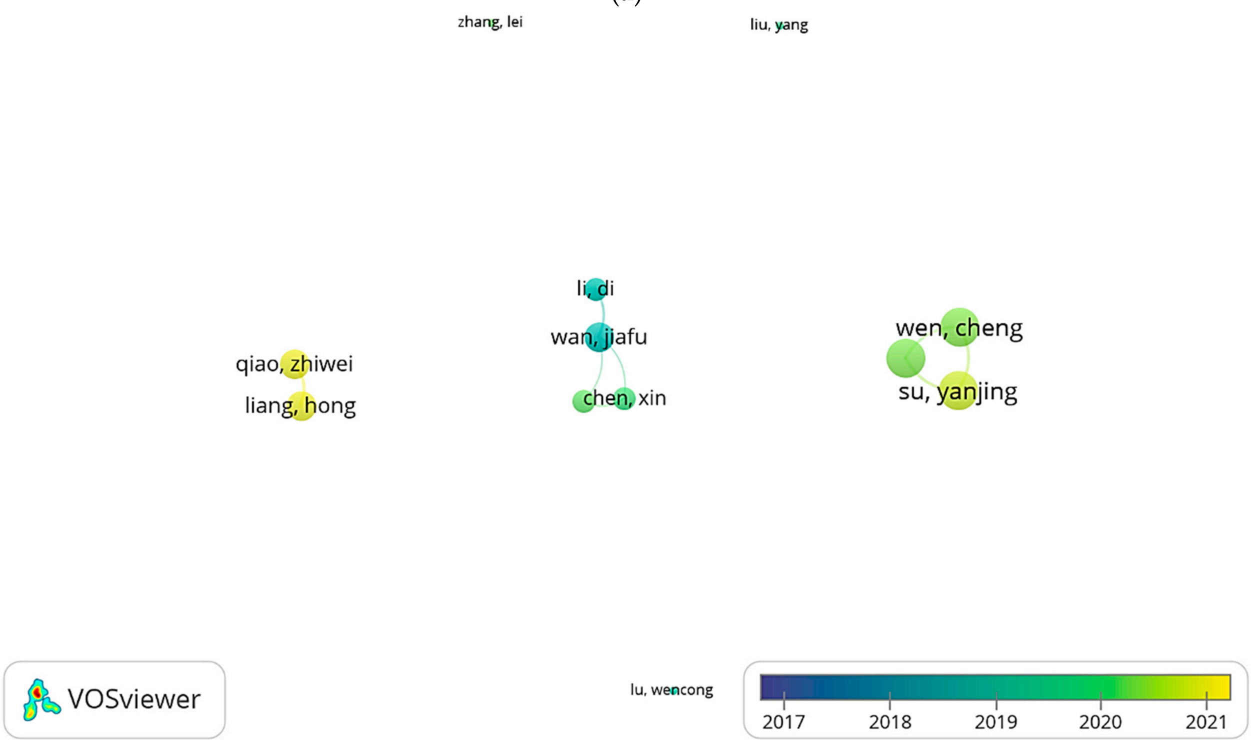
The mean total citation per year reached a higher peak in 2018, after which it decreased similarly in both databases (see Figure 2b). The decay of said metric may respond to the time required by the researchers to identify newly published works, their novelty, their accessibility, and the spreadability of science, among other reasons [33–35].

3.2. Most Cited Authors and Their Collaborations

The Scopus and WoS databases highlight Zhang Yan as one of the most productive researchers in issues related to industry 4.0 applicated to materials (see Table 1). As a general observation, Wang J. and Liu J. produced a higher quantity of TC, whereas Zhang Yan delivered the largest number of scientific papers. In addition, as shown in Figure 3a, Zhang Yan is the researcher with the most collaborations (60) in Scopus, followed by Li J. (51) and Wang J. (48) (see Table A1 from Appendix A). Although Wen C., Xue D., and Su Y. are the authors with the most link strengths from WoS, with 8 collaborations each. As such, Zhang Yan can be considered the most influential author in the studied subjects. In his latest research, he has used machine learning for material design and microstructure evolution prediction [36,37]. It is worth noting that images from Figure 2 are not tailored to the data of Table 1 since these networks' charts are focused on searching for collaborations—total link strength—and they depend on the minimum number of articles per author and on the decision of presenting the interconnection of nodes. In this case, the node size is proportional to the number of associations per author. The same logic applies to the following VOSviewer figures and their interpretations, along with the document.



(**a**)



(**b**)

Figure 3. The most collaborative authors in material science combined with industry 4.0 from 2017 to 2021 in (**a**) Scopus and (**b**) WoS, considering a minimum of 12 and 5 documents in VOSviewer, respectively. Each node's size is proportional to the number of associations per author.

Table 1. The top 10 most-cited authors in material science coupled with industry 4.0 from 2017 to 2021.

	Scopus				WoS			
Rank	**Author**	**h-Index**	**TC**	**No. of Paper**	**Author**	**h-Index**	**TC**	**No. of Paper**
1st	Zhang Y	16	1452	44	Zhang Y	12	886	23
2nd	Liu Y	16	1606	39	Li Y	9	321	21
3rd	Wang J	18	2453	37	Li H	9	314	20
4th	Wang Y	15	690	33	Zhang Z	8	230	19
5th	Li J	14	797	32	Liu Y	8	897	18
6th	Li Y	14	624	31	Li J	8	159	17
7th	Zhang Z	11	348	30	Wang J	11	956	15
8th	Zhang J	12	862	28	Wang Y	8	216	14
9th	Li X	11	470	27	Zhang L	6	755	14
10th	Li H	11	364	25	Zhang X	9	181	14

3.3. Most Cited Research Articles

As shown in Table 2, the three most-cited papers were written by Zhong RY. (2017), Tao F. (2018), and Frank AG. (2019). The work of Zhong is a review only hosted in Scopus that counts the highest number of citations and is about intelligent manufacturing [38]. The paper written by Tao deals with the use of big data in product life cycle management, proposing a new method for its design, manufacture, and service driven by digital twins [39]. Frank surveyed 92 manufacturing companies to study the implementation of the internet of things, cloud services, big data, and analytics in smart manufacturing, smart products, smart supply chain, and smart working. This research work highlighted the need for named technologies in Smart manufacturing since they play a central role within companies [40]. Furthermore, 60% of the topics extracted from Table 2 are associated with manufacturing in the industrial sector. At the same time, machine learning (ML) is the preferred technology, followed by its deep learning (DL) branch and big data. As previously argued, ML and DL -artificial intelligence- have become usual techniques for the discovery and design of materials at a molecular level. Regarding the use of big data, the so-called 5 V model has been found to be essential for data management and data preservation in the material science context. This model considers the variability of unstructured data, volume of data in zettabytes, velocity in streaming data, noise removal veracity, and added value [41].

3.4. Journals That Host a Higher Number of Articles

Table 3 shows that the journals with more participation in material science linked to technologies from the fourth revolution are *Computational Materials Science*, *IEEE Access*, and *Journal of Physical Chemistry Letters*. Even though, this latter source isn't part of the WoS' top three. The cumulate average of research works hosted in these three journals is below 8%, therefore, there exists a large spectrum of journals (>92%) publishing articles regarding material science addressing technologies from industry 4.0.

Table 2. The top 10 most-cited articles in industry 4.0 applied to material science from 2017 to 2021 [14,38–40].

Autor, Year	Document Title and Journal Name	Journal Name	TC Scopus	TC WoS
Zhong RY, 2017	Intelligent Manufacturing in the Context of Industry 4.0: A Review	Engineering	1207	N/A
Tao F, 2018	Digital twin-driven product design, manufacturing, and service with big data	Int J Adv Manuf Technol	1136	822
Frank AG, 2019	Industry 4.0 technologies: Implementation patterns in manufacturing companies	Int J Prod Econ	795	633

Table 2. *Cont.*

Autor, Year	Document Title and Journal Name	Journal Name	TC Scopus	TC WoS
Wang J, 2018	Deep learning for smart manufacturing: Methods and applications	J Manuf Syst	747	583
Wu Z, 2018	MoleculeNet: a benchmark for molecular machine learning	Chem Sci	637	N/A
Qi Q, 2018	Digital twin and big data towards smart manufacturing and industry 4.0: 360-degree comparison	IEEE Access	595	434
Schütt KT, 2018	SchNet—A deep learning architecture for molecules and materials	J Chem Phys	579	N/A
Ghobakhloo M, 2018	The future of manufacturing industry: a strategic roadmap toward Industry 4.0	J Manuf Technol Manage	503	N/A
Liu Y, 2017	Materials discovery and design using machine learning	J Materiomics	NA	469
Chmiela S, 2017	Machine learning of accurate energy-conserving molecular force fields	Sci Adv	461	N/A

Table 3. Top 10 most articles hosted by the journal in industry 4.0 applied to material science from 2017 to 2021.

	Scopus			WoS		
Rank	Journal Name	No. of Papers (%) N = 2157	Impact Factor SJR (2021)	Journal Name	No. of Papers (%) N = 937	Impact Factor JCR (2021)
1st	Computational Materials Science	58 (2.69)	0.777	Computational Materials Science	45 (4.80)	3.572
2nd	IEEE Access	38 (1.76)	0.927	IEEE Access	26 (2.77)	3.476
3rd	Journal of Physical Chemistry Letters	32 (1.48)	2.009	International Journal of Advanced Manufacturing Technology	19 (2.03)	NA
4th	Journal of Chemical Information and Modeling	31 (1.44)	1.223	ACS Applied Materials & Interfaces	15 (1.60)	10.383
5th	Journal of Physical Chemistry C	30 (1.39)	1.103	Journal of Intelligent Manufacturing	15 (1.60)	7.136
6th	NPJ Computational Materials	29 (1.34)	2.967	Advanced Theory and Simulations	14 (1.49)	4.105
7th	Sustainability (Switzerland)	26 (1.21)	0.664	Journal of Manufacturing Systems	13 (1.39)	9.498
8th	Chemistry of Materials	24 (1.11)	2.93	Materials & Design	13 (1.39)	9.417
9th	Journal of Chemical Physics	24 (1.11)	1.103	Acta Materialia	11 (1.17)	9.209
10th	ACS Applied Materials & Interfaces	23 (1.07)	2.143	Applied Sciences-Basel	11 (1.17)	2.838

On the other hand, by introducing Bradford's law, it was feasible to classify sources into core areas, related areas, and non-relevant areas concerning the targeted field, as observed in Equation (1).

$$r_0 = 2\ln(e^{\gamma}Y) \tag{1}$$

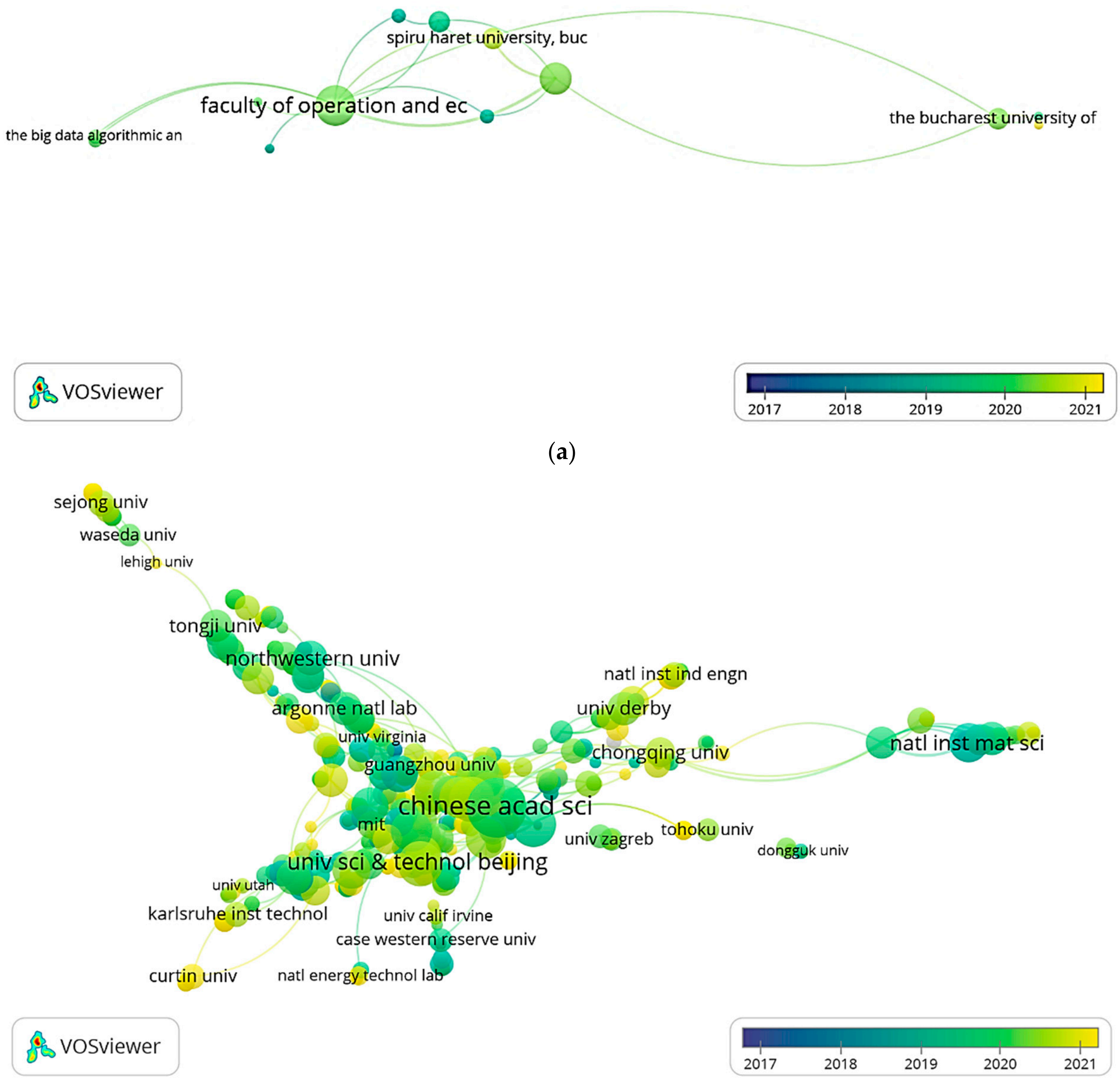
where r_0 represents the number of journals that make up the core area, γ is the Euler's constant (~0.577), and Y is the number of papers published in the journal with the most hosted documents [42]. In this case, since we this study involves two databases, $Y_1 = 58$ in Scopus and $Y_2 = 45$ in WoS. Thus, $r_{0-1}(\text{Scopus}) \cong 9$ and $r_{0-2}(\text{WoS}) \cong 9$. As a result, only the source Applied Sciences-Basel from WoS is removed from the core collection, bearing in mind that *ACS Applied Materials & Interfaces* from Scopus is inside the WoS list of publications with the higher JCR impact factor. Also, it is noteworthy that *Computational Materials Science* is the preferred journal to publish articles around industry 4.0 connected with material sciences.

3.5. Most Productive Institutions and Their Collaborations

Considering an array of only interconnected nodes in VOSviewer, Scopus and WoS delivered the same result regarding the most productive institutions. The top 3 universities in Scopus publish more papers than those in WoS. Accordingly, the University of Science and Technology Beijing is positioned as the most contributive institution, followed by the University of California and Shanghai University (see Table 4). Meanwhile, from the collaborative viewpoint, the Chinese Academy of Sciences is positioned as the most collaborative institution with a total link strength of 58, as counted in Table A2 from Appendix B and as appreciated in Figure 4b. Other research studies have highlighted the implementation of technologies from industry 4.0 at the Chinese Institute of Computer Science [43].

Table 4. The top 10 most-productive institutions in industry 4.0 applied to material science from 2017 to 2021.

	Scopus			WoS		
Rank	**Affiliations**	**Country**	**No. of Paper**	**Affiliations**	**Country**	**No. of Paper**
1st	University of Science and Technology Beijing	China	59	University of Science and Technology Beijing	China	55
2nd	University of California	United States	47	Shanghai University	China	42
3rd	Shanghai University	China	42	University of Chinese Academy of Sciences	China	28
4th	Massachusetts Institute of Technology	United States	38	Nanyang Technological University	Singapore	26
5th	Zhejiang University	China	33	Chongqing University	China	25
6th	Shanghai Jiao Tong University	China	30	Beihang University	China	24
7th	University of Chinese Academy of Sciences	China	28	Northwestern Polytech University	China	24
8th	Chongqing University	China	24	University of Illinois	United States	24
9th	South China University of Technology	China	24	Guangzhou University	China	22
10th	Tsinghua University	China	24	Zhejiang University	China	22



(**a**)

(**b**)

Figure 4. The most collaborative institutions in material science combined with industry 4.0 from 2017 to 2021 in (**a**) Scopus and (**b**) WoS, considering a minimum of 1 document in VOSviewer. Each node's size is proportional to the number of associations per institution.

In this regard, Scopus did not provide visual evidence regarding the leader institution, (see Figure 4a) but indicated partial partnerships among most universities. Table A2 shows that below the Chinese Academy of Sciences, its managed institution, the University of Chinese Academy of Sciences, hosts 22 fewer partnerships. The dominance of China and the United States is visible in Table 4. Nevertheless, Figure 3b suggests that new organizations, such as Curtin University from Australia, have been increasing their teamwork in the past few years.

3.6. Most Participative Funding Agencies

The studied databases were consistent in finding the National Natural Science Foundation of China (NSFC) and the National Science Foundation (NSF) from the United States as the principal funding agencies (see Table 5). Both institutions have been compared according to their influence on the development of artificial intelligence-associated research in the past decade [44]. The main findings suggest that from 2010 to 2019, the NSF supported more AI research than the NSFC, injecting 1.7 billion more dollars into research. Despite the greater volume of published works by the NSFC, reaching 15 thousand more papers than the NSF, it awarded less money. However, it is expected that by 2023 the NSFC will surpass the NSF in the quantity of money awarded. In the addition to these two mighty powers, organizations from Belgium and Germany are financing research in industry 4.0 to sustain the growth of the field in Europe countries.

Table 5. The top 10 most-participative funding agencies in industry 4.0 applied to material science from 2017 to 2021.

	Scopus			WoS		
Rank	**Affiliations**	**Country**	**No. of Paper**	**Affiliations**	**Country**	**No. of Paper**
1st	National Natural Science Foundation of China	China	350	National Natural Science Foundation of China	China	184
2nd	National Science Foundation	United States	182	National Science Foundation	United States	68
3rd	U.S. Department of Energy	United States	122	National Key Research and Development Program of China	China	44
4th	National Key Research and Development Program of China	China	94	Fundamental Research Funds for The Central Universities	China	35
5th	Office of Science	United States	79	U.S. Department of Energy	United States	33
6th	Fundamental Research Funds for the Central Universities	China	72	Ministry of Education Culture Sports Science and Technology	Japan	25
7th	Japan Society for the Promotion of Science	Japan	52	European Commission	Belgium	23
8th	Ministry of Science and Technology of the People's Republic of China	China	50	Japan Society for the Promotion of Science	Japan	22
9th	Horizon 2020 Framework Programme	Belgium	49	German Research Foundation	Germany	18
10th	Basic Energy Sciences	United States	48	Grants-in-Aid for Scientific Research	Japan	16

3.7. Most Contributing Countries and Their Collaborations

Scopus and WoS coincide in attributing the leading countries in materials science studies developed under the perspective of industry 4.0. China ranks as the country that has successfully incorporated ideas, technology, and innovation from computers to the architecture of materials and additive manufacturing [45]. In spite of the higher number of citations received by the studies carried out by the United States rendering to Scopus (see Table 6). Two rungs below, countries like Japan, Germany, and the United Kingdom, appear with standardized scientific productions.

The esteemed position of China in this field is not a matter of luck since this country thoroughly planned today's ubication by introducing the "Made in China 2025" plan, which was directed to catch up with industry 4.0 technologies. This plan was ten years ahead of planning that pursued to become the country a global manufacturing powerhouse [46]. However, despite Chinese expectations, only 57% of their companies are adequately prepared for Industry 4.0 technologies. This low average of prepared companies to receive these technologies in China is surpassed by the United States (71%) and Germany (68%) [47].

Table 6. The top 10 countries in industry 4.0 applied to material science from 2017 to 2021.

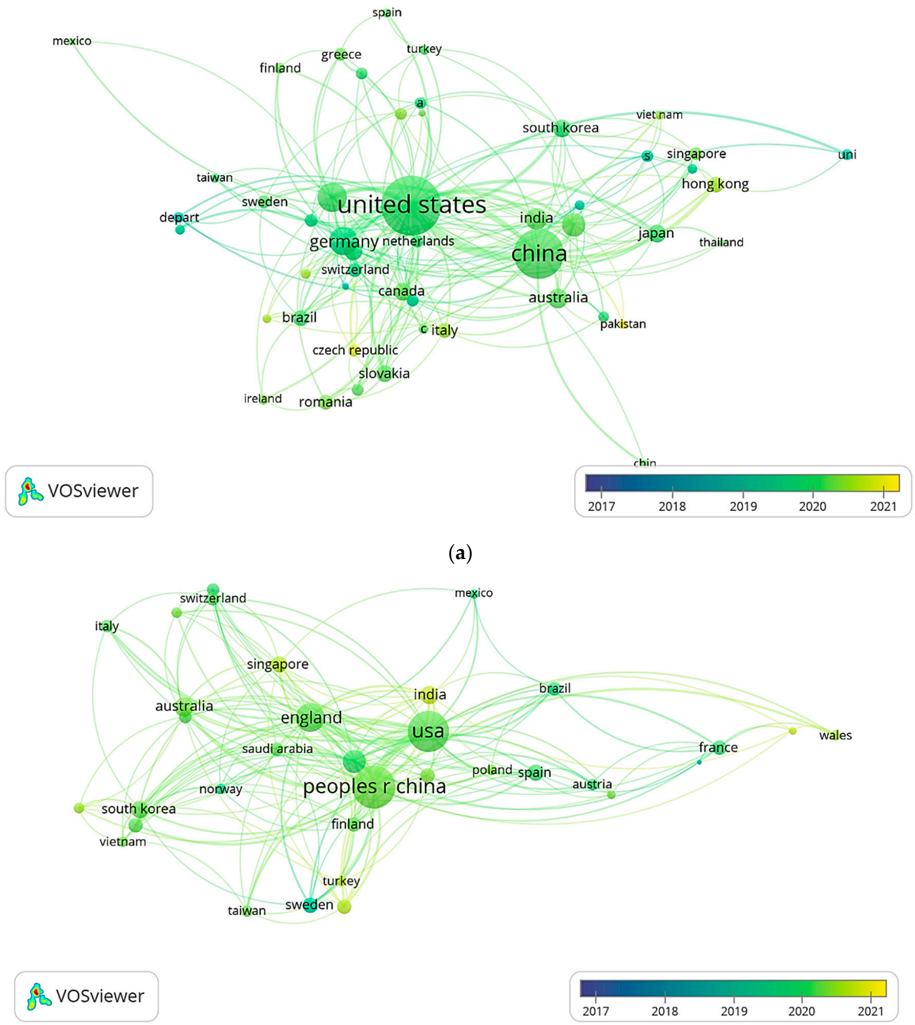
	Scopus			Wos		
Rank	**Country**	**Frequency**	**Total Citations**	**Country**	**Frequency**	**Total Citations**
1st	China	1453	11514	China	1226	7238
2nd	United States	1318	12957	United States	784	4661
3rd	Japan	311	1310	Japan	210	698
4th	Germany	246	1448	Germany	175	684
5th	United Kingdoms	229	1673	India	162	325
6th	India	227	795	South Korea	158	413
7th	South Korea	210	1158	United Kingdoms	149	998
8th	Canada	107	545	Australia	92	393
9th	Australia	106	524	Spain	87	208
10th	Spain	103	462	Singapore	76	547

According to the databases explored, among the most collaborative countries are the United States, China, and United Kingdom (see Table A3 in Appendix C). The first two countries, however, are interchanged in the first places in Scopus and WoS. This perhaps demonstrates a preference by China to publish in WoS journals (see Figure 5) as a result of its policy to measure research excellence [48]. Otherwise, Figure 5 shows that India, Turkey, and the Czech Republic are countries that have increased their collaborations in recent years.

Keywords are loyal representations of scientific research works in articles, and their frequent implementations may reflect the hotspots of a particular study field. The word-cloud visualization of Scopus and WoS database in Biblioshiny (see Figure 6) allowed us to define the most relevant keyword introduced by authors in material science associated with industry 4.0 technologies.

We highlight smart manufacturing, additive manufacturing, and molecular dynamics as part of the material science keywords while machine learning, deep learning, and big data for industry 4.0. As previously mentioned most productive institutions may fluctuate, yet, more generally, machine learning and deep learning are the most prioritized technologies in material science studies (see Figure A1 in Appendix D). Machine learning and deep learning are recognized as the brains behind smart manufacturing. In this regard, both technologies are used for decision-making support systems, fault diagnosis, predictive analytics, advanced robotics, and scheduling [49]. Additive manufacturing, also known as 3D printing, is used to determine fabrication parameters, quality of the workpieces, and processing time. Furthermore, it is expected that additive manufacturing will achieve 5d-printing, through the implementation of time and artificial intelligence tools as the fourth and fifth dimensions, respectively [50]. In the case of molecular dynamics, artificial intelligence is employed to contribute to understanding materials' properties by simulating the interaction of atoms and molecules. Even though some studies lead to considerable differences between accuracy and efficiency, machine learning and deep learning are still considered helpful tools to match efficiency with ac-curacy in molecular simulation [51].

On the other hand, Figure 7 shows possible new trends for technologies from the fourth industrial revolution based on the keywords extracted from both studied databases. While AI technologies continue to be tightly associated with new trends, it is notable that materials science fields, such as high entropy alloys and corrosion, are gaining traction in computer sciences. The predictive properties of high entropy alloys may allow for the design of new materials by selecting key-related features of alloys [52]. Additionally, the detection and classification of corrosive issues from images of industrial facilities have been successfully performed through AI [53]. We believe these applications belong to a new pathway of industry 4.0 as applied to material science and serve as a guide for future routes to be explored by scientists.



(a)

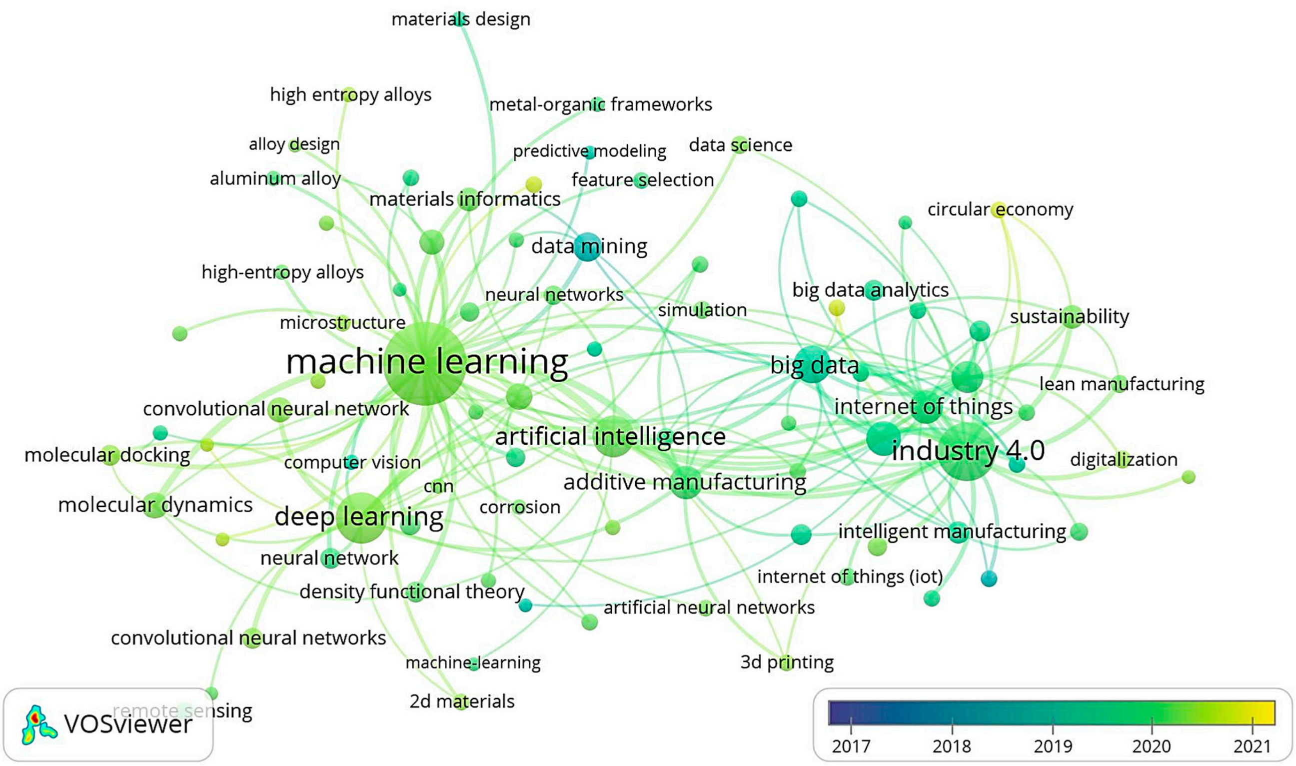
(b)

Figure 5. The most collaborative countries in material science joined with industry 4.0 from 2017 to 2021 in (**a**) Scopus and (**b**) WoS, considering a minimum of seven documents in VOSviewer. Each node's size is proportional to the number of associations per country.

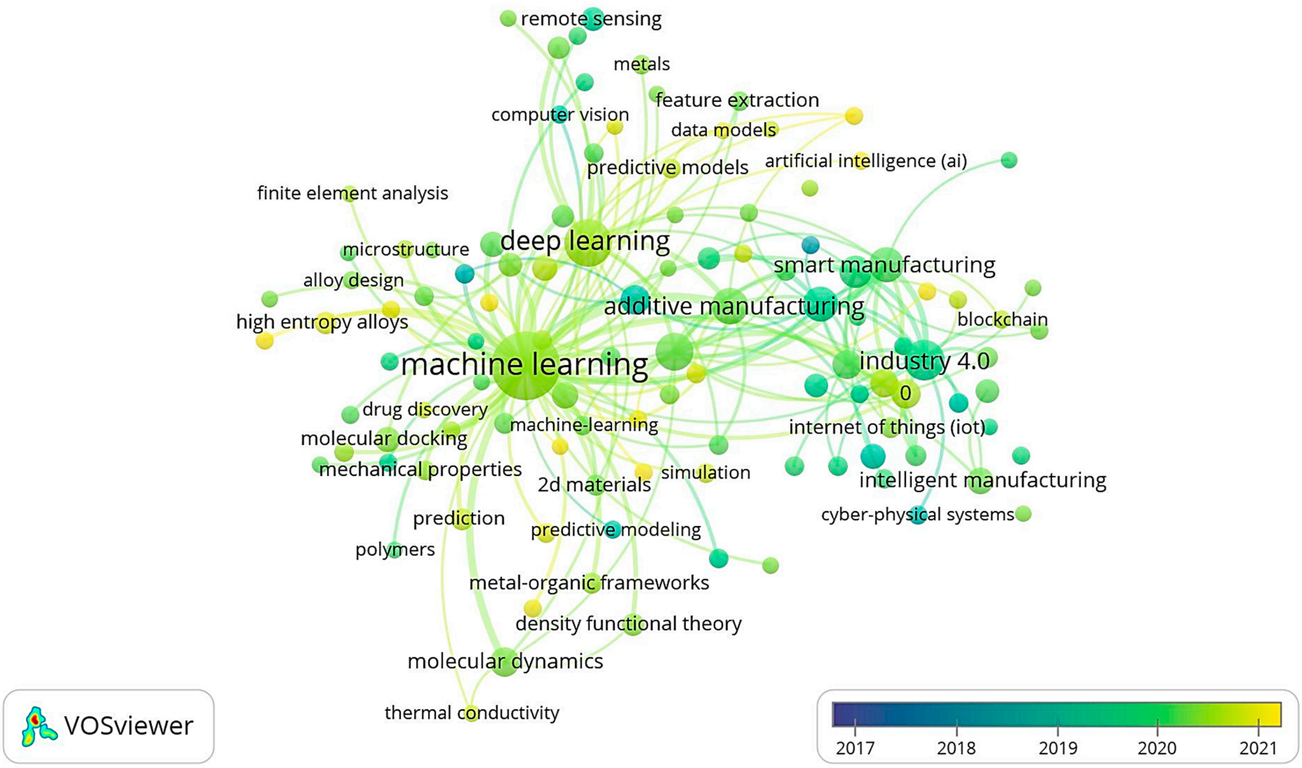
(a)

(b)

Figure 6. Word clouds of authors' keywords in industry 4.0 applied to material science from 2017 to 2021 from (**a**) Scopus and (**b**) WoS.



(**a**)



(**b**)

Figure 7. Keywords most used by authors in material science studies combined with industry 4.0 from 2017 to 2021 in (**a**) Scopus and (**b**) WoS, considering a minimum of eight and five occurrences in VOSviewer, respectively. Each node's size is proportional to the keywords' frequency of use.

4. Conclusions

This bibliographic review brings us closer to the recent growing interest shown by institutions, journals, researchers, countries, and funding agencies in the study of material science linked to the emerging technological tools provided by industry 4.0. The main conclusions delivered by responding to each one of the settled research questions are the following:

- The production of original papers in the explored field is exponentially growing.
- A minimum of 14 published papers are required to become one of the most cited authors on the tracked type of research.
- Most cited articles in these fields deal with artificial intelligence and big data applications in manufacturing industries.
- The top journals preferred to spread initiatives of industry 4.0 in conjunction with the material science field count with a JCR higher than 2.5.
- The most productive institutions delivered at least 22 documents to be part of the top ten.
- Funding agencies pursuing the top ten of given awards need to support a minimum of 16 papers.
- China and the United States are the most implicated countries regarding the fourth industrial revolution applied to material science, whose success stems from the incorporation of specific public policies.
- Deep learning represents the most attractive technology in machine learning to perform new studies in material science.

Even though AI is the research hotspot technology in material science studies, and it has become commonly used in molecular simulations and manufacturing issues, opportunities stills exist to discover and design new high entropy alloys and corrosion detection. In general terms, this bibliometric analysis offers an updated viewpoint regarding material science for developing subsequent research and generating consciousness about the impact of introducing new technologies in the promotion, discovery, design, management, and operation of materials used by companies.

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Appendix A

Table A1. The top 5 most collaborative authors in industry 4.0 applied to material science from 2017 to 2021.

	Scopus			WoS		
Rank	**Author**	**No. of Paper**	**T. Link Strength**	**Author**	**No. of Paper**	**T. Link Strength**
1st	Zhang Y	44	60	Wen C	5	8
2nd	Li J	32	51	Su Y	5	8
3rd	Wang J	37	48	Xue D	6	8
4th	Liu Y	38	44	Liang H	5	5
5th	Li Y	33	42	Qiao Z	5	5

Appendix B

Table A2. The top 5 most collaborative institutions in industry 4.0 applied to material science from 2017 to 2021.

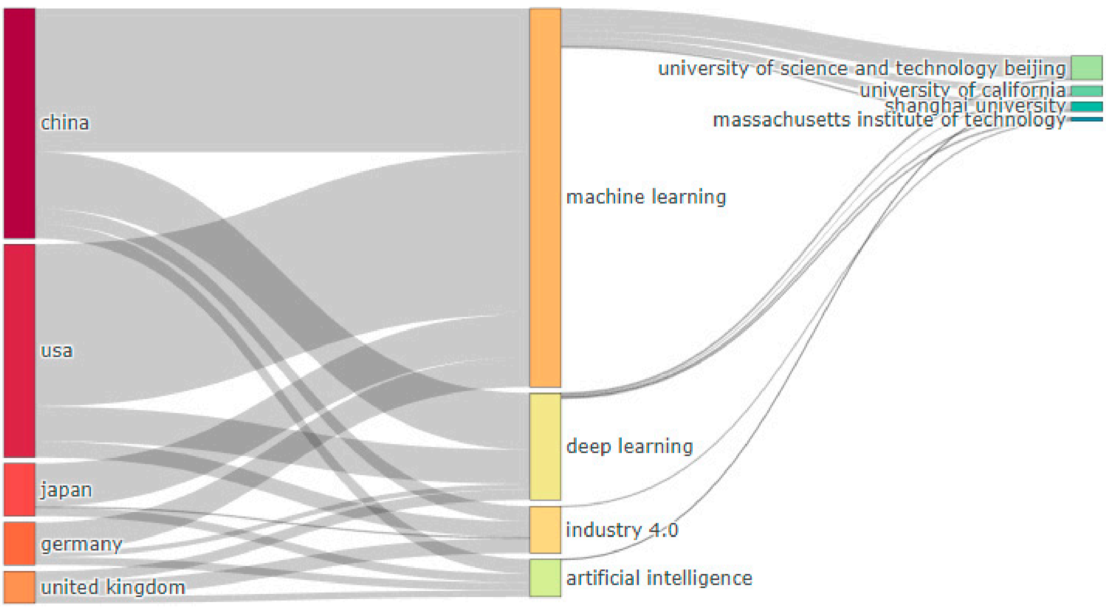
	Scopus			WoS		
Rank	**Institution**	**No. of Paper**	**T. Link Strength**	**Institution**	**No. of Paper**	**T. Link Strength**
1st	Technical University of Berlin	8	14	Chinese academy of sciences	27	58
2nd	University of Zilina	10	12	University of Chinese academy of sciences	14	32
3rd	Cadi Ayyad University	3	8	Northwestern polytechnic university	12	32
4th	The institute of smart big data analytics	5	8	University of science and technology Beijing	18	31
5th	University of Chinese academy of sciences	7	8	Georgia institute of technology	8	26

Appendix C

Table A3. The top 5 countries in industry 4.0 applied to material science from 2017 to 2021.

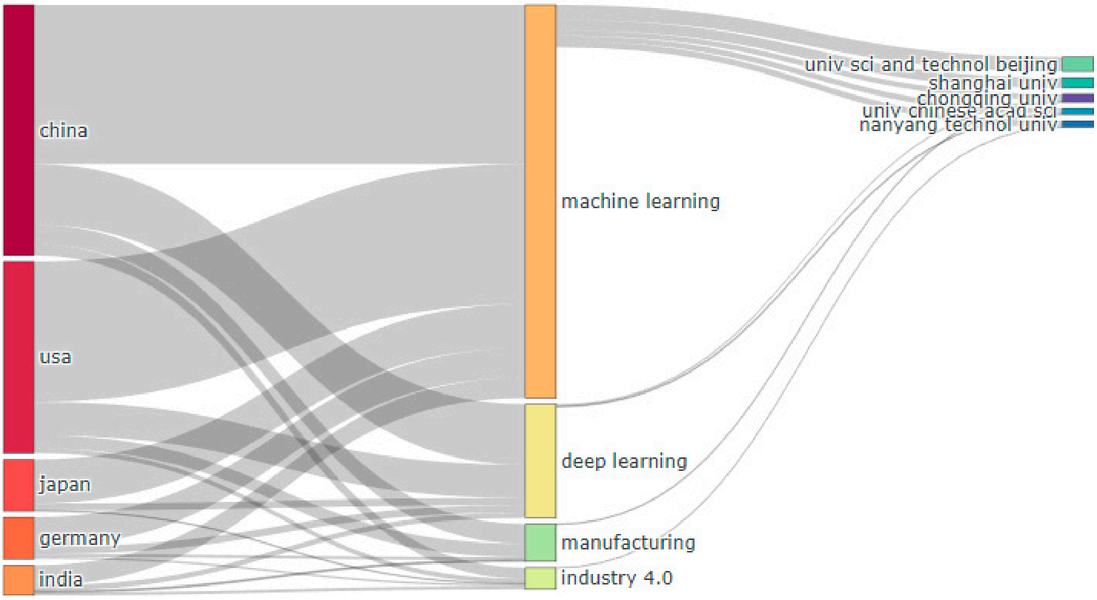
	Scopus		WoS	
Rank	**Country**	**Total, Link Strength**	**Country**	**Total, Link Strength**
1st	United States	252	China	154
2nd	China	176	United States	143
3rd	United Kingdom	63	United Kingdom	70
4th	Germany	56	Germany	45
5th	India	33	Australia	31

Appendix D



(a)

Figure A1. *Cont.*



(**b**)

Figure A1. Relationship between institutions, countries and most used keywords in industry 4.0 applied to material science from 2017 to 2021 from (**a**) Scopus and (**b**) WoS.

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