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TOPICAL REVIEW

Blockchain and Artificial Intelligence: Scientometric Analysis and Visualization

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ABSTRACT Integrating Artificial Intelligence (AI) with Blockchain Technology (BT) is deemed the fourth generation of BT applications (Blockchain 4.0). This generation has gained considerable attention from the research community. Such attention has led to a vast amount of scientific literature. However, a comprehensive quantitative analysis of this literature is still missing. The present study conducts a scientometric analysis to explore and characterize the development track and trends of BT-AI research. Using the Web of Science (WoS) Core Collection database, a total of 2615 peer-reviewed journal articles were identified between 2017-2023 and extracted for analysis, while employing VOSviewer and Biblioshiny as software tools. First, the publication trend was analyzed, and the pivotal articles were identified. Second, the scientific collaboration networks were analyzed and mapped to identify the key researchers, countries, and organizations. Third, the sources' productivity and citation were analyzed and mapped to identify the dependable sources of information and the best-fit sources for publishing the BT-AI studies. Fourth, the conceptual structure for the BT-AI literature was analyzed and visualized using keywords co-occurrence and keywords thematic evolution to explore and identify the research hotspots and emerging themes. The findings of this study can help in further familiarizing new researchers with BT-AI literature and assist practitioners, policy-makers, and editors to focus on the promising and arising BT-AI trends for further development.

INDEX TERMS Artificial intelligence, bibliometrics, blockchains, data visualization, reviews.

I. INTRODUCTION

Blockchain Technology (BT) is a revolutionary technology that Satoshi Nakamoto introduced in 2008 as a back-engine for the Bitcoin network. BT utilizes digital distributed ledgers for maintaining transactional data across a peer-to-peer network without being governed by a central authority or managed by an intermediary [1]. The inner processing of BT networks relies on validating data using coded protocols and consensus mechanisms that are powered by the networks' peer nodes, then chronologically recording and securing such data in a chain of blocks via cryptography [2]. According to Chang et al. [3], Penzes et al. [4], the significant features of BT can be summarized as follows:

- Decentralization: The records are duplicated over the entire network's nodes, which signifies their availability and reduces the single point failure, corruption, or attack.
- Immutability: The record blocks have unique hashes that are linked together. As a result, the modification in a record block needs to make changes in its hash and the entire network's blocks.
- Transparency: The records' validation is performed by almost all peer nodes without using trusted third parties, which removes the hurdles to check the records every time requested by nodes.

Blockchain networks can be categorized into permissionless, permissioned, and consortium based on the ability-to-participate and add-validate-read privileges. The permissionless blockchain is also known as the public blockchain in which any participant can join and download the network protocol like Bitcoin and Ethereum. In such networks, the participant can add, validate or view transactions

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without restrictions regarding the write/read operations. Permissionless blockchains depend heavily on consensus mechanisms to ensure the reliability and consistency of transactions and guarantee the accuracy and security of ledgers. Most of permissionless blockchains have some challenges regarding performance, scalability, privacy, power consumption, dynamic data channels, and smart contracts support [4], [5]. The permissioned blockchain is also known as the private blockchain in which only predefined participants can join and download the network protocol like Hyperledger Fabric. In such networks, a pre-approved participant may have full operator privileges to add, validate or view transactions, writer privileges to only add and validate transactions, or reader privileges to only view transactions. Such privileges are pre-decided and settled in the initiation phase. However, permissioned blockchains may confront some concerns regarding centralization. They offer higher performance, lower block time and size, better scalability, higher data privacy, and more efficient consensus mechanisms compared to permissionless ones [5]. The consortium blockchain is a partially permissioned blockchain that allows participants' pre-definition and privileges without being owned by a single organization. Such blockchain operates under a group's governance, while offering the permissioned blockchain's benefits, including performance, scalability, privacy, and efficiency [6], [7].

Over the last decade, BT has been evolved through four major generations; Blockchain 1.0, 2.0, 3.0, and 4.0 [8], [9]. Blockchain 1.0 refers to the typical utilization of BT for managing and circulating cryptocurrencies, like Bitcoin. Blockchain 2.0 is related to the adoption of smart contracts as general-purpose programmable infrastructures that allow blockchain networks to automatically execute some logic based on predefined conditions then exchange or transact the generated computational outputs. Blockchain 3.0 denotes the expansion of Blockchain 2.0 applications in other industries or domains like healthcare, e-commerce, logistics, energy trading, and e-voting. Blockchain 4.0 is associated with integrating Artificial Intelligence (AI) technologies into BT applications. Currently, converging AI with BT applications is under intensive research and development in diverse domains such as healthcare records management [10], [11], [12], [13], supply chain management [14], [15], [16], construction project management [17], [18], [19], [20], and Internet of Things (IoT) [21], [22], [23], [24], [25], which has led to a mounting growth of literature. Such amount of scientific literature is overwhelming and challenging for scholars and practitioners to build an inclusive grasp of relevant information. Accordingly, many researchers have provided recent state-of-the-art studies on BT-AI with valuable contributions [26], [27], [28], [29], [30]. Despite that, these studies have followed a qualitative review approach which may be significantly impacted by subjective biases or judgments concerning the interpretation of findings based on researchers' cognitive limitations and values. Furthermore, they have not been able to dynamically recap and quantitatively analyze the field's development based on a vast number of research records over an extended time scale. In the light of these points, a study that affords a comprehensive quantitative analysis for the BT-AI literature is still missing. To seal this gap, the present study conducts a scientometric analysis for the research domain of BT-AI.

As a branch of information science, scientometric analysis is a quantitative approach that encompasses bibliometric methods and tools to explore and visualize the significant patterns, emerging trends, knowledge structures, and their evolution in research domains based on large bibliographic datasets [31], [32]. Such analysis is performed at the level of titles, keywords, abstracts, and/or citation records since these items are considered an evident and concise characterization for the researches' content and direction [33], [34], [35]. The study's objectives are; (1) Analyzing the annual growth of BT-AI publications and identifying the most impactful ones; (2) Identifying the key contributors (researcher, countries, and organizations) to the BT-AI research; (3) Identifying the top sources (journals) of BT-AI researches; and (4) Identifying the research hotspots and emerging themes. Accordingly, this study can contribute to the field in diverse ways by; (1) Helping practitioners and new researchers to secure a full understanding of the field; (2) Supporting decision-makers and institutions in planning and funding research efforts related to the BT-AI field; and (3) Identifying the promising research areas and detecting the gaps in the existing body of knowledge.

The remainder of this paper is structured as follows. Section II describes the research methodology in detail. Section III is related to data acquisition and preparation. Section IV describes the used methods and software tools. Section V comprises the results and findings from the scientometric analysis. Sections VI and VII provide thorough discussion and conclusions.

II. RESEARCH METHODOLOGY

The research methodology is structured to comprise three stages, as shown in Figure 1. The first stage is extracting the bibliographic data from the WoS Core Collection database. The second stage is specifying the analysis methods and the software tools. The third stage is related to analysis and findings and encloses four sub-stages: (1) analyzing the publication output and identifying the influential articles; (2) exploring the scientific collaboration networks in BT-AI research; (3) analyzing the sources' productivity and citation in BT-AI field; and (4) exploring and analyzing the conceptual knowledge structure of BT-AI literature.

III. DATA COLLECTION

The data source in this study was decided to be the WoS Core Collection database only rather than employing other databases, such as Scopus or Google Scholar. The rationale of this decision is illustrated as follows. First, the WoS database ensures the completeness, consistency, and reliability of research records concerning authors (full names),

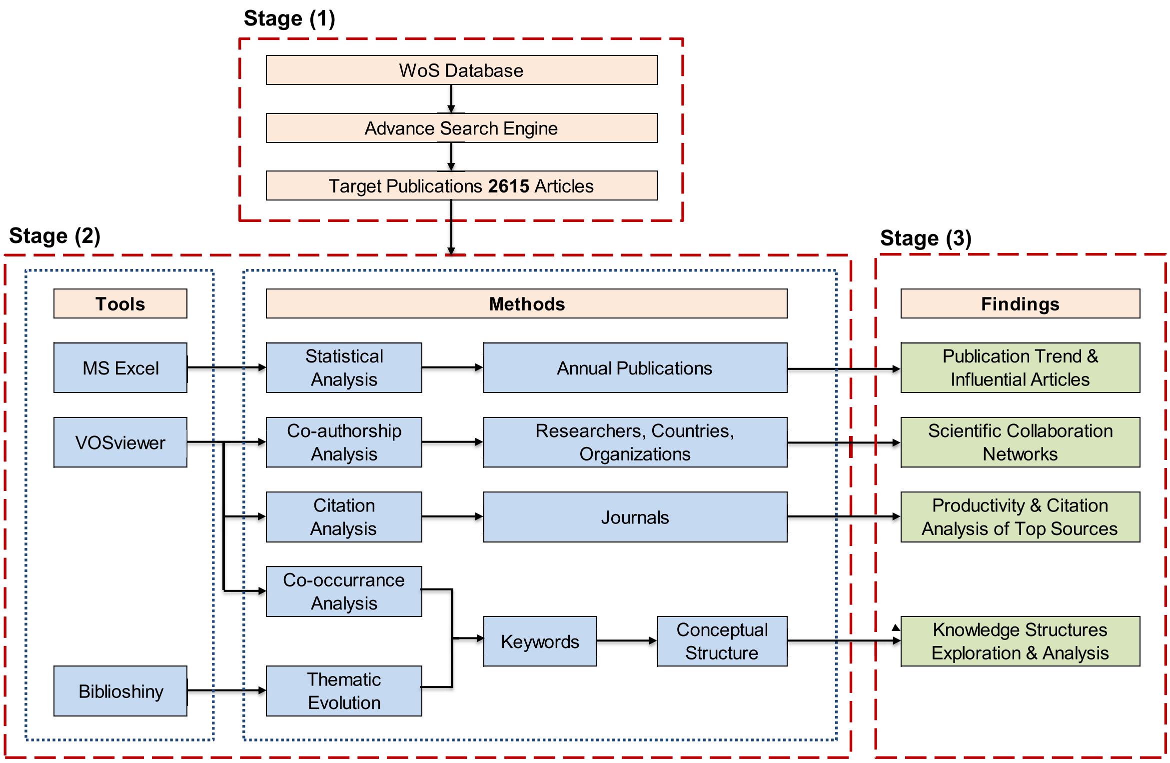


FIGURE 1. Research methodology map.

organizations (unified enhanced names), countries, and cited references. Second, WoS provides the option to perform an advanced search based on a string format, while permitting users to refine, edit and combine different search sets and develop detailed statistical reports about the research records. Third, using a single data source helps avoid duplications that would occur when using a combination of different literature databases. The main search terms were selected to be "blockchain", "block chain", "block-chain", "blockchains", "block chains", "block-chains", "hyperledger fabric", and "ethereum". These terms, along with terms "artificial intelligence", "machine learning", "deep learning", "reinforcement learning", "computer vision", "image processing", "neural network", "expert system", "fuzzy logic", "robotics", and "natural language processing" were used to direct the literature search towards the BT-AI related publications, while utilizing the following query string format:

TS = ("blockchain") OR TS = ("block chain") OR TS = ("block-chain") OR TS = ("blockchains") OR TS = ("block chains") OR TS = ("block-chains") OR TS = ("hyperledger fabric") OR TS = ("ethereum"))

AND

(TS = ("artificial intelligence") OR TS = ("machine learning") OR TS = ("Deep Learning") OR TS = ("reinforcement learning") OR TS = ("computer vision") OR TS = ("image processing") OR TS = ("neural network") OR TS = ("expert system") OR TS = ("fuzzy logic") OR TS = ("robotics") OR TS = ("natural language processing"))

LANGUAGE: (English)

DOCUMENT TYPES: (Article)

Timespan = 2017-2023

The literature search was conducted on the title, abstract, author keywords, and keywords-plus sections of publications using the terms mentioned above. The "date range" was set between 2017 and 2023. The "document type" was restricted to "article". The rationale for selecting peer-reviewed journal articles only is clarified' as follows. First, for science mapping purposes, this type of publication represents the most important reputable research work. Second, including all publication types like "review", "book", "book chapter", "book review", "proceedings paper", and "letter" would add noise to the bibliographic data and make the analyses' findings misleading. The "publication language" was limited to English only. Accordingly, in July 14th, 2023, 2615 publications were identified. All bibliographic data for these publications, including (full record and cited references), were exported and downloaded as a plain text file to form the dataset for conducting the scientometric analysis and visualization.

IV. BIBLIOMETRIC METHODS

In line with the aforementioned objectives, the bibliometric methods involved in this study are co-authorship analysis, citation analysis, keywords co-occurrence analysis, and keywords thematic evolution.

- Co-authorship analysis is a quantitative method that detects the collaboration patterns between researchers, organizations, or countries based on the number of their co-authored publications [36], [37].
- Citation analysis is a quantitative method that measures the relatedness between documents, researchers, organizations, countries, or sources based on the number of times they cite each other [36], [37].
- Keywords co-occurrence analysis is a quantitative method that measures the interconnection between keywords based on the number of publications in which they appear together [31], [36], [38].
- Keywords thematic evolution is a method that dynamically analyzes and explores the keywords' developmental tendency over multiple successive time-slices [39], [40].

Several scientometric tools exist with diverse strengths and capabilities. This study uses two scientometric software VOSviewer and Biblioshiny to analyze and visualize the extracted 2615 publications. VOSviewer is a software tool that uses the VOS mapping technique to produce and visualize bibliometric networks in an easy-to-understand way, while being able to handle large-scale data [41]. In this study, VOSviewer is used to map and visualize the scientific collaboration between researchers, countries, and organizations using the co-authorship analysis function. Moreover, it is used to identify the top sources in the BT-AI field using the citation analysis function and to explore and map the relations between publications' keywords using the co-occurrence analysis function. Biblioshiny is a web interface that performs science mapping analysis based on the main functions of the bibliometrix R-package that was introduced by Aria and Cuccurullo [39]. In this study, Biblioshiny is used to map and visualize the research themes' temporal evolution and distribution based on the author-keywords using the thematic evolution function.

V. ANALYSIS AND FINDINGS

A. PUBLICATION TREND AND INFLUENTIAL ARTICLES

1) ANALYSIS OF PUBLICATION OUTPUTS

The number of annual publications is a remarkable indicator that reflects the scientific research trends, knowledge accumulation, and maturity [37], [42]. Figure 2 depicts the number of BT-AI research articles published between 2017 and 2023 in chronological order. The number of articles published between Jan 2017 – Dec 2018 was 41 articles. However, after 2018, the number of articles experienced rapid growth with 126 articles in 2019, 311 articles in 2020, 579 articles in 2021, 995 articles in 2022, and 563 articles till July 14th, 2023 while it is estimated to reach 1043 articles by the end of 2023. This growth reveals that BT-AI research becomes more prevalent and interdisciplinary as time passes. Moreover, it refers to the BT-AI field as a promising area for further study and exploration.

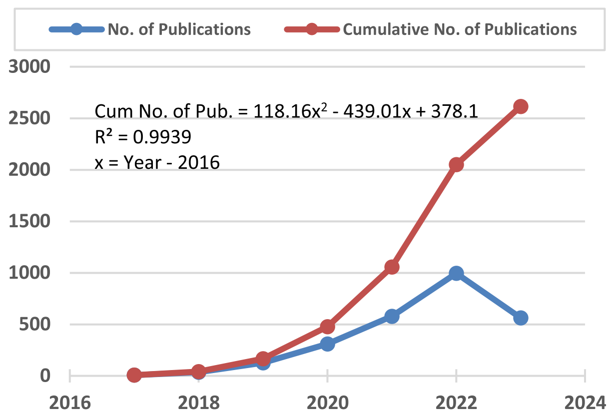


FIGURE 2. Publications growth over time.

2) INFLUENTIAL ARTICLES

Identifying the most impactful publications is beneficial for determining the high-demand scientific areas in a certain field [38], [43]. Accordingly, the most impactful publications were identified based on three major indices; citations score (CS), local citations score (LCS), and document average citations per year (DACY). CS is a reliable measure to capture the overall scientific value and influence for a publication, while LCS between the extracted bibliographic data is a direct measure for the publications' deep influence in a certain field and the knowledge evolution over related publications. However, such scores take time probably years to accumulate [44]. Therefore, the DACY was calculated and used in tandem with CS and LCS to tackle the publishing year effect. Based on these indices, the top 20 publications with the highest CS, the top 20 publications with the highest DACY, and the top 20 publications with the highest LCS are tabulated in Table 1. Interestingly, 18 out of the 20 most cited publications were published between 2019 and 2020, while 16 out of the 20 most local cited publications were also published between 2018 and 2020. In contrast, 13 out of the top 20 publications concerning the DACY were published between 2019 and 2020. Such finding is consistent with what was previously stated about being CS and LCS not able to entirely capture the scientific value or influence of publications.

B. SCIENTIFIC COLLABORATION NETWORKS IN BT-AI RESEARCH: CO-AUTHORSHIP ANALYSIS

Exploring the scientific collaboration patterns for a specific research domain can facilitate access to expertise and funds and widen the knowledge extent. According to [37] and [45], such patterns can be reliably recognized and tracked through analyzing and visualizing the co-authorship networks. In this light, an analysis for the co-authorship networks in terms of researchers, countries, and organizations is provided in the next sub-sections.

TABLE 1. Influential BT-AI publications.

Title	DOI	Year	CS	LCS	DACY
Building Dynamic Capabilities for Digital Transformation: An Ongoing Process of Strategic Renewal	10.1016/j.lrp.2018.12.001	2019	532	4	106
A Survey on IoT Security: Application Areas, Security Threats, and Solution Architectures	10.1109/ACCESS.2019.2924045	2019	447	27	89
Blockchain and Federated Learning for Privacy-Preserved Data Sharing In Industrial IoT	10.1109/TII.2019.2942190	2020	408	90	102
Digital Twin: Enabling Technologies, Challenges and Open Research	10.1109/ACCESS.2020.2998358	2020	388	6	97
6G Wireless Communication Systems: Applications, Requirements, Technologies, Challenges, and Research Directions	10.1109/OJCOMS.2020.3010270	2020	342	15	86
Impact of Covid-19 Pandemic on Information Management Research and Practice: Transforming Education, Work and Life	10.1016/j.ijinfomgt.2020.102211	2020	328	2	82
On Big Data, Artificial Intelligence and Smart Cities	10.1016/j.cities.2019.01.032	2019	300	10	60
The Future of Healthcare Internet of Things: A Survey of Emerging Technologies	10.1109/COMST.2020.2973314	2020	285	15	71
Incentive Mechanism for Reliable Federated Learning: A Joint Optimization Approach To Combining Reputation and Contract Theory	10.1109/JIOT.2019.2940820	2019	272	45	54
Blockchained On-Device Federated Learning	10.1109/LCOMM.2019.2921755	2020	263	83	66
Time To Seize The Digital Evolution: Adoption of Blockchain In Operations and Supply Chain Management Among Malaysian SMEs	10.1016/j.ijinfomgt.2019.08.005	2020	243	17	61
Industry 5.0: A Survey on Enabling Technologies and Potential Applications	10.1016/j.jii.2021.100257	2022	236	11	118
Efficient and Privacy-Enhanced Federated Learning for Industrial Artificial Intelligence	10.1109/TII.2019.2945367	2020	228	22	57
Industry 4.0: Opportunities and Challenges for Operations Management	10.1287/msom.2019.0796	2020	223	5	56
Reliable Federated Learning for Mobile Networks	10.1109/MWC.001.1900119	2020	205	35	51
Deepchain: Auditable and Privacy-Preserving Deep Learning With Blockchain-Based Incentive	10.1109/TDSC.2019.2952332	2021	194	78	65
Privacy-Preserving Support Vector Machine Training Over Blockchain-Based Encrypted IoT Data In Smart Cities	10.1109/JIOT.2019.2901840	2019	191	45	38
The Strategic Role of Logistics In The Industry 4.0 Era	10.1016/j.tre.2019.06.004	2019	186	8	37
Industrial Internet of Things: Recent Advances, Enabling Technologies and Open Challenges	10.1016/j.compeleceng.2019.106522	2020	180	6	45
Blockchain and Deep Reinforcement Learning Empowered Intelligent 5G Beyond	10.1109/MNET.2019.1800376	2019	175	54	35
Cooperative Computation Offloading and Resource Allocation for Blockchain-Enabled Mobile-Edge Computing: A Deep Reinforcement Learning Approach	10.1109/JIOT.2019.2961707	2020	174	35	44
Blockchain Empowered Asynchronous Federated Learning for Secure Data Sharing In Internet of Vehicles	10.1109/TVT.2020.2973651	2020	173	56	43
Performance Optimization for Blockchain-Enabled Industrial Internet of Things (Iiot) Systems: A Deep Reinforcement Learning Approach	10.1109/TII.2019.2897805	2019	173	56	35
Blockiotintelligence: A Blockchain-Enabled Intelligent IoT Architecture With Artificial Intelligence	10.1016/j.future.2019.09.002	2020	170	41	43
Swarm Learning for Decentralized and Confidential Clinical Machine Learning	10.1038/s41586-021-03583-3	2021	165	20	55
An Empirical Study on Modeling and Prediction of Bitcoin Prices With Bayesian Neural Networks Based on Blockchain Information	10.1109/ACCESS.2017.2779181	2018	162	37	27
Blockchain-Enabled Data Collection and Sharing for Industrial IoT With Deep Reinforcement Learning	10.1109/TII.2018.2890203	2019	158	41	32
Decentralized Privacy Using Blockchain-Enabled Federated Learning In Fog Computing	10.1109/JIOT.2020.2977383	2020	157	53	39
Federated Learning With Blockchain for Autonomous Vehicles: Analysis and Design Challenges	10.1109/TCOMM.2020.2990686	2020	143	52	36
Privacy-Preserving Blockchain-Based Federated Learning for IoT Devices	10.1109/JIOT.2020.3017377	2021	143	48	48
IoT, Big Data, and Artificial Intelligence In Agriculture and Food Industry	10.1109/JIOT.2020.2998584	2022	125	6	63
A Blockchained Federated Learning Framework for Cognitive Computing In Industry 4.0 Networks	10.1109/TII.2020.3007817	2021	116	34	39
Blockseciotnet: Blockchain-Based Decentralized Security Architecture for IoT Network	10.1016/j.jnca.2019.06.019	2019	116	34	23
Machine Learning Adoption In Blockchain-Based Smart Applications: The Challenges, and A Way Forward	10.1109/ACCESS.2019.2961372	2020	114	36	29
Transforming Business Using Digital Innovations: The Application of Ai, Blockchain, Cloud and Data Analytics	10.1007/s10479-020-03620-w	2022	111	9	56
Federated Learning Meets Blockchain In Edge Computing: Opportunities and Challenges	10.1109/JIOT.2021.3072611	2021	110	37	37
A Survey on Metaverse: Fundamentals, Security, and Privacy	10.1109/COMST.2022.3202047	2023	98	0	98
Federated Learning for Smart Healthcare: A Survey	10.1145/3501296	2023	52	5	52

1) RESEARCHERS

Researchers are the knowledge producers. Hence, a detailed analysis for the researchers' productivity, citation, and co-authorship can easily identify the pioneer ones and explore their social cooperation patterns. This is beneficial for junior researchers to find opportunities for future collaborations and enlarge their research networks [38], [44]. Based on the 2615 publications in which 8466 different researchers were credited, the co-authorship was mapped in Figure 3 using VOSviewer. For network processing, the thresholds for the number of documents per author (NP), number of citations per author (CS), and total link strength (TLS) were set at 5, 50, and 1, respectively, to clearly identify the prominent researchers (n = 126). In Figure 3, each node refers to a specific researcher, while the lines between nodes refer to the collaboration relations between researchers, and their thickness reflects the researchers' collaboration strength in terms of mutual documents. The nodes' size variation and coloring scheme in Figure 3a refer to the researchers' number of publications and the count of their collaboration relations, respectively. In contrast, the nodes' size variation and coloring scheme in Figure 3b reflect the researchers' citations score and their average citation per document, respectively. Table 2 lists the pioneer researchers of BT-AI domain in terms of NP, collaboration links (CL), CS, and average citations per document (ACD). Through Figure 3 and Table 2, a number of interesting observations can be deduced.

Regarding the document productivity, Sudeep Tanwar was the top productive researcher with 46 documents. Sudeep Tanwar research interests were related to BT-AI applications in privacy protection [46], [47], supply-chain management [48], Healthcare [49], [50], [51], unmanned ariel vehicles [52], [53], [54], and cryptocurrency price prediction [55], [56], [57].

Regarding the collaboration intensity, Dusit Niyato was the top collaborated researcher with 25 collaboration links. Dusit Niyato research interests were related to BT-AI applications in federated learning [58], [59], [60], [61], [62], Digital twin [63], resource management/sharing [64], [65], [66], and Metaverse [67], [68], [69].

Concerning the strength of collaboration, the strongest collaborations were among Rajesh Gupta-Sudeep Tanwar (25 Mutual Documents), Yung-Cheol Byun-Zeinab Shahbazi (13 Mutual Documents), Neeraj Kumar-Sudeep Tanwar (13 Mutual Documents), Randhir Kumar-Rakesh Tripathi (13 Mutual Documents), Govind P. Gupta-Prabhat Kumar (12 Mutual Documents), Govind P. Gupta-Rakesh Tripathi (12 Mutual Documents), Prabhat Kumar-Randhir Kumar (12 Mutual Documents), Prabhat Kumar-Rakesh Tripathi (12 Mutual Documents), Pronaya Bhattacharya-Sudeep Tanwar (11 Mutual Documents), Govind P. Gupta-Randhir Kumar (11 Mutual Documents), Jianhua Li-Jun Wu (11 Mutual Documents), and Dinh C. Nguyen-Pubudu N. Pathirana (10 Mutual Documents). This type of intense collaborations ($\geq$ 10 mutual documents) was very limited and represents less than 5% of the total collaborations (363 relations) shown in Figure 3.

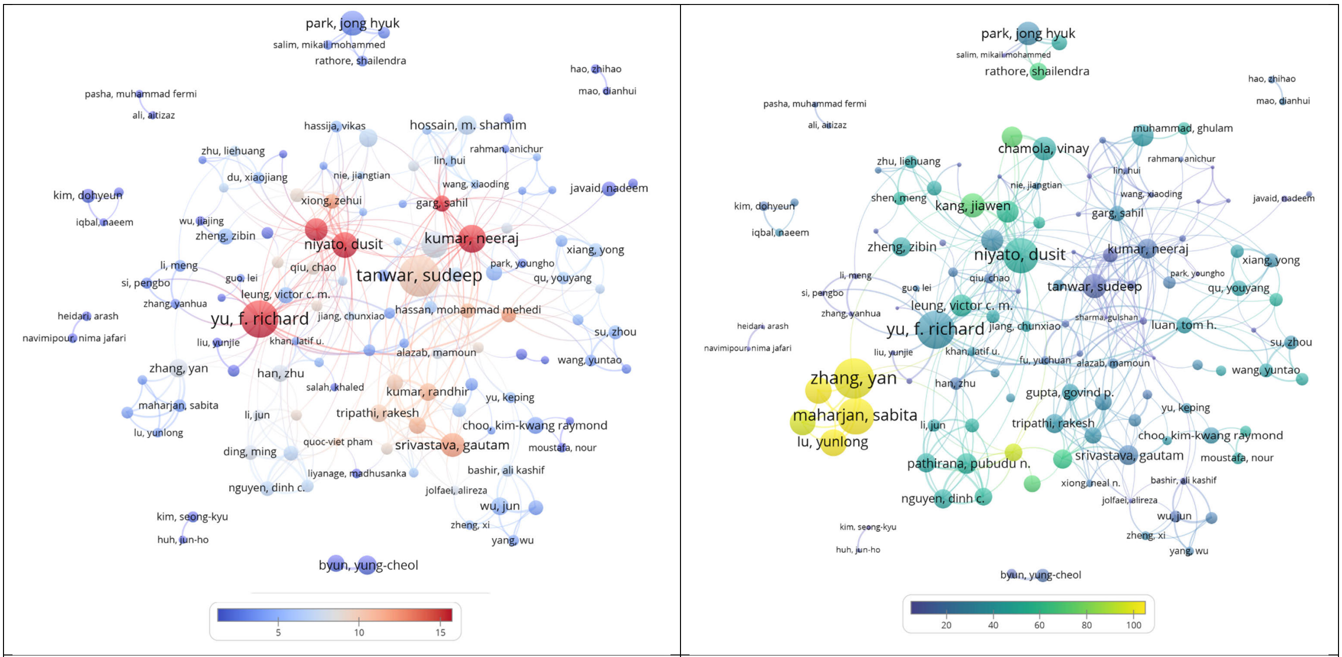
TABLE 2. Top BT-AI researchers.

Author	Organization	Country	APY	NP	CL	CS	ACD
Sudeep Tanwar	Nirma University	India	2021.8	46	10	694	15
F. Richard Yu	Carleton University	Canada	2021.0	40	21	1334	33
Neeraj Kumar	Thapar Institute of Engineering and Technology	India	2021.7	27	25	537	20
Rajesh Gupta	Nirma University	India	2021.9	25	8	339	14
Dusit Niyato	Nanyang Technological University	Singapore	2021.3	24	25	1181	49
Mohsen Guizani	Qatar University	Qatar	2021.4	20	24	622	31
Yan Zhang	Oslo University	Norway	2020.6	15	8	1459	97
Sahil Garg	Ultra Communications	Canada	2021.3	12	17	378	32
Sabita Maharjan	Oslo University	Norway	2020.2	9	4	1257	140
Ke Zhang	University of Electronic Science and Technology of China	China	2020.5	8	4	749	94
Yunlong Lu	Beijing University of Posts and Telecommunications	China	2020.7	6	4	815	136
Xiaohong Huang	Beijing University of Posts and Telecommunications	China	2021.0	6	4	782	130

Regarding the citation/influence and the average citations per document, Yan Zhang was the most influential/cited researcher with 1459 citations, while Sabita Maharjan had the most average citation score with 140 citations per document. Both researchers co-authored a lot and their research interests were directed towards BT-AI applications for industrial IoT [70], [71], 5G and beyond [72], [73], internet of vehicles [74], digital twin [75], [76], [77], and vehicular edge computing and networks [78].

2) COUNTRIES

Investigating the countries' scientific collaboration helps in exploring the geographical distribution of publications and identifying the influential countries in the BT-AI field [31], [35]. Using VOSviewer, the co-authorship network for countries was created, as shown in Figure 4. For network processing, the thresholds for NP, CS, and TLS were set at 5, 50, and 1, respectively. As a result, out of 109 countries, only 64 met the thresholds and were included for analysis. In Figure 4, each country is represented by a definite node, while the lines between nodes refer to the collaboration relations between countries, and their thickness reflects the countries' collaboration strength in terms of mutual documents. In contrast, the nodes' size variation and coloring scheme in Figure 4a and 4b were set as per Figure 3a and 3b, respectively. Table 3 encloses the leading countries in BT-AI research with respect to NP, CL, CS, and ACD. Based on Figure 4 and Table 3, several important findings were noted. In contrary to the researchers' network in Figure 3, the countries' network is more homogenous



(a) Overlay Visualization Based on NP and CL

(b) Overlay Visualization Based on CS and ACD

FIGURE 3. Co-authorship network for researchers.

and fully interconnected [33]. China, in tandem with USA and India, stand out as the superior countries in the BT-AI research with respect to the number of publications, the extent of collaboration, and the total citations score. This implies the dominant role of these three countries in enriching and moderating the BT-AI research globally.

Concerning the strength of collaboration, the strongest collaborations were among China-USA (113 mutual documents), China-Canada (83 mutual documents), India-Saudi Arabia (81 mutual documents), China-Australia (47 mutual documents), China-England (47 mutual documents), India-USA (46 mutual documents), Saudi Arabia-Pakistan (45 mutual documents), India-Taiwan (44 mutual documents), China-Japan (40 mutual documents), China-Saudi Arabia (39 mutual documents), China-India (37 mutual documents), USA-South Korea (37 mutual documents), China-Singapore (33 mutual documents), USA-Australia (31 mutual documents), Saudi Arabia-Egypt (31 mutual documents), China-South Korea (30 mutual documents), USA-Canada (28 mutual documents), India-South Korea (28 mutual documents), India-Australia (26 mutual documents), Saudi Arabia-Canada (26 mutual documents), Saudi Arabia-England (26 mutual documents), South Korea-Pakistan (25 mutual documents), Saudi Arabia-Taiwan (25 mutual documents), India-England (23 mutual documents), USA-Saudi Arabia (23 mutual documents), Canada-Taiwan (22 mutual documents), Saudi Arabia-South Korea (22 mutual documents), India-Canada (21 mutual documents), and USA-England (21 mutual documents). This highlights that the organizations in such eminent countries followed analogous policies on boosting the intellectual collaboration with each other to further improve global knowledge exchange in the BT-AI research. Moreover, this type of intense collaborations (more than 20 mutual documents) was very limited and mainly existed among a few developed countries, while representing less than 5% of the total collaborations (810 relations) shown in Figure 4. This may indicate the need for extra cross-country publications to promote more international collaboration in the BT-AI research. Concerning the average citations per document, Denmark, New Zealand, Scotland, Wales, and Sweden had the highest ACD score ($\geq$40), which reflects the robust impact of their publications on the BT-AI research community.

3) ORGANIZATIONS

Exploring and analyzing the collaboration, productivity of organizations that have high interest and investment in the BT-AI research can assist in supporting potential academic partnerships, fund allocation, and policy-making [37], [79]. Using VOSviewer, the co-authorship network for organizations was created, as shown in Figure 5. The network was visualized based on the same configurations for processing the countries' network concerning the selection thresholds, nodes' size variation, and coloring schemes. As a result, out of 3221 organizations, only 226 were identified and included for analysis. Table 4 lists the leading organizations with respect to NP, CL, CS, and ACD.

As shown in Figure 5 and Table 4, King Saud University (66 documents, 1304 citations) and University of Electronic Science and Technology of China (40 documents, 2097 citations) were the top contributors in terms of document productivity and total citations score. For the extent of

TABLE 3. Top contributing countries in BT-AI field.

Country	APY	NP	CL	CS	ACD
China	2021.6	867	54	14406	17
India	2021.9	512	54	6359	12
USA	2021.3	393	60	9726	25
Saudi Arabia	2021.9	258	51	3124	12
South Korea	2021.4	216	41	5088	24
England	2021.4	188	55	4418	24
Sweden	2021.6	25	24	1011	40
Scotland	2021.6	22	25	953	43
Denmark	2021.0	17	18	783	46
Wales	2021.5	11	16	470	43
New Zealand	2021.2	9	11	411	46

collaboration, King Saud University in tandem with Nanyang Technological University and Xidian University had the widest collaboration network with 43 collaboration relations. Concerning the strength of collaboration, Brandon University and China Medical University built the deepest collaborative relation with 21 mutual documents as evinced by the wideness of their connecting line. Nevertheless, the intensity of deep organizational collaborations (more than 5 mutual documents) was very limited and generally represented less than 5% of the total collaborations (1303 relations) shown in Figure 5. This indicates, to some extent, the need for building more multi-organization consortiums to foster the scientific collaboration and knowledge evolution in BT-AI research. Regarding the ACD values, Simula Metropolitan Center for Digital Engineering in Norway had the highest ACD score (131), which indicates the high scientific impact of its publications.

Further, it is worth mentioning that among the leading organizations in Table 5, there are three organizations located in China which it refers to its outstanding endeavors in enriching the BT-AI research and is consistent with the finding in previous section about being China the top-ranked contributor in terms of total citations score and total number of publications.

C. TOP SOURCES FOR RESEARCH ON BT-AI: DIRECT CITATION ANALYSIS

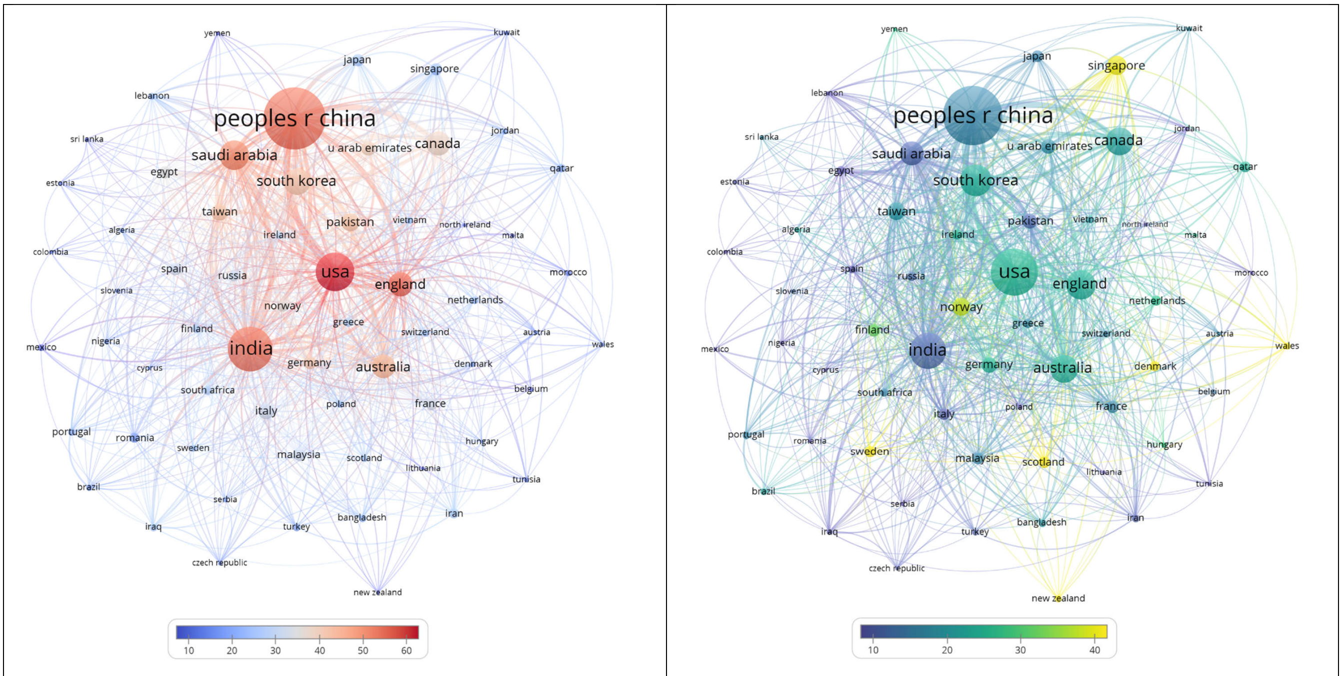
The productivity and citation analysis for sources is an effective method to explore and identify the pioneer ones in the BT-AI field [44]. Such analysis could be beneficial for editorial boards to adjust and refine the scope of their sources, for readers to find the dependable sources of information, and for authors to specify the best-fit sources for publishing their studies. In this study, the direct citation network of sources was generated using VOSviewer, as shown in Figure 6. For network processing, the thresholds for NP, CS, and TLS were set at 5, 50, and 1, respectively. As a result, out of 753 sources, only 78 met the thresholds and were included for analysis. In Figure 6, each source is represented by a specific node, while the lines between nodes refer to the local citation relations between sources, and their thickness reflects the sources' local citation intensity. In contrast, the nodes' size variation and coloring scheme in Figure 6a and 6b were also set as per Figure 3a and 3b, respectively. Table 5 lists the pioneer sources of BT-AI domain in terms of NP, CS, and ACD. Using Figure 6 and Table 5, some important findings can be disclosed. Regarding the source productivity, IEEE Access was the most productive source for research on BT-AI with 180 documents (accounting for 6.88%) and was followed by IEEE Internet of Things Journal, Sensors, Electronics, and Sustainability in descending order. These sources only constitute around 19% of the total published documents. Concerning the total citations score, IEEE Access was also the most cited source with 3944 citations and was succeeded by IEEE Internet of Things Journal, IEEE Transactions on Industrial Informatics, IEEE Communications Surveys and Tutorials, and IEEE Network, respectively. These sources only constitute around 32% (12492/ 38910) of the overall citations for the 2615 published documents. In contrast, International Journal of Information Management, IEEE Open Journal of the Communications Society, Journal of Industrial Information Integration, IEEE Communications Surveys and Tutorials, and IEEE Transactions on Industrial Informatics were the sources with the highest ACD values. With respect to the sources' local citation lines, Darko et al. [31] stated that the number of local citation lines for top productive and cited sources could act as a straightforward indicator for the bi-directional flow of information between sources. Hence, there was significant information flow (through local citations) IEEE Access, IEEE Internet of Things Journal, Sensors, Electronics, Sustainability, IEEE Transactions on Industrial Informatics, IEEE Network, IEEE Communications Surveys and Tutorials, International Journal of Information Management, IEEE Open Journal of the Communications Society, and Journal of Industrial Information Integration to the remaining 67 sources in the network by more than 400 flows of local citations.

D. STRUCTURES OF THE BODY OF KNOWLEDGE ON BT-AI

Author-Keywords are the terms that refer to the topic and focal concept of publications. Therefore, analyzing keywords affords a great potential for characterizing the prime interests in a given research field [37], [38], [79]. In this study, the keywords were analyzed based on their co-occurrence frequency and their thematic evolution over time.

1) KEYWORDS CO-OCCURRENCE NETWORK

The keywords co-occurrence network is able to characterize and explicate the conceptual structure for a particular research domain while shedding light on its major topics and how these topics are cognitively associated and organized [32], [80]. Using VOSviewer, the co-occurrence network was created, as shown in Figure 7. For network processing, the thresholds of keyword frequency and TLS were set at 10, and 1 respectively. At the same time, a thesaurus file was also used to merge identical terms in the network, for instance, 'big-data' to 'big data', 'iot' to 'internet of things', 'iiot' to 'industrial internet of things' and block-chain to 'blockchain'.



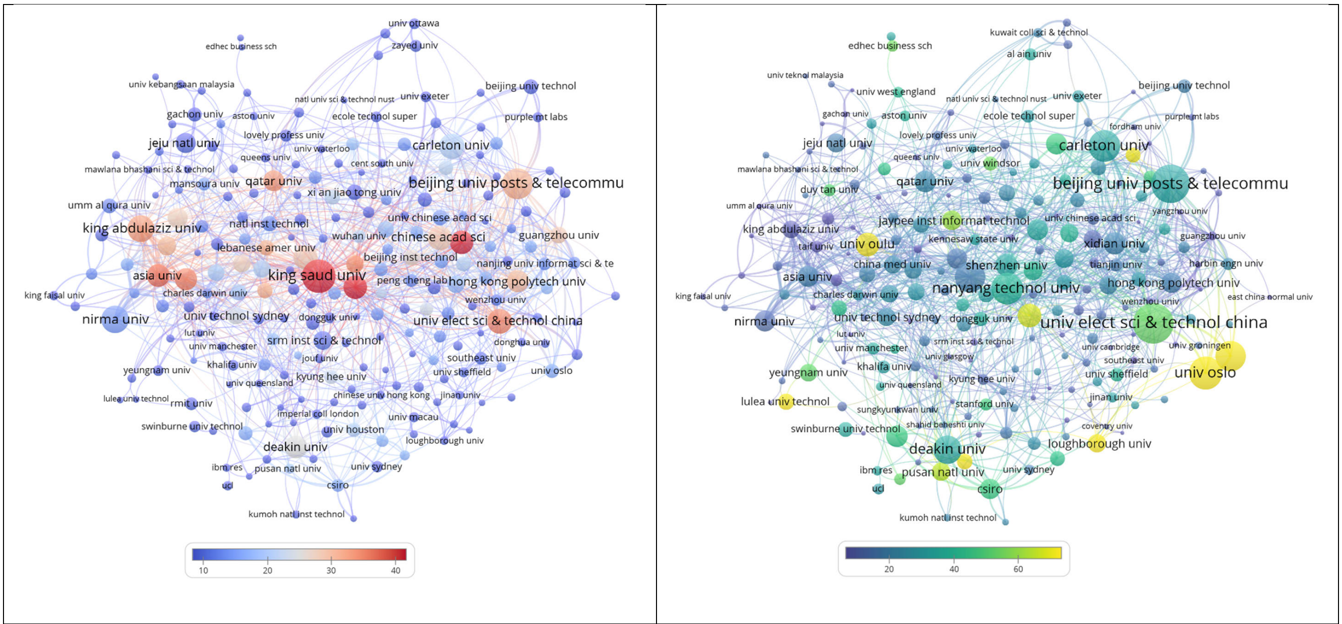
(a) Overlay Visualization Based on NP and CL

(b) Overlay Visualization Based on CS and ACD

FIGURE 4. Co-authorship network for countries.

Accordingly, 174 out of 5528 keywords were identified and included in the network. In Figure 7, each keyword is represented by a node, while the lines between nodes refer to the co-occurrence relations between keywords, and their thickness reflects the keywords' co-occurrence strength in terms of mutual documents. In contrast, the nodes' size variation and coloring scheme in Figure 7 refer to the keywords' frequency and the count of their co-occurrence relations, respectively. Table 6 shows the top keywords in BT-AI research that were extensively investigated in the extracted bibliographic data in terms of frequency and co-occurrence relations. The ranking and the relatedness of the keywords – as shown in Table 6 and Figure 7, respectively – disclose some important findings. With excluding the search terms, the keywords 'internet of things', 'security', 'smart contracts', 'federated learning', 'privacy', 'edge computing', 'digital currencies', 'servers', 'industry 4.0', 'cloud computing', 'data models', 'big data', 'covid-19', 'task analysis', 'computational modeling', 'training, data privacy', and '5g' were at the forefront of the top keywords that received immense attention from the BT-AI research community over the last seven years. Accordingly, these keywords were further analyzed using the three-field-plot function in Biblioshiny to deeply detect and visualize their relations with the top 10 productive authors and sources as depicted in Figure 8 and summarized as follows:

- The keyword '**internet of things**' was targeted and explored by all of the top authors and 5 of the top sources while it was intensively co-occurred with 'blockchain' in 340 documents, 'artificial intelligence' in 138 documents, 'security' in 87 documents, 'machine learning' in 84 documents, and 'deep learning' in 56 documents.
- The keyword '**security**' was targeted and explored by all of the top authors and 4 of the top sources while it was intensively co-occurred with 'blockchain' in 216 documents, 'privacy' in 83 documents, 'artificial intelligence' in 56 documents, 'machine learning' in 49 documents, and 'deep learning' in 42 documents.
- The keyword '**smart contracts**' was targeted and explored by all of the top authors and 4 of the top sources while it was intensively co-occurred with 'blockchain' in 180 documents, 'machine learning' in 40 documents, 'artificial intelligence' in 32 documents, 'internet of things' in 30 documents, and 'security' in 26 documents.
- The keyword '**federated learning**' was targeted and explored by 9 of the top authors and 4 of the top sources while it was intensively co-occurred with 'blockchain' in 147 documents, 'data models' in 49 documents, both of 'internet of things' and 'training' in 41 documents, and 'security' in 39 documents.
- The keyword '**privacy**' was targeted and explored by 9 of the top authors and 4 of the top sources while it was intensively co-occurred with 'blockchain' in 92 documents, 'federated learning' in 35, 'internet of things' in 31 documents, and both of 'artificial intelligence' and 'machine learning' in 29 documents.
- The keyword '**edge computing**' was targeted and explored by none of the top authors and 4 of the top sources while it was intensively co-occurred with 'blockchain' in 89 documents, 'internet of things' in 53 documents, 'cloud computing' in 25 documents, 'artificial intelligence' in 22 documents and both of



(a) Overlay Visualization Based on NP and CL

(b) Overlay Visualization Based on CS and ACD

FIGURE 5. Co-authorship network for organizations.

'federated learning', 'machine learning' and 'servers' in 20 documents.

- The keyword '**digital currencies**' was targeted and explored by only none of the top authors and 4 of the top sources while it was intensively co-occurred with 'blockchain' in 49 documents, 'bitcoin' in 33 documents, 'machine learning' in 24 documents, 'artificial intelligence' in 18 documents, and 'ethereum' in 16 documents.
- The keyword '**servers**' was targeted and explored by none of the top authors and 2 of the top sources while it was intensively co-occurred with 'blockchain' in 74 documents, both of 'federated learning' and 'training' in 36 documents, 'data models in 33 documents, and 'security' in 32 documents.
- The keyword '**industry 4.0**' was targeted by none of the top authors and 4 of the top sources while it was intensively co-occurred with 'blockchain' in 45 documents, 'artificial intelligence' in 32 documents, 'internet of things' in 28 documents, 'digitalization' in 12 documents, and 'big data' in 10 documents.
- The keyword '**cloud computing**' was targeted and explored by none of the top authors and 5 of the top sources while it was intensively co-occurred with 'blockchain' in 67 documents, 'internet of things' in 44 documents, 'artificial intelligence' in 29 documents, both of 'security' and 'machine learning' in 24 documents, and 'servers' in 19 documents.
- The keyword '**data models**' was targeted and explored by none of the top authors and 2 of the top sources while it was intensively co-occurred with 'blockchain' in 72 documents, 'training' in 42 documents, 'computational modeling' in 35 documents, both of 'machine learning', 'security', and 'collaborative work' in 24 documents.
- The keyword '**big data**' was targeted and explored by none of the top authors and 5 of the top sources while it was intensively co-occurred with 'blockchain' in 58 documents, 'artificial intelligence' in 48 documents, 'internet of things' in 39 documents, 'machine learning' in 17 documents, and 'digitalization' in 10 documents.
- The keyword '**covid-19**' was targeted and explored by none of the top authors and 5 of the top sources while it was intensively co-occurred with 'blockchain' in 37 documents, 'artificial intelligence' in 24 documents, 'internet of things' in 20 documents, 'machine learning' in 15 documents, and 'deep learning' in 14 documents.
- The keyword '**task analysis**' was targeted and explored by none of the top authors and 2 of the top sources while it was intensively co-occurred with 'blockchain' in 66 documents, 'servers' in 30 documents, 'reinforcement learning' in 29 documents, 'computational modeling' in 22 documents, and 'data models' in 20 documents.

2) THEMATIC DISTRIBUTION AND EVOLUTION

Even though Figures 7-8 and Table 6 provided important findings regarding the overall up-to-date state of keywords, they were not able to reflect or illustrate their evolution and distribution over time. This may not be contributory for evaluating and capturing the temporal development and relevance of research trends. For this regard, the thematic evolution function in Biblioshiny was used. The thematic evolution function allows analyzing and mapping the keywords' evolution over multiple successive time slice maps, as shown in

TABLE 4. Top contributing organizations in BT-AI field.

Organization	Country	APY	NP	CL	CS	ACD
King Saud University	Saudi Arabia	2021.5	66	43	1304	20
Beijing University of Posts & Telecommunications	China	2021.4	58	31	1912	33
Nirma University	India	2021.8	47	14	697	15
King Abdulaziz University	Saudi Arabia	2022.0	45	33	514	11
Carleton University	Canada	2020.9	41	21	1374	34
University of Electronic Science and Technology of China	China	2021.3	40	35	2097	52
Xidian University	China	2021.8	37	43	780	21
Nanyang Technological University	Singapore	2021.4	36	43	1384	38
Asia University	Taiwan	2021.5	35	36	716	21
University of Oslo	Norway	2020.6	16	16	1505	94
Simula Metropolitan Center for Digital Engineering	Norway	2020.3	10	8	1311	131
Loughborough University	England	2020.6	7	10	564	81
Copenhagen Business School	Denmark	2021.2	6	5	434	72
Lulea University of Technology	Sweden	2020.8	5	4	457	91

TABLE 5. Top sources in BT-AI field.

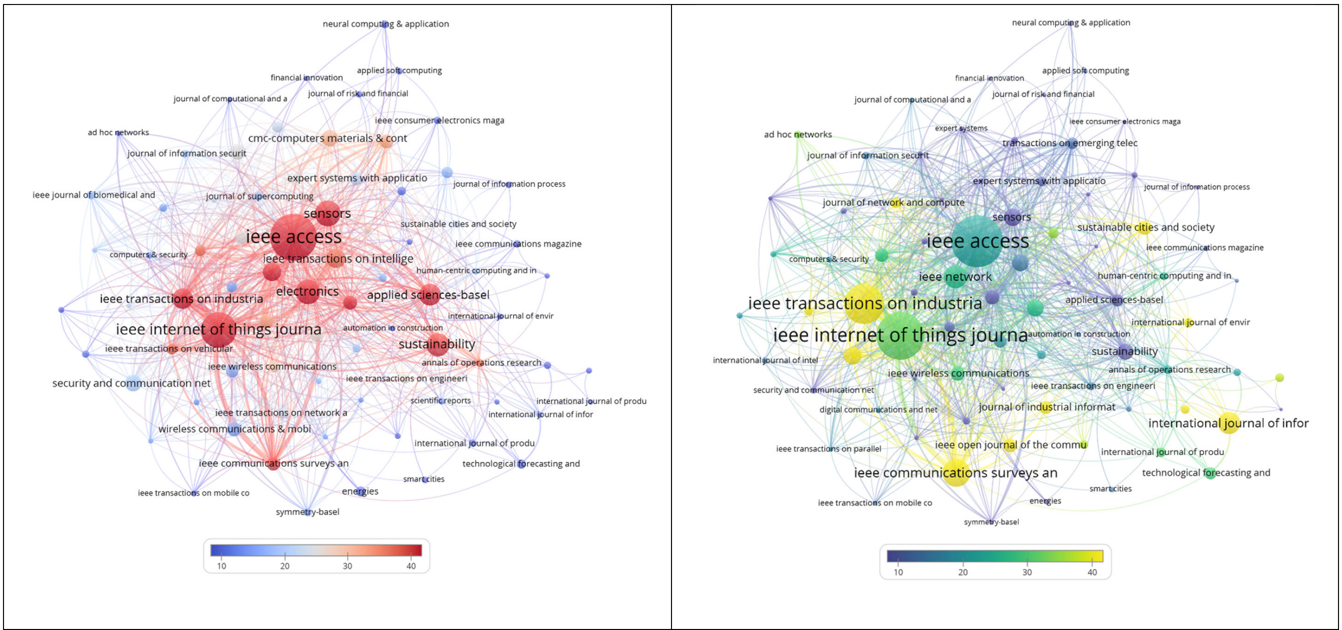
Source Title	APY	LCL	NP	CS	ACD
IEEE Access	2021.2	68	180	3994	22
IEEE Internet of Things Journal	2021.6	56	113	3508	31
Sensors	2021.8	44	67	668	10
Electronics	2021.7	47	60	458	8
Sustainability	2021.7	39	57	575	10
IEEE Transactions on Industrial Informatics	2021.4	56	47	2572	55
IEEE Network	2020.8	45	39	1039	27
IEEE Communications Surveys and Tutorials	2021.5	39	22	1379	63
International Journal of Information Management	2020.3	12	6	982	164
IEEE Open Journal of the Communications Society	2021.6	16	5	434	87
Journal of Industrial Information Integration	2021.6	14	5	412	82

Figure 9. For each time slice map, the involved keywords are clustered into different thematic areas or themes based on their co-occurrence relations while each thematic area is being 2D-visualized with specific label and size and being positioned based on its Callon centrality (X-axis) and Callon density (Y-axis) [81], [82]. The label refers to the most frequent keyword in the theme, while the size (circle diameter) is proportional to the total frequencies of all keywords in the theme. In contrast, Callon Centrality is a measure for the theme or thematic area's importance or relevance in the research field, while Callon Density is a measure for the thematic area's development status [40], [83]. Accordingly, the themes are classified into four different typologies as follows:

- Themes in the upper-right quadrant (motor themes) are recognized by high density and high centrality, which means that these themes are well-developed and important for the research field;
- Themes in the lower-right quadrant (basic themes) are recognized by low density and high centrality, which means that these themes are important for the research field and concern general topics that are related to different research areas in the field;
- Themes in the upper-left quadrant (niche themes) are recognized by high density and low centrality, which means that these themes are well-developed with limited importance for the research field.
- Themes in the lower-left quadrant (emerging or declining themes) are recognized by low centrality and low density, which means that these themes are either emerging or being marginal and weakly developed.

To highlight the main BT-AI research themes over time, it was decided to divide the temporal interval of extracted data into four time-slices. The full details for each time-slice including different themes and related keywords are provided in supplemental material.

- In the first time-slice (2017:2018) (Figure 9a), there were 41 published documents. The research front of these documents enclosed only two thematic areas as basic themes (agents/multi-agent systems and anomaly detection), one thematic area as motor theme (blockchain), and four thematic areas as declining or emerging themes (robotics, digitalization, digital currencies, and foresight).
- In the second time-slice (2019:2020) (Figure 9b), there were 437 published documents. Their research front enclosed three thematic areas as basic themes (blockchain, artificial intelligence, and digital currencies), two thematic areas as motor themes (reinforcement learning and security), one thematic areas as declining or emerging themes (financial technologies and artificial neural networks), and three thematic areas as niche themes (digitalization, sustainability, and distributed ledger technology).
- In the second time-slice (2021:2022) (Figure 9c), there were 1574 published documents. Their research front enclosed one thematic area as basic theme (artificial intelligence), two thematic areas as motor themes (blockchain and security), two thematic areas as declining or emerging themes (digitalization and artificial neural networks), and one thematic area as niche theme (digital currencies).
- In the second time-slice (2023) (Figure 9d), there were 563 published documents. Their research front enclosed two thematic areas as basic themes (artificial intelligence and machine learning), three thematic areas as motor themes (blockchain, reinforcement learning, federated learning), three thematic areas as declining or emerging themes (digital currencies, digital twin, and



(a) Overlay Visualization Based on NP and CL

(b) Overlay Visualization Based on CS and ACD

FIGURE 6. **Citation network for sources.**

industry 4.0), and two thematic areas as niche themes (bibliometric analysis and digitalization).

After analyzing each time-slice separately, the temporal evolution for associated BT-AI themes was traced. In Figure 10, a so-called Sankey diagram is utilized to present how the themes were linked and developed through the sequential time-slices. The different themes shown in Figure 10 were scaled using the inclusion index [84], while considering the keywords' frequencies for each theme per time-slice. BT-AI research was originally established in 2017-2018 by researchers interested in blockchain technology in tandem with digital currencies, digitalization and anomaly detection whereas in 2019-2020, the attention was more focused on blockchain technology, digital currencies, and digitalization besides artificial intelligence, reinforcement learning, artificial neural networks, distributed ledger technology, and security. Later in 2021-2022, blockchain technology, digitalization, digital currencies, security, artificial intelligence, and artificial neural networks kept occupying the researchers' focus. In contrast, in 2023, blockchain technology, digitalization, digital currencies, artificial intelligence kept occupying the researchers' focus while new themes surfaced; machine learning as a basic theme, federated learning as a motor theme, reinforcement learning as a motor theme, and industry 4.0 as an emerging theme. Accordingly, the 2023 themes can be collectively referenced as the recent or promising research trends for further development and exploration. These themes were deeply illustrated as follows:

- Thematic area #1 was labeled as machine learning while it refers to the BT-AI applications coupled with deep learning, smart contracts, artificial neural networks, cybersecurity, and long short term memory.
- Thematic area #2 were related to digital currencies prices prediction especially for bitcoin and ethereum using time series analysis.
- Thematic area #3 was labeled as federated learning while it refers to the BT-AI applications coupled with privacy, servers, data models, training, privacy preservation, cloud computing, computational modeling, internet of medical things, healthcare, and medical services.
- Thematic area #4 was labeled as artificial intelligence while it refers to the BT-AI applications coupled with covid-19, big data, and supply chain management.
- Thematic area #5 was labeled as blockchain while it refers to the BT-AI applications coupled with internet of things, security, edge computing, convolutional neural networks, peer-to-peer computing, 5g, task analysis, 6g, privacy protection, smart healthcare, consensus algorithms, interplanetary file system, intrusion detection system, scalability, and software-defined networking.
- Thematic area #6 was labeled as reinforcement learning while it refers to the BT-AI applications coupled with industrial internet of things, mobile edge computing, resource management, internet of vehicles, optimization, and drones.
- Thematic area #7 and thematic area #8 were related to industry 4, digitalization, digital technologies, and sustainability applications.

VI. DISCUSSION

A. KEY FINDINGS

This study provides a scientometric analysis to explore and visualize the development track and trends for BT-AI research. The key findings from the analysis address

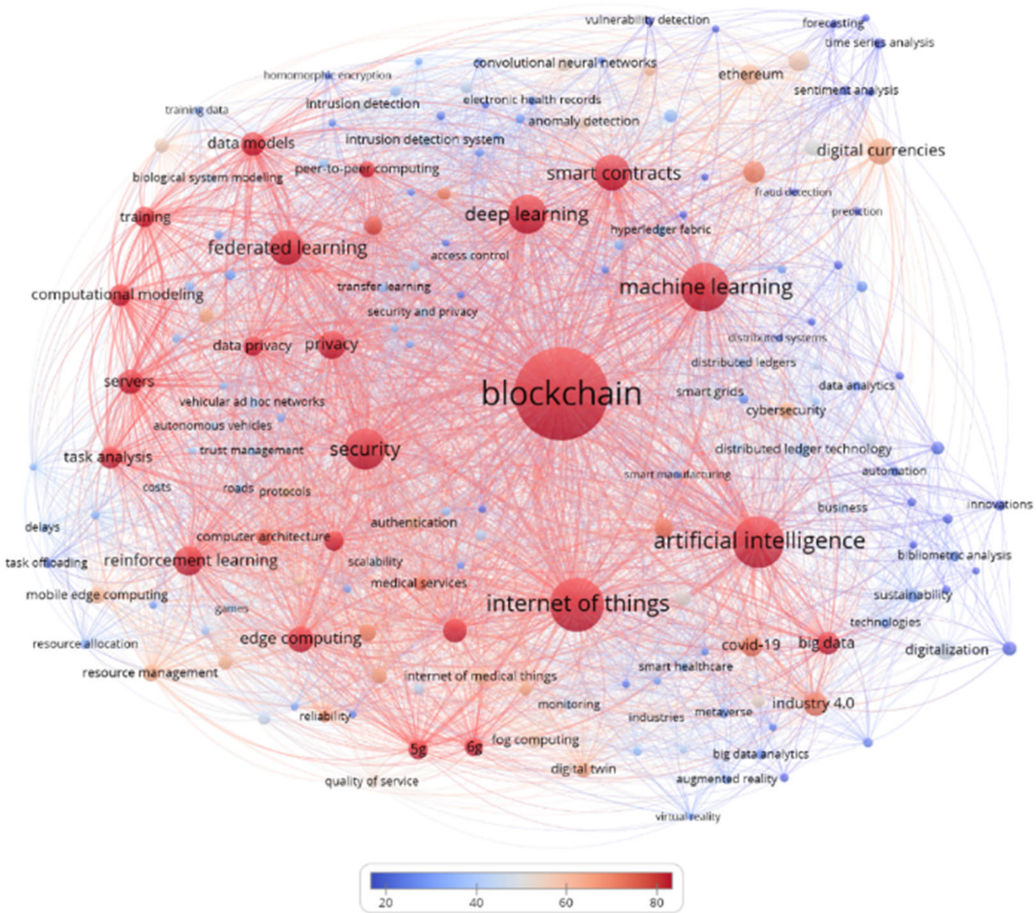


FIGURE 7. Co-occurrence network for keywords.

the aforementioned research objectives and are presented in this section. Through the publication outputs analysis, the numbers of annual publications showed a growing nature, indicating that the BT-AI field stands out as a promising interdisciplinary research area.

Through the co-authorship analysis of researchers, less than 2 % of researchers (n = 126/8466) were credited on at least five BT-AI documents with minimum citations score and TSL of 50, and 1 respectively. This might point out that many new researchers were just stepping inside the BT-AI research domain. Sudeep Tanwar was identified as the most productive researcher with 46 documents while Dusit Niyato was the most collaborated researcher with 25 collaboration links. In contrast, Yan Zhang was the most cited researcher with 1459 citations, while Sabita Maharjan had the highest ACD with 140 citations per document.

According to the co-authorship analysis of countries, China, USA and India were the superior countries in the BT-AI research in terms of the number of publications, the extent of collaboration, and the total citations score. At the same time, Denmark, New Zealand, Scotland, Wales, and Sweden had the highest ACD score with $\geq$ 40 citations per document. Based on the co-authorship analysis of organizations, it was noticed that research on BT-AI gained considerable attention from the 3221 organizations. However, most of them are still in the primary exploration phases, with only 226 organizations being credited on at least five documents with minimum citations score and TSL of 50, and 1 respectively. King Saud University and University of Electronic Science and Technology of China were identified as the most productive cited organizations. In contrast, Nanyang Technological University, Xidian University in tandem with King Saud University were identified as the top organizations regarding the extent of collaboration. At the same time, Simula Metropolitan Center for Digital Engineering in Norway had the highest ACD score with > 130 citations per document. Further, it was observed that three organizations among the leading organizations listed in Table 5 were located in China, which points out China's emphasis on the BT-AI research domain.

Concerning the citation analysis of sources, IEEE Access, IEEE Internet of Things Journal, Sensors, Electronics, and Sustainability were identified as the top productive sources. Additionally, two of these sources (IEEE Access, IEEE Internet of Things Journal) besides IEEE Transactions on Industrial Informatics, IEEE Communications Surveys and

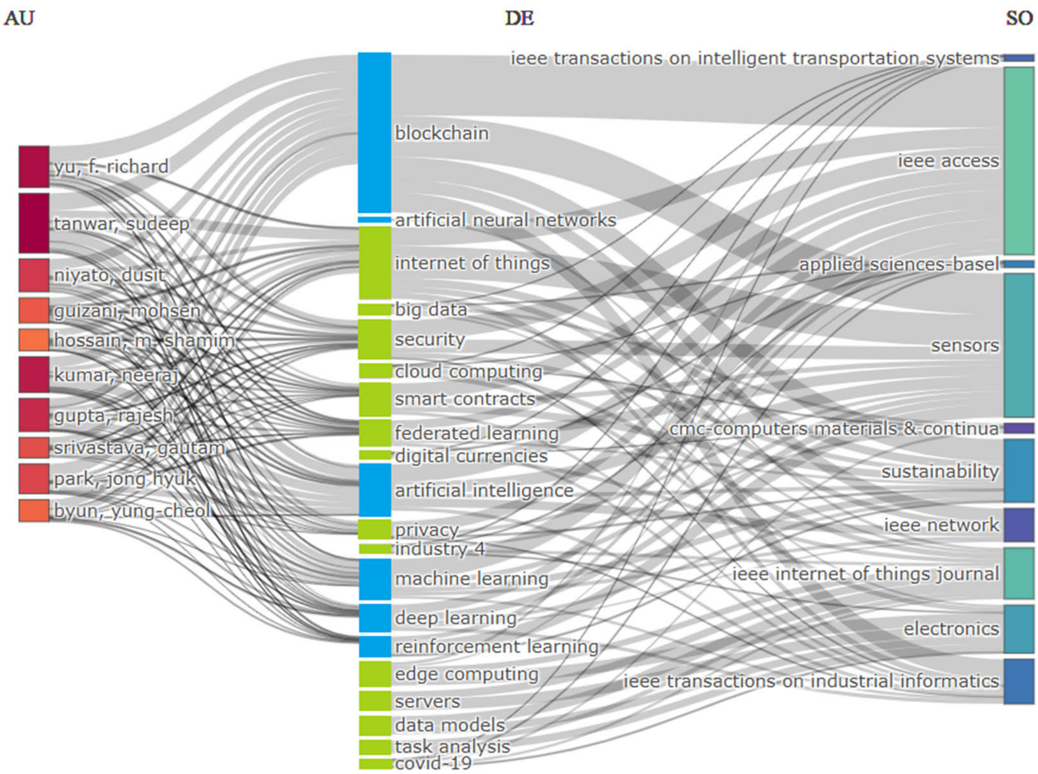


FIGURE 8. Three field plot for sources-keywords-authors.

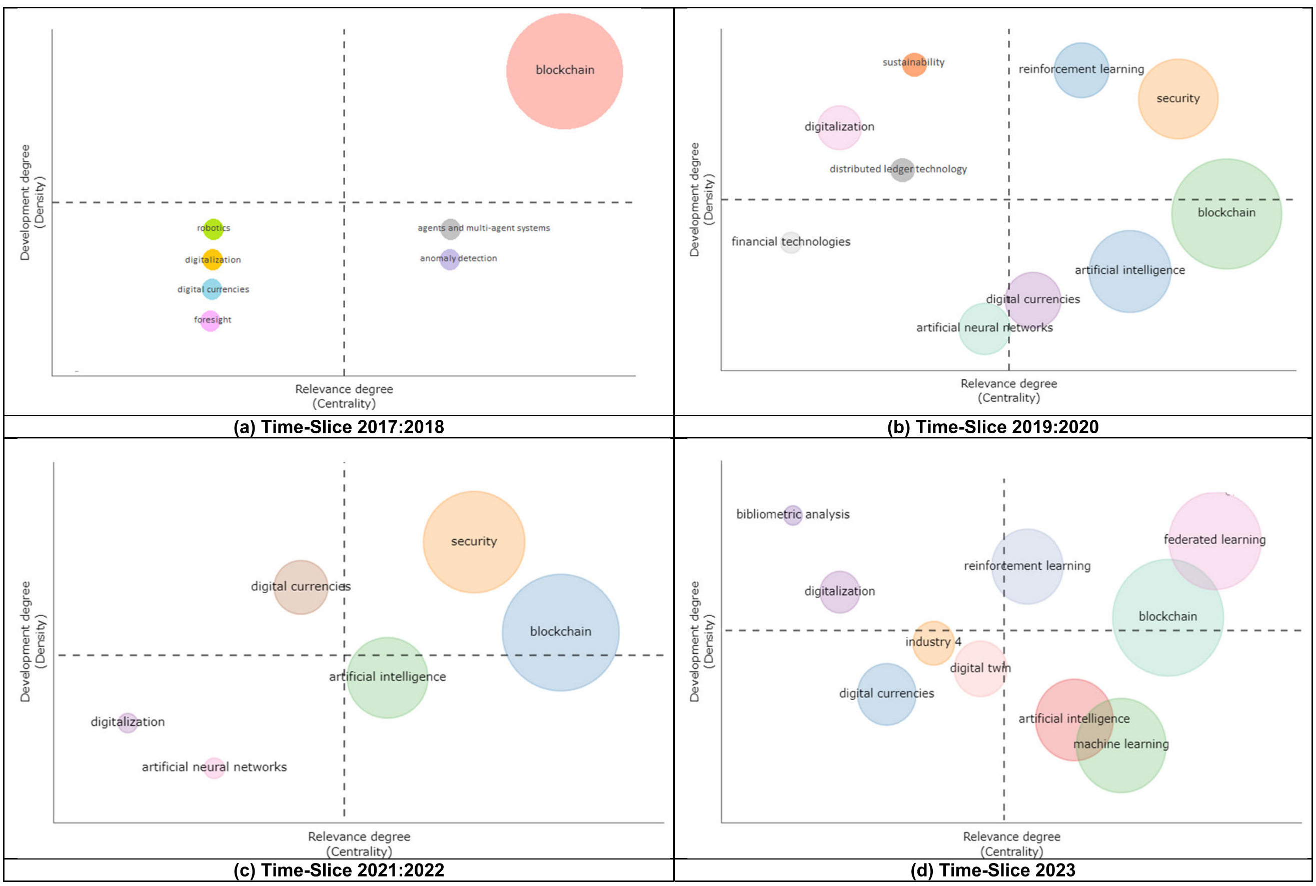


FIGURE 9. Keywords' themes.

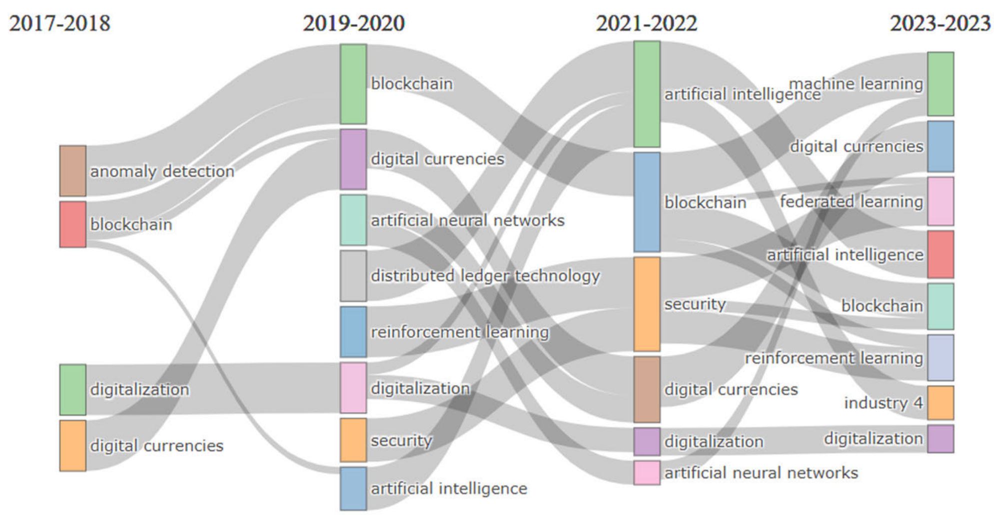


FIGURE 10. Sankey diagram for associated themes' evolution.

Tutorials, and IEEE Network were identified as the most influential sources. This indicates to some extent that a minority of highly productive sources have a significant influence on BT-AI research. However, a few sources (International Journal of Information Management, IEEE Open Journal of the Communications Society, and Journal of Industrial Information Integration) without publishing many documents still have high influence in terms of ACD score. With regard to the keywords co-occurrence analysis, the hot research topics that occupied the interest of the BT-AI research community were mainly distributed among: internet of things', 'security', 'smart contracts', 'federated learning', 'privacy', 'edge computing', 'digital currencies', 'servers', 'industry 4.0', 'cloud computing', 'data models', 'big data', 'covid-19', 'task analysis', 'computational modeling', 'training, data privacy', and '5g' without including the keywords used in data extraction. Furthermore, the keywords temporal evolution and distribution were evaluated, and the recent dominant and arising research trends were captured in terms of basic and motor themes as per year 2023 in Figures 9e and 10.

TABLE 6. Top keywords in BT-AI field.

Keyword	APY	Frequency	CL
Blockchain	2021.5	1459	173
Internet of Things	2021.6	487	160
Artificial Intelligence	2021.4	462	153
Machine Learning	2021.5	400	161
Security	2021.8	284	153
Deep Learning	2021.7	260	141
Smart Contracts	2021.5	214	139
Federated Learning	2022.0	205	117
Reinforcement Learning	2021.6	148	113
Privacy	2021.8	136	127
Edge Computing	2021.4	118	112
Digital Currencies	2021.5	111	64
Servers	2021.6	104	110
Industry 4.0	2021.5	97	72
Cloud Computing	2021.5	95	114
Data Models	2021.7	94	113
Big Data	2021.3	86	84
Covid-19	2021.8	84	71
Task Analysis	2021.6	83	104
Artificial Neural Networks	2021.4	80	70

B. CONTRIBUTIONS AND IMPLICATIONS

The scientometric analysis in this study is an exploratory effort to visualize the basic characteristics of BT-AI literature. The study's findings afford valuable information for different stakeholders to secure an in-depth understanding of BT-AI research. The quantitative analysis of BT-AI literature has reduced the effect of subjective judgments associated with manual reviews or qualitative appraisals of literature while enhancing the results' objectivity and reliability. The analyses' network maps and information tables that were provided show the status of the BT-AI domain more comprehensively compared to the extant research studies and reviews. These maps and tables can be utilized to help new researchers, universities, and editorial boards to identify and focus on the promising BT-AI research trends for further exploration and development.

C. LIMITATIONS AND FUTURE WORKS

Some limitations associated with the current study should be noted. Firstly, the scope of research was confined to English peer-reviewed articles collected from the WoS database. Secondly, this paper highlighted the main hotspots and frontiers of the BT-AI research based on the articles' abstracts, keywords, and titles without examining their core contents. Thirdly, concerning VOSviewer, CiteSpace, and Biblioshiny, the analyses' results may vary slightly when the researcher uses different parameter settings. Hence, this work can be evolved in the future by performing an in-depth content analysis combined with a scientometric analysis using publications from multiple databases (e.g., WoS, Scopus, and

Google Scholar) to provide extra insights and expand the findings herein.

VII. CONCLUSION

The current study presents a scientometric analysis for the BT-AI literature using a three-stage methodology. First, 2615 publications were identified between 2017 and 2023 and extracted for analysis using the WoS Core Collection database. Second, the analysis methods were specified to include co-authorship analysis, citation analysis, keyword co-occurrence analysis, and keyword thematic evolution, while VOSviewer and Biblioshiny were selected as the software tools. Third, the analysis was performed based on the following sequence; 1) evaluating the publication output and specifying the influential research works; 2) investigating the collaboration networks of researchers, countries, and organizations in BT-AI research; 3) evaluating the sources' productivity and citation; and 4) exploring and analyzing the knowledge structures of BT-AI literature. The analysis findings can be employed to further familiarize new researchers with the BT-AI literature while guiding practitioners, policy-makers, and editorial boards to focus on the promising and emerging research topics for more exploration.

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